Essays on Volatility Forecasting, Conditional Correlations and Uncertainty Shocks: Evidence from the Non-Ferrous Metals Market

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Table of Contents

Abstract

This thesis comprises three interconnected topics within the area of finance, contributing to our understanding of volatility by applying novel techniques to forecast and model volatility within the non ferrous metals commodity market, providing valuable insight into their potential usage by industrial users, financial institutions and policy makers for hedging strategies, portfolio diversification, and risk management purposes.

Chapter 2 compares the forecasting performance of univariate GARCH models, the GARCH-MIDAS model of Engle, Ghysels and Sohn (2013) with trading volume as a long run component of volatility and the Generalised Autoregressive Score (GAS) model of Creal et al. (2013). We find the standard GARCH model following students-t distribution produces the most accurate forecasts, with trading volume as a predictor variable not able to improve forecasting accuracy. Further VaR analysis corroborates our findings from the MCS test that the standard GARCH model is the most favourable model.

In the third chapter, we use various multivariate GARCH models to assess conditional correlations of non ferrous metals with gold, brent crude and the S&P500 index, with likelihood ratio test conducted to select best fitting model to assess hedging effectiveness. Findings highlight that all metals show spikes in conditional correlation for all models in crisis periods, with strong reversals following a crisis period. Results from further wavelet analysis showcase evidence of low comovements between metals at the low frequency horizon.

In chapter 4, we explore the effects of geopolitical risk and UK policy uncertainty on non ferrous metals using VAR, SVAR and the TVP-VAR-SV model of Nakajima (2011). Impulse responses at different time horizons produced by selected VAR models exhibit properties of higher non ferrous metal volatility in response to GPR and UK policy uncertainty shocks at short time horizons and during major geopolitical events, although these effects diminish at longer horizons.

Chapter 1: Introduction

Volatility modelling and forecasting of financial assets, especially energy commodities such as crude oil, natural gas and various other types of commodities, has become an important widely researched area within finance. The volatility of commodities is of great importance to both industry professionals and academics, due to its wide ranging uses and consequences. Typically, forecasts are used in risk management, derivatives pricing and hedging, market making, market timing, portfolio selection and many other financial activities (Engle and Patton, 2007). Commodity and options traders will want to know the volatility of assets to correctly hedge their position to account for the future volatility of their asset. Additionally, fund and portfolio managers will want to know when to sell an asset within their portfolio before it becomes too volatile, so they can sell or buy an asset to maintain beta neutral portfolios to minimize exposure to risk. It is also important for bulk buyers and industrial users of commodities, who will want to know the future volatility of a commodity to be able to buy their commodity at the best possible price.

Non ferrous metals are an important class of commodity not only due to their increasing usage in portfolio selection and risk management purposes, but also due to their wide usage in industrial applications. Non ferrous metals, which are metals that are not iron based alloys, are typically more expensive than ferrous metals and have widespread usage in residential, commercial and industrial applications due to their superior properties, such as high electrical conductivity (copper), lightweight and malleability (aluminium), corrosion resistance (tin and nickel), and high melting point (zinc) etc. (Shu et al. 2023). As important raw materials for the production of clean energy, increasing prices of non ferrous metals will push up the production costs of clean energy, and the increasing demand for the production of clean energy enterprises and their usage in the aviation industry prompts the increasing demand for non ferrous metals which may result in huge swings in external markets (Gustafsson et al. 2021). In addition to their usage for industrial and consumer applications, non ferrous metals are widely traded financial instruments with various properties that make them unique for hedging and portfolio diversification purposes. According to the futures industry association (FIA), non ferrous metals such as copper and aluminium are some of the most widely traded commodities, with purchase costs of non ferrous metals accounting for almost 60% of total costs in production and processing enterprises (Sharma et al, 2015) thus the price stability of non ferrous metals is essential to the maintenance of stable growth in industries and economy (Zhu et al. 2017; Qu et al. 2019; Ciner et al. 2020; Zhu et al. 2021). Moreover, metals have proven their ability to be used as alternative investment instruments because of their weak integration within and among financial markets, with metals such as gold serving as an effective diversifier, hedge and safe haven asset for financial markets (Baur and Lucey, 2010; Sumner et al. 2010; Mensi et al. 2021). However, despite their importance for industrial, economic and academic purposes, scarce literature exists regarding non ferrous metals (Mensi et al. 2021), with only 45 such studies being produced during the period 1980-2002 (Todorova et al. 2014), with copper and zinc receiving limited attention in the literature, although together with aluminium, they represent more than 85% of annual global non ferrous metal production (Boulamanti and Moya, 2016; ECORYS, 2011).

This thesis aims to contribute to the literature of volatility modelling by using novel techniques to investigate areas such as volatility forecasting, conditional correlations and the effects of uncertainty shocks and policy shocks, within the non ferrous metals market. Chapter 2 explores the forecasting performance of various univariate generalized autoregressive conditional heteroskedasticity (GARCH) type models and the Generalized Autoregressive Score (GAS) model with regards to non ferrous metals. This chapter adds to the scarce literature regarding volatility forecasting of non ferrous metals by incorporating the GAS model of Creal et al. (2013), of which little literature exists regarding its forecasting performance in commodity markets. We also follow the approach of Liu et al. (2022), whereby trading volume is used as a macroeconomic predictor variable for the GARCH-MIDAS model of Engle, Ghysels and Sohn (2013) to explore whether trading volume can be used to improve volatility forecasts. In our findings, following evaluation of various functions and the MCS procedure of Hansen (2011) to assess forecasting performance, the standard GARCH model following a students-t distribution performs best when forecasting non ferrous metal returns. To validate the results of the MCS procedure, we conduct further value at risk (VaR) backtesting using the Kupiec (1995) and Christoffersen (1998) procedures, which confirm our findings that the standard GARCH model produced better forecasting accuracy than competing models.

Chapter 3 has a focus on conditional correlations and dynamic linkages between non ferrous metals and other widely traded financial commodities and instruments, namely gold, Brent crude oil and the S&P500 index. When diversifying a financial portfolio or hedging a position, investors look to different commodities or financial instruments with differing correlations, to offset potential downturns in commodity prices. We incorporate the use of multivariate GARCH and DCC-MIDAS model to model conditional correlations and potential volatility spillover effects between non ferrous metals and gold, brent crude and the S&P500 index representing two widely traded commodities and one of the most influential stock indexes globally. In our results, we strong correlations between gold and copper for all models in periods of low correlation with brent crude and the S&P500, with similar properties for aluminium, with slightly less variance in conditional correlations, with stronger correlations for nickel. Results from likelihood ratio test indicate that DCC-MIDAS model is the best performing model, with BEKK-GARCH producing the lowest goodness of fit, which is likely due to overparameterization of the model. As the best performing model, we compute dynamic optimal hedge ratio to showcase how non ferrous metals can be used in a hedging strategy in conjunction with different commodities. This chapter aims to contribute to the literature of non ferrous metals by using various multivariate GARCH models and the DCC-MIDAS model to showcase conditional correlations between non ferrous metals and various widely traded commodities, and how they can potentially be implemented in hedging strategies. Furthermore, the use of wavelet analysis in this chapter allows for conditional correlations to be showcased in both the time and frequency horizon, the results of which exhibit weak correlations for all metals with gold, brent crude and the S&P500 index and the low frequency horizon, indicating weak correlation in the short term.

Finally, in chapter 4, we explore whether geopolitical risk (GPR) and policy uncertainty plays any role in non ferrous metal returns. Non ferrous metals are a widely used naturally occurring industrial resource, meaning they are vulnerable to geopolitical uncertainty. Caldara and Iacoviello (2022) define geopolitical risk as “the risks associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations”. The 21st century has seen major geopolitical events such as the September 11th attacks in 2001, the 2008 financial crisis, the 2020 COVID pandemic and the escalation of the Russia-Ukraine conflict in 2022 etc. have profound impacts on stock and commodity markets globally. Political uncertainty additionally contributes to supply and cost of commodities, with the 2016 Brexit referendum in the United Kingdom to exit from the European union having immediate adverse effects on the liquidity of non US stocks, particularly from the UK and EU (Kim, Mazumder and Su, 2024) and the recent announcement of US trade tariffs imposed on Canadian, Mexican and Chinese imports following the reelection and inauguration of Donald Trump as US president in 2025 increasing importing costs in order to encourage domestic growth resulting in European futures declining by as much as 3.4%[1]. To assess the impacts of geopolitical risks and policy uncertainty on non ferrous metals markets, we use a vector autoregressive model (VAR), structural vector autoregressive model (SVAR) and the time varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) approach of Nakajima (2011). Following impulse response analysis of VAR and SVAR models, GPR shocks and UK policy shocks have significant positive and negative effects on non ferrous metal returns in the short run, with these effects diminishing over longer time horizons. The TVP-VAR-SV model showcases impulse responses at different time horizons, in which non ferrous metals are sensitive to major geopolitical shocks and policy shocks in the short run, although in our findings, these effects are not persistent in longer period horizons, indicating that effects of shocks dissipate at longer time horizons. To our knowledge, little literature exists regarding the sensitivity of non ferrous metals to geopolitical uncertainty and policy shocks at the daily frequency, in chapter 4 aims to address.

[1] https://www.theguardian.com/business/2025/feb/03/asian-sharemarkets-tumble-in-response-to-trump-tariffs

Chapter 2. Volatility Forecasting and VaR Estimation of non-ferrous Metals. A GARCH and GAS approach

Abstract

We use a combination of Generalised Autoregressive Conditional Heteroskedasticity (GARCH) and Generalised Autoregressive Score (GAS) models to produce volatility forecasts and Value at Risk (VaR) forecasts for 5 different non-ferrous metals traded on the London Metal Exchange (LME) using daily spot price data. Out of sample forecasting performance is evaluated using five different loss function and the MCS procedure ranking models based on their forecasting performance. Additional VaR evaluation is conducted using the Kupier (1995) and Christoffersen (1998) tests of unconditional and conditional coverage. Our results show that, on average, the standard GARCH model is not outperformed by other types of GARCH and GAS models when forecasting metal returns, with the EGARCH, GJR-GARCH and GAS models following a students-t distribution also providing satisfactory forecasting performance and outperforming corresponding models following a normal distribution and the GARCH-MIDAS model. We find the addition of trading volume as an explanatory variable does not improve forecasting accuracy when sampled at the monthly frequency.

2.1 Introduction

The estimation and forecasting of volatility, particularly for financial assets, has become a vast area of research in many different areas such as risk and portfolio management, derivatives pricing and investment analysis, with Poon and Granger (2003) suggesting that volatility forecasts are a 'barometer for the vulnerability of financial markets and the economy'. Modelling and forecasting of volatility plays an important role in econometric models and portfolio selections, however, the exploration of volatility modelling in the non-ferrous metals market is a rather understudied area within the topic of finance, with only 45 such studies being produced during the period 1980-2002 (Todorova et al. 2014).

Non-ferrous metals are metals that do not contain a significant amount of iron in their chemical composition. Important nonferrous metals produced in large quantities include aluminium, copper, zinc, lead, nickel and tin and their alloys – these are widely used in the industries of construction, batteries, electronics, mobility and in other advanced specification and high technology goods.[2] Due to their wide industrial applications and demand in emerging economies, non-ferrous metal futures have become an essential component in futures markets, with investment firms, banks, speculators and other market participants showing an increased interest in these commodities in recent years. In contrast to other commodities and financial derivatives, non-ferrous metals prices are influenced by a wide range of factors, such as exchange rate fluctuations, import and export policies and funds' short term and long-term trading strategies, which makes them more volatile than other classes of assets (Wang et al. 2020). Value at Risk (VaR) is a popular measure to evaluate the market risk of a portfolio, identifying whether the loss that is likely to be exceeded by a specified probability that ranges between 0.95 and 0.99 over a defined period (Jiang, Hu and Yu, 2022).

[2] https://www.sciencedirect.com/topics/engineering/non-ferrous-metal

Many previous empirical works regarding volatility forecasting are conducted using stock market data or commodities such as crude oil (Lv, 2018; Zhang et al. 2019 Li et al. 2022) and other agricultural futures (Luo et al. 2022; Degiannakis et al. 2022) and despite the important role non-ferrous metals play in both industry and academia, limited research has been done on the forecasting of non-ferrous metals. The Covid-19 pandemic has also resulted in unprecedented economic upheaval and disruption in all areas of the economy, with the very large downturn and subsequent rebound of financial markets resulting in periods of high volatility.

In this first chapter, we discuss the in-sample estimation results and compare the out of sample volatility forecasting performance of GARCH and GAS type models using copper, aluminium, zinc, tin and lead returns data, providing comprehensive coverage of non-ferrous metals traded on the London Metal Exchange. Model forecasting performance is examined using relevant loss functions, with the Model Confidence Set (MCS) test of Hansen et al. (2011) used to rank models based on out of sample volatility forecasting performance. Value-at-Risk evaluation is conducted using the Kupiec (1995) test of unconditional coverage and the Christoffersen (1998) test of conditional coverage to assess the suitability of each model in a risk management setting. This first chapter departs from previous studies in that we include the use of spot returns data to model non-ferrous metal returns. Previous works studying the volatility of non-ferrous metals have used futures returns data to model non-ferrous metals and, to our knowledge, no such attempt has been made to model and forecast non-ferrous metals using LME spot price data, despite the important role that spot prices play in options and futures pricing. Additionally, little existing literature on modelling Value-at-Risk in non-ferrous metals markets using GARCH-MIDAS and Generalized Autoregressive Score models. This first chapter aims to add to the scarce literature surrounding non-ferrous metals and contribute to the new wave of research brought about by the challenges and constraints caused by the Covid-19 pandemic, necessitating a need for new research.

2.2 Literature Review

2.2.1 Measures of Volatility:

Measuring and forecasting volatility has many important applications in many areas of finance including asset allocation, option pricing and risk management (Brownlees and Gallo, 2010). Of the various different methods used to measure volatility, the most straightforward method is historical volatility calculation, which is well known as the standard deviation of a data series. However, it is only real use is in foundational financial issues because of its fixed indicators and unpredictable nature. As volatility changes over time, historical volatility calculation is not the optimal method to accurately forecast volatility. A paper by Martens and Zein (2002) indicated that historical, high-frequency data used by a GARCH model has superior forecasting ability than the implied volatility index.

Alternatively, implied volatility is also broadly applied in research and the Volatility Index (VIX) is commonly used to measure expectations of volatility. Well known as a "fear index" (Whaley, 2000) for asset markets, it reflects both stock market uncertainty (the "physical" expected volatility), and a variance risk premium, which is also the expected risk premium from selling stock market variance in a swap contract (Bekaert and Hoerova, 2014). Although the VIX is a good indicator of expected volatility, previous literature has shown that this accuracy of implied volatility can be outperformed by empirical models. Martens and Zein (2002) showed that high frequency data, used with a GARCH model was able to produce better forecasts of volatility than implied volatilities. When compared with implied volatility, GARCH models are better at producing accurate predictive forecasts. This is illustrated by Agnolucci (2009), who states that this might be due to volatility persistence.

Realised volatility is another measure of volatility that is broadly used in the prediction of volatility. Since Andersen and Bollerslev (1998) showcased a strong improvement in volatility forecasting performance of daily GARCH models by using 5 min data as a volatility measure, several studies have found evidence that implied volatility is a biased an inefficient predictor of realised volatility (Becker et al. 2006, Neely 2005). Similar findings were also reported by Szakmary et al. (2003), who looks at evidence from 35 futures markets for the information content of implied volatility. Overall, they note that implied volatility holds no significant information, with realised volatility providing a benchmark for comparing the performance of historical and implied volatility. Similarly, Koopman et al. (2005) used historical, realised and implied volatility measurements to forecast variability of the S&P 100 stock index. Their results show that the realised volatility model produced vastly more accurate forecasts compared to models based on daily returns, with the ARFIMA-RV model producing the most accurate forecasts of all models employed. Corsi (2009) proposes a Heterogeneous Autoregressive model of realised volatility (HAR-RV), which is able to model long-memory properties and fat tails in a very parsimonious way and argued that it outperformed short-memory models at daily, weekly and bi-weekly time horizons when forecasting the volatilities of the S&P 500, USD/CHF exchange rate and T-bond.

2.2.2 Previous Research on GARCH-type models and Alternative Volatility Models:

The family of GARCH type models have been widely used in the literature to estimate the volatility and performance of financial assets. It is important to start with the autoregressive moving average model (ARMA), which holds the stationary property, which can be defined such as the variances are constant and uncorrelated with time (Diebold, Killian and Nerlove, 2010). These models perform well when modelling stationary time series with constant volatility, however, issues arise when using time series processes such as financial time series whereby the variances for this kind of data are time varying, so the stationary property of the ARMA model is no longer valid. The seminal paper of Engle (1982) would break new ground in regards to volatility modelling, who explored the variance of United Kingdom inflation. Engle (1982) captured the changing variance of UK inflation by introducing the autoregressive conditional heteroskedasticity model (ARCH), allowing for conditional variance to change over time as a function of past errors. Since this seminal paper, many other adaptations of the ARCH process have been developed and proposed. Bollerslev (1986) would develop upon the ARCH process by introducing a model that also allows for past variances as well as past error terms, coining it as a generalised ARCH model (GARCH).

Following Bollerslev (1986), a large number of extending models based on linear GARCH models have been proposed, such as non-linear GARCH models and non-parametric GARCH models. The non-linear EGARCH model by Nelson (1991) and the GJR-GARCH model proposed by Glosten, Jagannathan and Runkle (1993) captures volatility clustering like the GARCH model, but also includes the leverage effect, which refers to the impact or the type or nature of news on stock prices. Previous literature has documented that bad or negative news results in greater levels of volatility than good or positive news (Mandelbrot 1963). Leverage effect can also be defined as an increase in debt-to-equity ratio because of a fall in stock prices due to the effect of negative news, resulting in increased volatility

(Fisher 1976). The CGARCH model proposed by Engle and Lee (1999) considers short and long run volatility effects in a very similar manner to the decomposition of conditional mean models for economic time series introduced by Beveridge and Nelson (1981). Alternatively, the long memory nature of the FIGARCH model of Baillie et al. (1996) allows for greater flexibility in modelling the conditional variance, which allows it to be better suited to modelling volatility for stock returns, exchange rates and inflation rates. GARCH in mean adds a heteroskedasticity term into the equation. Selcuk (2005) found that change in volatility is much more significant after a fall in stock prices compared to an increase in stock prices due to shocks.

Previous empirical studies comparing the performance of linear and non-linear GARCH models in stock markets have provided contrasting results towards standard GARCH. Despite the success of the linear GARCH model, it cannot capture asymmetry and skewness of the stock market returns series (Gokcan 2000). Franses and Van Dijk (1996) compare the performance of the GARCH model and two of its non-linear counterparts, namely QGARCH and GJR-GARCH, to forecast weekly stock market volatility in Germany, Netherlands, Spain, Italy and Sweden. They found that QGARCH model can significantly improve on the linear GARCH model in cases where the forecasting models are calibrated on data which includes extreme events such as the 1987 stock market crash, although they cannot recommend the GJR-GARCH model. Chong et al. (1999) found that nonlinear EGARCH models outperformed the linear GARCH (1,1) model when observing 5 daily stock indices from the Kuala Lumpur stock exchange, with the integrated GARCH model performing the worst out of all models used. Similarly, Gokcan (2000) extends the works of Franses and Van Dijk (1996) compares the forecasting ability of linear and non-linear GARCH models in seven emerging markets, instead comparing the EGARCH model with the linear GARCH model. In contrast to the findings of Franses and Van Dijk (1996), he notes that even if returns series are significantly skewed, linear GARCH models were very helpful in explaining the volatility of the time series, with the linear model also produced better estimates than the non linear GARCH model for all countries in the sample. This was also the case for out of sample monthly volatility estimates. Alternatively, Ederington and Guan (2005) couldn't state choose between the GARCH or EGARCH model when modelling the S&P 500 index, JPY/USD exchange rate, three month Eurodollar rate, 10 year treasury bond rate and five equities from the Dow Jones industrial index. Lin (2018) examined the performance of four classes of GARCH models in modelling volatility of the SSE Composite Index. She found that the EGARCH model performed best in comparison to the linear GARCH model and the TARCH 1,1 model of Zakoian (1990) and Glosten et al. (1993). However, findings from Sharma et al. (2020) provide alternative findings to those of Lin (2018), concluding that the GARCH 1,1 model was superior to alternative non-linear GARCH models in modelling volatility in 5 major emerging economies, including China. They believe this is due to the leverage effect being insignificant.

More recent literature has also explored the performance of non-linear GARCH models in futures markets. Moshiri and Foroutan (2006) forecast nonlinear crude oil futures prices dating from 1983 to 2002 using ARIMA and GARCH models. Their results support previous findings that crude oil futures reported in NYMEX follow a nonlinear dynamic process. Kang et al. (2009) investigate the efficacy of four classes of GARCH model in modelling the volatility for three crude oil markets: Brent, West Texas Intermediate (WTI) and Dubai. All models used were found to fit the crude oil data well, however, for out of sample estimates, the FIGARCH model was superior to the other models for all three-time horizons from 1 day to 1 month, stating that CGARCH and FIGARCH models provide the best choice when providing forecasts, at least for crude oil. A similar such study was also conducted by Wei et al. (2010), who compare the performance of linear and non-linear models to capture the volatility of two crude oil markets, Brent and WTI. Unlike the findings from Kang et al. (2009), they find that no model can outperform all of the models for either Brent or the WTI market, although also go on to state that the nonlinear models do perform better than the linear ones in long-run volatility forecasting of crude oil prices. Further extending previous studies on oil futures, Arouri et al. (2012) investigate the relevance of structural breaks and long memory modelling and forecasting conditional volatility of spot and futures prices using a variety of GARCH class models, using WTI crude oil, gasoline and heating oil spot and futures prices covering the period January 2nd 1986 to march 15th 2011 . Referring to their empirical results, the standard GARCH 1,1 model successfully captured time-varying patterns of conditional volatility when conducting in-sample analysis. Long memory tests showed all series exhibited strong evidence of long-memory pattern as the null hypothesis of no persistence was rejected at the 1% level, and taking into account structural breaks, the FIGARCH model provided the most accurate forecasts. These findings contrast those of Sadorsky (2006)'s findings that standard linear GARCH models are superior than more complex bivariate GARCH models. Applying nonlinear models to a different market, Lv and Shan (2013) investigate the use of linear and nonlinear models in the natural gas market. They point out three differing conclusions: firstly, when forecasting price volatilities of 1 month spot and futures contracts, their evidence shows that in this regard, neither of the models could outperform others across different criteria of loss functions. Secondly, they note that during periods of contango, linear GARCH class models seemed to outperform nonlinear models, whereas nonlinear models are the better choice during periods of backwardation. Thirdly, simple linear GARCH class models overwhelmingly outperformed nonlinear models in forecasting spot price accuracy, however, nonlinear models are superior to linear models under some loss criteria in forecasting futures price volatility. Efimova and Serletis (2014) Aim to contribute to literature by filling gaps in univariate GARCH modelling of energy commodity volatility, noting lack of studies since 2005, and use of both univariate and multivariate models over same data set to compare performance of models. Using daily US data for crude oil, natural gas and electricity wholesale prices between January 2nd 2001 to April 26 2013, both models were found to produce similar estimates, although univariate models produced more accurate forecasts, suggesting future studies on electricity volatility using variables such as wind speed data in key producing regions. In a novel approach, Lin et al. (2020) propose a model combining long-memory GARCH-M models with wavelet analysis to evaluate crude oil returns, with the proposed hybrid forecasting model achieving robust and significant forecasts during periods of extreme volatility. Multivariate GARCH models incorporating long memory were found to outperform short memory models in forecasting conditional covariance matrix and associated risk magnitudes in crude oil and refined oil products (Marchese et al. 2020). Modifying GARCH innovations with polynomially adjusted distributions was found to improve the precision of out of sample forecasts when modelling the returns of four different types of financial assets (Vacca et al. 2022).

Naturally, questions have arisen as to what models provide the best volatility forecasts. As an alternative to conditional volatility, time-varying volatility can also be estimated by using a stochastic volatility model (Taylor 1982, 1986), who proposes to model the logarithm of volatility as an AR(1) process. Stochastic volatility models treat variance as an unobserved component that follows a particular stochastic process (Sadorsky, 2005). Stochastic volatility models are also attractive as they are close to the models that are often used in financial theory to represent the behaviour of financial prices (Broto and Ruiz 2004). The stochastic volatility model can be estimated by using Markov Chain Monte Carlo (MCMC) methods in the context of Bayesian inference. A stochastic volatility model was used by Melino and Turnbull (1990) in pricing foreign currency options and add that the model showed optimal forecasting ability. Likewise, Benzoni (2002) used two stochastic volatility diffusion models to evaluate the properties of S&P 500 returns and found that it greatly improves the performance of the option pricing model by reducing option pricing errors. More recently, Ozturk and Richard (2015) applied a stochastic volatility model with leverage effects to analyse the return properties 24 companies from 6 different industries listed on the S&P 500. It points out that although financial and energy industrial performed differently from other industries, it still demonstrates that there are connections between markets. Stochastic volatility models have also been applied in conjunction with GARCH models to estimate S&P 500 daily returns and USD/CAD exchange rates, although the GARCH model was indicated to be the better model (Gerlach and Tuyl, 2006). In an earlier such study using data from the FTSE 100 stock index suggests that the performance of the GARCH 1,1 and EGARCH 1,1 performed better than the SV model in out-of-sample comparisons, although the performance of the SV model could be dramatically improved by using more sophisticated estimation algorithms, although this would make it even more computationally demanding compared to the simpler GARCH models (Pederzoli, 2006). A direct comparison between GARCH and stochastic volatility was made by Chan and Grant (2016), in a Bayesian model comparison exercise, using nine series of oil, petroleum product and natural gas. Using marginal likelihood to assess the models, they find stochastic volatility models dominated their GARCH counterparts, providing an alternative to more conventional linear GARCH models. A review of 93 studies that conduct volatility forecasting methods by Poon and Granger (2005) could not determine a clear winner between historical volatility and ARCH type models, although then go on to they are both better than SV models, finding no clear evidence that they provide superior forecasts, despite the added flexibility and complexity of SV models. A weakness of GARCH type models is that they typically use only daily opening and closing prices which unavoidably leads to loss of intraday information Tan et al. (2019)

Additionally, there has also been research relating to volatility models that incorporate more variables to improve forecasting accuracy, namely the GARCH-MIDAS model of Engle, Ghysels and Sohn (2013), which enables the link of macroeconomic variables to the long-term volatility component. Conrad et al. (2018) apply the GARCH-MIDAS model to extract short and long term volatility components of cryptocurrenies, finding that S&P500 realized volatility has a detrimental and highly significant effect on long term cryptocurrency volatility. effect Wang et al. (2020) use the MIDAS approach to evaluate the effects of asymmetry and extreme volatility on stock returns from the S&P500 index, finding that asymmetry has a far greater negative impact than the extreme volatility effect. GARCH-MIDAS model with monthly trading volume as a macroeconomic variable was evaluated by Liu, Lee and Choo (2021), and compared the forecasting ability of the model to the traditional GARCH and intraday GARCH in forecasting the China stock market. In their results, GARCH-MIDAS is not able to compete with traditional GARCH model when estimated by the same predictors but do note a positive correlation between trading volume and volatility. Khaskheli et al. (2022) explore whether news relating to precious metals is likely to affect their volatilities using a GARCH-MIDAS model. Assessing the effect of Google Trends on precious metals price volatility, they note that google trends positively impacts precious metals volatility, before and during the COVID-19 period, with the exception of palladium. eli Raza et al. (2023) use GARCH-MIDAS to forecast the volatility of precious metals prices in the COVID-19 period, with global economic policy uncertainty as a predictor. Wu, Zhao and Cheng (2023) propose a real time GARCH-MIDAS model to estimate and forecast volatility in the China stock markets. Their results show the real time GARCH-MIDAS model outperforms the standard GARCH and MIDAS model and the real time GARCH model in both in sample return fitting and out of sample volatility forecasting.

Literature has also explored the Generalized Autoregressive Score (GAS) approach introduced by Creal et al. (2013) which encompasses other well-known models such as GARCH, autoregressive conditional duration and other observation driven models. The effectiveness of the GAS model for out of sample hedging is explored by Xu and Lien (2019), who compare the hedging performance of the GAS model with time-varying GARCH models in terms of volatility reduction and Value at Risk reduction for crude oil and natural gas futures. They concur from their results that the GAS framework outperforms tGARCH model in terms of risk reduction and improving dollar values of hedged portfolios, indicating the potential of a GAS model in a hedging strategy. Tafakori et al. (2018) evaluate the accuracy of Value at Risk forecasts of asymmetric exponential GAS model in Australian electricity markets and find in their results that AR-GAS model outperforms EGARCH and GJR-GARCH models. Troster et al. (2019) use the GAS model in conjunction with GARCH models to forecast volatility and VaR of Bitcoin returns finding that GAS models with heavy tail distribution outperformed traditional GARCH models, providing the best conditional and unconditional coverage for 1% VaR forecasts. Similar findings are obtained by Ivanovski and Hailermariam (2021) who employ a GAS(1,1) model and DCC-GARCH multivariate model forecast dynamic relationship between WTI crude oil prices and S&P 500 stock prices from 1871 to 2020. The forecasting ability and dynamic correlations of the GAS(1,1) model is preferred to those of the DCC-GARCH, however, forecasting performance is found to be similar among longer forecasting horizons of 20 or more.

2.2.3 Forecasting Volatility Using Daily and High-Frequency Data:

One aspect of the literature on volatility forecasting studies the benefits and drawbacks of using daily or high-frequency data and comparing the two different frequencies of data to identify which frequency is best suited for volatility forecasting. Getting the ball rolling for research into the use of high frequency data, Nelson (1991) state that ARCH models do a good job at estimating conditional variances when using high frequency data. Andersen and Bollerslev (1998) measure and forecast volatility in the 24-hr foreign exchange market using intraday returns. A paper by Beltratti & Morana (1999) examined volatility using high frequency data for the deutsche mark-US dollar exchange rate and compared the results to volatility models estimated using daily data. The high frequency data selected covers 1st January 1996 to 31st December 1996, excluding bank holidays and weekends, resulting in 12576 observations, while the daily data used starts December 31st 1972 to January 31st 1997, resulting in 6545 observations. They categorized the data into three categories: raw returns, deterministically filtered returns and stochastically filtered returns, following which they apply MA(1)-GARCH(1,1), MA(1)-GARCH(2,1) and MA(1)-FIGARCH(1,d,1) models to the three kinds of returns. They show that at the high (half-hour) frequency the coefficients of the GARCH volatility model are not very different from those estimated on the basis of an IGARCH model. Martens (2001) explores volatility forecasts of foreign exchange using half-hour high frequency data of two exchange rates: spot rates between Japanese Yen and US Dollar (JPY/USD) and between German Deutsche mark and US dollar (DEM/USD) for the period covering 1996, excluding weekends, leaving 261 days each with 48 half-hour returns. GARCH models are used to produce forecasts of volatility. The empirical results for the DEM/USD and JPY/USD exchange rates show the same pattern, the higher the frequency used, the better the out-of-sample daily volatility forecasts.

Another paper by Martens (2002) forecasts S&P 500 index futures using high frequency data and compares the performance of three forecasting models. He employs high-frequency data for S&P 500 index futures, using this data instead of index data for two reasons: the S&P 500 index is calculated based on the last transaction price of each of the 500 stocks comprising the index, not every stock trades each minute, resulting in an infrequent trading problem, whereby the index lags actual developments, especially at the opening of trading since it takes some time before each of the 500 stocks begin trading. They show that the daily GARCH model is inferior to the daily GARCH model extended with intraday information, however, for weekly and monthly horizons, intraday returns are not as important, but still improve forecasting power. The results obtained show that modelling the volatility of intraday returns leads to optimal forecasting performance. Martens and Zein (2004) found that the use of high frequency data improves both measurement accuracy and forecasting performance, while also noting that long memory models improve forecasting performance. Furthermore, Pong et al. (2004) compare exchange rate volatility forecasts from an option implied volatility model, a short memory ARMA model, a long memory ARFIMA model and a GARCH model. They show that volatility forecasts using high frequency returns were more accurate than forecasts generated using a long memory specification. Malik (2005) uses hourly data of the British Pound and the Euro in relation to the US dollar in his study of the foreign exchange market. The data used in his sample starts from December 2001 and ends in March 2002, and applies four classes of GARCH model and SV models to forecast the two currencies. They find that the Euro was considerably more volatile than the Pound at both the hourly and daily frequencies. Adding to the literature regarding the use of high frequency data in the foreign exchange market, Chortareas, Jiang and Nankervis (2011) assess the performances of traditional time series volatility models and realised volatility models. They find that using a long-memory specification in high frequency data can significantly improve forecasting power and accuracy, echoing the statements from Martens and Zein (2004) and Corsi (2009), which is also on the contrary to the argument of Pong et al. (2004), who suggests the improvement in forecasting performance is solely from the high frequency of the data. An Increase in time frequencies does not necessarily improve the forecasting performance of the GARCH 1,1 model (Khalifa, Miao, Ramchander 2010).

Noh and Kim (2006) use high frequency returns when comparing the ability of historical volatility and implied volatility to forecast S&P 500 and FTSE 100 futures. Their results were rather inconclusive, as they show that both implied and historical volatility could outperform each other in forecasting volatility, as implied volatility was found to hold more incremental forecasting information for S&P 500 futures whereas historical volatility has more incremental forecasting information for the FTSE 100 futures. Wei and Wang (2010) also used high frequency data when forecasting volatility of the Shanghai Stock Exchange Composite Index (SSEC) using multifractal volatility measures and other historical measures of volatility. Volatility models based on high frequency data produced better forecasts than those based on daily data. An additional paper by Wei (2012) also used high frequency data in conjunction with GARCH type models, SV models and realised volatility model to forecast volatility of oil futures traded in China. The realised volatility AFIRMA model based on intraday data produced much better volatility forecasting accuracy than the historical models based on daily returns, particularly the GARCH type models. They further advise that models based on intraday data should be the first-choice economists, practitioners and policymaker, with the SV model being more suitable if intraday information is not obtainable. Using high-frequency data for non-ferrous metals traded on the Shanghai Futures Exchange, Zhu et al. (2016) look into leverage effects and time varying volatility of copper and aluminium futures. Employing a range of HAR models, their findings note that copper and aluminium futures volatility exhibits strong heterogeneity, and there exists significant mid-term leverage effects in realised volatility, reflecting that bad news increases volatility mid-term. Chen et al (2020) forecast oil price volatility using high frequency intraday data as it contains richer information than daily and low frequency data. High frequency data was found to slightly improve forecasting accuracy over one-to-five day horizons, although accuracy tends to diminish and become indistinguishable over longer time horizons, partly due to volatility having long memory characteristics and therefore only changes gradually on a day by day basis (Lyocsa et al. 2021).

2.2.4 Predictability in Stock and Commodity Markets:

Different types of financial assets and commodities are sensitive to economic cycles and are thus challenging to model and predict (Fernandes et al. 2022), with non-ferrous metals in particular showcasing highly irregular and nonlinear price fluctuations that make them challenging to predict accurately and robustly (Liu et al, 2022), nonetheless, the predictability of these commodities is of great interest to academics and practitioners. The efficient market hypothesis (EMH) implies that when information is limited to historical information, then the market is weak form efficient, and prices can't be accurately predicted using only past price data. Additionally, if prices reflect all available public information, then the market is said to be semi-strong form efficient and strong form efficient when prices reflect all public and private information. The efficient market hypothesis swayed the general consensus into believing that stock prices reflect all available information and, therefore, no market participants are able to beat the market to make abnormal profits (Fama 1970). It is of the belief that the market is weak form efficient, however, critics of the EMH argue that investor behaviour such as overreaction and overconfidence can be predictable (See DeBondt and Thaler, 1985; Barber and Odean, 2001), and the presence of a momentum effect in stock returns (Jegadeesh and Titman, 1993). Being able to predict the prices of commodities is of importance to academics and practitioners with knowledge of volatility being important for risk management for producers and consumers, and because their correlations with stocks are typically low, commodities are a useful tool to help achieve portfolio diversification, also providing a good hedge against inflation (Sadorsky, 2002; Symeonidis et al. 2012).

Empirical research into the predictability of stock and commodity markets has resulted in a wide range of evidence and interpretations. Zunino et al. (2011) consider a novel approach to predictability analysis derived from information theory. Lutzenberger (2014) rejects the null hypothesis that commodity returns are unpredictable, both in sample and out of sample, rather they are dependent on factors such as price level and movements, economic conditions and investor sentiment. Gargano and Timmermann (2014) use commodity spot indices to examine the predictive ability of various commodities over a longer sample period than previous literature. They note that at the quarterly time horizon, industrials and metals were the most predictable, with predictability being closely linked to economic cycle, with commodity prices being most predictable in recessions due to higher slope coefficients in return regressions. Park and Lim (2018) explored the market efficiency of six base metals traded on the London Metal Exchange from 2000 to 2016. With the exception of Zinc, they reject the null hypothesis that 3-month futures prices are unbiased estimators of spot prices in the LME. In in-sample and out of sample forecasts, commodity prices were found to be good predictors of stock returns in G7 countries, with structural breaks further improving the forecasting accuracy (Salisu et al. 2019). Tharann (2019) uses monthly price data for four precious metals and copper to evaluate returns predictability. The author finds that there is a substantial degree of return predictability for all commodities both in sample and out of sample, with gold returns being the most predictable. Hollstein et al. (2021) use more than 140 years of data to explore predictability in a wide range of commodity markets, in order to assess the introduction of derivatives trading on return predictability. The introduction of futures options was found to have a mixed impact on volatilities, observing an increase in volatilities among agricultural and energy commodities but also note that volatilities decreased for all metals after the introduction of futures options. Contrary to findings from Gargano and Timmermann (2014), commodity returns and, in particular, volatilities are more predictable in periods of economic expansions than they are in recessions. Data for 25 different commodities spanning four centuries was able to successfully predict stock returns in three different markets in sample and out of sample with agricultural, energy and livestock markets in particular providing the most accurate predictions of stock returns (Iyke and Ho 2021).

The recent COVID-19 pandemic has presented many challenges and problems across global industries and markets, which has inspired a new wave of literature focussing on the impact of the pandemic on the economy and financial markets in general. Umar, Gubareva and Teplova (2021) analyse the impact of the COVID-19 pandemic on volatility in various commodity markets, including precious and non-precious metals, with the authors conducting their analysis based on wavelet coherence and wavelet phase difference techniques, which allow the authors to show their results in the form of time-frequency heat maps and providing insights on the joint behaviour of indices in different time scales. The authors find that precious metals could serve as potential safe havens even during global catastrophe, while non-precious metals exhibit superior diversification benefits during periods of recovery. Ji, Ji, Zhang and Zhao (2020) study the search of safe haven assets during the COVID-19 pandemic, discussing the effectiveness of safe-haven assets typically explored in the literature. Following the introduction of a sequential monitoring procedure to detect changes in the left quantiles of asset returns, they conclude that gold and soybean commodity futures can be used as safe-haven assets during the COVID-19 outbreak, further confirming that gold has an irreplaceable role in preserving the value of an investment. Tanin et al. (2021) address the question of whether volatility indices of different asset classes reduce the safe-haven appeal of gold throughout the COVID-19 pandemic using the NARDL approach used by Shin et al. (2014), which is a dynamic and asymmetric model that is able to differentiate between long term and short term effects, which doesn't suffer from the same convergence issues of nonlinear vector error correction models. Their findings are in line with previous findings during the COVID-19 period, showcasing no evidence of short memory and that gold market is efficient.

2.2.5 Empirical Studies on non-ferrous metals:

While the volatility of various different asset classes and commodities is well defined in the literature, there only exists and small number of empirical works exploring the volatility of non-ferrous metals, with only 45 such articles published between 1980-2002 (Todorova et al. 2014). One of the earliest such papers was Bresnahan and Suslow (1985), who examined the state of the copper market, and note that demand for copper is volatile over time, due to its use as an important war material and broad industrial applications. Price falls of copper could be predicted, but only when the spot price was quite high. Chowdury (1991) uses cointegration to examine whether the efficient market hypothesis holds for metals traded on the LME. The copper market would again be visited by Bracker and Smith (1999), hoping to add to the scare literature of volatility modelling in the copper futures market using the iterated cumulative sum of squares (ICSS) algorithm developed by Inclan and Tiao (1994) and comparing the predictive power of four different GARCH models. Copper returns were found to be negatively skewed over the 1974-1996 period, whilst the GARCH and EGARCH models were found to be superior to the GJR-GARCH model, AGARCH model and a random walk model, which allowed large negative shocks to have a greater effect on the conditional variance.

Slade (1991) was one of the earliest papers to give a broader overview of the wider spectrum of non-ferrous metals. She sought to explain the relationship between the organisation of markets and the behaviour of prices in the metals market. She points out that, using data for six metals traded on the LME covering the 1970-1986 period, volatility tended to increase over time, arguing that producer pricing regimes generated prices that were less volatile than prices set on organised markets. This was especially prevalent in the 1980s. However, building upon this, findings by Brunetti and Gilbert (1995) firmly reject the findings of Slade (1991). Using a similar dataset with the length of the sample extended to 1995, they find that metals price volatility is stationary, with little to no change in the mean of the volatility process over the same period, despite period of high volatility possibly due to speculative movements. Ferretti and Gilbert (2001) revisit the claims of Slade (1991) that the increase in metals price volatility in the 1980s is associated with a move from producer pricing to exchange pricing.

Although they do find a link between producer pricing and lower price variability in the initial sample period from 1970-86, their findings only partially support the findings from Slade (1991) as the removal of Silver from the sample weakened these claims. Extending the sample shows no significant divergence between producer and exchange price variability. They also refute the second claim that the volatility of non-ferrous metals increases over time, as the Hunt manipulation of the silver market in March 1980 may have unduly manipulated the sample.

Expanding upon the findings by Brunetti and Gilbert (1995), McMillan and Speight (2001) use the same dataset and Brunetti and Gilbert (1995) and further extended the length of the sample period to 2000. Unlike previous literature, they employ a variant of the GARCH model to estimate their results, as they found this was better able to capture long memory properties of volatility. Their findings were largely consistent with the earlier findings of Brunetti and Gilbert (1995), but also note that long run price volatility is stationary and mean reverting. Watkins and McAleer (2002) employ a similar methodology to McMillan and Speight (2001), using a AR(1)-GARCH(1,1) model to forecast the volatility of Aluminium and Copper 3-month futures traded on the LME from 1982-2001. They found evidence of periods exhibiting high volatility between October 1987 and May 1990, which coincided with the largest negative return entering the estimation window, followed by numerous periods of large and positive returns. They would retouch upon pricing of non-ferrous metals in 2008, this time updating their sample period to include up to 2006. Despite substantial movements in both the price of copper and aluminium in 2004, the increased presence of speculator and investment funds throughout the 2000s did not bring about any periods of increased volatility relative to previous periods.

A study by Heany (2001) sought to explain whether knowledge of the cost of carry model could help improve forecasting in futures markets, using lead contracts from the LME as a case study. He finds that the ability of futures prices to predict subsequent cash prices over long periods favours models that include carrying costs, with cash prices remaining quite volatile from quarter to quarter with considerable variation left unexplained by the vector error correction models and Brennan and Kroner models employed. Heany (2002) would further expand upon the findings by Heany (2001), using quarterly spot and futures data for three metals traded on the LME between 1975 to 2000, whereby underlying asset price volatility and futures contract price volatility were used as variables in convenience yield approximation. Watkins and McAleer (2006) sought to test the long run relationship of 7 metals traded on the LME using Engle-Granger (1987) and Johansen (1991) cointegration. At least one statistically significant long run relationship between futures price, spot price, stock level and interest rate were found in most samples for the seven metals markets. Watkins and McAleer (2008) explore whether the increased presence of new market players (speculators and investment funds) has brought about increases in volatility. Employing a rolling GARCH(1,1) model, they find that both short and long run volatility persistence vary over a wide range as the model changes. Despite substantial movement in copper and aluminium prices post 2004, they find few extreme outliers during this period relative to previous periods of large price movements.

The area of non-ferrous metals has been the focus of much more attention from academics and scholars in recent years, with a wave of new literature covering the area over the last decade. Hoping to answer a question of whether global commodity markets exhibit the same information transmission mechanisms as equity markets, Lien & Yang (2009) examine the short run dynamic relations of returns and volatility across three copper futures markets: London, New York and Shanghai. Using a BEC-DCC-GARCH model proposed by Engle (2002), allowing to capture time-varying volatility correlation between returns in two markets, they find that LME and NYME are strongly integrated in the sense that bi-directional spillovers of both mean and volatility are strong and significant. There was also a bi-directional spillover effect between LME and SHFE, however only volatility spillover from SHFE to NYME in detected, suggesting Chinese markets are more closely integrated to the LME market. Cochran et al. (2012) examine the long memory properties and return volatilities of four metals: copper, gold, platinum and silver. They also seek to identify whether implied volatility, as measured by the Cboe volatility index (VIX), plays a significant role in determining metal returns. The FIGARCH model proposed by Baillie et al. (1996) is employed as conditional variance follows a hyperbolic rate of decay and this specification reveals the true extent of long memory in the conditional variance of metal returns. In their results, gold was found to be the least responsive to movements in the world equity index, whereas copper was found to be the most responsive. The weak returns of gold and strong returns of copper were consistent with earlier findings from Roache (2008), and similarly share a sentiment from Ciner (2001), who states that gold possesses significant portfolio reduction properties. Todorova et al. (2014) add to the literature by investigating volatility spillover effects between five metals traded on the London Metal Exchange (LME) between June 2006 to December 2012: aluminium, copper, lead, nickel and zinc.

Using a multivariate HAR model, which reveals the role of volatility components over time, their results imply the presence of spillovers in non-ferrous futures market, especially in the long run. Citing the importance of modelling and forecasting of volatility in financial markets for financial applications such as asset management and government regulation, Lyocsa et al. (2017) compare the forecasting ability of HAR multivariate models and GARCH models using data of five non-ferrous metals traded on the LME (copper, zinc, nickel, lead and aluminium) over an 8.5 year sample period. The high frequency HAR models employed were found to outperform GARCH models based on daily data, although forecasting does not improve when the modelling of covariances is included in forecasting models. Gong and Lin (2018) use high frequency data for copper futures traded on the Shanghai futures exchange to look for structural breaks and volatility predictability in the copper market, motivated by the limited studies of volatility prediction using high frequency data for non-ferrous metals. Commonly employed GARCH type models and SV models are selected, alongside four HAR type models, in order to test whether HAR type models are suitable for high frequency data. In their results, they find evidence of structural breaks in the volatility of copper returns, particularly in the period surrounding the 2008-10 financial crisis. Further contributing to the literature, Mayer et al. (2017) look at whether futures trading has an influence on spot prices and volatility. To test this, they use data for four major metal commodities over a timeframe from January 1993 to December 2013. Their results show less evidence of trading positions substantially driving commodity prices and volatility, conversely finding that spot prices cause greater changes in traders' positions. Realised volatility was also found to be informative in explaining the convenience yield of four major metals traded on the LME between January 2010 and November 2015 (Omura et al. 2018).

Researchers have also focused on the investigation of spillover effects between different metals and other commodity markets. Existence of volatility spillover implies that one large shock implies that one large shock increases the volatilities not only in its own asset or market but also in other assets or markets as well (Hong, 2001). GARCH models were used to examine the behaviour of three strategic metals: gold, silver and copper, in the presence of crude oil and interest rate shocks. In this regard, GARCH and EGARCH model were sufficient in modelling the volatility of the metals against crude oil shocks, as oil volatility seemed to negatively influence some metals volatilities, but also add that metals have different degrees of volatility because they are not only driven by macroeconomic factors, but also by their own special factors, such as strong demand for copper in China. Dutta (2018) also points out that metal manufacturing industries appear to be highly energy intensive, consequently, any fluctuations in global energy markets can result in significant fluctuations and variations is metals pricing. An accurate and robust non-ferrous metals pricing forecast is a difficult and challenging problem due to fluctuations and irregular cycles in the metal price evolution (Liu et al. 2020).

Ciner et al. (2020) analysed the interrelationships in the global base metals markets over the years from 1994-2016 using a variety of different econometric methods including wavelet analysis. Strong evidence of co-movements between all non-ferrous metals is found, however, this is dependent on time and frequency bands. Han, Liu and Wang (2022) consider an alternative approach to model and forecast volatility, using R-vine copula analysis to study dependence between non-ferrous metal futures. Consistent with the findings of Ciner et al. (2020), Copper and Zinc were found to be the main stress transmitters between non-ferrous metals, and provide further evidence of an increase in the level of connectedness between non-ferrous metals between Q3 2007-Q4 2013 and a decrease in connectedness between Q1 2014-Q4 2016, by reporting structural breaks in August 2008 and January 2014. Furthermore, Jia and Kang (2022) analyse futures return predictability in the LME industrial metals markets, documenting that financial and macroeconomic variable predict metal spot and futures prices in a procyclical manner with favourable out of sample R^2, Clark and West (2007) test and Giacomini and White (2006) test results. They encourage further research into metals traded on the LME, with gold and steel being important metals in the global economy that should be studied when sufficient historical data is available. Umar, Gubareva and Teplova (2021) analyse the impact of the COVID-19 pandemic on volatility in various commodity markets. Among the energy and non-energy commodities analysed in the study, non-precious metals were found to be the most attractive investment in the recovery period, being capable of providing strong hedging attributes, making them strongly suitable for investors wishing to diversify assets in a portfolio and therefore play the role of a main causality driver in periods of recovery from recessions and global financial crises.

2.2.6 Empirical Studies of Precious Metals:

Precious metals such as gold, silver and platinum have a broad range of applications in risk and portfolio management, and as such, are of great interest to researchers and practitioners. The diversification benefits of gold are widely documented in the literature. Reboredo (2013) finds that gold is a hedge against devaluation of the US dollar. Similarly, gold serves as a hedge and a small safe haven for the US stock market based on data between 1995 and 2010 (Hood and Malik 2013). Looking at spillover effects between precious metals and regional stock markets of the US, Europe, Asia and Japan, Mensi et al. (2013) find that precious metals were net receivers of spillovers during the global financial crisis. Additionally, precious metals allowed for higher diversification, thereby adding gains to investor portfolios. Pierdzioch, Risse and Rohloff (2016) use Bayesian additive regression trees to examine whether precious metals can be used to hedge against foreign exchange rate depreciation. Gold and silver were found to be strong hedges against several major exchange rates, with platinum and palladium are strong hedges with respect to movements against the Canadian and Australian dollar. Peng (2020) examines the safe haven properties of precious metals on China's stock, bond, commodity and foreign exchange markets over 12-year period from October 2006 to October 2018, employing a DCC-GARCH model to measure dynamic conditional correlation between markets. The author's findings indicate that precious metals are generally a safe haven against financial risk in the event of market turmoil, however, the effects vary across financial markets due to investor reaction. Platinum was also found to outperform gold and silver in the Chinese bond market, although gold was the best safe haven in financial crises. Using a wavelet coherence approach, Al-Yahyaee et al. (2020) analyse co-movements and spillovers between precious and non-ferrous metals, and the impacts on portfolio selection using a wavelet based approach. The authors show that aluminium is the highest contributor to risk among all metals, while copper and lead were the lowest transmitters. Gold was also found to offer superior diversification benefits to all non-ferrous metals under 2-4 days, although these diversification benefits decrease as the scale of time period increases. Using a similar approach, Bhatia, Das and Kumar (2020) examine the hedging effectiveness of precious metals across stock markets of G7 developed nations. In contrast to the existing literature, silver was found to offer better hedging capabilities than other precious metals for both short and long run time horizons. Alqaralleh and Canepa (2022) use a wavelet approach to investigate the dependence structure between precious metals and the stock market. In their findings, the authors attempt to compute optimal portfolio weights and hedge effectiveness of precious metals and select stock indexes. They observe that precious metals can be successfully used to balance portfolios even in period of market distress, with gold in particular being able to act as a safe haven for medium to long run investment horizons, noting that for a $1 portfolio, nearly 60 cents should be invested in gold and 40 cents in the index across short investing horizons, reducing weighting the longer the investment horizon. This may be explained by the fact that economic drivers for gold and silver are different from the other base metals. Abuzayed et al (2022) examine the impact of Brexit on stock portfolios with gold and oil. Estimations from using a DCC multivariate GARCH model indicate dynamic co-movements across the UK stock market, and gold was found to have significant implications for hedging strategies and portfolio diversification for investors in the UK market. Additionally, investors should hold more gold than oil to minimize stock portfolio risk without reducing expected returns.

Price behaviour and characteristics of precious metals are also of interest to researchers. One such study by Ciner (2001) found no evidence of cointegration relationship between gold and silver futures traded on the Tokyo commodity exchange between 1992 and 1998. Strong evidence of long run dependence in daily conditional returns and volatility processes were found for gold, silver, platinum and palladium futures from January 1999 to March 2011 when employing multiple parametric and semi parametric models (Arouri et al. 2012). Sensoy (2013) estimates the dynamic correlation between four major precious metals using DCC-GARCH and DECO-GARCH models The author finds that they are initially uncorrelated at the start of 1995, but become strongly correlated by 2013, reducing diversification benefits. The turbulent year of the 2008 crisis is also shown to have no significant effects on volatility for Gold and Silver. Bentes (2015) employ GARCH, IGARCH and FIGARCH frameworks to identify which specification is best suited to forecasting volatility in gold returns. Long memory volatility processes were best described by a FIGARCH (1,d,1) model, with the standard GARCH (1,1) model was the worst model to capture linear dependence. Mensi et al. (2021) analyse volatility spillover characteristics of four major precious metals and seven major currencies at three different time horizons. Employing the DY and BK approach, spillovers vary between 50% and 70% in the short term but drop to less than 30% in the medium and long term. They conclude that adding precious metals to currency portfolios provides diversification and hedging benefits over all time horizons. Lahiani et al. (2021) investigate long run and short run asymmetric properties between precious metals and the S&P 500 index, and their safe haven properties. They found in their sample of December 2019 to June 2021 to represent the COVID pandemic period, asymmetric effects on S&P 500 were shown for copper, palladium, aluminium and gold and play the role of safe haven assets against the S&P 500 in the short term, with only gold a safe haven asset in the long run. Alfeus and Nikitopoulos (2022) provide evidence that FIGARCH models are successful in capturing long memory characteristics of commodity markets, including gold, silver, platinum and copper.

2.2.7 Value-at-Risk Evaluation

In volatility forecasting and risk management, Value-at-Risk has been an important tool used to evaluate the market risk of a portfolio, identifying whether the loss that is likely to be exceeded by a specified probability that ranges between 0.95 and 0.99 over a defined period (Jiang, Hu and Yu, 2022). While VaR is still the widely used and important measure of market risk and exposure, Expected Shortfall (ES) is additionally slowly becoming a primary risk measure for market risk, as proposed by the Basel III Accords with a proposed confidence level of 97.5%. Expected Shortfall considers losses that are beyond the VaR level and it is shown to be sub-additive in order to combat the issues apparent in the VaR approach. Expected Shortfall and Value at Risk evaluation has been conducted on a wide variety of financial assets, including precious metals. Ardia et al. (2018) use single-regime and markov-switching GARCH models to produce Expected Shortfall, VaR and left tail distribution forecasts for daily, weekly and ten-day equity log returns of 426 stocks. In their results, markov-switching models are found to outperform single-regime models for producing VaR forecasts, although note it is difficult to discriminate between the estimation methods, based on VaR forecast accuracy. Similarly, Muhammad et al. (2019) model volatility of precious metals using regime switching GARCH models, additionally, VaR forecasts are produced and models ranked according to best performance. Their findings conclude that out of sample analysis showed that regime switching models outperform their singe regime counterparts when producing VaR forecasts for gold and platinum, but otherwise find mixed results for palladium. Lazar and Xue utilize intraday information in the GAS model of Patton et al. (2019) to forecast Expected Shortfall and Value at Risk in 4 different international stock market indices, namely NIKKEI 225, S&P 500, FTSE 100 and the Dow Jones Industrial Average. Results from GAS-FZ models outperformed ES and VaR forecasts based on GARCH models or historical simulations. Le (2020) apply the MIDAS framework to backtest forecasts for Expected Shortfall and Value at Risk using daily data of 42 international indices and the MSCI world index from January 1996 to December 2017. Le (2020) reports that MIDAS models significantly outperform GARCH and alternative semiparametric models, which rely on single period quantile regression. Additionally, models that incorporate asymmetry in the quantile dynamics and the AL density to jointly estimate ES and VaR produced the most accurate forecasts. Taylor (2020) uses individual forecasts from univariate models and additionally consider a quantile forecast combination approach to estimate ES and VaR, using scoring functions to assess model performance. Following a simulation study based on data generated by three data-generating processes to check robustness of results, individual methods were found to be outperformed by the combing methods Junior et al. (2022) employ 38 different VaR model specifications, namely 32 GARCH and 6 GAS models assuming normal and non-gaussian distributions to model VaR forecasts of precious metals including gold, silver, platinum and palladium. In their results, GARCH models are typically found to outperform GAS models for both 1% and 5% VaR forecasts for each of the metals analysed.

2.3 Data and Methodology Framework

2.3.1 Data Collection

The original data we obtain are daily data for spot price data for 5 non-ferrous metal contracts offered by the London Metal Exchange[3]. The London Metal Exchange is the world's largest market in standardised futures contracts, forward contracts and options for non-ferrous metals, with 145 million lots traded on the LME in 2021, equating to $15.6 trillion and 3.3 billion tonnes of notional trades[4]. The selection of 5 non-ferrous metals: Copper, Aluminium, Tin, Zinc and Lead provides wide coverage of the metals predominantly used for financial risk management purposes and industrial applications, and as such, are frequently used in the literature. Although there is debate surrounding the advantages and drawbacks of high-frequency data in financial modelling, daily price data has been found to be sufficient in forecasting volatility in the absence of high frequency data when using GARCH and GAS type models. At longer forecasting horizons, the differences in forecasting accuracy tend to diminish and become statistically indistinguishable and because high frequency data are seldomly available, low frequency data might be sufficient (Lyocsa et al. 2021). Therefore. The units of future price for metals are dollars per metric tonne for non-ferrous metals (US/mt.). The daily historical price data for all non-ferrous metals is available on the Bloomberg Terminal database, with the data being used in this chapter spans the period 2nd January 2010 to 31st December 2021, covering 3033 trading days. Additionally, monthly trading volume for each non-ferrous metal is also employed in the GARCH-MIDAS regression as a predictor variable at mixed frequency, in an effort to see whether the addition of a predictor variable can improve volatility forecasts.

[4] https://www.lme.com/Company/About

Daily squared returns are used as the proxy for model estimation which can be calculated by first the daily return, The return series is stationary, so it can be used to model without any transformation. The equation below represents the formula to calculate the daily return, which also is as known as the rate of increase in price (Bentes, 2015). In volatility modelling, returns are the input variable. Once this is calculated, we can calculate the daily squared return. As previously defined, volatility can be understood as the uncertainty of price changes over time. E(μ) is the expectation value of the mean, which is constant. Volatility is used to measure the uncertainty (E(εt)). The asset returns normally is a mean-reverting process, which implies that it is changing over time but around the same average value-μ (Dokuchaev, 2007).

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

Figures 2.1 to 2.5, which can be found in the appendix section, shows a comparison of the daily prices of Copper, Aluminium, zinc, tin and lead spot returns for the period 2nd January 2010 to 31st December 2021. We can observe notable trends between the five price series', with a notable downward trend for all metals until 2016. Oversupply of natural resources and weakening demand for non-ferrous due to economic slowdown in emerging economies such as China and Brazil would cause prices of non-ferrous metals to hit their lowest point in our sample period. A bullish market as a result of an increase in global demand for industrial metals shows a rebound for all non-ferrous metals in the period 2017-18. Economic sanctions and measures in top consumer China as the spread of Covid-19 created fears about global economic growth and demand for industrial metals. This would see copper drop to a low of $4,371 per tonne, its lowest price since January 2016 and LME Tin slump to a decade low. A large rally in commodity prices in 2021 would see non-ferrous metals hike to record prices caused by supply toughness, logistical and mining disruptions such as the blockage of the Suez Canal in March 2021 and increased spending of western economies. Copper prices reached a high of $10,417 per tonne in May 2021, the highest since February 2011, Tin reaching a record high of $39,159 in November 2021 and Aluminium prices hiking up 62% year on from October 2020. The Russian invasion of Ukraine, which commenced on 24th February 2022, and subsequent economic sanctions have resulted in further economic upheaval affecting many areas of the economy. Russia is one of the world's largest exporters of many base and precious metals including platinum, palladium, gold and aluminium, while Ukraine is additionally a large exporter of copper to the eastern European region.[5] The war had pushed the price of aluminium to near unprecedented levels, with LME aluminium spot trading at a high of $3,984 per tonne on 7th March 2022. Market prices for LME aluminium would decline over the coming months as price hikes would discourage demand, but it would not be until September 2022 until the price of LME aluminium would return to pre-war levels.

Volatility clustering results in volatility persistence and this is common among financial assets. Specifically, volatility clustering refers to the fact that large changes in observations tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes (Mandelbrot, 1963). We can observe the high levels of volatility persistence in each of the series. We can observe that all price series observed tend to be sensitive to market fluctuations, with lead being the most volatility persistent and tin the least persistent.

Table 2.1 shows the table of descriptive statistics. There are a total of 3130 observations for each return series. The means of daily returns are very close to zero mean, and the standard deviations (%) are large, which is a common trend among return series. The absolute maximum and minimum return values for all return series are also relatively similar. A standard normal distribution has a skewness of 0 and a kurtosis of 3. Interestingly, only aluminium returns exhibit positive skewness (skewed to the right), while each of the return series for copper, lead and tin returns exhibit negative skewness (skewed to the left). Negative skewness means that the lower tail of the distribution is fatter than the upper tail (Cashin and McDermott, 2002). Under this assumption, the mean and median of copper, lead and tin returns are smaller than the mode, with the mean and median for aluminium returns being greater than the mode.

[5] https://www.eiu.com/n/russian-and-ukrainian-commodities-review-base-metals/

The kurtosis of tin returns is greater than 3 (standard normal distribution), thus are leptokurtic, with the corresponding series for copper, aluminium and lead exhibiting platykurtic distribution.

Figure 2.11 indicates the autocorrelation function of the return series for each non-ferrous metal. We can observe that, for the squared returns, the lags do not have significant effect. The only value is the spike at lag 0, indicating that the values are independent of each other and therefore past returns do not explain future returns.

Table 2.2 shows the results of the preliminary tests for each of the metal returns data. The Jarque-Bera tests (normal distribution test) at the 1% level strictly reject normality. The ljung-box test q-statistic rejects the hypothesis of no serial autocorrelation at 1% significance level up to the 20th order for all series, except for zinc and lead returns. Furthermore, the ljung-box test on squared standardized residuals for each return series only indicates significance at 1% level for lead. The Augmented Dickey-Fuller (ADF) and Phillips-perron (P-P) tests both conclude rejections of a unit root at the 1% significance level for all return series, thus, all series are stationary and can be directly employed into estimations with no transformations necessary.

2.3.2 Methodology Framework

The Autoregressive Moving Average (ARMA) model is one of the most widely used general frameworks to capture returns series characteristics. The classis assumption of this conventional model is homoskedasticity, in which each variable has the same finite variance. The plot of the return figures demonstrates however, that the economic time series' exhibit periods of excess volatility which are followed by periods of relative calm and stability, therefore going against the assumption of homoskedasticity. In this instance, the ARCH model proposed by Engle (1982) and the GARCH model originated by Bollerslev (1986) would be more suitable, as they assume volatility with time varying characteristics. Simply put, ARCH and GARCH models treat heteroskedasticity as a variance to be modelled and results do not suffer from the stationary constraint (Engle, 2001).

The ARCH model was introduced by Engle (1982) to estimate the variance in United Kingdom inflation. The standard ARCH(1) model is given as the following:

$$\sigma_t^2 = var\left(\frac{u_t}{u_{t-1}}\right)$$

$$\sigma_t^2 = c_\sigma + au_{t-1}^2$$

Where σ_t^2 denotes the variance of u_t conditional on the value of u_{t-1}, meaning that the variances of the current period are determinant on the error term of the previous period. The variance of the current period (σ_t^2) cannot be known until the variance of the previous period (σ_{t-1}^2) is known.

Based on the work of Engle (1982), the GARCH model introduced by Bollerslev (1986) is one of the most popular methods of modelling volatility. Previous literature has demonstrated that the standard GARCH(1,1) model was a good fit for modelling volatility among numerous types of assets (Sadorsky, 2006; Efimova & Serletis, 2014). In the empirical literature, one order is the most popular choice for the ARCH effect term, GARCH effect term and the leverage effect term. The standard GARCH(1,1) model for daily returns is given as the following:

$$r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t, z_t \sim NID(0,1),$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where μ_t is the conditional mean and σ_t^2 is the conditional variance with the parameter restrictions $\omega > 0, \alpha > 0, \beta > 0$ and $\alpha + \beta < 1$. GARCH models allow for both heteroskedastic and moving average components in the heteroskedastic variance. In comparison to the regular ARCH model, the GARCH model provides more accurate estimation of the conditional variances. This is because the variance in the last period increases the additional explanation ability for volatility modelling, as the variance that comes out is always dependent on the result of the last period. In this sense, GARCH type models are also expected to produce more accurate one step ahead forecasts than the standard ARCH model.

To take into account the stylized facts and unpredictability of financial markets, additional classes of GARCH model have been developed to better capture short memory and long memory volatility effects and leverage effects. Because of the non-linear setting of these more recently developed models, they are more widely known as nonlinear GARCH class models in the literature. The GJR-GARCH model introduced by Glosten, Jagannathan and Runkle (1993) was proposed to help fill in the gap of being able to explain the leverage effect in time series data, which cannot be adequately be explained by the standard GARCH(1,1) model. It allows bad news (negative shocks) and good news (positive shocks) to have different effects on volatility. Although it is easier to understand the advantages of the GJR model in a stock example, the advantages of the GJR model can still be well understood using a commodity example. The GJR model setup is given as follows:

$$\sigma_t^2 = \omega + [\alpha + \gamma I(\varepsilon_{t-1} < 0)]\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,$$

Where σ_t^2 again is the conditional variance, $I(.)$ is an indicator function i.e. if the ε_{t-1} is negative then $I(.) = 1$, and is otherwise zero if it is not met. γ is the asymmetric leverage coefficient which captures asymmetric leverage effects of the volatility.

The EGARCH model of Nelson and Cao (1991) is another extension of the GARCH model which captures the volatility leverage effect. This was developed to allow for asymmetric effects between the positive and negative shocks on the conditional variance of future observations. Nelson and Cao (1991) further point out that another advantage of the EGARCH model is that there are no constraints on the α and β parameters. We can give the EGARCH model as:

$$log(\sigma_t^2) = \omega + \alpha z_{t-1} + \gamma(|z_{t-1}| - E|Z_{t-1}|) + \beta \log(\sigma_{t-1}^2)$$

Where γ is again the asymmetric leverage coefficient to describe volatility leverage effect.

GARCH models previously mentioned above better capture short-term volatility features while there are arguments that the fractionally integrated GARCH model (Baillie et al. 1996, 2004, Andersen and Bollerslev, 1997) better captures the long memory properties of volatility. Better long memory properties are a result of the FIGARCH model assuming the finite persistence of volatility shocks (no such persistence exists in the standard GARCH framework) i.e. long-memory behaviour characteristics and a slow rate of decay after volatility shocks. In comparison, an IGARCH model instead implies the complete persistence of a shock, and apparently quickly fell out of favour.

The GARCH-MIDAS approach proposed by Engle, Ghysels and Sohn (2013) has a notable advantage over the traditional GARCH-class model, in that it composes the conditional variance into two components: short-term volatility and long-term volatility. In this chapter, the long run component is determined by monthly trading volume. The GARCH-MIDAS approach can be surmised as:

$$r_{i,t} = u + \sqrt{\tau_t g_{i,t} \varepsilon_{i,t}}, \qquad \forall i = 1, \dots, N$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1),$$

Where $r_{i,t}$ is the return on day i in month t, u is the conditional mean and $\varepsilon_{i,t}$ is the error term with a normal distribution. The short run component can be expressed as:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - u)^2}{\tau_t} + \beta g_{i-1,t}$$

And the long run component can be expressed as:

$$\tau_t = m + \theta \sum_{k=1}^{k} \varphi_k(\omega_1, \omega_2) X_{t-k}$$

Where X_{t-k} is the low frequency predictor, k is the number of lags, and $\varphi_k(\omega_1, \omega_2)$ is the weighting function. The conditional variance can then be expressed as:

$$\sigma_{i,t}^2 = \tau_t g_{i,t}$$

Although generally the lag length in previous literature is between 12 and 36 months, a lag length of 3 months is chosen due to the relatively small out of sample period of 508 days, indicating that the long run component volatility is obtained by taking the weighted average of the past three-month values.

The newer class of Generalized Autoregressive Score models (GAS) introduced by Creal et al. (2013) offer an alternative to the traditional GARCH family of models to model the conditional variance of financial returns.

Let the $N \times 1$ vector y denote the dependent variable, f_t the time varying parameter vector, x_t a vector of exogenous variables, all at time t and θ a vector of static parameters. They capture the dynamics of time varying parameters using autoregressive term and lagged scores, which can be defined as the gradient of the log-likelihood function. The time varying parameter follows the recursion:

$$f_t = \omega + \sum_{i=1}^{M} \beta_i x_{ti} + \sum_{j=1}^{p} a_j S(f_{t-j}) \nabla(y_{t-j}, f_{t-j}) + \sum_{k=1}^{Q} \varphi k f_{t-k} ,$$

Where ω is a column vector of constants, β_i are exogenous regressors, a_j are score parameters, φk are autoregressive parameters, x_{ti} are exogenous variables $S(f_{t-j})$ is the score scaling function and $\nabla(y_{t-j}, f_{t-j})$ is the score, which is given by:

$$\nabla(y_{t-j}, f_{t-j}) = \frac{\partial lnp(y_t | f_t)}{\partial f_t}$$

The GAS class of models incorporated many well-known econometric models, such as the GARCH model of Bollerslev (1986) and the Autoregressive Conditional Duration model of Engle and Russel (1998).

In summary, the standard GARCH, EGARCH, GJR-GARCH and Generalized Autoregressive Score models at different distributions, and the GARCH-MIDAS model are used to describe and forecast the volatility of five different metal commodities traded on the London Metal Exchange, using daily return series for each type of metal respectively. Additional Value-at-Risk evaluation is then performed to analyse the suitability of each forecasting model to non-ferrous metal returns.

2.3.3 Forecasting Methodology

In this paper, the rolling window method is used to obtain the out of sample volatility forecasts, following the previous works Verma (2021), Liu et al. (2020), Lv (2018), Wei et al. (2012) and Kang et al. (2009). In addition, VaR evaluation is also carried out in order to assess the suitability of each model for forecasting non-ferrous metals. The out of sample forecasting performance is evaluated using the Diebold and Mariano (1995) test and average losses and models are then ranked on performance. The observations for each time series are from 4th January 2010 to 31st December 2021 and we divide the whole sample into two subgroups: the first subgroup for in-sample data and the second subgroup for out-of-sample data. The in-sample data, used for volatility modelling covers the period 2nd January 2010 to 31st December 2019, and the out-of-sample data, which will be used for forecasting and VaR evaluation, covers the period 1st January 2020 to 31st December 2021 covering 523 trading days i.e., the last two years of the total data sample.

In accordance with Verma (2021), Lv (2018), Wei et al. (2012) and Kang et al. (2009), we assess the daily actual volatility (variance) using daily squared returns (r_t^2), which we will denote σ_t^2 from here onwards. The volatility forecasts obtained using the GARCH class model is denoted by $\hat{\sigma}_t^2$. Various loss functions can be considered to assess the predictive accuracy of a volatility model. Instead of limiting ourselves to using one loss function to assess the predictive accuracy of the models, we will use 6 different loss functions to measure forecasting ability. Koopman, Jungbacker and Hol (2005) apply MSE and MAE to measure the forecasting of GARCH family models. We will use the following loss functions:

Mean Square Error Function:

$$MSE = \frac{1}{N}\sum_{1}^{N}(\sigma_t^2 - \hat{\sigma}_t^2)^2$$

Mean Absolute Deviation Function:

$$MAD = \frac{1}{N}\sum_{1}^{N}|(\sigma_t^2 - \hat{\sigma}_t^2)|$$

Mean Square Error adjusted for Heteroskedasticity Function:

$$HMSE = \frac{1}{N}\sum_{1}^{N}(1 - \frac{\sigma_t^2}{\hat{\sigma}_t^2})^2$$

Gaussian Quasi-Likelihood Estimator:

$$QLIKE = \frac{1}{N}\sum_{1}^{N}(LN(\tilde{\sigma}_t^2) + \frac{\sigma_t^2}{\tilde{\sigma}_t^2})$$

R^2LOG:

$$R^2LOG = n^{-1}\sum_{t=1}^{n}[\ln(\sigma_t^2 / \hat{\sigma}_t^2)]^2$$

Where N is the number of forecasting data. The mean square error (MSE) is the average squared difference between the actual variances and the predicted variances of the model and the mean absolute deviation (MAD) is the absolute value of the differences. The proxy used in this study is daily squared returns. Wang et al. (2020) used MSE and MAE as loss functions for evaluating the forecasting accuracy of GARCH class models. Generally, other extensional models are all based on these two loss functions. HMSE is a heteroskedasticity adjusted versions of the MSE loss function, which is a non-linear loss measurement. In addition, QLIKE corresponds to the estimated loss implied by a gaussian likelihood. The Gaussian quasi-maximum likelihood estimator was suggested by Bollerslev, Engle and Nelson (1994) to employ in evaluating the performance of GARCH models. GMLE holding a lower value indicates that the model has better estimating ability (Huang et al. 2008)

Although the above loss functions and statistics of forecast errors are useful for the comparison of the estimated models, they do not provide any statistical tests on the difference of the models. it is crucial to attempt to determine whether any reductions in the forecasting errors are statistically significant. It should be noted that we cannot conclusively decide whether a single model provided superior predictive performance than another by using a particular loss function. Previous literature has explored testing frameworks to determine whether a particular model outperforms another model (Diebold and Mariano, 1995; White, 2000; Hansen, 2005). Therefore, we will use the Model Confidence Set test of Hansen, Lunde and Nason (2011) to evaluate the performance of the forecasts.

The MCS test has been shown to have good power properties and provides a more robust approach than other approaches. In comparison to alternative approaches, the MCS approach allows us to compare the performance of multiple forecasting models at a given time, and ranks each model with a given level of confidence. In addition, the MCS is free from determining the benchmark model in advance, which is necessary for most other evaluation methods such as the DM test proposed by Diebold and Mariano (1995). The MCS test aims to find a superior model in which all models have equal predictive ability, which is the null hypothesis of the MCS test (Liu et al. 2020). Following similar works from Liu et al. (2020) we set the confidence level at 95% and carry out 5000 bootstrap replications to obtain the MCS test statistic and Tmax statistic. For a complete description of the MCS procedure, one may refer to Hansen et al. (2011) and Hansen and Lunde (2005).

The most popular methods of backtesting for Value-at-Risk. The Kupiec (1995) test of unconditional coverage is concerned as to whether the reported VaR is more (or less) than $\alpha \times 100\%$ of the time. Kupiec (1995) proposed a proposition of failures that examines how many times VaR is violated over a select period. If the number of VaR violations exceeds a certain threshold, the accuracy of the model is to be considered. The Kupiec (1995) test statistic takes the form:

$$POF = 2log\left(\left(\frac{1-\hat{\alpha}}{1-\alpha}\right)^{T-1(\alpha)}\left(\frac{\hat{\alpha}}{\alpha}\right)^{I(\alpha)}\right)$$

$$\alpha = \frac{1}{T}I(\alpha)$$

$$I(\alpha) = \sum_{t=1}^{T} I_t(\alpha)$$

Inspection of the test reveals if the proportion of VaR violations, $\hat{\alpha} \times 100\%$, is exactly equal to $\alpha \times 100\%$ then the POF (proportion of failures) test takes a value of zero, indicating there is no evidence of inadequacy in the VaR model. Kupiec's POF test of unconditional coverage is one of the most well known and widely implemented examples of VaR backtesting, however suffers from low power in small samples. The test is based on the frequency of tail losses and potentially neglects important information such as the size of tail losses and temporal dependence.

An alternative approach to VaR backtesting developed by Christoffersen (1998) estimates a confidence interval to the number of exceptions based on the sample and verify whether the number of VaR exemptions is consistent with forecasts. Unlike the Kupiec test, Christoffersen's test only measures the dependency between consecutive days. The t-stat for the Christoffersen approach can be expressed as:

$$LR_{CCI} = -2log\left(\frac{(1-\pi)^{n00+n10}\pi^{n01+n11}}{(1-\pi)^{n00}\pi_0^{n01}(1-\pi_1)^{n10}\pi_1^{n11}}\right)$$

whereby $n00$ is the number of periods with no failures followed by a period with no failures, $n10$ is a period with failures followed by a period with no failures, $n01$ is a period with no failures followed by a period with failures, and $n11$ is a period of failures followed by a period with failures. Additionally, π is the probability of having a failure in period t, and under the null hypothesis, the t-statistic is distributed like a chi-square with two degrees of freedom. Although Christoffersen (2003) criticizes first order markovian process as a limited approach in comparison to other forms of clustering, the Christoffersen (1998) approach is easy to implement and has the advantage of evaluating the dynamic behaviour of exceptions sequence. This allows to verify in the case of a rejection of the model if it is due to incorrect estimate of failures frequency or the dependence of them.

2.4 Empirical Results

In this section, I discuss the results of the in-sample estimation of the corresponding GARCH and GAS models and compare the out of sample forecasting abilities of the models. Returns for LME copper, aluminium, zinc, tin and lead spot returns are used, with returns data covering the period 4th January 2010 to 31st December 2019 used for in-sample model estimation and the data covering the period 1st January 2020 to 31st December 2021 used to evaluate out of sample forecasting performance. During the 2020-2021 period, the COVID-19 crisis greatly affected the economies of various countries and industries, so is therefore a good period to evaluate the performance of the different volatility models.

The parameter estimation results for each returns series is presented within table 2.3 to 2.7, located within the appendix section. For brevity, the estimation results for all metal series are presented within the appendix section and can be found therein. Tables 2.3 to 2.7 present the in-sample estimation results for the presented models and the estimated parameters for each model. For all series, estimated GARCH terms (β) are larger than 0.9 and are close to 1, which strongly shows series autocorrelation in conditional variances, indicating a high persistence of volatility in the data, and therefore, a significant and high level of volatility persistence in each market. This effect appears to be slightly stronger for zinc returns and slight weaker for aluminium and tin returns. Results for the asymmetric leverage coefficient (γ) for EGARCH and GJR-GARCH models are mixed. The estimation results report that the γ coefficient are positive for aluminium returns when estimating the EGARCH model and positive for copper, zinc and lead returns when estimating the GJR model. Negative leverage effect indicates that high negative returns are followed by higher volatility growths than positive leverage effect. The GARCH MIDAS model estimates also display a great amount of volatility persistence across each metal series, as specified by a high coefficient of β and mean reverting properties, with $\alpha + \beta < 1$. Likewise, parameter estimates for GAS models indicate the presence of properties typically found in financial econometric literature.

Swanson et al. (2006) argues that we should choose a model based on its forecasting performance rather than in sample model estimation. Therefore, following the in-sample estimation of the models, out of sample forecasting is conducted to evaluate the performance of the models.

2.4.1 Forecasting Results

Tables 2.8 to 2.12 present the out of sample average losses for the out of sample and goodness of fit tests for the corresponding metals traded on the LME. The out of sample period is from 1st January 2020 to 30th December 2021 and covers a total of 508 trading days. The MSE, MAD, HMSE, R2LOG and QLIKE rank the forecasting performance of each model, with the smallest recorded value for each loss function indicating the best fitting forecasting model. Upon further inspection of the relevant loss functions, the GARCH model following a students-t distribution is the dominant model for all metal series, with the exception of the GJR-GARCH model with students-t distribution for the copper series. Although the EGARCH, and GARCH-MIDAS models incorporate more information than the standard GARCH model, the EGARCH model following a normal distribution and the MIDAS model are found to produce the highest MSE value for two forecasts each, indicating these models may be unpreferable for forecasting non-ferrous metals volatility. When adjusted for heteroskedasticity, the HMSE loss function, the standard GARCH model was found to be the favourable model for forecasting metal returns, being the dominant model for aluminium, zinc and lead volatility forecasts. Much higher MSE estimates for each model when forecasting tin returns data could be due to the higher Jarque-Bera results, which indicates a lower goodness of fit. Across the board, R2 and QLIKE estimates are broadly similar for each forecasted model for every metal return series. It is also important to note that models following a student's-t distribution tend to produce more accurate forecasts that counterparts following a normal distribution. Results from evaluating the relevant loss functions indicate that the standard GARCH following the students-t distribution is best suited for one-day ahead volatility forecasts, however, we cannot deduce which model produces the best forecasts just from cross-evaluating the different loss functions. In order to check the reliability and the robustness of the forecasts, we will conduct MCS tests on MSE and MAE loss functions and refer to the results of the MCS test for more information.

In order to confirm the forecasting results are statistically significant and to check the reliability and the robustness of the volatility forecasts, we will refer to the MCS test for more information. Table 2.13 to 2.17 contain results from the Model Confidence Set procedure of Hansen et al. (2011) to test the robustness of the forecasts. The MCS algorithm constructs an optimal set of models on the assumption of equal predictive ability at a given confidence level. Results from the MCS tests confirm prior examination of the loss functions, with the GARCH model following the students-t distribution to be the dominant model, with the MCS test ranking it to be the best performing model for 3 of the 5 forecasts, with GJR-GARCH with t-distribution the best performing model for tin volatility forecasts and EGARCH with t-distribution the outstanding performer for lead forecasts, although the MCS test has difficulty distinguishing which model is dominant for lead forecasts. In continuation with the loss function evaluation, models following the students-t distribution performed better than their counterparts following a normal distribution for each series.

2.4.2 Value-at-risk backtesting results

To validate results obtained from MCS test with regards to forecasting accuracy and robustness, we conduct further VaR backtesting, using the Kupiec (1995) and Christoffersen (1998) tests of unconditional and conditional coverage. Results from the backtesting of VaR models using the Kupiec (1995) approach can be seen in table 2.18 within the appendix section, testing the null hypothesis of whether proportion of failures exceeds the number of expected VaR violations. In order to test the ability of the models to capture the true VaR, we will backtest the forecasts using 5% and 1% confidence levels. A good model should fail to reject the null hypothesis, that is, correctly identifying the number of VaR violations. Considering a 5% significance level and 95% confidence level, we reject the null hypothesis if the likelihood ratio of the test exceeds the critical value of 3.841 in each case, with 25 expected VaR violations at the 5% confidence level and 5 for the 1% confidence level for a rolling window length of 508. A good model should fail to reject the null hypothesis. Given the backtesting length of 508, The results presented show that each of the models pass the unconditional coverage test at the 5% significance level, indicating that the number of VaR violations are not understated or overstated by the model. At the 1% confidence level, we note that the only rejection of the null hypothesis, namely the EGARCH model with normal distribution for tin series. This would be in line with the volatility forecasts and evaluation of the loss functions and MCS test, which rank the EGARCH model with normal distribution as the worst model for tin returns. In all other cases, the Kupiec t-statistic is below the 3.841 critical values, with corresponding p-values greater than the 0.01 threshold, indicating no evidence to reject the null hypothesis. Based on the proximity of the actual violation ratio to the expected violations, forecasts based on the GARCH-STD and EGARCH-STD models produce accurate out of sample proportion of violations the highest number of times, with the highest corresponding p-values at the 5% level, with the 1% confidence level demonstrating the superiority of the GARCH-STD model.

Upon inspection from the results of the Christoffersen conditional coverage test, which can be observed in table 2.19, we observe exceedance of the 5.99 critical value for the EGARCH with normal distribution, Univariate GAS and Multivariate GAS model for tin returns at the 5% level of significance level. In these instances, we reject the null hypothesis of correct exceedances and independence of failures, meaning that the model cannot correctly identify the number of VaR failures and the independence of failures, with corresponding p-values below 0.05 indicating statistical significance. At the 5% level, the standard GARCH and EGARCH model following students-t distribution yields the highest success rate, with the highest p-values that are statistically significant in most cases. A similar observation can be noted at the 1% confidence level, with the GARCH-STD, EGARCH-STD and GJR-STD models producing the highest hit rate, with no exceedances of the 9.21 critical value for any VaR forecasts, thus we fail to reject the null hypothesis for these models in each metal series. Our results differ to those of the study of Patton et al. (2019) and those of Tafakori et al. (2018) and Ivanovski and Hailermariam (2021), whereby GAS models were found to produce better forecasting accuracy than GARCH type models but are more consistent with those of Junior et al. (2022) in which GARCH models outperformed GAS models.

2.5 Concluding Remarks

In this chapter, I investigate the performance of volatility modelling and forecasting in non-ferrous metals markets. In particular, I compare the performance of standard GARCH, EGARCH model and GJR model at normal and students-t distributions, the GARCH-MIDAS model of Engle, Ghysels and Sohn (2013) using lagged monthly trading volume as a long run component of volatility and the Generalized Autoregressive Score model of Creal et al. (2013) at normal and students-t distributions concerning the estimation and volatility forecasting ability of selected models in non-ferrous metals markets. Value at Risk forecast evaluation is also conducted using the Kupiec (1995) and Christoffersen (1998) tests of unconditional and conditional coverage in order assess model suitability in a risk management setting.

According to the findings presented in this paper, we present evidence from evaluation of relevant loss functions and MCS test indicating that the standard GARCH model following the students-t distribution to be the model to produce the most accurate forecasts of volatility and VaR, outperforming the GAS model at both normal and t-distribution and GARCH-MIDAS model for each metal series. Additionally, models following a students-t distribution are found to outperform corresponding model forecasts using a normal distribution. In order to evaluate forecasting performance, various loss functions are employed to assess performance, with the MCS test of Hansen et al (2011) being used to validate the robustness and statistical significance of our results, and results from the MCS test confirmed our findings. The data we use in this paper covers the period of 2010-2021, a period including the COVID-19 crisis, which is more up-to-date than the data covered in the small but expanding literature regarding non-ferrous metals and similar methodologies are employed.

There are several aspects and areas to improve for future research. It has been shown that univariate GARCH-type models and Generalized Autoregressive Score models provide sufficient predictive ability, so it would additionally be valuable to employ and compare the performance of multivariate GARCH and GAS type models in fitting non-ferrous metals prices, along with the study of stochastic volatility models. Secondly, while this study has used a wide range of LME metals and uses spot price data not previously used in the existing literature, it would be worthwhile to further explore other commonly traded metals such as nickel and iron, which are not covered in this chapter, and precious metals such as gold, silver and platinum, which are also widely used in portfolio allocation. Finally, forecasting evaluation could be further improved by employing the use of high-frequency intraday data.

On a final note, arbitrarily choosing a volatility model to forecast returns based on the existing literature is not wise. Findings presented in this chapter provide evidence on how to select a model for volatility forecasting for financial practitioners, economists and policymakers, however, choice of data sample length and loss functions make evaluating the forecasting performance of different models vary. The future directions where I intend to take my research is to further investigate volatility within the non-ferrous metals market, where the forecasting used from this chapter can be applied in conjunction with high-frequency intraday data to explore volatility spillovers and comovements between LME non-ferrous metals markets, benchmark stock indices and exchange traded funds and whether transmissions and shocks occur between these markets. This will be followed by showcasing how non-ferrous metals can be best implemented and used to create minimum variance portfolios to highlight their potential use in hedging strategies and asset allocation.

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Appendix

Table 2.1 *Descriptive Statistic for LME Spot returns*

	Copper	Aluminium	Zinc	Tin	Lead
Summary Statistics					
Mean	-0.785	1.899	2.869	6.802	-0.505
Std Dev	22.01	20.136	25.686	24.854	26.664
Skewness	0.167	-0.058	-0.083	-0.127	-0.13
Kurtosis	5.765	5.253	4.86	10.924	4.998
VaR-0.01	-3.638	-3.071	-4.13	-4.49	-4.446
VaR-0.025	-2.84	-2.39	-3.237	-3.296	-3.329
VaR-0.05	-2.234	-1.892	-2.552	-2.359	-2.594
VaR-0.1	-1.567	-1.481	-1.945	-1.63	-1.978
ES-0.01	-4.902	-4.264	-5.322	-6.355	-5.888
ES-0.025	-3.838	-3.277	-4.259	-4.785	-4.595
ES-0.05	-3.19	-2.701	-3.566	-3.804	-3.744
ES-0.1	-2.533	-2.189	-2.902	-2.887	-3.009
Skew-t density					
DoF	6.657	9.917	14.089	4.807	9.862
Skewness	-0.003	0.052	-0.033	-0.079	-0.04

Table 2.2 *Preliminary tests for metals return series*.

	Jarque-Bera	Q(20)	$Q^2(20)$	ADF	P-P
Copper	839.18**	36.346**	14.455	-52.798**	-52.722**
Aluminium	764.52**	38.762**	12.928	-57.163**	-57.165**
Zinc	583.72**	30.662	23.58	-55.184**	-55.188**
Tin	7926.15**	39.136**	12.979	-55.862**	-55.923**
Lead	266.12**	17.526	55.62**	-57.774**	-56.314**

** indicates rejection at the 1% significance level

Table 2.3 *Parameter estimates for copper return series.*

	Copper								
	GARCH	GARCH(T)	EGARCH	EGARCH(T)	GJR	GJR(T)	MIDAS	GAS	GAS(T)
ω	0.027	0.004	0.015	0.04	0.06	0.05			
α	0.048	0.04	0.017	0.091	0.0419	0.018	0.074	0.077	0.113
β	0.941	0.951	0.983	0.989	0.9581	0.962	0.839	0.986	0.988
g			0.004	0.04	0.05	0.05			
μ							-0.044		
q							0.092		
w							4.987		
m							0.403		
κ_1								-0.007	-0.012
κ_2								0.006	0.002
κ_3									-2.63

Table 2.4 *Parameter estimates for aluminium return series.*

	Aluminium								
	GARCH	GARCH(T)	EGARCH	EGARCH(T)	GJR	GJR(T)	MIDAS	GAS	GAS(T)
ω	0.046	0.047	0.018	0.0112	0.048	0.049			
α	0.053	0.052	0.148	0.133	0.057	0.06	0.072	0.089	0.145
β	0.916	0.918	0.961	0.965	0.913	0.912	0.928	0.973	0.964
g			0.007	0.012	-0.002	-0.01			
μ							0.006		
q							0.098		
w							1		
m							0.022		
κ_1								-0.013	-0.025
κ_2								0.011	0.006
κ_3									-1.674

Table 2.5 *Parameter estimates for zinc return series.*

	Zinc								
	GARCH	GARCH(T)	EGARCH	EGARCH(T)	GJR	GJR(T)	MIDAS	GAS	GAS(T)
ω	0.016	0.013	0.009	0.007	0.018	0.014			
α	0.038	0.034	0.095	0.088	0.02	0.015	0.073	0.062	0.075
β	0.954	0.96	0.99	0.991	0.958	0.964	0.928	0.994	0.994
g			-0.02	-0.02	0.027	0.027			
μ							0.034		
q							0.098		
w							1.01		
m							0.027		
κ_1								0.002	-0.006
κ_2								0.005	0.009
κ_3									-1.36

Table 2.6 *Parameter estimates for tin return series.*

Tin									
	GARCH	GARCH(T)	EGARCH	EGARCH(T)	GJR	GJR(T)	MIDAS	GAS	GAS(T)
ω	0.011	0.015	0.009	0.004	0.006	0.012			
α	0.044	0.06	0.095	0.12	0.013	0.032	0.074	0.061	0.161
β	0.95	0.936	0.99	0.988	0.965	0.945	0.095	0.993	0.99
g				-0.03	0.033	0.034			
μ							-0.024		
q							0.091		
w							4.97		
m							0.011		
κ_1								-0.036	-0.004
κ_2								0.004	0.002
κ_3									-4.021

Table 2.7 *Parameter estimates for lead return series.*

Lead									
	GARCH	GARCH(T)	EGARCH	EGARCH(T)	GJR	GJR(T)	MIDAS	GAS	GAS(T)
ω	0.014	0.015	0.007	0.005	0.015	0.017			
α	0.031	0.035	0.047	0.027	0.026	0.026	0.082	0.006	0.095
β	0.963	0.959	0.954	0.973	0.955	0.959	0.913	0.994	0.995
g			-0.01	-0.013	0.017	0.015			
μ							0.006		
q							0.101		
w							1.39		
m							0.711		
κ_1								-0.013	-0.004
κ_2								0.006	0.005
κ_3									-1.77

Table 2.8 *Loss functions for copper volatility forecasts*

Copper					
	MSE	MAD	HMSE	R2LOG	QLIKE
GARCH (T)	2.725	0.141	0.058	0.006	1.774
GARCH (G)	4.755	0.152	0.031	0.028	1.730
EGARCH (T)	0.424	0.273	0.025	0.026	1.698
EGARCH (G)	5.278	0.017	0.047	0.034	1.705
GJR (T)	**0.224**	**0.138**	0.007	0.009	1.679
GJR (G)	3.292	0.164	0.029	0.016	1.677
GARCH-MIDAS	5.675	0.424	0.020	0.018	1.780
GAS	3.155	0.241	0.032	0.018	1.780
GAS (T)	3.061	0.225	0.032	0.018	1.780

* values in **bold** indicate best performing model

Table 2.9 *Loss functions for aluminium volatility forecasts*

Aluminium					
	MSE	MAD	HMSE	R2LOG	QLIKE
GARCH (T)	**3.406**	0.169	0.018	0.017	1.384
GARCH (G)	4.915	0.189	0.019	0.014	1.420
EGARCH (T)	4.935	0.171	0.024	0.205	1.407
EGARCH (G)	5.861	0.193	0.022	0.017	1.430
GJR (T)	3.706	**0.161**	0.019	0.018	1.390
GJR (G)	5.194	0.174	0.022	0.016	1.420
GARCH-MIDAS	4.591	0.197	0.073	0.008	1.400
GAS	4.102	0.190	0.073	0.015	1.410
GAS (T)	3.929	0.185	0.075	0.015	1.410

* values in **bold** indicate best performing model

Table 2.10 *Loss functions for zinc volatility forecasts*

	Zinc				
	MSE	MAD	HMSE	R2LOG	QLIKE
GARCH (T)	**0.113**	0.105	0.004	0.006	1.786
GARCH (G)	0.582	**0.092**	0.006	0.006	1.771
EGARCH (T)	1.160	0.130	0.008	0.007	1.749
EGARCH (G)	3.741	0.369	0.012	0.013	1.812
GJR (T)	0.365	0.128	0.005	0.006	1.747
GJR (G)	0.847	0.155	0.057	0.006	1.750
GARCH-MIDAS	2.171	0.134	0.006	0.007	1.787
GAS	1.528	0.291	0.007	0.006	1.810
GAS (T)	1.426	0.227	0.007	0.006	1.810

* values in **bold** indicate best performing model

Table 2.11 *Loss functions for tin volatility forecasts*

	Tin				
	MSE	MAD	HMSE	R2LOG	QLIKE
GARCH (T)	**0.724**	**0.420**	0.158	0.031	1.998
GARCH (G)	1.742	0.522	0.027	0.043	1.977
EGARCH (T)	3.180	0.424	0.045	0.067	2.010
EGARCH (G)	7.192	0.626	0.116	0.048	1.914
GJR (T)	2.150	4.770	0.036	0.039	1.916
GJR (G)	3.371	0.528	0.025	0.046	2.000
GARCH-MIDAS	5.399	0.581	0.038	0.049	1.953
GAS	5.563	0.599	0.038	0.050	1.980
GAS (T)	5.563	0.599	0.380	0.050	1.980

* values in **bold** indicate best performing model

Table 2.12 *Loss functions for lead volatility forecasts*

	Lead				
	MSE	MAD	HMSE	R2LOG	QLIKE
GARCH (T)	**0.113**	**0.106**	0.004	0.005	1.776
GARCH (G)	0.115	0.119	0.006	0.005	1.814
EGARCH (T)	0.113	0.135	0.005	0.006	1.780
EGARCH (G)	0.135	0.142	0.007	0.006	1.817
GJR (T)	0.199	0.128	0.006	0.007	1.810
GJR (G)	0.383	0.114	0.004	0.005	1.771
GARCH-MIDAS	0.425	0.202	0.008	0.006	1.790
GAS	0.401	0.138	0.008	0.006	1.780
GAS (T)	0.399	0.138	0.008	0.006	1.780

* values in **bold** indicate best performing model

Table 2.13 Results of *MCS Tmax stat and model ranking for copper forecasts*

	Copper			
	MSE	Rank	MAE	Rank
GARCH-N	1.000	3	0.929	3
GARCH-STD	1.000	1	1.000	1
EGARCH-N	0.588	5	0.629	4
EGARCH-STD	1.000	2	0.989	2
GJR-N	0.321	8	0.555	6
GJR-STD	0.989	4	0.423	5
GARCH-MIDAS	0.300	9	0.303	9
GAS-UNI	0.509	7	0.533	7
GAS-STD	0.549	6	0.531	8

Table 2.14 Results of *MCS Tmax stat and model ranking for aluminium forecasts*

	Aluminium			
	MSE	Rank	MAE	Rank
GARCH-N	1.000	3	0.994	2
GARCH-STD	1.000	1	1.000	1
EGARCH-N	0.826	8	0.922	4
EGARCH-STD	0.943	5	0.837	5
GJR-N	1.000	4	0.929	3
GJR-STD	1.000	2	0.779	6
GARCH-MIDAS	0.799	9	0.725	8
GAS-UNI	0.835	7	0.772	7
GAS-STD	0.855	6	0.681	9

Table 2.15 Results of *MCS Tmax stat and model ranking for zinc forecasts*

	Zinc			
	MSE	Rank	MAE	Rank
GARCH-N	0.999	3	0.990	2
GARCH-STD	1.000	1	1.000	1
EGARCH-N	0.990	5	0.934	3
EGARCH-STD	1.000	2	0.933	4
GJR-N	0.994	4	0.900	5
GJR-STD	0.305	8	0.478	6
GARCH-MIDAS	0.282	9	0.414	9
GAS-UNI	0.759	7	0.443	7
GAS-STD	0.761	6	0.428	8

Table 2.16 Results of *MCS Tmax stat and model ranking for tin forecasts*

	Tin			
	MSE	Rank	MAE	Rank
GARCH-N	0.765	8	0.118	7
GARCH-STD	0.999	3	0.090	8
EGARCH-N	0.839	7	0.896	4
EGARCH-STD	1	2	1.000	2
GJR-N	0.995	5	0.953	3
GJR-STD	1.000	1	1.000	1
GARCH-MIDAS	0.737	9	0.039	9
GAS-NORM	0.995	6	0.803	5
GAS-STD	0.996	4	0.855	6

Table 2.17 Results of *MCS Tmax stat and model ranking for lead forecasts*

	Lead			
	MSE	Rank	MAE	Rank
GARCH-N	0.918	4	0.982	4
GARCH-STD	1.000	2	0.996	2
EGARCH-N	1.000	3	0.986	3
EGARCH-STD	1.000	1	1.000	1
GJR-N	0.899	8	0.858	6
GJR-STD	0.968	5	0.893	5
GARCH-MIDAS	0.878	9	0.828	9
GAS-UNI	0.909	7	0.858	7
GAS-STD	0.909	6	0.828	8

Table 2.18 Results of *Kupiec (1995) unconditional coverage test for VaR forecasts*

Kupiec Unconditional Coverage Test					
	COPPER	ALUMINIUM	ZINC	TIN	LEAD
5% Level of Significance, Critical Value = 3.841					
GARCH-N	1.21	3.29	2.87	.246	2.51
uc: p-value	.269	.07	.095	.63	.113
GARCH-STD	1.21	2.51	3.42	.104	2.51
uc: p-value	.27	.113	.06	.747	.113
EGARCH-N	0.057	2.51	2.19	2.19	2.51
uc: p-value	.47	.113	.138	.138	.113
EGARCH-STD	1.21	1.85	2.19	.015	2.51
uc: p-value	.269	.173	.138	.903	.113
GJR-N	1.67	3.29	1.67	.015	2.51
uc: p-value	.19	.07	.196	.903	.113
GJR-STD	2.78	2.51	3.42	1.21	1.85
uc: p-value	.095	.113	.06	.27	.173
GARCH-MIDAS	2.78	3.29	3.42	1.82	3.25
uc: p-value	.095	.07	.06	.176	.07
GAS-N	0.85	3.25	1.25	1.82	3.25
uc: p-value	.35	.08	.265	.176	.07
GAS-STD	.053	3.25	2.19	1.70	3.25
uc: p-value	.46	.08	.138	1.91	.07
1% Level of Significance, Critical Value = 6.635					
GARCH-N	5.22	1.44	1.67	3.75	0.16
uc: p-value	.022	.23	.21	.053	.69
GARCH-STD	2.48	0.65	0.656	.656	0.16
uc: p-value	.115	.418	.418	.418	.69
EGARCH-N	5.22	1.44	5.22	**6.88**	0.16
uc: p-value	0.02	.23	.022	.009	.69
EGARCH-STD	3.75	1.44	1.44	2.48	0.16
uc: p-value	.053	.23	.23	.115	.69
GJR-N	5.22	2.48	2.48	3.75	0.16
uc: p-value	.022	.115	.115	.053	.69
GJR-STD	3.75	1.44	0.16	.656	0.16
uc: p-value	.053	.23	.69	.418	.69
GARCH-MIDAS	3.77	1.44	1.44	5.22	0.16
uc: p-value	.05	.23	.23	.022	.69
GAS-N	3.77	0.162	0.66	2.51	0.16
uc: p-value	.05	.686	.415	.113	.69
GAS-STD	3.77	0.255	0.66	2.51	0.16
uc: p-value	.05	.589	.415	.113	.69

* values in **bold** indicate rejection of null hypothesis at corresponding confidence level.

Table 2.19 Results of *Christoffersen (1998) conditional coverage test for VaR forecasts*

Christoffersen Conditional Coverage Test					
	COPPER	ALUMINIUM	ZINC	TIN	LEAD
5% Level of Significance, Critical Value = 5.991					
GARCH-N	1.851	4.47	3.52	5.93	3.84
cc: p-value	.39	.106	.173	.051	.15
GARCH-STD	1.851	3.434	2.82	3.71	3.84
cc: p-value	.39	.146	.221	.156	.15
EGARCH-N	.589	2.21	2.19	**7.07**	3.841
cc: p-value	.745	.331	.332	.003	.147
EGARCH-STD	3.024	1.96	2.19	5.05	3.552
cc: p-value	.22	.373	.332	.06	.165
GJR-N	1.67	4.47	1.67	4.08	3.84
cc: p-value	.34	.106	.34	.13	.15
GJR-STD	3.02	3.84	1.85	3.71	3.55
cc: p-value	.22	.147	.399	.156	.17
GARCH-MIDAS	2.15	4.47	1.85	4.80	4.471
cc: p-value	.31	.106	.399	.009	.106
GAS-N	1.65	4.471	1.81	**6.47**	4.47
cc: p-value	.437	.106	.403	.04	.108
GAS-STD	0.60	5.19	2.18	**7.93**	4.673
cc: p-value	.74	.07	.403	.01	.101
1% Level of Significance, Critical Value = 9.21					
GARCH-N	**10.83**	1.7	1.70	**10.13**	0.30
cc: p-value	.004	.428	0.428	.006	.86
GARCH-STD	2.81	.852	.852	3.77	0.30
cc: p-value	.245	.653	.653	.152	.86
EGARCH-N	5.715	1.7	5.71	**11.79**	0.30
cc: p-value	.057	.428	.057	.003	.86
EGARCH-STD	2.81	1.7	1.7	4.63	0.30
cc: p-value	.245	0.428	.428	.99	.86
GJR-N	5.715	2.81	2.8	**10.13**	0.46
cc: p-value	.057	.245	.245	.001	.78
GJR-STD	5.715	1.7	.303	3.77	0.30
cc: p-value	.057	.428	.86	.152	.86
GARCH-MIDAS	5.72	1.70	1.70	**10.13**	0.46
cc: p-value	0.057	.428	.43	0.006	.78
GAS-N	4.17	.307	.85	**9.75**	0.31
cc: p-value	.123	.858	.652	.007	.85
GAS-STD	2.81	.307	.85	**10.13**	0.31
cc: p-value	.245	.858	.652	.006	.85

* values in **bold** indicate rejection of null hypothesis at corresponding confidence level.

Figure 2.1 *Price trend of Copper LME Spot returns*

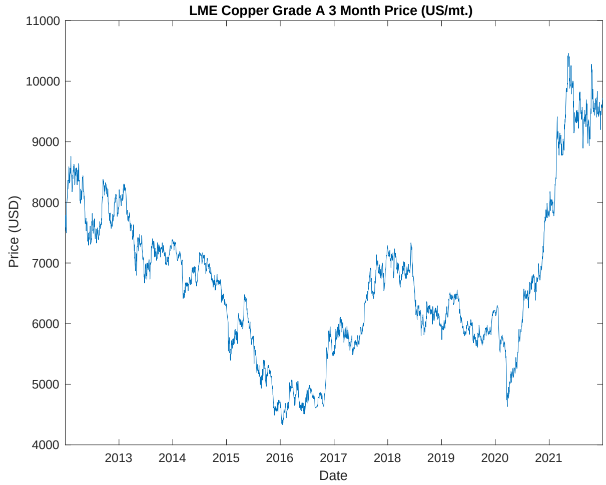


Figure 2.2 *Price trend of Aluminium LME Spot returns*

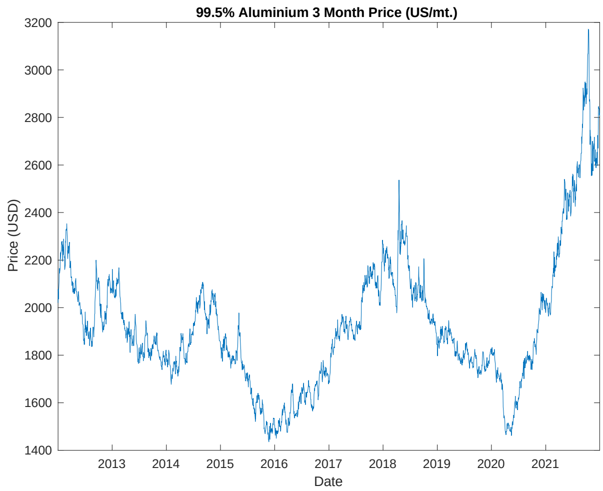


Figure 2.3 *Price trend of Zinc LME Spot returns*

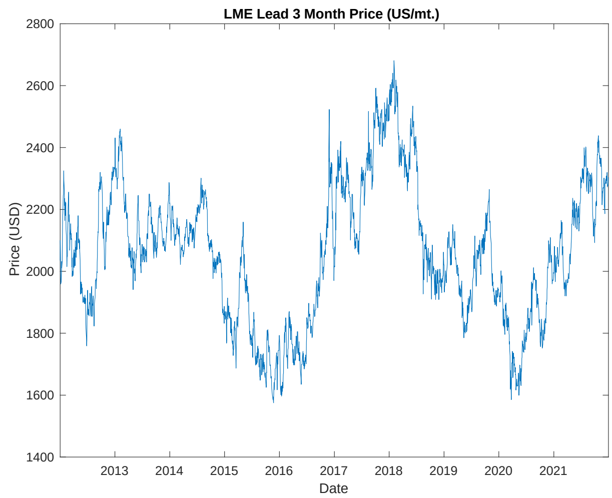


Figure 2.4 *Price trend of Tin LME Spot returns*

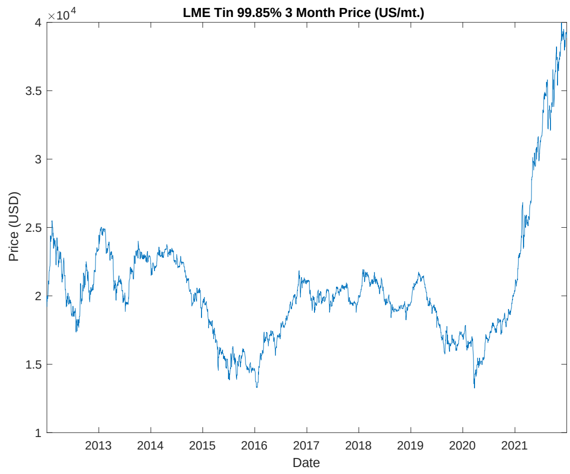


Figure 2.6 *Time path of LME Spot returns*

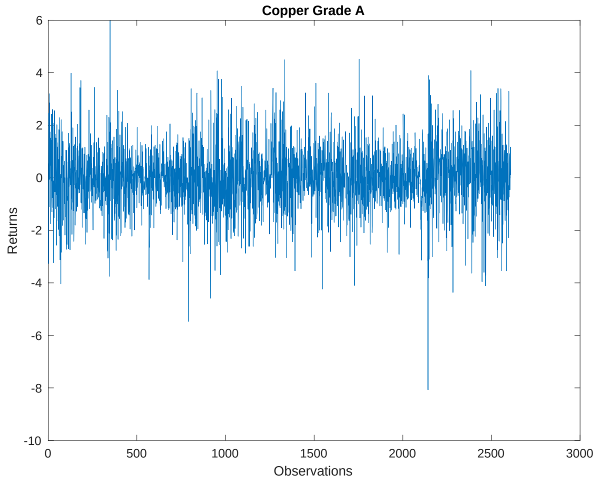


Figure 2.7 *Time path of LME Aluminium returns*

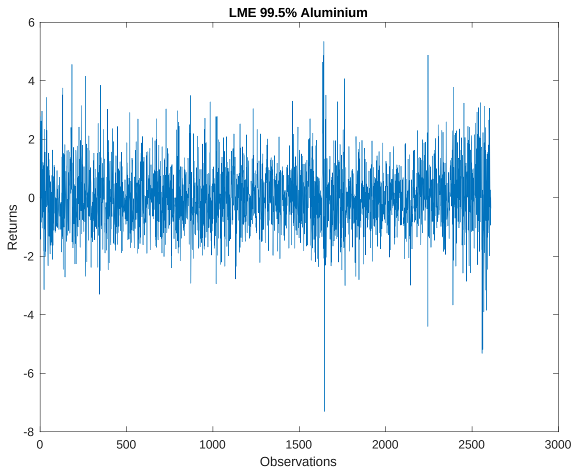


Figure 2.8 *Time path of LME Zinc returns*

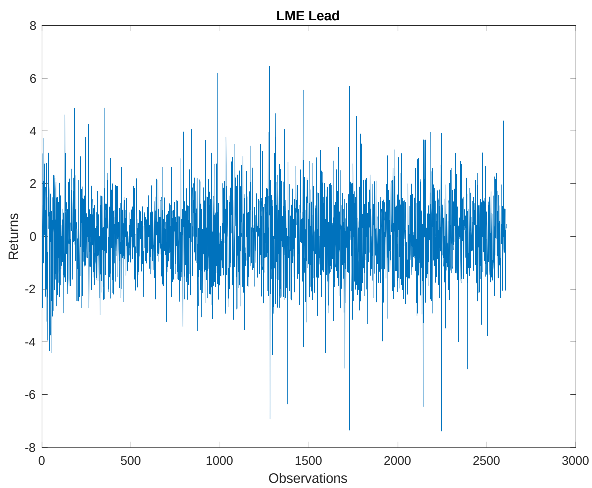


Figure 2.9 *Time path of LME Tin returns*

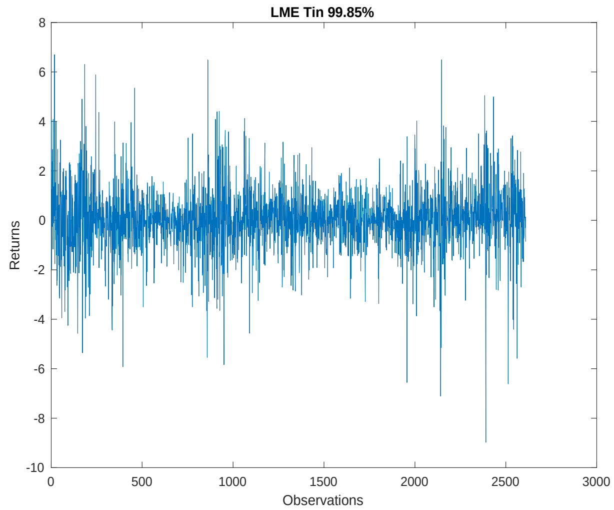


Figure 2.10 *Time path of LME Lead returns*

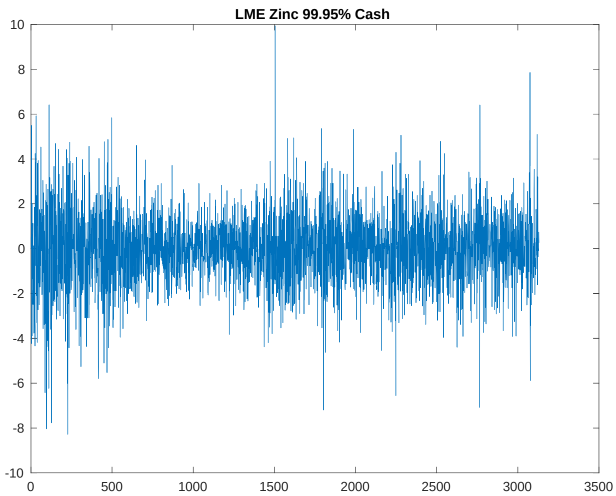
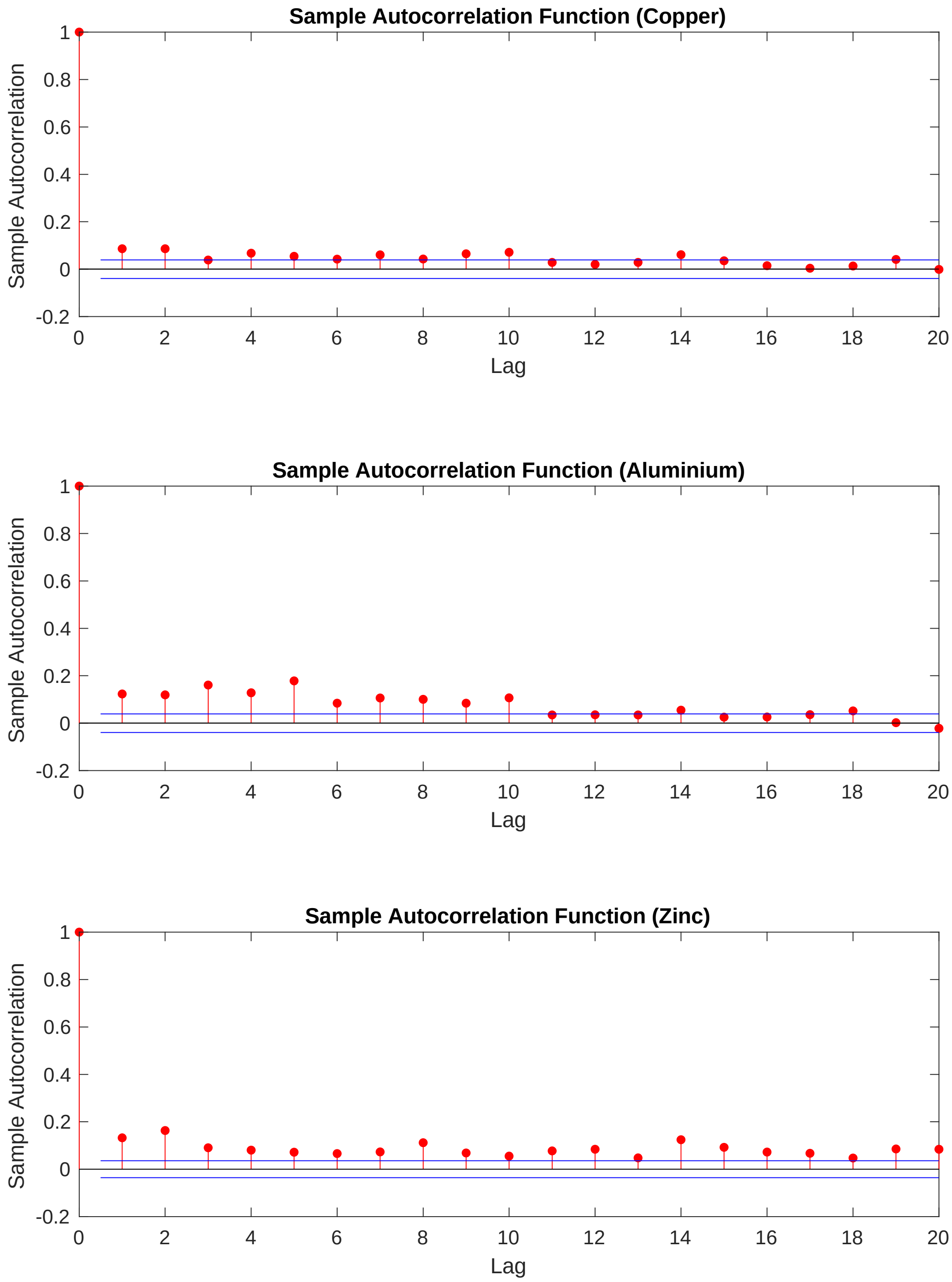
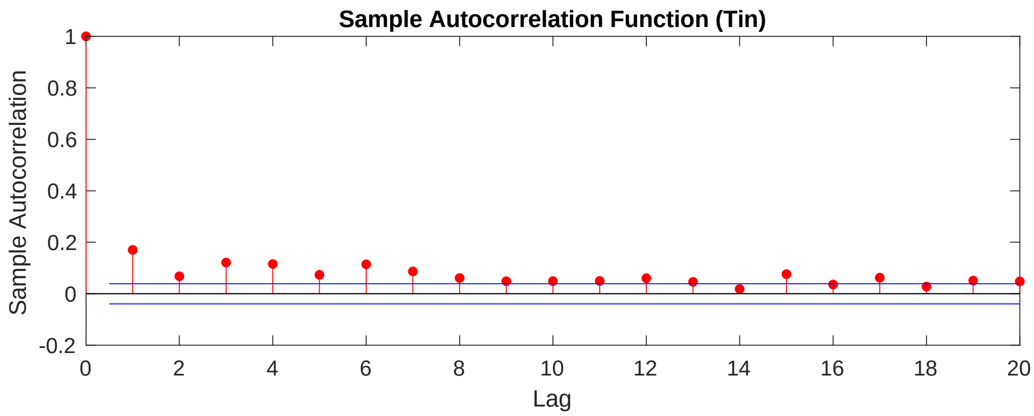
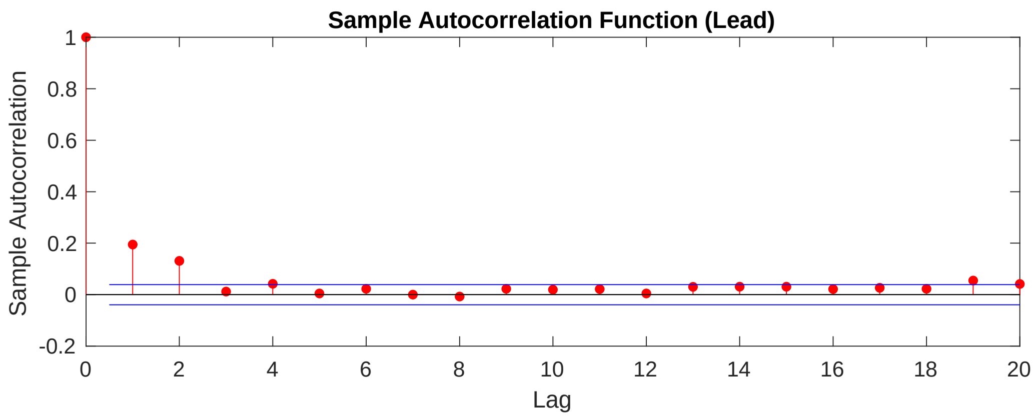


Figure 2.11 *Autocorrelation function for daily squared returns series*




Sample Autocorrelation Function (Tin)
Sample Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
0
2
4
6
8
10
12
14
16
18
20


Sample Autocorrelation Function (Lead)
Sample Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
0
2
4
6
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12
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18
20

Chapter 3. Investigating conditional correlations of industrial metals and gold, oil and S&P500: A multivariate GARCH analysis

Abstract

This chapter examines conditional correlations of five non-ferrous metals (copper, aluminium, zinc, tin, nickel) with three different types of widely traded commodity, namely LBMA gold, ICE Brent Crude. Futures and the S&P 500 index using six types of multivariate GARCH model (CCC, DCC, BEKK, OGARCH, GOGARCH and DCC-MIDAS), with additional wavelet coherence analysis to further showcase conditional correlation at the time and frequency horizon. Copper, aluminium and metals are found to have strong correlations with gold in periods of low correlation with brent crude and the S&P 500, with biggest gaps in correlations in periods of crisis. Results from Likelihood ratio tests highlight the DCC-MIDAS model as the model with best goodness of fit relative to benchmark CCC model, with the BEKK model performing the worst, likely due to overparameterization. We further use the DCC-MIDAS results to compute conditional hedge ratio to showcase how non ferrous metals can be implemented in a trading strategy.

3.1 Introduction

The relationship between stock and commodity markets has been a subject of interest and debate among academics and practitioners alike in recent years. It is important to analyse the relationship between differing classes of stocks and commodities, with differing types of commodities reacting differently to economic conditions, with behavioural characteristics that are largely independent of stock and bond returns, thereby allowing for greater portfolio diversification and lowering the risk exposure of an overall portfolio.[6] With a wide range of practical applications, the main bulk of previous studies has been exploring the behavioural characteristics of stock markets and their associated risks. Economic and global crises in previous decades such as the dot-com bubble of the late 1990's and early 2000's, the 2008 financial crisis and the economic downturn following the 2020 COVID pandemic has prompted industry professionals to diversify investment portfolios with alternative types of financial instruments such as non-ferrous metals and as such, the comovement of commodity prices has become a widespread matter of interest.

How different classes of financial instruments interact and influence the market dynamics of each class of instrument plays an important role in determining investment strategies and portfolio allocation. In a risk management setting, portfolio managers seek to diversify portfolios by looking for different types of asset classes and financial instruments with differing correlations so negative movements are counteracted by positive movements with negative correlations. Most rational choices of portfolio models suggest that investors should hold diversified portfolios in order to reduce or eliminate non-compensated risk, with virtually all asset pricing models positing that financial instruments and securities are priced by. A diversified, marginal investor who demands little or no compensation for holding idiosyncratic risk (Goetzmann and Kumar, 2008). Dynamic correlations between stock markets, crude oil markets and non-ferrous metals can have an impact on investor decision-making and

[6] https://europe.pimco.com/en-eu/resources/education/understanding-commodities#:~:text=Commodities%20are%20a%20distinct%20asset,overall%20portfolio%20and%20boosting%20returns.

behaviour. Non-ferrous metals are metals that do not contain iron, and have widespread industrial usage thanks to their desirable properties, including their light weight, high conductivity, non magnetic properties or resistance to corrosion,[7] and additionally play an important part in economies, with their prices having impacts on extraction, processing and manufacturing facilities (Watkins and McAleer, 2004). Furthermore, with Russia the largest exporter of non-ferrous metals, representing 9.71% of non-ferrous metal exports totalling $8.36 billion in 2018[8], the 2022 Russian invasion of Ukraine has had global repercussions for the trading and exporting of non-ferrous metals, with the global economy still suffering aftereffects of the global COVID-19 pandemic from 2020 to 2021. This chapter seeks to shed light on whether non-ferrous metals present an opportunity to be used in hedging strategies or used for diversification benefits in portfolio management, by using multivariate GARCH models and DCC-MIDAS model to examine dynamic conditional correlations and volatility spillover of non-ferrous metals, with precious metals and crude oils which represent two commodities widely used in trading and hedging strategies, and the S&P500 indexe, which represents one of the foremost stock market indices globally. While many studies have previously explored the effects of conditional correlation and volatility spillover effects, no such studies exist exploring linkages between European and Western non-ferrous markets with precious metals, crude oil, and stock markets, and whether these non-ferrous metals present potential hedging and diversification opportunities for investors and industrial professionals.

[7] https://www.twi-global.com/technical-knowledge/faqs/what-metals-are-non-ferrous
[8] https://oec.world/en/profile/sitc/non-ferrous-metals-5768

3.2 Literature Review

3.2.1 Conditional Correlation in Commodity Markets

The subject of dynamic conditional correlation and volatility spillovers has been addressed in previous studies, however, the conditional correlation between non-ferrous metals and other types of investment vehicles has not been previously well studied and as such is not currently well defined, which this study aims to address, with a body of previous literature exploring conditional correlation covering crude oil markets. Among the previous literature to address conditional correlation and volatility spillovers in crude oil markets, Chang et al. (2013) explores conditional correlations and volatility spillovers between WTI and Brent crude oil markets and the FTSE 100, Dow Jones Industrial Average and the S&P 500 stock markets between 1998 and 2009, using various multivariate models such as the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer, Hoti and Chan (2009). Based on the CCC model, estimated conditional correlations were not statistically significant, meaning conditional shocks were correlated only in the same market and not across markets, with VARMA-GARCH and VARMA-AGARCH models additionally providing little evidence of dependence between the crude oil and financial markets. Block et al. (2015) additionally explore dynamic conditional correlation of crude oil but instead explore the potential link between fuels, gasoline, diesel and other fuels having a strong influence over prices, using Copula-DCC-GARCH. The presence of cointegration between West Texas Intermediate (WTI) and all fuels with the exception of natural gas is found, indicating long-term dependence. Through a similar approach, Pal and Mitra (2019) investigate conditional correlations between WTI crude oil and four major agricultural commodities, namely, corn, soybeans, oats and wheat, in the period from January 3rd 2000 to January 4th 2018. In their results, dynamic conditional correlations between WTI crude oil and corn were positive for DCC-GARCH, ADCC-GARCH and GO-GARCH models, with soybean conditional correlation also in a similar vein. Correlations between WTI and oats oscillate between negative and positive, indicating gains from diversification. Sarwar et al. (2019) assess hedging capabilities and volatility spillovers between three Asian stock markets, namely, NIKKEI 225, Shanghai stock exchange and Bombay stock exchange, and crude oil returns in the top three Asian importing countries using four different multivariate GARCH estimating techniques including DCC-GARCH, corrected DCC-GARCH of Aielli (2013) and GO-GARCH model of Van der Weide (2002) and BEKK-GARCH. In their findings, shocks in Indian markets have a more significant effect on current volatility of stock markets, however, in general, stock markets of developing Asian countries are not overly sensitive to oil price shocks and fluctuations. In a similar vein, Liu et al. (2020) analyse implied volatility and risk transmission effects between WTI crude oil market and U.S. stock markets using the same methods used by Sarwar et al. (2019) with the addition of using Vector Autoregressive Model to analyse mean spillover. With regard to their results, the authors comment that conditional correlation between OVX and VIX indices appears to be highly time-varying, implying a highly interdependent relationship between OVX and VIX markets. They also note economic and geopolitical events cause changes in the dynamic conditional correlation, in particular, correlation between oil and stock markets showed a significant increase during the period of the global financial crisis of 2008-2011, with policy changes having the opposite effect. Yildirim et al. (2022) utilize the DCC-GARCH model of Engle and Sheppard (2001) to analyse the impact of COVID-19 on return and volatility transmissions between crude oil and precious metals over the period of January 2019 to April 2021. Precious metals and oil prices are found exhibit heterogeneous behaviour throughout the sample period, with negative correlation is noted between gold and silver throughout most of the period, exhibiting safe haven properties in periods of oil price fluctuation. Additionally, a positive correlation is found between oil price returns, platinum and palladium, which may be explained by platinum and palladium having industrial uses within the economy. Upon examination of causality tests, the COVID-19 pandemic is found to have strengthened the transfer of volatility from oil to precious metals. Chen et al. (2022) investigate the relationship between crude oil and agricultural commodities in a similar vein to Pal and Mitra (2019), expanding their sample to Brent crude oil and seven agricultural commodities in China from a period of January 1999 to August 2021. Applying cDDC-GARCH and DECO-GARCH models, correlations between crude oil and soybean oil futures is stronger than the relationship between crude oil and other agricultural futures, additionally noting co-movements between crude oil and global agricultural commodities is greater than that of China’s agricultural commodities.

Previous literature exploring conditional correlation has also covered various precious metals. In an earlier such example, Sensoy (2013) detect for volatility shifts and connectedness for four major precious metals (gold, silver, platinum, palladium) from 1999 to 2013, using an approach introduced by Lavielle (2005) to detect mean shifts in dynamic correlation and volatility shifts. The 2008 financial crisis is not found to influence volatility levels of gold and silver but has significant effects on platinum and palladium volatility, but additionally state that based on increased correlation levels among them, they should be classified as a single asset class in the future. Gold is also found to have a volatility shift effect on other precious metals, additionally noting silver has a similar effect on platinum and palladium. Rehman and Vo (2020) investigate the relationship between cryptocurrency and precious metal returns from March 2017 to August 2019. Using a quantile-cross spectral approach, they note that in the short run, silver offers greater diversification benefits than any other metal analysed due to its strong negative correlation values, with Palladium and Nickel exhibit strong positive correlation with all cryptocurrencies. Long run precious metal returns are also found to exhibit negative correlation with cryptocurrency returns, highlighting their potential for diversification benefits. Dynamics and correlations of Platinum group metal spot prices are explored by Bao (2020) using EGARCH and Vector Error Correction Model (VECM). Over the period July 1st 1992 to August 15th 2019, all platinum group metals have similar features and strong correlations with high volatility clustering yielding significant leverage effects. Using a hybrid wavelet based DCC approach, Bhatia, Das and Kumar (2020) assess the hedging effectiveness of precious metals by conducting correlation analysis. Their results indicate a presence of dynamic correlation between precious metals (gold, silver, platinum, and palladium) and different stock markets, further suggesting an opportunity for portfolio diversification. Using a wavelet-based approach combined with DCC-GARCH, Nekhili et al. (2021) analyse comovements among precious metals and their implications in a portfolio allocation setting. They find that comovements between all precious metal pairs are more pronounced in the medium and long term than in the short term, however, gold and silver pair shows strong comovements between different frequencies. Correlations between all precious metals jumped to higher values after the COVID-19 pandemic, although this is only wavelet coherence reports such attitude. Dinh et al. (2022) investigate time-varying dynamics of volatility and correlation in precious metal markets, using GARCH-MIDAS and DCC-

MIDAS approach to capture short and long components of volatility. Monthly realized volatility used as a driver of long-term volatility outperforms other variables used. Chinese economic drivers have less impact on correlations than US counterparts, notably, long-term volatility of gold and long term correlations of gold-silver and platinum-palladium commodity pairs are reported to be most affected by economic variables, backing the findings of Klein (2017) that this behaviour can be explained by the different uses of each metal, with gold and silver used as investment assets and platinum and palladium mainly used as industrial metals. Additionally, all four precious metals react negatively and significantly to US stock market returns, while only long-term volatility of spot precious metals returns has a significant positive response to stock returns in China and EPU growth of G7 countries has a significant positive effect on precious metal volatility, concluding economic cause a stronger effect on volatility rather than correlation. Jain et al. (2022) examine frequency based linkages between two prominent stock indices, namely S&P500 and STOXX50 indices, and precious metals. In a similar vein to Rehman and Vo (2020), Abrar et al. (2024) investigate whether precious metals provide diversification avenues from cryptocurrencies and whether cryptocurrencies are net transmitters of volatility spillovers into precious metal returns. Following their results using GJR-GARCH and quantile VAR, they report higher volatilities between cryptocurrencies and precious metals at extreme left and right tails, likewise corroborating the findings of Rehman and Vo (2020) that precious metals may provide avenues for portfolio diversification.

3.2.2 Multivariate GARCH Models and Conditional Correlation

Since the development of multivariate generalized autoregressive conditional heteroskedasticity models, a large body of literature has been centered on exploring the usage of various multivariate GARCH models to estimate the dynamic conditional correlations between classes of financial instruments and the hedging effectiveness of commodity and equity portfolios. The DCC-GARCH model of Engle (2002) is employed in the literature of conditional correlation and connectedness because it can explain time varying volatility spillover between classes of financial instruments and additionally provides information about the volatility of assets. Celik (2012) uses DCC-GARCH to explore connectedness and contagion effects between the US and 19 developed and emerging markets during the US subprime crisis. In their findings, DCC-GARCH was found to report unconditional correlation increased in crisis periods, especially for developing economies due to their instability, exaggerating the effects of shocks. Hemche et al. (2016) study contagion effects for ten developed and emerging stock markets, with respect to the US subprime mortgage crisis of 2006-2008 using a DCC-MGARCH approach. They observe the presence of positive dynamic cross market correlations between the US market and major developed and emerging stock markets under, which vary significantly over time and on a country-by-country basis, appearing higher for developed countries but are more volatile for emerging countries. DCC-GARCH was additionally employed by Park et al. (2017) to examine conditional relationships between stock market returns and implied volatility. In the case of the Korean KOPSI200 and VKOSPI, exchange rate returns have significant impact on conditional correlations between the KOPSI200 returns and the VKOSPI. The leverage effect of the asymmetric DCC-GARCH model also effectively reduced the sign bias in the model. Chen and Xu (2019) use a multivariate Generalized Autoregressive Score (GAS) model and DCC-GARCH model to forecast volatility and examine correlations between the oil and gold market. In relation to the crude oil-gold market, the multivariate GAS model is found to have better forecasting performance than the DCC-MIDAS model, with the DCC model additionally overestimating gold and crude oil volatilities, especially in crisis periods. Volatility impulse responses and transmission mechanisms between currencies are explored by Gabauer (2020) using a DCC-GARCH model. Using this approach, volatility spillovers are found to be highly persistent across all series, with persistency across European currencies higher with respect to the JPY, possibly indicating regional currency contagion. The Swiss franc is also found to be the biggest net transmitter of shocks, with the British Pound and Japanese Yen being the biggest net receivers. Zhang, He and Hamori (2022) used DCC-GARCH t-copula approach to assess dynamic connectedness in ESG stock indes and renewable energy stocks. The DCC-GARCH approach was able to adequately explain dynamic connectedness of volatility between markets.

The BEKK-GARCH model is also widely employed in the literature surrounding conditional correlations and volatility spillover, as The BEKK model allows permits the interaction of conditional variances and covariances of several time series, thereby making it suitable to examine volatility transmission effects (Katsiampa, Corbet and Lucey, 2019). Chang, McAleer and Tansuchat (2011) evaluate the performance of various multivariate models, including the CCC, DCC and BEKK-GARCH approaches for two major international crude oil markets. In their results, models that assume constant conditional correlation have differing optimal portfolio weights than dynamic conditional correlation models, namely DCC and BEKK GARCH models. The diagonal BEKK model was found to produce the best optimal hedge ratio calculation in terms of variance of portfolio reduction, while the standard BEKK-GARCH model produced the worst results. Caporin and McAleer (2012) compare the BEKK and DCC models, citing issues surrounding the BEKK model, namely its 'curse of dimensionality' issue that the DCC model does not have, as motivation for their research. In their concluding remarks, they demonstrate that the optimal model for estimating conditional covariances (and thereby conditional correlations) was the scalar BEKK model, regardless of whether targeting was used. Liu et al. (2017) investigate the evolution of mean and volatility spillover effects between the S&P 500, MICEX index and WTI crude oil markets between January 2003 and December 2014 using a wavelet based BEKK-GARCH model. Results from the wavelet based BEKK-GARCH model showcase that mean and volatility spillovers are time varying, with significant spillover effects between the US crude oil market and the S&P 500 index, although the model found no linkages at long tern scales. Katsiampa (2019) analyse volatility and comovement between two cryptocurrencies, namely Bitcoin and Ether, using bivariate BEKK-GARCH model. Supporting previous findings, the BEKK model showcased that both cryptocurrencies are significantly affected by cross products of previous shocks, supporting interconnectedness. Xie et al. (2021) explore dynamic linkages between the international crude oil markets and the Chinese stock market using a BEKK-GARCH approach. In their results, linkages are found between the international crude markets and the Chinese stock market, noting that the Chinese stock market plays the role of risk sender, due to high sensitivity to volatile changes in international oil price.

Limited literature has also explored the use of MIDAS models to explain conditional correlations and volatility spillover. Colacito, Engle and Ghysels (2011) propose a DCC-MIDAS model to extend the idea of component models for volatility, with MIDAS specification allowing for the extraction of a short run and long run correlation component via mixed data sampling. Applying the DCC-MIDAS model to portfolios of energy stocks, hi-tech stocks and 10-year bonds over a 35 year period, the DCC-MIDAS correlation outperformed the DCC estimator in a large majority of cases, potentially highlighting the efficiency gains of the addition of a long run estimator, even in the context of short-horizon assets. Likewise, Asgharian et al. (2016) use a DCC-MIDAS specification to investigate long run correlations between 10-year government bond returns and the S&P500 stock index from the first quarter of 1986 through to the second quarter of 2013. Their results show that long-run stock bond correlation has a positive relationship with the state of the economy and a negative relationship with uncertainty factor. Zheng et al. (2020) employed the DCC-MIDAS model to analyse comovements between the Chinese business cycle and financial volatility throughout 1994 to 2017. Liu and Lee (2022) used the DCC-MIDAS approach to investigate whether gold is a long run hedge, diversifier, or safe haven for crude oil market futures. Results from DCC-MIDAS estimation indicate persistency of gold-oil correlation, with past shocks exerting a small impact on the movement of gold-oil correlations, with long run correlations being significant and persistent. Yaya et al. (2022) conduct analysis of time variation between metal commodities and oil with the impact of oil shocks, using GARCH-MIDAS and DCC-MIDAS models. In their analysis, four precious metals (gold, silver, platinum, palladium) are employed, as well as WTI crude oil data from March 2014 to October 2021 with monthly oil shock data covering the same period. In their results, following DCC-MIDAS estimation, there was found to be varying levels of convergence between precious metals and WTI crude oil, only finding statistically significant short term effects for gold and silver, with the latter exhibiting higher persistence. They conclude that they find evidence of dynamic correlations between the precious metals market and crude oil market, with silver markets being used as a substitute to gold markets and thus serving similar functions, explaining for the long run equilibrium relationship as a result.

3.2.3 Wavelet Coherence and Conditional Correlations

Wavelet methods have been used in various waves of literature to measure the correlation between two different signals, enabling their usage in the literature to measure the correlation between financial assets. Wavelet analysis is a model free approach, with this property making it a very powerful tool in comparison to other methods and models which rely on parameters as well as the estimation method (Vacha and Barunik, 2012). Davidson et al. (1998) was one of the first studies to propose wavelet methods to analyse commodity data. Aloui and Hkiri (2014) explore comovements of GCC emerging stock markets during the period of 2005-2010, using wavelet squared coherence to analyse comovements, noting its ability to assess comovements in time and frequency domains, with VaR analysis for portfolio management purposes. They note that co-movements depend on both time and frequency and is strongly affected by the 2008 financial crisis. The wavelet approach was additionally able to uncover changes in comovements to relatively higher frequency overlaps with the inception of the financial crisis. Huang et al. (2016) use wavelets to analyse time-frequency featured comovement between stock prices of the Shanghai Composite Index, brent crude and London gold prices from January 1991 to September 2014. Results from wavelet coherence and multiple wavelet coherence in the time frequency domain showcased strong correlations in the low frequency bands (256-512) days but weak correlations in high frequency bands of 1-16 days, indicating weak short term correlations. In a similar study, Reboredo et al. (2017) conduct wavelet based testing for comovements and causality WTI crude oil and 6 different types of energy indices covering the period from January 2006 to March 2015. In their results, renewable energy indices dynamically changed throughout time frequencies, with strong dependence at low frequencies and weak dependence a at high frequencies up to mid-2013, turning into weak dependence at both the short and long run horizons up to the end of the sample. Mixed evidence of causality from oil to renewable energy prices is also noted. Volatility spillovers and dynamic correlations from crude oil are also explored by Boubaker and Raza (2017), aalysing spillovers between oil and BRICS stock markets using multivariate GARCH models and wavelet analysis. Comovements and dynamic correlations of financial and energy markets between January 2012 and March 2017 are explored by Ghosh, Sanyal and Jana (2019) using wavelet analysis and DCC-GARCH model. Empirical results from bivariate GARCH-cDDC and wavelet based multiresolution analysis demonstrate the continuous wavelet transform method was able to effectively showcase periods of strong long run correlations between energy, crude oil, natural gas, Dow Jones Industrial Average stock index and NIFTY index. Pal and Mitra (2019) explore comovements between oil price and four major automobile stock market indices in the time frequency domain between August 1996 and June 2017 using wavelet coherence analysis. Likewise in Redorebo et al. (2017), they find that the strength of comovement between crude oil and automobile stock returns are frequency dependent, indicating that comovement between oil and automobile stock returns are more prominent in longer scale frequencies of 264 days and above and is far weaker in short term frequencies of 16 days or less, finally stating crude oil no longer continues to be a safe haven against bearish automobile stock markets. Cross currency behaviour and comovements are analysed by Firouzi and Wang (2019). Results from their continuous wavelet transform yield a clear view of comovement between two sets of currency time series and improves forecasting ability. Furthermore, wavelet coherence clearly showed highly negative correlation in both low and high frequency periods. Goodell and Goutte (2021) apply wavelet methods to data of COVID-19 related fatalities and daily bitcoin price data to analyse correlations between the impacts of the coronavirus pandemic and bitcoin prices. Results from wavelet coherence analysis indicated that levels of COVID-19 caused a rise in bitcoin prices. Khan et al. (2023) investigate the presence of dynamic linkages between Islamic stock indices and gold prices, oil prices and news based uncertainty. From January 1996 to December 2018, wavelet based granger causality tests indicate that in the short run and scale, Islamic stocks, oil prices and global policy uncertainty reveal significant bi-directional granger causality at different significance levels. They additionally note that wavelet transforms illustrate higher variance in the short and medium runs, with an increase in long run average variance in the crisis period from 2007 to 2009.

Wavelet based analysis has also been widely used to investigate bilateral relationships between different foreign exchange markets and stock markets. Yang et al. (2016) used wavelet methods to study interdependence of three foreign exchange markets (GBP/USD, EUR/USD and JPY/USD), finding that Afshan et al. (2018) used wavelet analysis to causality and linkages between exchange rates and stock prices in Pakistan using weekly observations from 1997 through 2016. Using wavelet analysis, they showcase evidence of long run bidirectional causality and comovement between exchange rates and stock returns in Pakistan. In an extension of the research of Afshan et al. (2018), He et al. (2023) investigate the causal relationship and correlations between exchange rate returns and stock market returns in the emerging markets, namely Turkey, over the period April 2000 to March 2019. Wavelet coherence analysis showcased evidence of strong correlation with USD/TRY currency pairing relative to EUR/TRY, with deeper analysis of wavelet coherence plots implying that in the short term and medium term, there is negative correlation between foreign exchanges markets and Turkish stock market returns, supporting the view that the depreciation of the Turkish lira against the US Dollar or the Euro reduces Turkish stock market returns.

3.2.4 Hedging Effectiveness of Commodities

Numerous studies have explored the hedging effectiveness of various types of commodities, including precious metals, stock indices and crude oil futures, using multivariate GARCH models, most notably the DCC model. Hedging effectiveness can be evaluated using various methods, with the optimal hedge ratio one of the most widely used methods to evaluate the hedging effectiveness of commodities and models. Classical methods to estimate optimal hedge ratios, such as using ordinary least squares (OLS) estimation for the slope parameter in the linear regression of spot and futures returns, have been used in previous studies, however, if the joint distribution of spot and futures prices is changing over time, then classical hedge ratio might not be appropriate, and time varying hedge ratios are better suited (Park and Jei, 2010). Choudhury (2003) showcase the superiority of time varying optimal hedge ratios using bivariate GARCH models in the context six cash and futures markets of Australia, Germany, Hong Kong, Japan, South Africa and the United Kingdom. Lai, Chen and Gerlach (2009) investigate the hedging performance of five Asian spot and futures stock markets using two threshold GARCH models to construct a bivariate copula GARCH model. In their results, with OLS and DCC ratios used as benchmarks, copula hedge strategies were found to be superior to traditional ones such as OLS, with copula strategies have higher mean returns and lower portfolio variance. Park and Jei (2010) estimate and evaluate the hedging effectiveness of bivariate GARCH models using the optimal conditional hedge ratio based on two BGARCH models. In the case of corn and soybean futures over the period covering January 1st 1997 to January 23rd 2001, they note that some BGARCH models have modest hedging improvements over traditional OLS strategies, however, the improvements are not big enough to guarantee that a bivariate GARCH hedging strategy is superior to a OLS hedging strategy. Chang et al. (2011) use BEKK, CCC, DCC and VARMA GARCH models to review the hedging performance in the context of Brent and WTI crude oil spot and futures prices. Optimal portfolio weights for all multivariate models for Brent suggest larger holdings in futures than spot. In addition, results from hedging effectiveness calculations indicate that the diagonal BEKK model produced the best results for hedging. Sadorsky (2014) looks into modelling volatility and conditional correlations between socially responsible investments, gold and oil using multivariate GARCH models, motivated by a lack of research in the area of socially responsible investing. Weekly data for the Dow Jones Sustainability Index (DJSI), the S&P 500 index, COMEX gold and WTI crude oil is used covering the period December 31st 1999 to May 31st 2012. For gold and oil, hedge ratios for DJSI are on average very similar to hedge ratios for the S&P 500, with an average hedge ratio of 0.05 for DJSI and oil comparable to an average hedge ratio of 0.07 for SP500 and oil. Basher and Sadorsky (2016) conduct research into the use of DCC, ADCC and GO-GARCH models to model volatilities and conditional correlations between emerging market stock prices, oil prices, VIX, gold prices and bond prices, additionally constructing forecasts of dynamic correlations and optimal hedge ratios. Hedging effectiveness was found to be highest for EM/oil hedge, indicating that WTI crude oil may be a more desirable hedge for emerging market stocks than VIX, gold or bonds, which were the second, third and fourth most effective hedging options respectively. In an extension on the previous work of Sadorsky (2014), Ahmad, Sadorsky and Sharma (2018) look at the hedging potential of clean energy stocks, to see how crude oil, US bonds, VIX, OVX and European carbon prices can be used to hedge against clean energy equities. Three variants of multivariate GARCH model (DCC, ADCC and GO-GARCH) are applied to daily data covering March 3rd 2008 to October 31st 2017, with dynamic correlations between DCC and ADCC models being very similar, with GO-GARCH differ, suggesting hedge ratios of GO-GARCH models will be different. Over their sample period, hedge ratios vary considerably, suggesting that they should be updated regularly, with VIX appearing to be the most attractive hedging asset for clean energy equities, showcasing the highest hedging effectiveness in all scenarios. Junttila, Pesonen and Raatikainen (2018) explore hedging against stock market risk in times of financial crisis, using crude oil and gold futures to analyse comovements between commodity futures and stock markets in periods of financial turmoil. In their results from computing risk minimizing optimal hedge ratios, WTI crude oil is found to have higher hedge ratios with S&P500 index, with peaks in optimal hedge ratio after the Dotcom bubble and the outbreak of the global financial crisis. Gold meanwhile has a negative optimal hedge ratio in the financial crisis, indicating that holding a long position in gold futures minimizes the risk of long position in S&P 500 total return index at the time. McAleer (2019) uses the DCC model to present the caveats of the model with regards to hedging purposes. Jalkh et al. (2021) examine which of the implied volatilities of US stocks and crude oil markets are more suitable for hedging the downside risk of US travel and leisure stocks, using the corrected dynamic conditional correlation process (cDDC). The risk-minimizing hedge ratio of the volatility index (VIX) against T&L stock index varies over time, with a notably sharp increase during the 2008 financial crisis, which is explained by the stronger correlation between assets during the crisis period, which is not the case for the OVX, with its correlation against T&L stock index remaining low. With a mostly positive hedge ratio, a short position in the VIX index can be used to minimize the risk of a long position in the T&L stock index. Dutta et a. (2021) investigate dynamic correlations of climate bonds, stock indices, gold and oil markets during the COVID-19 outbreak, additionally exploring the hedging effectiveness of using dynamic optimal hedge ratios, as used by Juntilla et al. (2018) and Jalkh et al. (2021). Using data for LO funds global climate bonds, as well as LBMA gold, WTI crude oil and S&P500 sport prices covering the period March 1 2017 to June 30 2020, they find that the average optimal hedge ratio is negative for climate bonds and US equities, suggesting that a $1 long position in US equities (crude oil) can be hedged for $1.931 with a long position in climate bonds. However, they note a positive optimal hedge ratio for climate bonds and gold, implying that a $1 long position in climate bonds can be hedged for $1.6792 with a short position in gold, in line with similar results earlier obtained by Junttila et al. (2018). Batten et al. (2021) study the feasibility of hedging stocks with oil using a DCC GARCH model to construct time varying hedge ratios and hedging effectiveness. Likewise with Ahmad et al. (2018), optimal hedge ratios are time varying, and significantly increase after the global financial crisis. The VIX is also found to be the most significant driver of hedge portfolio returns, which are negatively affected by this variable. MSCI Far east is also found to be an effective hedge against ICE brent futures contracts between January and August 1990, 1993 and between 1995 and 2004. Alshammari and Obeid (2023) analyse commodity futures and stock market indices, using two types of asymmetric DCC, namely range based and returns based DCC processes to evaluate the effectiveness of the strategies for short and long hedgers. In their results, ranged based DCC models tend to outperform returns based DCC models, with DCC-CARR model the most effective model with regards to hedging strategies. Ming et al. (2023) use a bivariate regime switching model to study whether gold is a safe haven asset, examining the properties of gold in 24 countries over the period covering 40 years ending December 31st 2020. In their analysis, gold was a strong hedge in Brazil, India, Indonesia, Italy, Mexico, Russia, South Korea, Thailand and Turkey, and a safe haven in Brazil, France, India, Indonesia, Italy, Mexico, Russia, South Korea and Turkey, showcasing the hedging properties of gold.

The use of metals, chiefly precious metals, in hedging strategies and their performance has been previously explored in the literature. Baur and McDermott (2010) use a GARCH model to look into the role of gold in the global financial system, and find that gold is an effective safe haven study for G7 countries, BRIC economies and Australia and Switzerland over the period 1979-2009. Hammoudeh et al. (2010) study the correlation dependency of four precious metals, and how they can be implemented into portfolio designs and hedging strategies. The most effective hedging strategy is to take a long position in gold and going short in palladium. Gold additionally commands the highest weight in optimal portfolio weights because it is considered the safest haven against fluctuations in the US dollar, with platinum also showcasing strong hedging properties. Liu et al. (2014) incorporate three stochastic volatility models to generate hedge ratios for China's copper and aluminium spot and futures markets. In sample hedge ratios are comparable across the three stochastic volatility models, but suggest that SV hedge ratios may not perform well when industrial metal spot and futures prices exhibit non-linear returns and price volatility jumps that are non contemporaneous. They additionally note that regardless of model the SHFE contracts showcase poor hedging performance. Umar, Shahzad and Kenourgios (2019) examine conditional correlations and the resulting optimal hedge ratios of US metal and mining credit default swaps and the prices of copper, gold, silver and platinum from December 14th 2007 to August 18th 2018 using multivariate GARCH models. In their results, copper is found to be the most effective hedge against credit default swaps, with the DCC, ADCC and GO-GARCH models all producing similar hedging effectiveness results, with gold found to be the least effective metal for hedging. Hernandez et al. (2019) analyse whether agricultural and precious metal futures can be used to diversify and hedge extreme downside risk and upside oil market risk in the oil market.

3.3 Data and Methodology

3.3.1 Data

In this chapter, we analyse the conditional correlation and spillover effects using five non ferrous metals traded on the London Metal Exchange (Copper, Aluminium, Zinc, Tin and Nickel), LMBA Gold, Brent Crude oil and the S&P 500 stock index, which represents two of the most commonly used commodities used in portfolio management and investment purposes, and one of the largest and most commonly traded stock indices. The non ferrous metals selected represent widespread coverage of some of the most commonly used and traded non ferrous metals and have numerous industrial uses but are also widely used in risk management for the purpose of portfolio diversification. For this chapter, we obtain daily price data for all assets used from Datastream for a sample period spanning from January 1, 1990, to December 29, 2023, whereby all daily historical price data is available for all non ferrous metals series, LBMA gold, brent crude oil and the S&P 500 index. This time frame has been chosen to allow for the coverage of major geopolitical and economic events, namely, the dot-com bubble of 2000-01, the 2008 financial crisis, the COVID-19 pandemic and the 2022 Russian invasion of Ukraine, which have each had major long lasting effects and repercussions on the global economy. We have chosen daily data, as news from markets can quickly spread to other markets, and aggregation of data may cause information to be hidden or removed (Chen et al. 2021).

3.3.2 Methodology

Univariate GARCH models are used to estimate conditional variances and volatility of a time series, however, the weakness of univariate GARCH is that it only allows for the estimation of a singular asset. Multivariate GARCH builds on this and allows us to capture dynamic conditional correlations between multiple variables at a single time. Daily returns are used as the proxy for model estimation, which can be expressed below as:

$$r_{i,t} = \left(lnp_{i,t} - lnp_{i,t-1}\right) \times 100$$

Where $p_{i,t}$ denotes the price of the commodity i at time t. Following Chen et al. (2021), an Autoregressive model is used to eliminate memory characteristics of returns, which can be denoted:

$$r_{i,t} = c_i + \phi_i r_{i,t-1} + \varepsilon_{i,t}$$

Where $r_{i,t} = [r_{1,t}, \dots \dots, r_{n,t}]'$ is a returns vector of n type of commodities, c_i is the constant term, ϕ_i is the coefficient matrix that corresponds to the autoregressive term, and $\varepsilon_t = [\varepsilon_{1,t}, \dots \dots, \varepsilon_{n,t}]'$ is a vector of residuals.

3.3.3 The BEKK-GARCH model

The BEKK class of multivariate GARCH model was first introduced in Engle and Kroner (1995) as a multivariate extension of the standard univariate GARCH model of Engle and Bollerslev (1986). The BEKK-GARCH model allows for the estimation and interaction of several time series in order to obtain conditional variances and conditional correlations, allowing us to identify conditional correlations and volatility transmission effects. We can express the conditional covariance matrix of the BEKK-GARCH model as:

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

Whereby W, A and B are matrices of parameters with appropriate dimensions, with W being an upper triangular matrix, and diagonal elements of the three parameter matrices being restricted to positive. Diagonal elements of H_t, $h_{ii,t}$ denote conditional variance terms, with off diagonal elements of H_t, $h_{ij,t}$ is a representation of conditional covariances where $i \neq j$. Additionally, the diagonal elements of matrix A captures the assets past shocks, and matrix B captures the assets past volatility. Off diagonal elements of matrices A and B, α_{ij} and β_{ij}, capture the cross market effects of shocks and volatility where $i \neq j$ (Li and Majerowska, 2008). The cross market events identified by the model allow for the examination of correlation effects and volatility spillover effects. The unrestricted form of the BEKK-GARCH model in bivariate form can be expressed as the following:

$$\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,1} \end{pmatrix} = W'W + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

$$+ \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

While the equation by equation model is given as the following:

$$h_{11,t} = w_{11}^2 + w_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2h_{1,t-1}2b_{11}b_{21}h_{1,2,t-1} + b_{21}^2h_{2,t-1}$$

$$h_{22,t} = w_{12}^2 + w_{22}^2\varepsilon_{1,t-1}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}\alpha_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2h_{11,t-1}2b_{12}b_{22}h_{1,2,t-1} + b_{22}^2h_{22,t-1}$$

$$h_{12,t} = h_{21,t} = w_{12}w_{11} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1}$$

After estimation of the model parameters, conditional correlation between two financial instruments is then estimated by the following equation:

$$r_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}} \cdots \sqrt{h_{22,t}}}$$

Whereby $h_{2,t}$ and $h_{2,t}$ represent the two financial instruments' conditional variances, while $h_{12,t}$ represents the final conditional covariance.

3.3.4 The CCC-GARCH model

The second class of multivariate GARCH model employed is based upon the decomposition of conditional covariance matrix into conditional standard deviations and correlations. The CCC-GARCH model of Bollerslev (1990) holds the key assumption that conditional correlations between elements of y_t are time invariant.

$$H_t = D_t^{1/2}RD_t^{1/2}$$

$$D_t = diag(h_{11,t}, \ldots, h_{nm,t})$$

Where Dt is a diagonal matrix with positive diagonal entries that are the conditional variances specified by a univariate GARCH model, and R is a positive defined correlation matrix, i.e.

$$R = \begin{pmatrix} 1 & \rho_{12} & \rho_{1n} \\ \rho_{21} & 1 & \rho_{2n} \\ \rho_{n1} & \rho_{n2} & 1 \end{pmatrix}$$

In the definition of the earlier equation, H_t is required to be positive definite. In the CCC-GARCH model, this condition is guaranteed by the requirement R and Dt are positive definite, particularly meaning that all of the conditional variances must be positive values, so that the constraints for positive conditional variance should be satisfied for each univariate GARCH model. The equation is then transformed to the following:

$$h_{ij,t} = \rho_{ij} \cdot \sqrt{h_{ii,t} h_{ij,t}}, \quad i \neq j$$

When R equals the identity matrix I so that $\rho_{ij} = 0$ when $i \neq j$, we get the case where all modelled assets are independent. For the purposes of this chapter, we will use the CCC-GARCH model as the benchmark for model evaluation,

3.3.5 The DCC-GARCH model

In addition to the BEKK model, the DCC-GARCH model of Engle and Sheppard (2001) and Engle (2002) is also employed. As an alternative extension of the CCC-GARCH model, one advantage of the DCC model is the detection of of possible changes in conditional correlations over time, which allows for the detection of dynamic responses to market shocks and innovations (Celik, 2012). In comparison to alternative multivariate GARCH models, such as the BEKK model, the DCC-GARCH model is relatively straightforward since the number of parameters to be estimated is relatively small (Park et al. 2017). Since volatility is adjusted by the procedure, time varying correlation does not have any bias from volatility, and the DCC-GARCH model continuously adjusts correlation for time varying volatility, hence providing a superior measure of conditional correlation.

The first step to estimating a DCC-GARCH model comprises two steps: firstly, estimating a univariate GARCH model, followed with the estimation of the conditional correlations. The two step DCC-GARCH model can be expressed as follows:

$$y_t = \mu_t + \epsilon_t \quad \epsilon_t | F_{t-1} \sim N(0, H_t),$$

$$\varepsilon = H_t^{\frac{1}{2}} u_t \quad u_t \sim N(0, I),$$

$$H_t = D_t R_t D_t,$$

Where F_{t-1} stands for the information available up to time t – 1. $y_t, \mu_{t,}$ ϵ_t and u_t are N x 1 dimensional vectors that represent the analysed time series, conditional mean term, error term and the standardized error terms respectively. In addition, R_t, H_t and $D_t = diag(h_{11t}^{\frac{1}{2}}, \dots, h_{NNt}^{\frac{1}{2}})$ are N x N dimensional matrices, illustrating dynamic conditional correlations, time varying conditional variance-covariance matrices and time varying conditional variances.

For the first step, to obtain D_t, a univariate GARCH model of Bollerslev (1986) is estimated for each series. Based on the study of Hansen and Lunde (2005), one shock and one persistency parameter are assumed:

$$h_{ii,t} = \omega + \alpha\epsilon_{i,t-1}^2 + \beta h_{ii,t-1}.$$

At the second stage, the dynamic conditional correlations are computed as follows:

$$R_t = diag(q_{iit}^{-\frac{1}{2}}, \dots, q_{NNt}^{-\frac{1}{2}})Q_t diag(q_{iit}^{-\frac{1}{2}}, \dots, q_{NNt}^{-\frac{1}{2}})$$

$$Q_t = (1 - a - b)\bar{Q} + au_{t-1}u'_{t-1} + bQ_{t-1}$$

Where Q_t and $\bar{Q}$ are N x N dimensional positive definite matrices which represent the conditional and unconditional standardized residuals' variance-covariance matrices respectively, and $a(\alpha)$ and $b(\beta)$ non-negative shock and persistency parameters, which satisfy $a + b < 1$ $(\alpha + \beta \leq 1)$. As long as $a + b < 1$ criteria is fulfilled, Q_t and hence R_t are varying over time, otherwise the model will converge to a CCC-GARCH model, where R_t parameter is constant over time.

3.3.6 The OGARCH model

Another class of multivariate GARCH model is the orthogonal GARCH (OGARCH) introduced by Ding (1994), which is based on a univariate GARCH model and principal component analysis. A popularly used to model conditional covariance of economic time series, the OGARCH model is additionally less computationally demanding than other competing multivariate GARCH models (Luo et al. 2015).

In the OGARCH model, observed time series are linearly transformed to a set of uncorrelated time series using principal component analysis. The OGARCH model can be described as follows:

Let Y_t be a multivariate time series of zero mean daily returns with k assets with length T and columns $y_1, \ldots, y_k$. The T x K matrix X_t whose columns $x_1, \ldots, x_k$ are given by the following equation:

$$x_t = \frac{y_t}{\sqrt{v_i}}$$

Where $V = diag(v_1, \ldots, v_m)$ with v_1 being the sample variance of the ith column of y_t. Let L denote a matrix of eigenvectors of the population correlation x_t and by $l_m = (l_{1,m}, \ldots, l_{k,m})$ its mth column. l_m is a k x 1 eigenvector corresponding to the eigenvalue λ_m. The column label of L is chosen so that $\lambda_1 > \lambda_2 > \cdots > \lambda_k$. Let D be the diagonal matrix of eigenvalues and $W_m = l_m\sqrt{D}$. The mth principal component of the model is then defined as:

$$p_m = x_1 l_{1,m} + x_2 l_{2,m} + \cdots + x_k l_{k,m}$$

If each vector of components p_m is placed as the columns of a T x k of matrix P, then: $P = XL$. The principal component columns are modelled by GARCH(1,1):

3.3.7 The GOGARCH model

The GO-GARCH model of Van Der Weide (2002) can be seen as a generalization of the OGARCH model, while being nested within the more general BEKK-GARCH model. Based on the GO-GARCH model, the returns r_t are the sum of the conditional mean m_t which can include an autoregressive term of order one (AR(1) term) and an error term e_t.

$$r_t = m_t + e_t$$

The difference between the returns and the conditional mean is mapped onto a set of unobservable independent factors denoted f_t.

$$e_t = Af_t$$

Where A is a mixing matrix which is decomposed into two different matrices, with the first being an unconditional covariance matrix denoted $\sum$ and the second an orthogonal rotational matrix denoted as U.

$$A = \sum^{1/2} U$$

The rows of the matrix correspond to the assets, with the columns corresponding to the factors. Each of the factors can be expressed as:

$$f_t = H_t^{1/2} z_t$$

Where z_t is a random variable which is zero mean ($E(z_{it}) = 0$) and a variance of one ($E\left(z_{it}^2\right) = 1$). In this specification, a GARCH process can be adopted to model the factor conditional variances h_{it}. Unconditional distribution of factors must satisfy these two conditions: $E(f_t) = 0$ and $E(f_t f'_t) = I$. When these equations are combined together, r_t can then be specified as:

$$r_t = m_t + AH_t^{1/2} z_t$$

And the conditional covariance matrix of $(r_t - m_t)$ is expressed as:

$$\textstyle\sum_t = AH_t A'$$

In the GO-GARCH model, Van der Weide (2002) assumes that the mixing matrix A is a time invariant and H_t is a diagonal matrix, with the condition that matrix A must be orthogonal.

3.3.8 The DCC-MIDAS model

The DCC-MIDAS model of Colacito, Engle and Ghysels (2011) allows for the conditional correlation between two different assets to be split into both long run and short run components. Likewise with the estimation of the DCC-GARCH model, we follow the two-step procedure of Engle (2002) by estimating the parameters of the univariate conditional volatility models, followed by estimating the DCC-MIDAS parameters with the standardized residuals. The first step to estimating DCC-MIDAS according to Colacito et al. (2011) is to estimate a GARCH-MIDAS model to obtain the standardized residuals which are dynamic correlations in constructed form. The GARCH-MIDAS approach can be surmised as:

$$r_{i,t} = u + \sqrt{\tau_t g_{i,t} \varepsilon_{i,t}}, \qquad \forall i = 1, \dots, N$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1),$$

Where $r_{i,t}$ is the return on day i in month t, u is the conditional mean and $\varepsilon_{i,t}$ is the error term with a normal distribution. The short run component can be expressed as:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - u)^2}{\tau_t} + \beta g_{i-1,t}$$

And the long run component can be expressed as:

$$\tau_t = m + \theta \sum_{k=1}^{k} \varphi_k(\omega_1, \omega_2) X_{t-k}$$

Where X_{t-k} is the low frequency predictor, k is the number of lags, and $\varphi_k(\omega_1, \omega_2)$ is the weighting function. In the second step to estimating a DCC-MIDAS model, the dynamic correlation between assets given by measuring the dependence of the standardized residuals is given by the following equation:

$$R_t = diag\left(\frac{1}{\sqrt{Q_t}}\right) Q_t diag\left(\frac{1}{\sqrt{Q_t}}\right),$$

Where Q_t is the short run correlation matrix with elements $q_{ij,t}$ specified as follows:

$$q_{ij,t} = \bar{\rho}_{ij,t}(1 - a - b) + a\xi_{i,t-1}\xi_{j,t-1} + bq_{ij,t-1}$$

Where $\xi_{i,t-1}$ and $\xi_{j,t-1}$ are the standardized residuals obtained by the univariate GARCH-MIDAS estimation, a and b are estimated parameters, $a > 0, b > 0$, and $a + b < 1$, and $\bar{\rho}_{ij,t}$ is the long run correlation, which is given by the following equation:

$$\bar{\rho}_{ij,t} = \sum_{k=1}^{k_c^{ij}} \varphi_k(\omega_r^{ij}) c_{ij,t-1}$$

Where $\varphi_k(\omega_r^{ij})$ is the weighting function, c_{ij} is the weighting function of assets i and j as given by:

$$c_{ij} = \frac{\sum_{k=t-N_c^{ij}}^{t} \xi_{i,k}\xi_{j,k}}{\sqrt{\sum_{k=t-N_c^{ij}}^{t} \xi_{i,k}^{\ 2}} \sqrt{\sum_{k=t-N_c^{ij}}^{t} \xi_{j,k}^{\ 2}}}$$

Where N_c^{ij} is the lag length in computing the realized correlation, K_c^{ij} is the span length of historical correlation. It is important to note that if $\bar{\rho}_{ij,t}$ remains constant, the DCC-MIDAS model turns into a regular DCC-GARCH model.

3.3.9 Wavelet Coherence Analysis

As previously implemented by Kang, McIver and Hernandez (2019), wavelet coherence is also employed to analyse comovements between non-ferrous metals and other classes of financial asset. In contrast to other multivariate GARCH based approaches to modelling conditional correlation, the bivariate wavelet coherence approach allows for the capture of comovements and correlations between two different financial instruments in two different domains, namely time and frequency, by implementing a framework based on continuous wavelet transform, which allows for various scaled forms of localisation (Rua & Nunes, 2009), thus allowing it to shed more light on comovements between selected non ferrous metals and other financial return series.

In accordance with the approach used by Kang, McIver and Hernandez (2020), to characterize the comovements in differing time and frequency domains between non ferrous metals and selected financial assets, we estimate wavelet coherence by using cross wavelet transform and cross wavelet method. We define the cross wavelet transform for time series x(t) and y(t) with continuous wavelet transforms (CWT) $W_n^X(u,s)$ and $W_n^{Xy}(u,s)$ as the following:

$$W_n^{Xy}(u,s) = W_n^x(u,s)W_n^{y*}(u,s)$$

Where u refers to the location. s is the scale and * denotes the complex conjugate. CWT reveals areas in the time frequency domain where evaluated time series show high power, which represents degrees of local covariance correlation between the two time series at each scale and frequency. The wavelet coherence method can detect comovements between two series in the time and frequency domains. Following Kang, McIver and Hernandez (2020) and Torrence and Webster (1999), the wavelet coherence of two time series can be defined as:

$$R^2(u,s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)}$$

Where S is considered as a smoothing operator over time as well as scale, with $0 \leq R^2(u,s) \leq 1$. The value of the wavelet squared coherence, denoted $R^2(u,s)$, gives a value between 0 and 1, with a lower value corresponding to period of low comovement and a high value denoting strong comovement.

Unlike standard correlation coefficient models such as DCC-GARCH, wavelet squared coherence is only represented as positive values. The graphical representation of wavelet coherence enables the identification of areas of comovement of assets in the time and frequency space.

3.3.10 Likelihood Ratio Test

The likelihood ratio test is used to measure the goodness of fit between two or more competing models in order to determine which of the models produces the best goodness of fit based on their log likelihood. The idea is simply that the less general model m_0, m which represents the null hypothesis, can be obtained by constraining some of the parameters of the more complex model m_a. A lower p-value indicates a better goodness of fit. Rejection of the null indicates that we reject the restricted model m_0, in favour of the alternative, unrestricted model m_a. In its simplest form, the likelihood ratio test can be expressed as:

$$LRT = -2log_e\left(\frac{m_o(\hat{\theta})}{m_a(\hat{\theta})}\right)$$

3.3.11 Hedging Effectiveness

Following the studies of Mensi et al. (2017) and Dutta et al. (2021) we compute the dynamic optimal hedge ratio in order to assess hedging effectiveness of non-ferrous metals again gold, brent and S&P500 futures respectively. The dynamic optimal hedge ratio used by Mensi et al. (2017), Jalkh et al. (2021) and Dutta et al. (2021) is based on the equation proposed by Kroner and Ng (1998), which can be calculated by the following:

$$w_t^c = \frac{h_t^s - h_t^{cs}}{h_t^s - 2h_t^{cs} + h_t^s}$$

Where h_t^c, h_t^s and h_t^{cs} are the conditional volatility of the commodity markets, conditional volatility of gold, brent or SP500 and the conditional covariance between the metal and instrument at time t. The conditional variances and covariances to calculate the hedge ratio are based on the best performing multivariate GARCH model in relation to the benchmark model, as outlined in the results of the likelihood ratio test. As a dynamic model, the optimal hedge ratio changes over time, in contrast to the standard optimal hedge ratio computed using OLS, which is stationary. This allows to visualise changes to the optimal hedge ratio throughout different periods, for instance throughout events such as the 2008 financial crisis and the COVID pandemic.

3.4 Results & Comments

3.4.1 Descriptive Statistics

In this section, we present the results of our findings along with the discussion and implications of our results. Table 3.1, which can be found in the appendix section, reports the descriptive statistics for the logged price return series of the five non-ferrous metals, four precious metals, two crude oil and two stock indices used in this chapter. There are a total of 8869 observation for each return series, covering a total of 33 years from January 1st 1990 to December 31st 2023. The average price returns are positive for each of the crude oils, the S&P500 index and the copper, tin and nickel non ferrous metals. Interestingly, all four precious metals analysed have negative average price returns, although all series analysed are close to zero mean. Moreover, Brent crude oil is the volatile commodity, as measured by a standard deviation of 2.548%, while gold represents the least volatile series, with a standard deviation of 0.963%. All price series with the exception of nickel showcase slight negative skewness, indicating that small positive returns with few large negative returns and a longer left tail. In contrast, nickel returns are positively skewed, indicating that large positive returns are more common than large negative returns, and the returns exhibit a longer right tail. In can be noted that all returns series have a kurtosis greater than 3, with Brent crude. Exhibiting the highest excess kurtosis, inferring that all return series are leptokurtic, and returns are clustered around the mean.

Table 3.2 showcases results of the unit root tests for the returns series using two tests, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips-Perron test (PP) proposed by. Phillips and Perron (1988). All the results for the ADF and PP tests present large negative values, rejecting the null hypothesis of a unit root at the 1% significance level. The consistency of the results for the two unit root tests indicate that all return series are stationary.

3.4.2 Conditional Correlations

As the CCC-GARCH model makes the assumption of constant conditional correlation, the conditional correlation plots for each model estimated are estimated as stationary figures. In our results, in the cases of aluminium, zinc and nickel, we noted conditional correlations appear to be highest with gold, with copper and tin having highest correlations with brent crude, with all non ferrous metals having lowest correlations with the S&P 500 index.

Figures 3.1.1 to 3.1.5 and 3.1.11 to 3.1.15, which can be located in the appendix section, showcase conditional correlation graphs for symmetric and asymmetric DCC-GARCH for LME copper, aluminium, zinc, tin and nickel with gold, brent crude and the S&P 500 stock index respectively over the time period of 2nd January 1990 and 28th December 2023. The asymmetric DCC-GARCH model incorporates the leverage effect of the GJR-GARCH model in an effort Upon examining the figures presented, we can observe differing spiking of conditional correlation, with copper exhibiting the greatest degree of variance. Examining the relationships between non-ferrous metals and gold, brent crude and the S&P500, we observe notable spiking in periods of crisis, most notably, the dot-com bubble of 2001, the financial crisis around 2008-09 and the COVID-19 pandemic beginning January 2020. An additional spike in conditional correlation can also be observed at the beginning of 2022, in conjunction with the Russian invasion of Ukraine. For all non-ferrous metals, the prominent spiking observed follow a similar trend and occurs in and around the periods of crisis. It is important to note for copper, aluminium and zinc a strong positive correlation with gold in periods with weak positive correlation with Brent crude and the S&P 500, and vice versa, suggesting that these metals could potentially as safe haven assets in these periods, however, it is important to note negative correlation between copper and gold at the beginning of the COVID crisis, indicating that conditional correlations between copper and gold may be time dependent. Nickel exhibits a negative correlation with the S&P500 in early 2020. Upon first inspection of the symmetric and asymmetric DCC-GARCH model, we can note an observable upward trend in conditional correlation over the sample period, although strong positive correlations with gold appear to be in periods with weak positive correlations with brent crude and the S&P500 index and vice versa.

Figures 3.1.6 to 3.1.10 and 3.1.16 to 3.1.20 display conditional correlation graphs for symmetric and asymmetric BEKK-GARCH for LME copper, aluminium, zinc, tin and nickel with LBMA gold, Brent crude and S&P500 stock index. In a similar case with the DCC model, symmetric and asymmetric BEKK model produces very similar results to each other, however, in contrast to DCC-GARCH, we observe far greater spikes in volatility, with more periods of negative correlation for all metals. In is interesting to note in the case of nickel, there are cases of negative correlation with the S&P500 index and brent crude oil which can be observed after the beginning of the COVID-19 pandemic, with a small positive correlation with gold in this period. Applying the categorization of Baur and Lucey (2010), in this case, we can note that nickel can be considered a hedge against brent and the S&P500. However, it is important to note that we can observe no clear trend with the BEKK-GARCH model, with more prominent spikes in positive and negative correlation in comparison to the DCC-GARCH model, where we can observe a general positive correlation. With the correlations of the BEKK model producing no discernible upward or downwards trend, with correlations converging to near mean zero, this could be due to overparameterization of the BEKK model, as the BEKK-GARCH incorporates additional information in model estimation. Upon inspection of the symmetric and asymmetric DCC and BEKK models, similar correlations are observable between the symmetric and asymmetric counterparts.

Estimations of OGARCH and GOGARCH models can be seen in figures 3.1.21 to 3.1.25 and 3.1.26 to 3.1.30 respectively. In contrast to results from the DCC and BEKK models, OGARCH model showcases strong negative correlation with Brent crude oil and positive correlations with gold in the cases of copper, aluminium and tin, with this trend reversing in periods of crisis, most notably the 2008 financial crisis in the case of gold and around the 2013-15 period in the case of brent crude. Interestingly, correlations with gold seem to further increase around the period of 2020, in conjunction with the outbreak of the COVID pandemic. In these cases, the results suggest that copper, aluminium and tin can be used in conjunction with gold for diversification and hedging purposes. We observe that nickel exhibits more typical behavioural properties, showcasing no or little positive correlation with brent and the S&P500, with spikes in correlation noted around periods of crisis. Additionally, nickel typically exhibits strong negative correlation with gold throughout the sample period, although, we can again observe large spikes in positive correlation with gold around the periods of the dot com bubble in early 2000 and the COVID outbreak in 2020. It is interesting to note that the results from OGARCH estimation appear to be in stark contrast to results from symmetric and asymmetric BEKK and DCC model estimations, with brent crude and S&P 500 correlations appearing to directly oppose conditional correlations with gold. With regard to results from OGARCH estimations, it would appear that non ferrous metals can be used with gold as an alternative to diversify portfolios.

Results for the DCC-MIDAS plots, which decomposes conditional correlation into short run and long run components, can be seen in figures 3.1.31 to 3.1.40, which depictions for short run and long run correlations respectively. The first 1500 observations are set aside to initialize the model, so they are eliminated from the plots. As expected, short run correlations have much greater volatility persistence, with long run correlations being largely mostly positive for each non ferrous metal, as prices for financial assets tend to converge over the long term. For each series, with the exception of nickel, correlations with gold appear to be strongest in periods where correlations with brent crude are weakest, most notably in periods in the financial crisis in 2008 and the COVID outbreak in 2020, where strong positive correlations with gold and negative correlations with brent are consistent across each non ferrous metal series, with nickel having largely even correlations with gold, brent and the S&P 500 index across the entire sample period. The long run correlation plots for each series are positive, as price trends tend to converge over time, with periods of stronger correlations with gold and weaker correlations with brent crude consistent with results from the OGARCH model.

3.4.3 Likelihood Ratio Test

The likelihood ratio test is used to compare the goodness of fit for two competing models. We use the CCC GARCH model as the benchmark model for symmetric and asymmetric DCC and BEKK models, OGARCH, GOGARCH and DCC-MIDAS models, to give a total of 7 competing models. Lower p-value indicates a better goodness of fit, with a p-value close to zero suggesting that there is strong evidence for rejection of the null. The results of the likelihood ratio test for the 7 selected models can be located in table 3.2.1 within the appendix section of this chapter. Values highlighted in bold indicate that the null, restricted model should be rejected in favour of the alternative unrestricted model. The results of the likelihood ratio test are presented in figure 7 located within the appendix section. At the 5% significance level, the DCC-MIDAS model is the best performing model for all non ferrous metals when compared to the benchmark CCC model, indicating strong evidence that the DCC-MIDAS model produces the best goodness of fit with the data. The OGARCH produces the second lowest p-value, however, there is no rejection of the null that the benchmark model should be rejected in favour of the unrestricted model, indicating that there is not strong enough evidence to reject the CCC model in favour of the OGARCH model at the 5% confidence level. Results from likelihood ratio tests indicate that the BEKK model is the worst performing model of all models in the sample, producing the highest p-value at the 5% significance level. Additionally, asymmetric DCC-GARCH and BEKK-GARCH were found to produce higher p-values, and therefore, lower goodness of fit, than symmetric DCC and BEKK counterparts. This could be explained by overparameterization of the BEKK model.

3.4.4 Wavelet Coherence analysis

The wavelet coherence approach enables the analysis of conditional correlations between two time series in the time and frequency space. The main advantage of the wavelet approach is its ability to decompose time varying comovements into different investment horizons, namely in the time and frequency horizons. Figures 3.2.1 to 3.2.15 located within the appendix of this chapter display the results of wavelet coherence tests between corresponding non ferrous metals with LBMA gold, Brent crude and the S&P 500 index respectively. The colours in the wavelet heatmaps refer to the strength and scale of the covariance between the series, with warmer colours such red and orange denoting a higher degree of dependence between the pair of instruments, more neutral colours such as yellow showcasing moderate dependence and cold, darker colours indicating weak covariance and black showing no correlation in the respective time and frequency space. The x-axis of the sample represents the time range of the sample in years, while the y-axis highlights the frequency of the period representing trading days with 4 representing a 4 day trading cycle, increasing up to a 256 day cycle approximating one year. Another advantage of the wavelet approach is that it allows us to see whether two series are in phase or out of phase, and which series in the main transmitter of volatility, with phase difference and volatility transmission indicated by the arrows in the heatmaps. Arrows pointing to the right indicate that the two markets are in phase, and arrows pointing to the left likewise indicate the two markets are out of phase. If the two markets are in-phase, this suggests that the two markets have a cyclical effect on each and an out of phase situation denotes that the two variables have an anti-cyclical effect on each other. Additionally, arrows pointing more upwards indicate that the nonferrous metal is leading the returns of either gold, brent crude or the S&P500, with arrows pointing downwards suggesting that gold, brent or the S&P500 are volatility transmitters to the selected non ferrous metal. Inspection results of wavelet coherence between copper and corresponding series, we observe weak short-term correlations across for all results at high frequency scale, indicating low comovements between the selected non-ferrous metals and gold, brent and the S&P500 index at short term time horizons. In the instances of high comovement, namely around the periods of the 2008 financial crisis and the 2020 COVID outbreak, we observe that non ferrous metals appear to be in sequence with gold, brent crude and S&P500 returns, as indicated by the rightward arrows in the wavelet heatmaps. This is most prevalent at the high frequency (long run) period, where there is persistent presence of strong covariance correlation around the time of the 2008 financial crisis for all series, however we notice significant long run correlation between copper and the S&P 500 index, beginning around the period of 2003 up until the end of the sample, implying copper prices may be strong influenced by fluctuations in the S&P 500 index. This appears to be the case for all non-ferrous metals evaluated in our sample, with aluminium also showcasing significant long run correlations with the S&P 500 index from the financial crisis until the end of the sample period, with further presence of medium and long run correlation around the period of the outbreak of the COVID-19 pandemic. Although long run correlations between Zinc and Nickel and the S&P 500 index are also present, these appear to be limited to the 2008 financial crisis. Interestingly, we can observe some instances in heatmaps for aluminium, tin and copper with gold and tin with the S&P500 of strong comovements where left downward relationships can be observed in the heatmaps, notably around the period of the early 1990s, and additionally the dot com bubble in the case of tin and SP500, indicating the phase difference between the sets of analysed variables.

3.4.5 Hedging Effectiveness

To showcase the potential use of non ferrous metals can be used in a potential hedging strategy, we calculate the dynamic optimal hedge ratio of non ferrous metals against gold, brent crude and the S&P500. As the most optimal model in accordance with the likelihood ratio test, we will use the DCC-MIDAS model to extract the conditional covariance matrixes. We can extract the conditional covariances of each metal and asset and the conditional variances to compute the dynamic optimal hedge ratio, which is advantageous over the standard optimal hedge ratio estimated using OLS which is stationary over time. An optimal hedge ratio closer to 1 indicates a position can be fully hedged, however, as the dynamic optimal hedge ratio changes over time, it is desirable for the dynamic optimal hedge ratio to remain as close to 1 as possible.

Figures 3.3.1 to 3.3.15 present the plots of dynamic optimal hedge ratio of each non ferrous with LBMA gold, ICE brent crude and the S&P 500 can be located within the appendix section of this chapter. Each non ferrous metal can be seen as a strong potential hedge to the S&P500 index in the period of 2010 to 2015 with optimal hedge ratio fluctuating between 0.10 and 1.4 in this period, with an optimal hedge ratio of 1 suggesting a perfect hedge, while an optimal hedge ratio over 1 suggests overhedging in non ferrous metal futures to protect against changes in the S&P500 index. In contrast to the S&P500 index, none of the non ferrous metals in our sample prove to be an effective hedge against ICE brent crude futures, with typical hedge ratio fluctuating between -0.1 and 0.2 throughout the sample period, however, we do note a period in which non ferrous metals hedging effectiveness is increased throughout the time period of 2010 to 2015, noting no negative hedge ratios in this period with a high of 0.5 in this period, suggesting non ferrous metals could potentially be effectively used as a hedge against Brent crude in this period. Following the Deepwater Horizon oil spill in 2010, this period is notable for a boom in Crude oil prices succeeded by a plunge throughout which oil prices rose throughout the early

2010 to a high of $112 per barrel in 2014, following which prices plunged to a low of $31 in January 2016 (Prest, 2018). Dynamic optimal hedge ratios revert to lower levels following 2016, suggesting non ferrous metals may be an effective hedge against Brent crude oil in periods of high volatility of crude oil. Optimal hedge ratios for non ferrous metals against gold exhibit more variance, with hedge ratios varying greatly between -1 and 2, with more periods where hedge ratios vary between 0.5 and 1. Gold and non ferrous metals potentially serve as an effective hedge against each other, however, sudden significant changes in the dynamic optimal hedge ratio over suggests that its feasibility appears to be over short time horizons.

3.5 Concluding remarks

In this chapter, the use of non-ferrous metals with relation to widely used commodities and financial instruments in portfolio optimization is analysed, using a wide range of multivariate GARCH, namely CCC GARCH, symmetric and asymmetric DCC and BEKK GARCH models, Orthogonal GARCH, GO-GARCH and the DCC-MIDAS model to model conditional correlation and volatility transmissions of five non ferrous metal (copper, aluminium, zinc, tin and nickel) with LBMA gold, ICE Brent crude oil and the S&P 500 stock index over the period covering January 1st 1990 to December 31st 2023, a period containing numerous major economic events including the dotcom bubble, the 2008 global financial crisis, the crude oil price plunge of 2014-16 and the coronavirus pandemic, which started in 2020 and with lasting effects still being felt today. Additional wavelet analysis is used to produce heatmaps of correlation between selected non ferrous metals and commodities to showcase conditional correlations in the time and frequency horizon. Log likelihood ratio test is then conducted to showcase the model which produces the best goodness of fit against the benchmark model (CC-GARCH). Conditional variances and correlation matrices of the best performing model are then extracted to compute dynamic optimal hedge ratios to assess the potential for non ferrous metals to be used as potential hedges against LBMA gold, Brent crude and the S&P 500 index.

Results from conditional correlation analysis highlight spikes in conditional correlations for all models in periods of crisis, followed by sharp downturns. Copper for all models generally appears to have strong correlations with gold in periods with lower correlations with brent crude and the S&P500 and vice versa, which are most prevalent around the 2008 financial crisis and the 2020 covid pandemic. Similar properties are also observed for aluminium although we note less overall variance in conditional correlations. Conditional correlations between tin and gold, brent and S&P500 are found to be the most volatile, with frequent spikes in conditional correlation. Both symmetric and asymmetric BEKK models are found to be overparameterized, with very noisy plots due to the incorporation of more variables in comparison to the DCC model. OGARCH model showcases all metals with the exception of nickel as potential hedges, with strong correlations with gold at times of weak correlation with brent and the SP500 index and vice versa. DCC-MIDAS model decomposes conditional correlation into short run and long run components, with short run correlations exhibiting much greater volatility persistence, and long run volatility being mostly positive, although this is to be expected, as prices tend to converge over the long run. Consistent with other models, correlations are strongest with gold when weakest with Brent crude and the S&P500 index and vice versa, with the DCC-MIDAS model. Results from likelihood ratio tests to analyse goodness of fit highlight the DCC-MIDAS model to be the best performing model, when compared to the benchmark CCC model, producing the lowest p-value at the 5% significance level. BEKK-GARCH is found to be the worst performing model, which may be explained by overparameterization. Symmetric DCC and BEKK models produce slightly better goodness of fit compared to asymmetric counterparts. Results from wavelet coherence analysis showcase that non ferrous metals largely showcase weak correlations with gold, brent crude and the S&P500 at short time horizons, although medium run positive correlations are more prevalent around the period of the 2008 financial crisis. Long run correlations are present for all metals with LBMA Gold, Brent crude and the S&P500 although this is to be expected as prices converge due to information being reflected in commodity prices. Estimation of dynamic optimal hedge ratios exhibits potential for non ferrous metals to serve as a potential hedge against the S&P 500 with persistent positive hedge ratios throughout the 2010s in our sample period for all non ferrous metals, although their ability to serve as a potential hedge for Brent crude futures is far more limited. These findings are of relevancy and importance to fund managers and market makers, by presenting evidence how non ferrous metals can be potentially implemented in a hedging strategy, furthermore, how their comovements with widely traded financial instruments can help drive financial decisions.

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Appendix

Table 3.1 Descriptive Statistics of Corresponding Nonferrous metals, precious metals, crude oil and Stock index return series.

	Copper	*Aluminium*	*Zinc*	*Tin*	*Nickel*	*Gold*	*Silver*	*Platinum*	*Palladium*	*Brent*	*OPEC*	*S&P500*	*FTSE100*
Mean	6.7472E-17	-4.301E-17	-2.032E-16	3.294E-16	1.2944E-17	-1.41E-16	-3.217E-17	-8.475E-17	-2.706E-16	3.7704E-17	5.5129E-17	5.4316E-17	-2.401E-16
Standard Error	0.017	0.013	0.018	0.016	0.023	0.010	0.019	0.015	0.022	0.027	0.022	0.012	0.011
Median	-0.014	-0.004	-0.008	-0.015	-0.008	-0.018	-0.017	-0.008	-0.024	-0.015	0.040	-0.003	-0.005
Mode	-0.014	-0.004	-0.008	-0.015	-0.008	-0.018	-0.017	-0.008	-0.024	-0.015	-0.016	-0.029	-0.013
Standard Deviation	1.570	1.227	1.698	1.487	2.128	0.963	1.833	1.415	2.079	2.548	2.076	1.126	1.078
Sample Variance	2.466	1.506	2.882	2.210	4.527	0.926	3.361	2.003	4.324	6.490	4.312	1.268	1.163
Kurtosis	4.699	3.601	4.149	7.629	40.588	7.607	10.745	8.607	7.394	67.752	42.672	11.108	7.909
Skewness	-0.180	-0.129	-0.302	-0.294	1.377	-0.377	-0.451	-0.540	-0.315	-1.826	-1.763	-0.398	-0.291
Range	22.201	18.626	24.368	25.688	68.939	17.544	37.864	29.005	34.821	105.572	65.006	23.722	20.897
Minimum	-10.490	-9.395	-14.427	-11.449	-18.114	-10.181	-19.603	-17.285	-17.883	-64.385	-43.002	-12.795	-11.526
Maximum	11.712	9.231	9.941	14.239	50.824	7.364	18.261	11.720	16.938	41.188	22.004	10.928	9.371
Sum	5.9841E-13	-3.814E-13	-1.802E-12	2.9214E-12	1.148E-13	-1.25E-12	-2.853E-13	-7.516E-13	-2.4E-12	3.344E-13	4.8894E-13	4.8173E-13	-2.129E-12
Count	8869	8869	8869	8869	8869	8869	8869	8869	8869	8869	8869	8869	8869

Table 3.2 Results of Unit Root Tests for Corresponding Nonferrous metals, precious metals, crude oil and Stock index return series.

	Copper	Aluminium	Zinc	Tin	Nickel	Gold	Silver	Platinum	Palladium	Brent	OPEC	S&P500	FTSE100
ADF	-99.301**	-94.785**	-94.169**	-91.34**	-90.866**	-94.455**	-99.671**	-93.349**	-89.967**	-93.145**	-82.278**	-102.124**	-95.462**
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phillips-Perron	-99.308**	-94.701**	-94.166**	-91.343**	-90.868**	-94.455**	.99.668**	-93.341**	-89.968**	-93.134**	-82.279**	-102.125**	-95.467**
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 3.1.1 Symmetric DCC-GARCH LME Copper Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

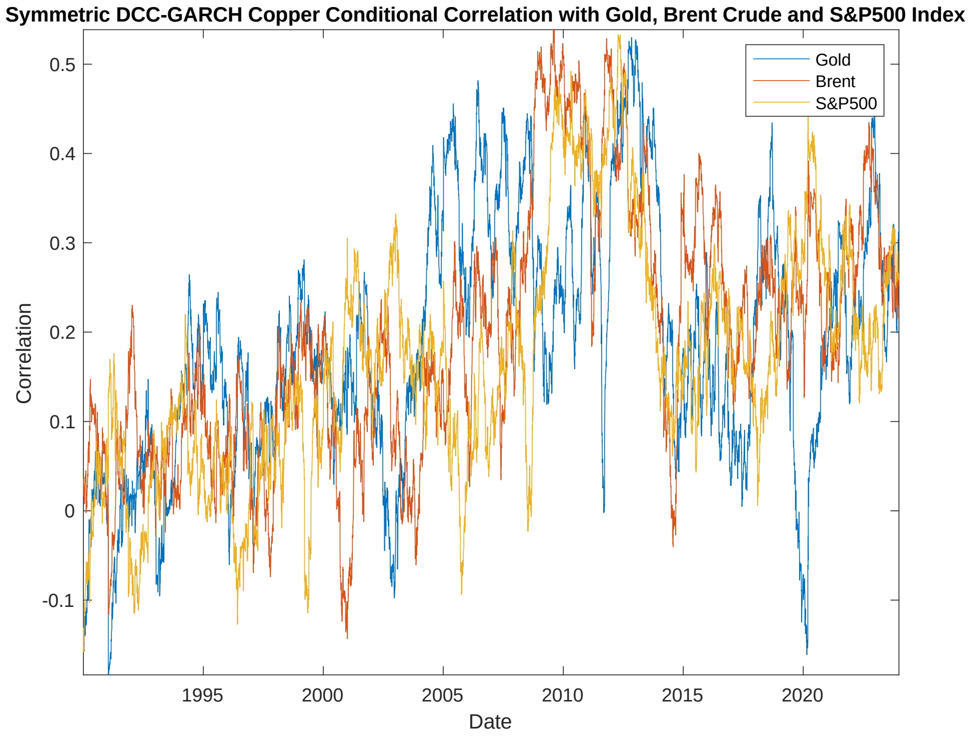


Figure 3.1.2 Symmetric DCC-GARCH LME Aluminium Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

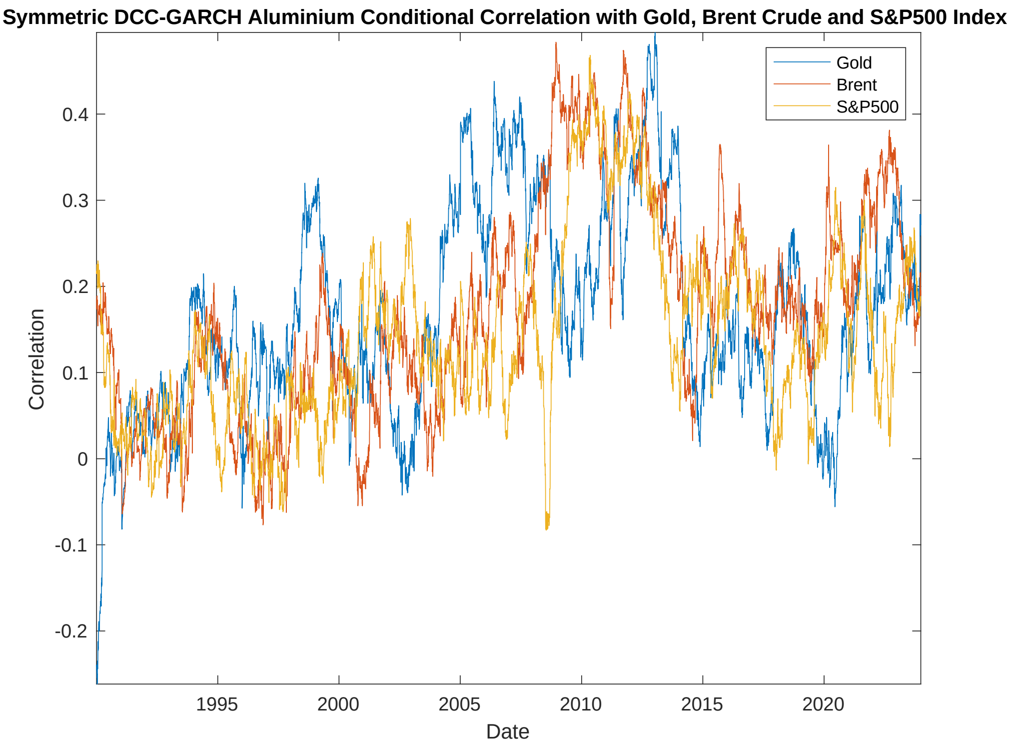


Figure 3.1.3 Symmetric DCC-GARCH LME Zinc Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

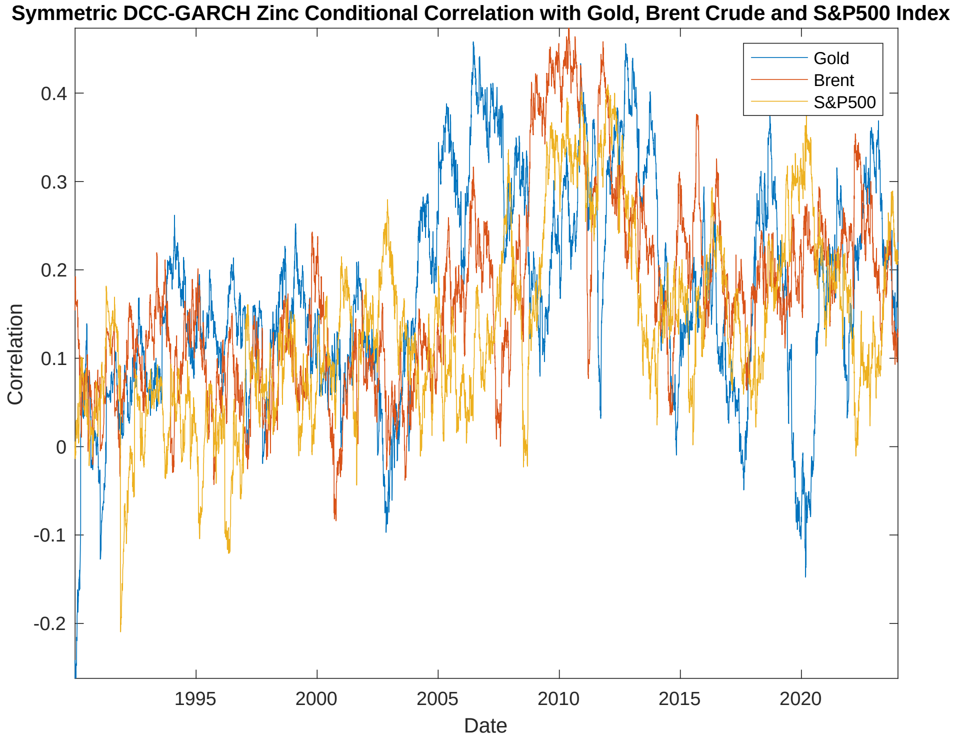


Figure 3.1.4 Symmetric DCC-GARCH LME Tin Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

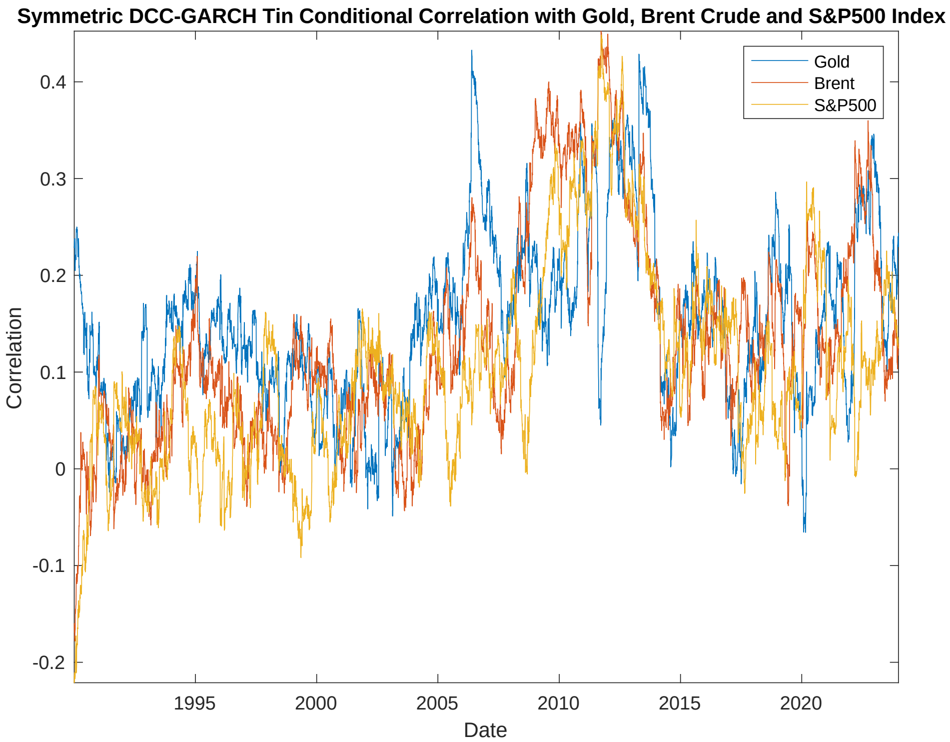


Figure 3.1.5 Symmetric DCC-GARCH LME Nickel Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

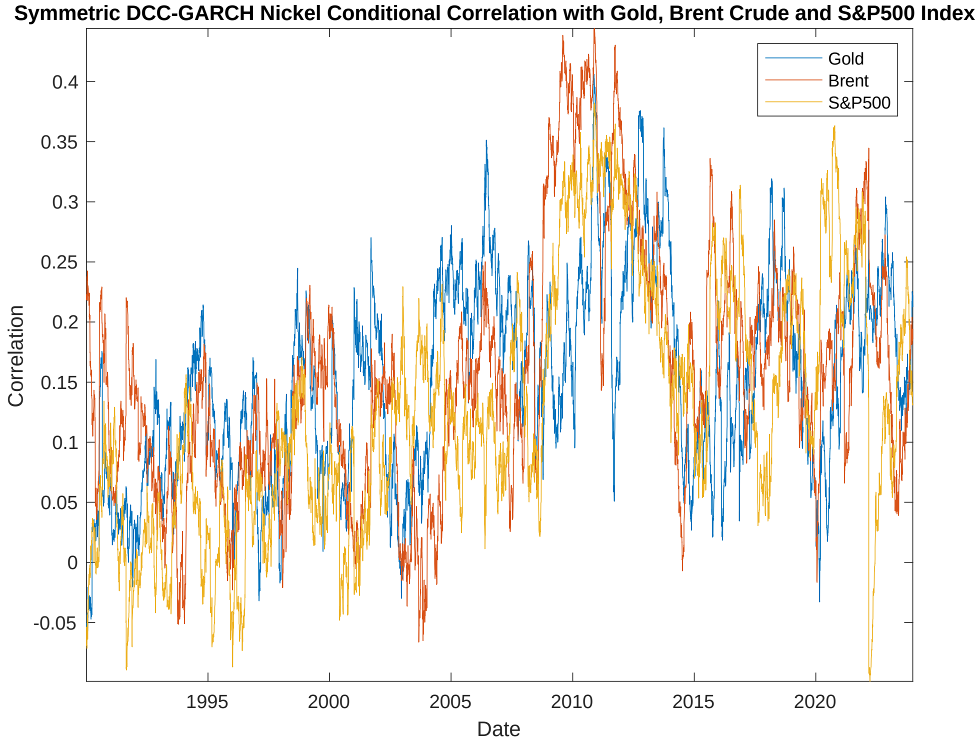


Figure 3.1.6 Symmetric BEKK-GARCH LME Copper Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

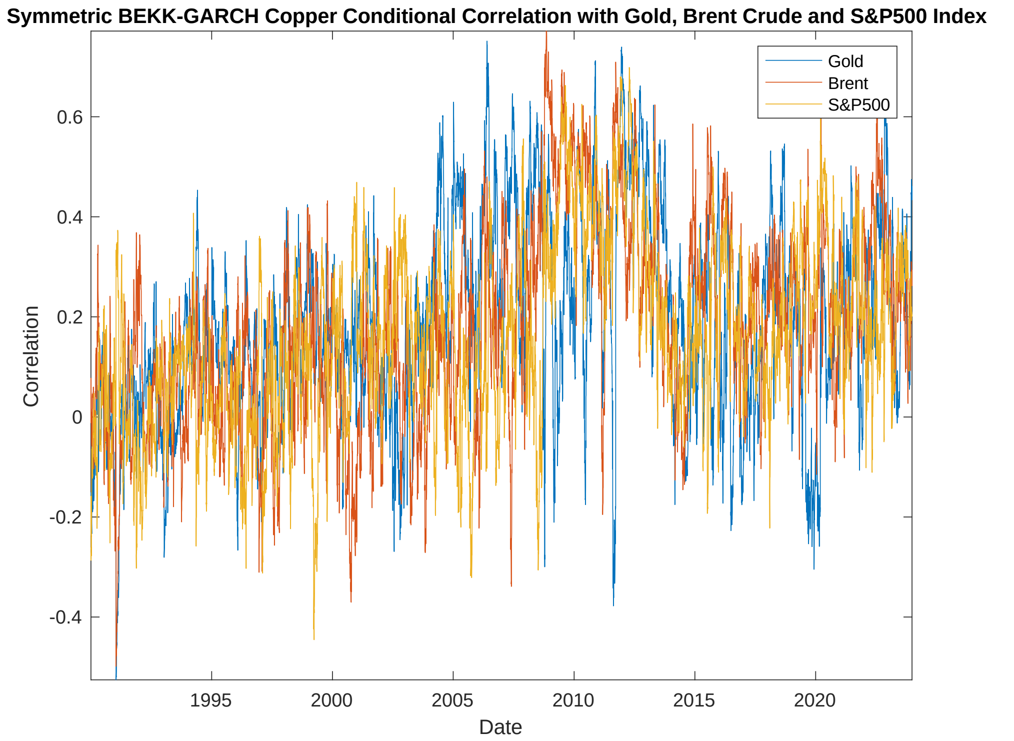


Figure 3.1.7 Symmetric BEKK-GARCH LME Aluminium Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

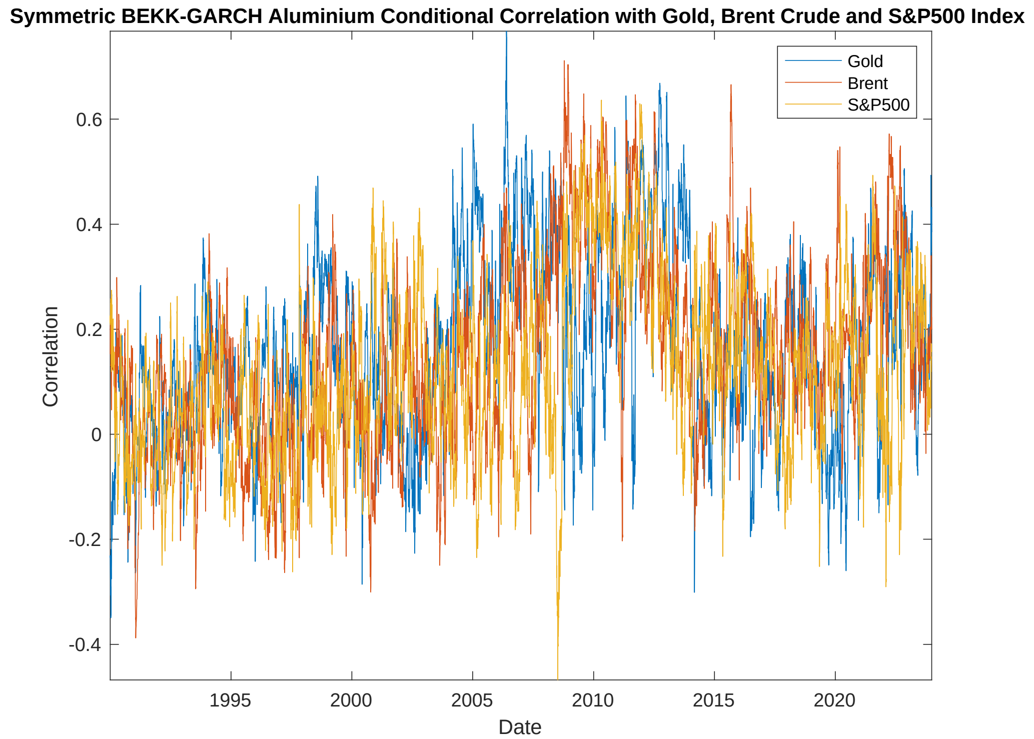


Figure 3.1.8 Symmetric BEKK-GARCH LME Zinc Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

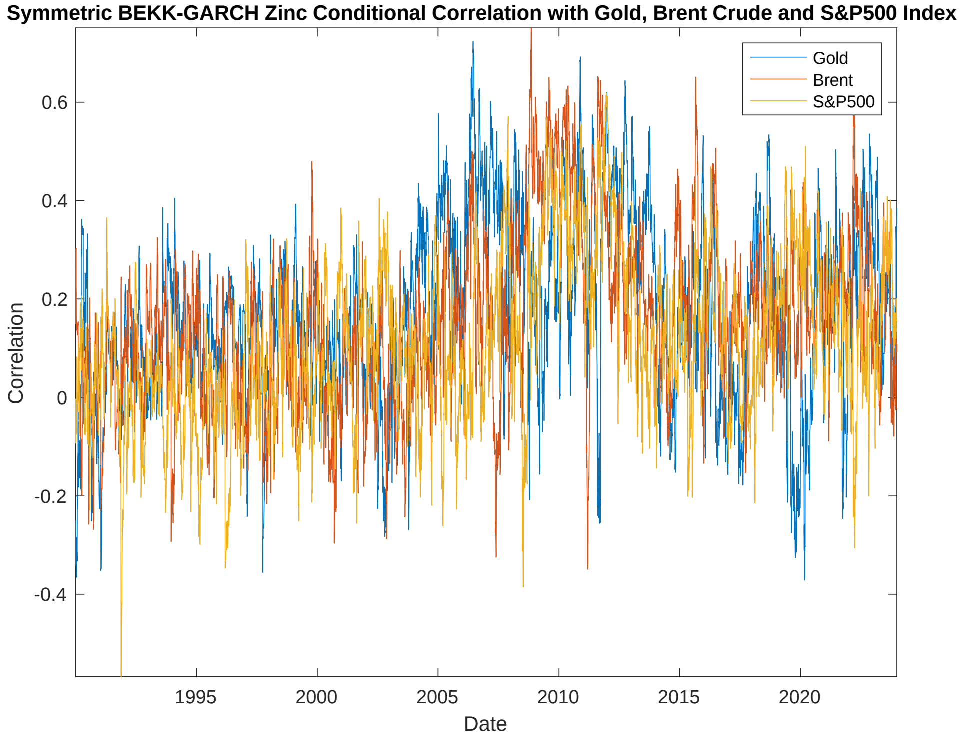


Figure 3.1.9 Symmetric BEKK-GARCH LME Tin Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

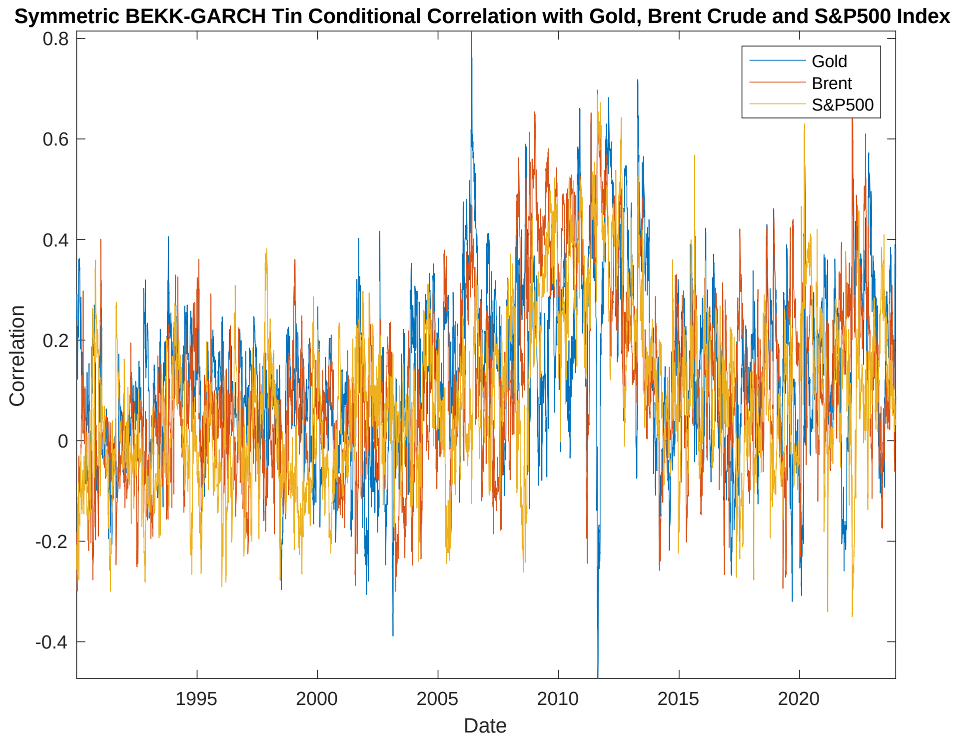


Figure 3.1.10 Symmetric BEKK-GARCH LME Nickel Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

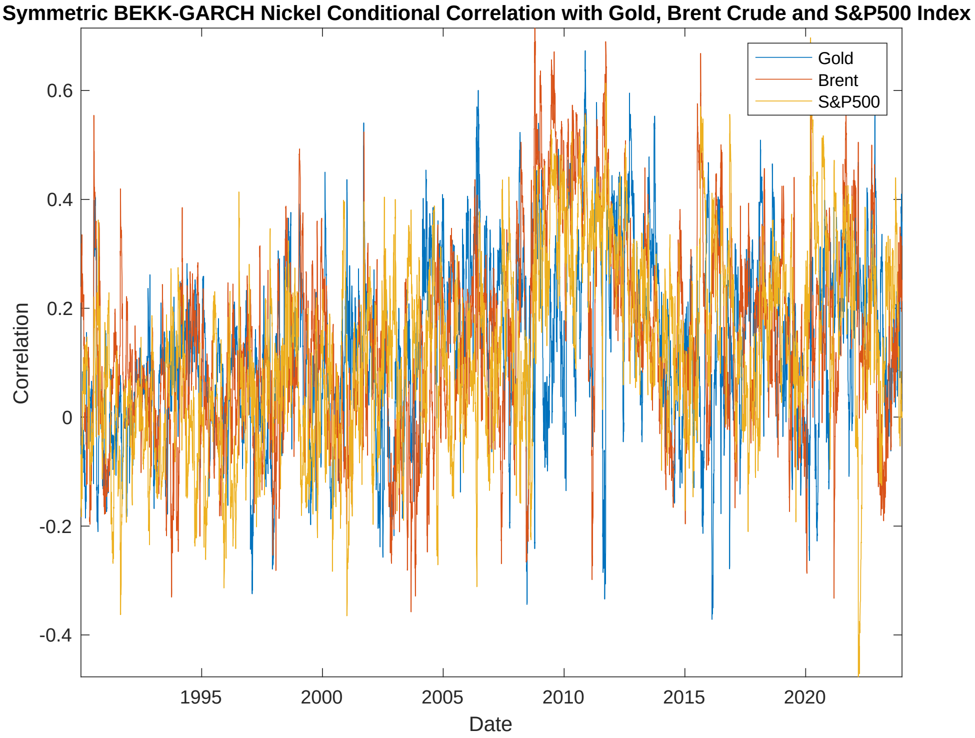


Figure 3.1.11 Asymmetric DCC-GARCH LME Copper Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

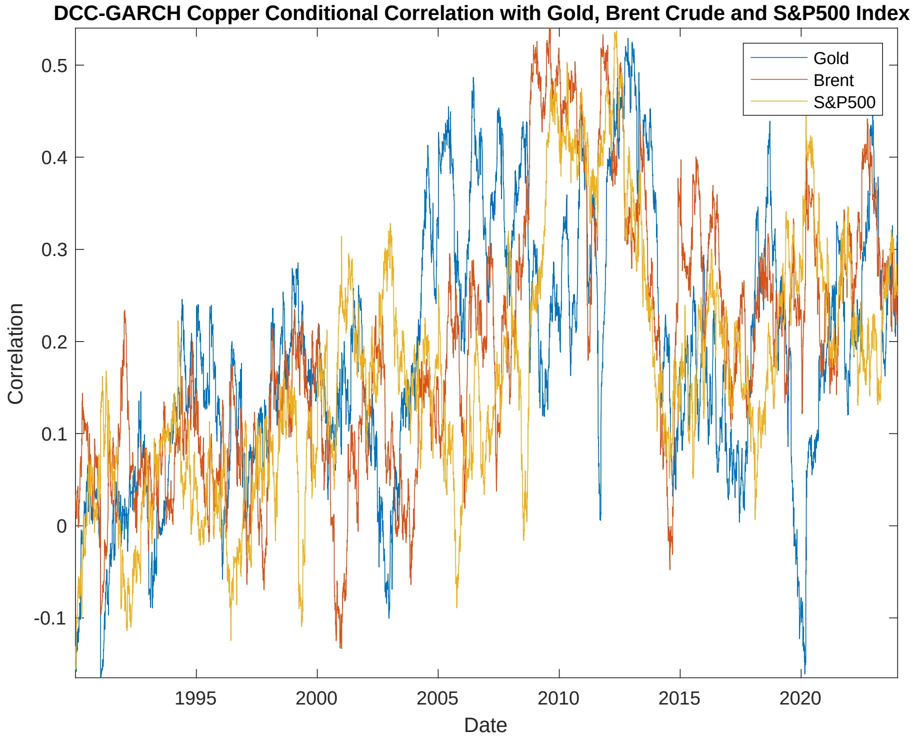


Figure 3.1.12 Asymmetric DCC-GARCH LME Aluminium Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

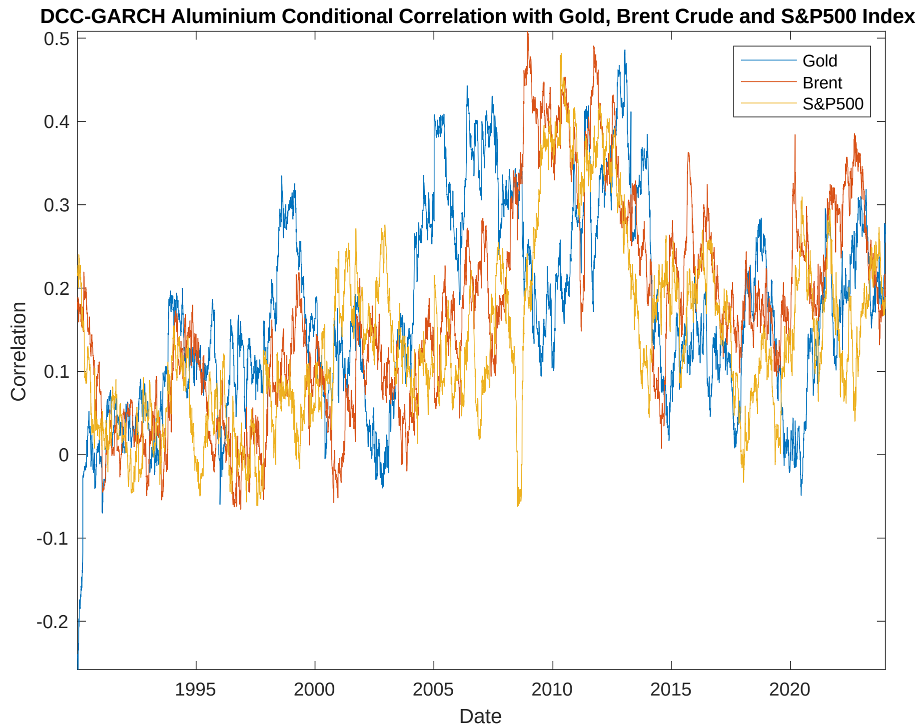


Figure 3.1.13 Asymmetric DCC-GARCH LME Zinc Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

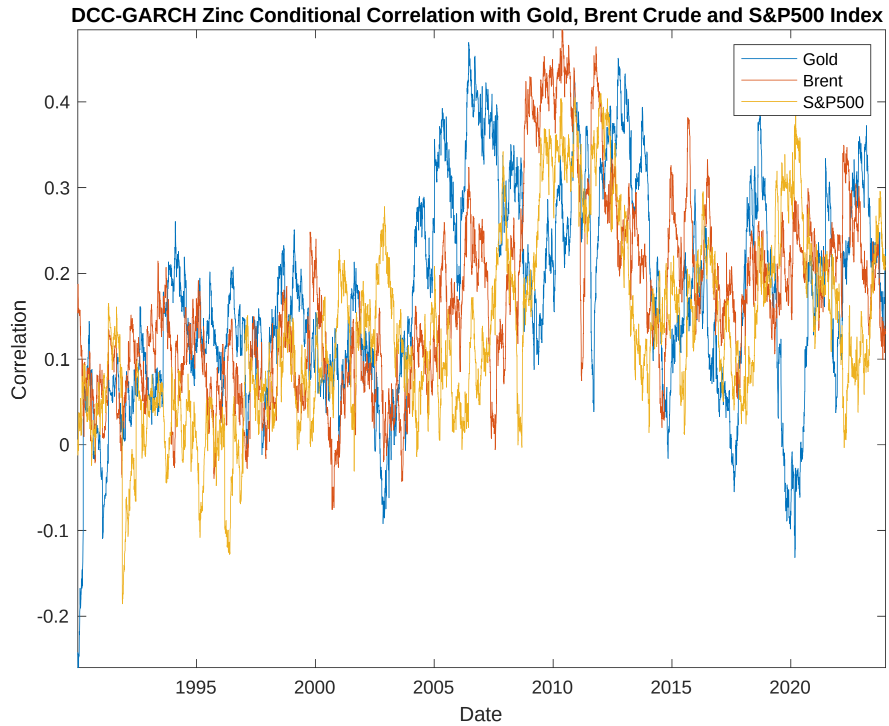


Figure 3.1.14 Asymmetric DCC-GARCH LME Tin Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

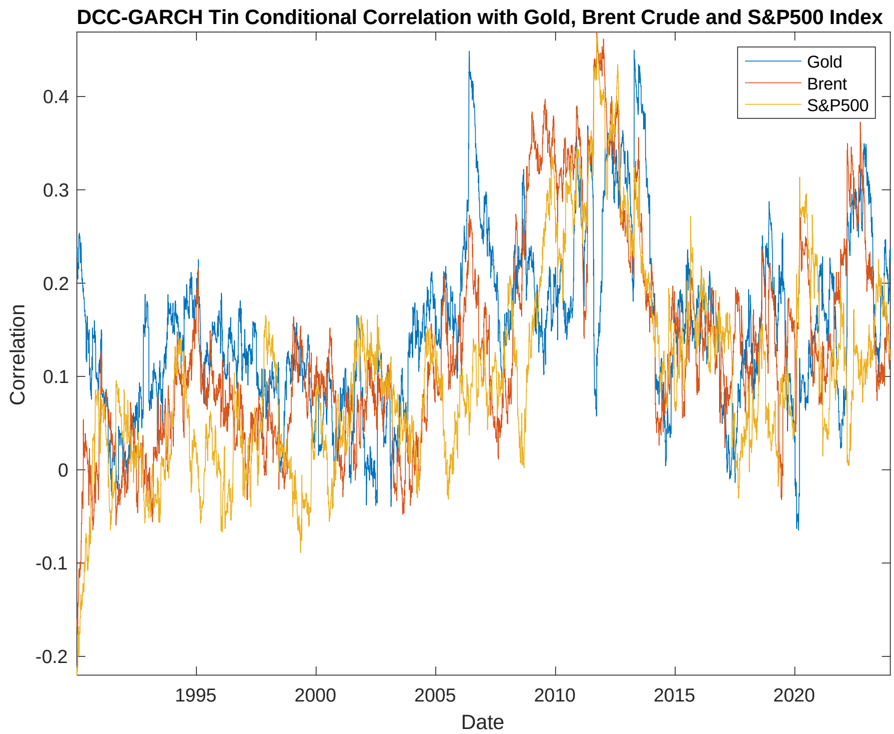


Figure 3.1.15 Asymmetric DCC-GARCH LME Nickel Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

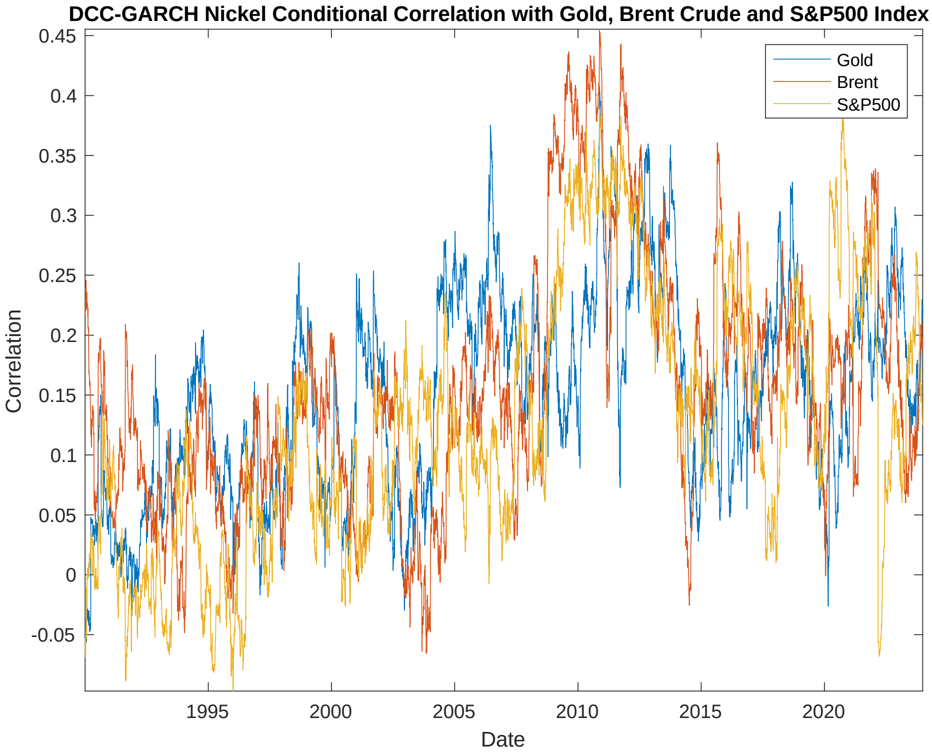


Figure 3.1.16 Asymmetric BEKK-GARCH LME Copper Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

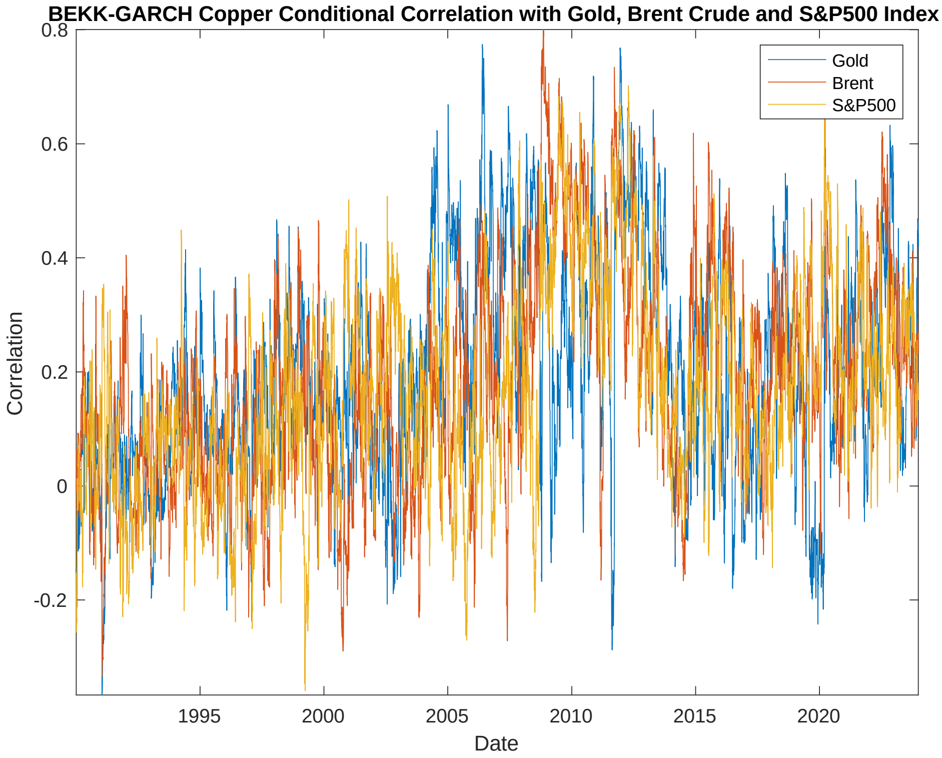


Figure 3.1.17 Asymmetric BEKK-GARCH LME Aluminium Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

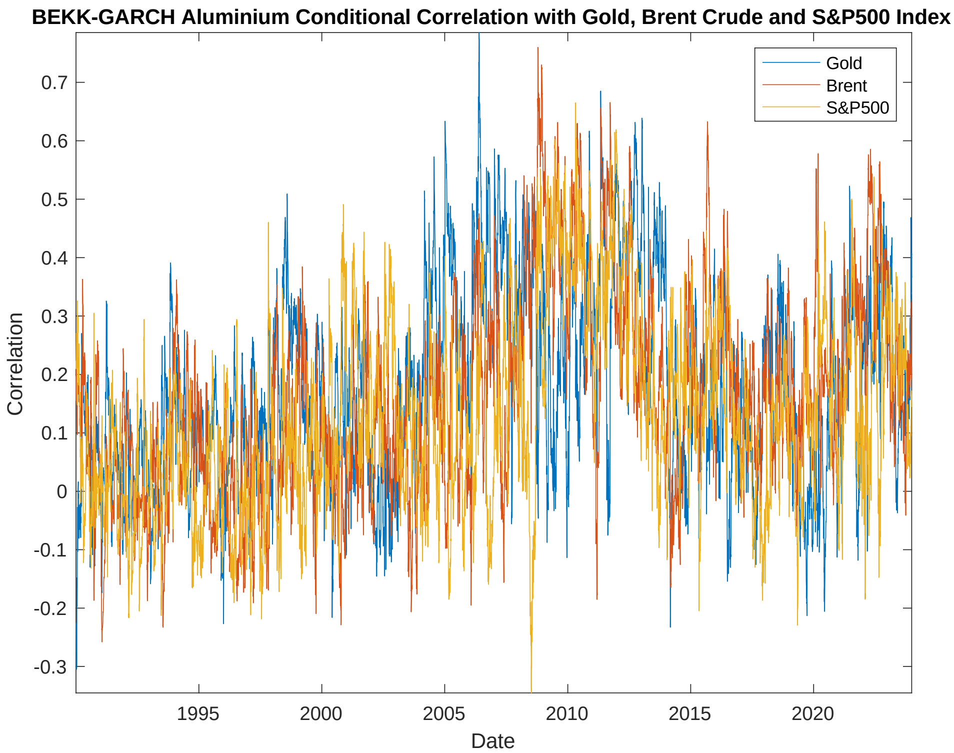


Figure 3.1.18 Asymmetric BEKK-GARCH LME Zinc Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

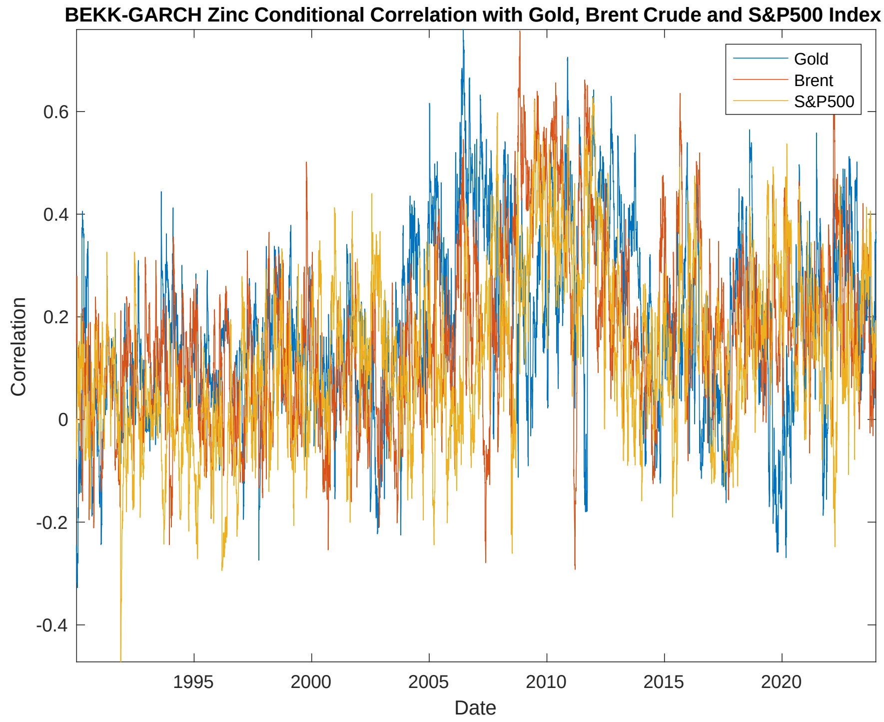


Figure 3.1.19 Asymmetric BEKK-GARCH LME Tin Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

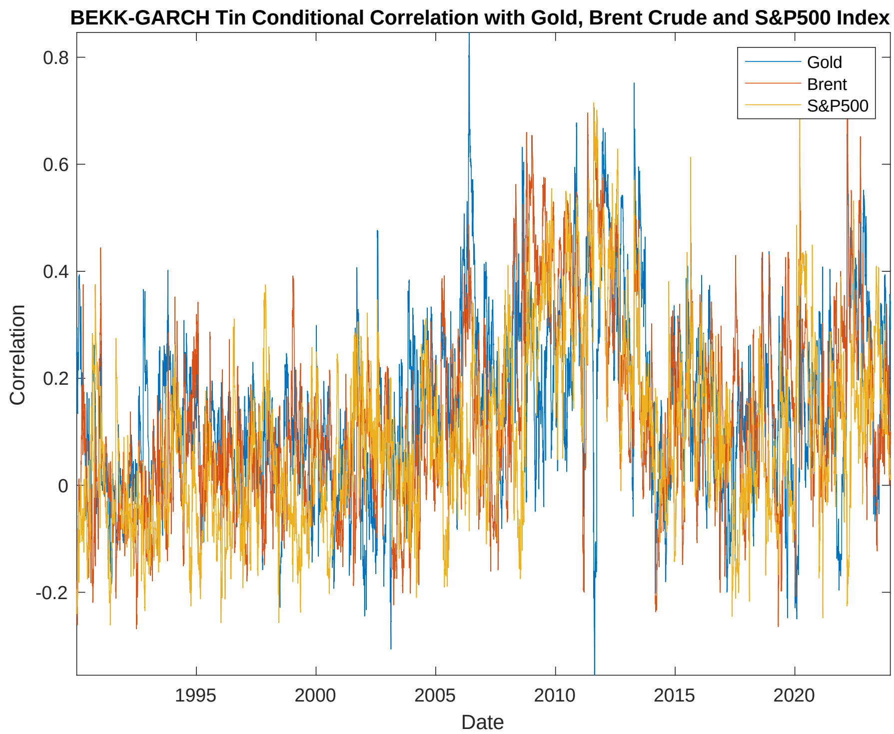


Figure 3.1.20 Asymmetric BEKK-GARCH LME Nickel Conditional correlation with LBMA Gold, Brent Crude and S&P 500 Stock Index

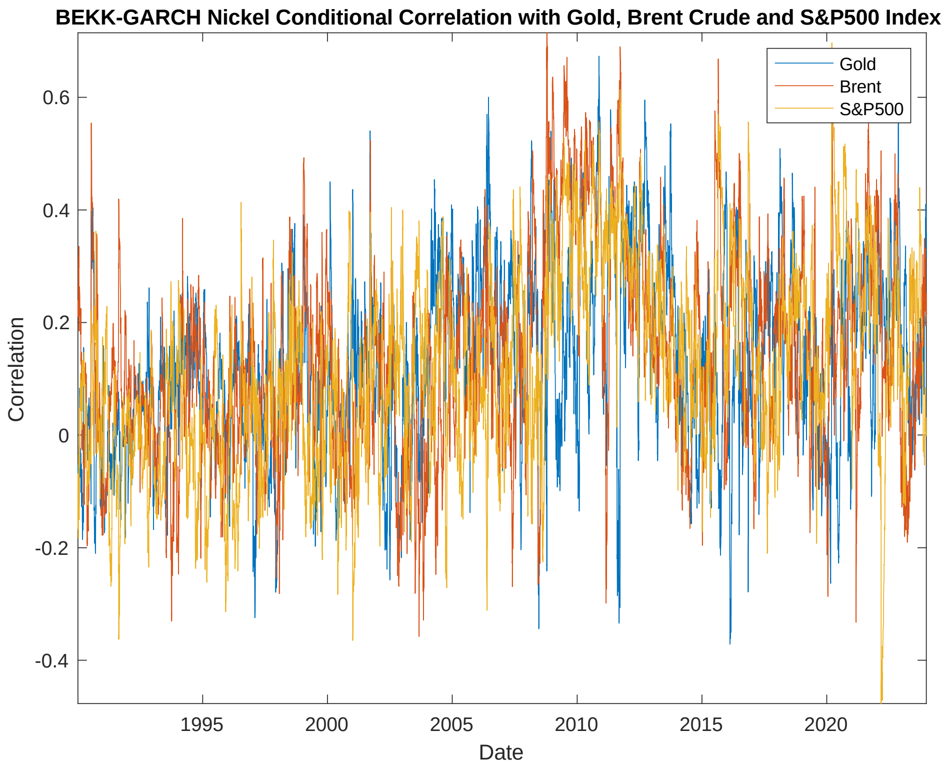


Figure 3.1.21 OGARCH copper conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

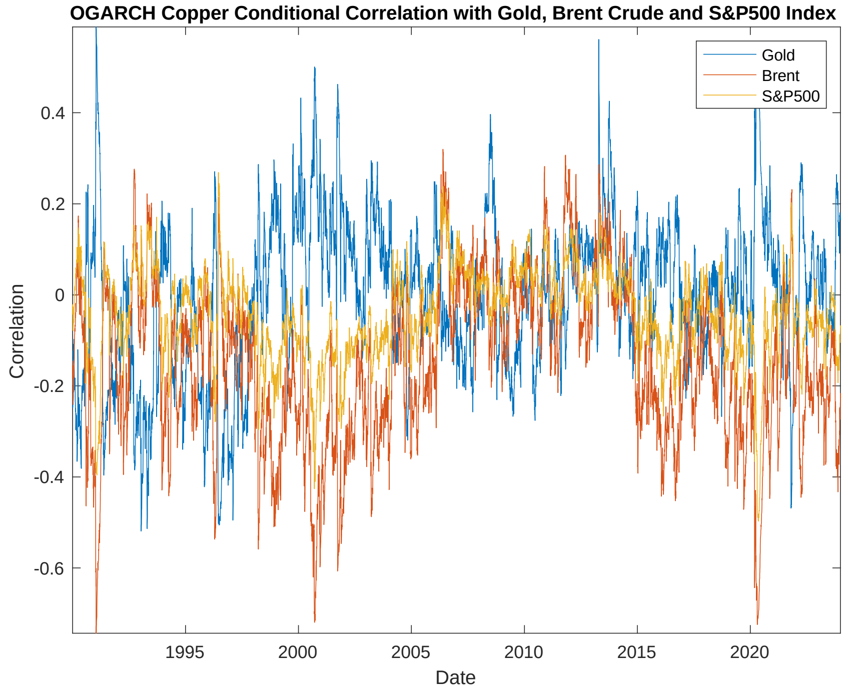


Figure 3.1.22 OGARCH aluminium conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

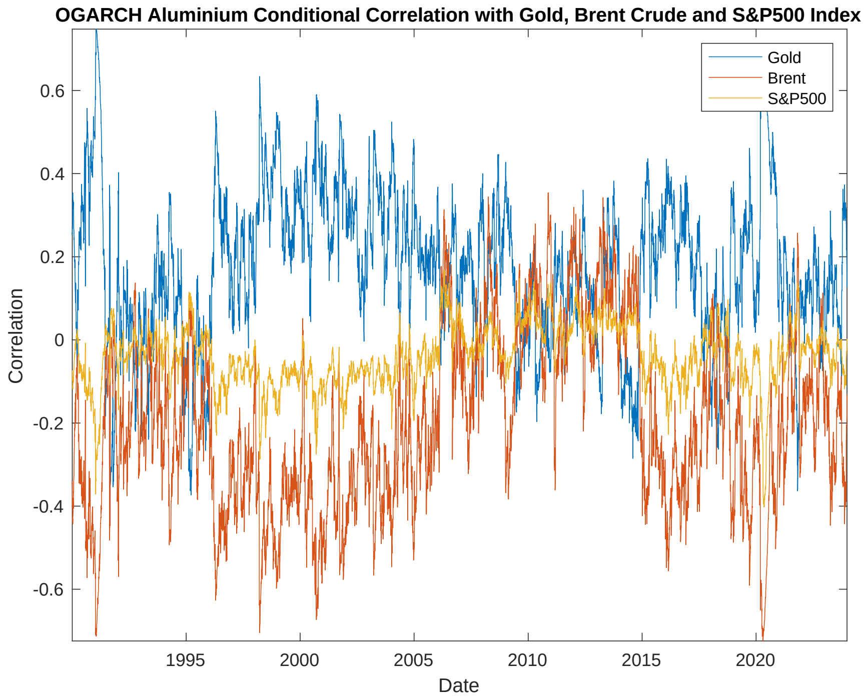


Figure 3.1.23 OGARCH zinc conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

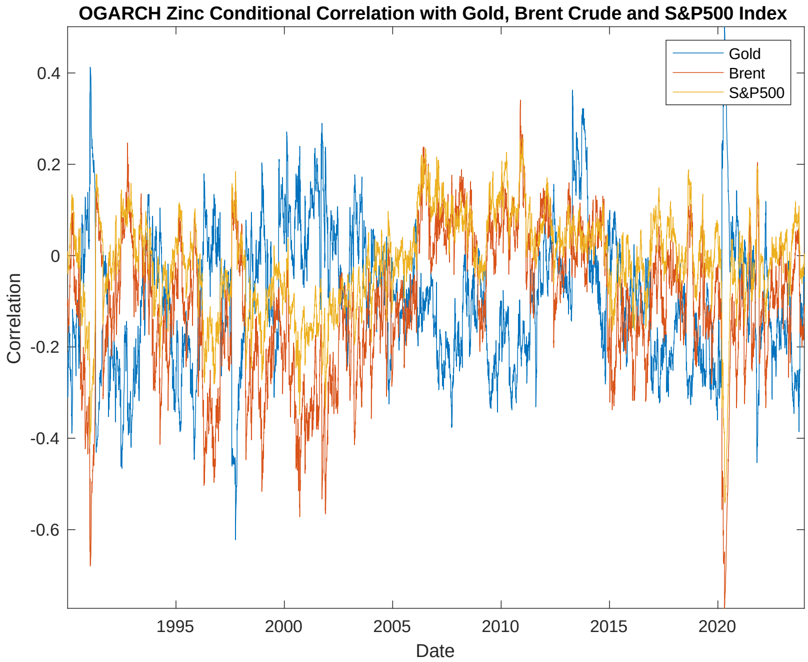


Figure 3.1.24 OGARCH Tin conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

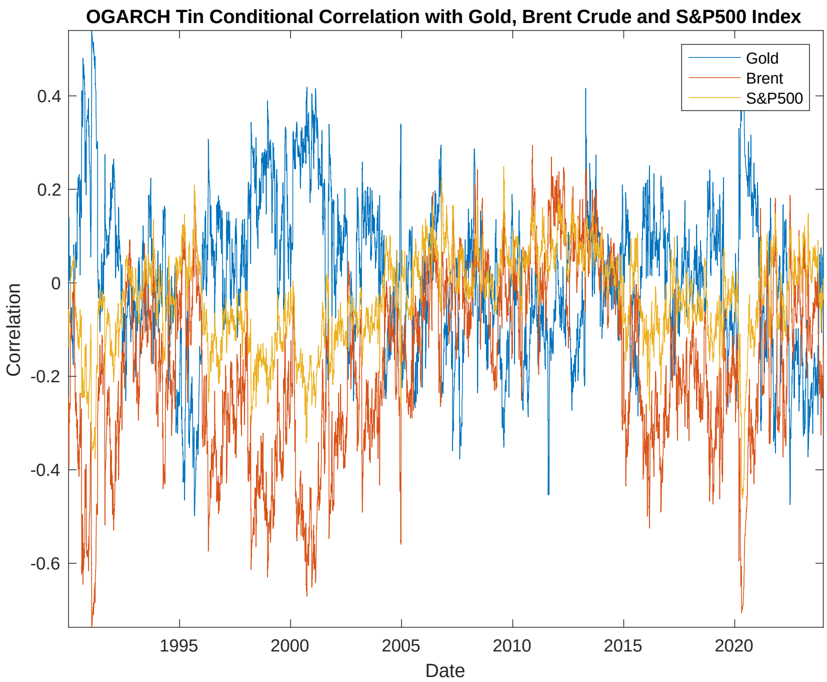


Figure 3.1.25 OGARCH Nickel conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

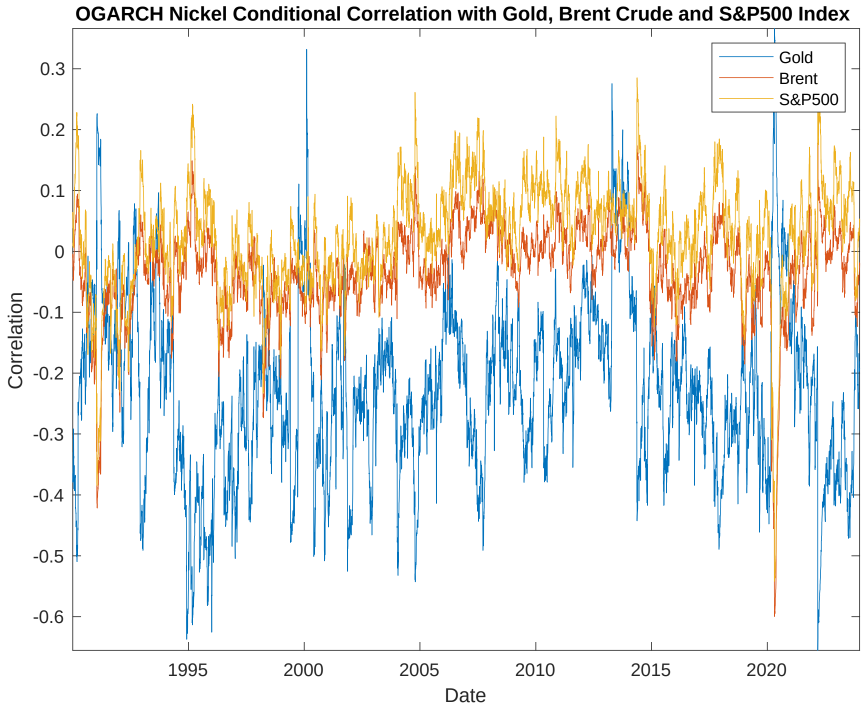


Figure 3.1.26 GOGARCH Copper conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

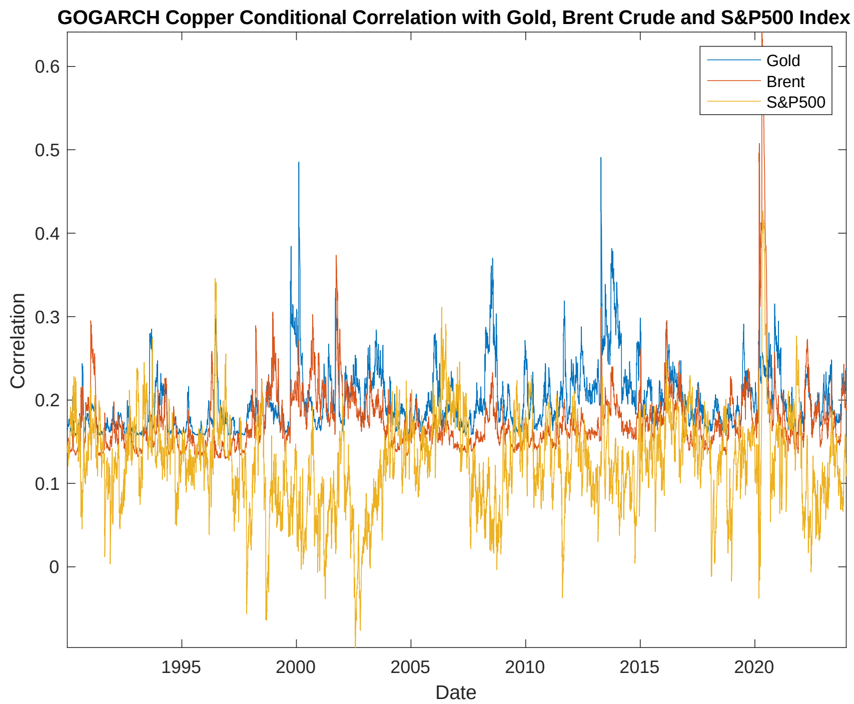


Figure 3.1.27 GOGARCH Aluminium conditional correlation with LBMA Gold, Brent crude and S&P 500 Index

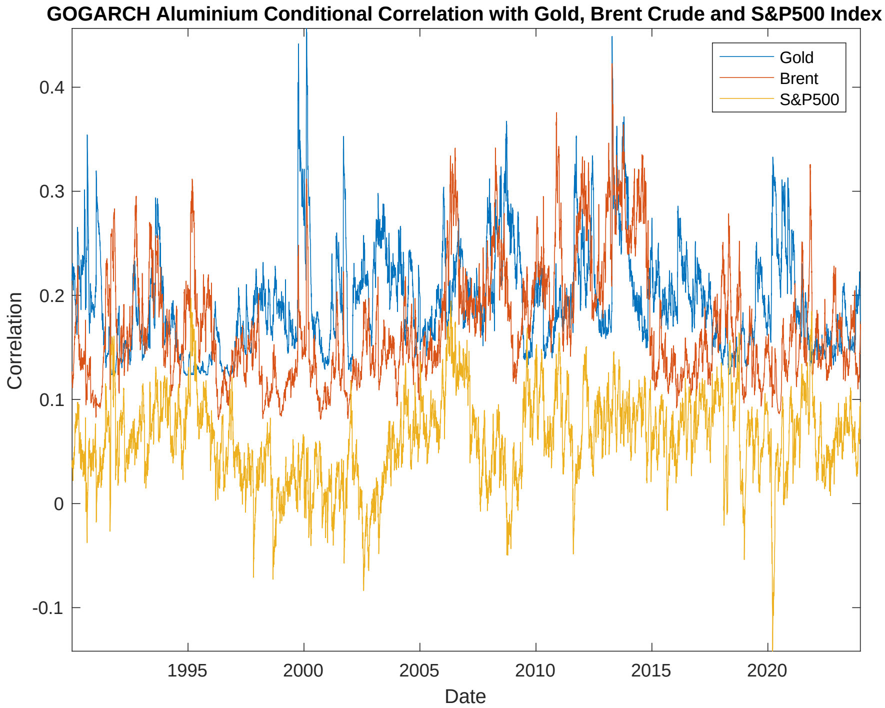


Figure 3.1.28 GOGARCH Zinc conditional correlation with LBMA Gold, Brent crude and S&P 500

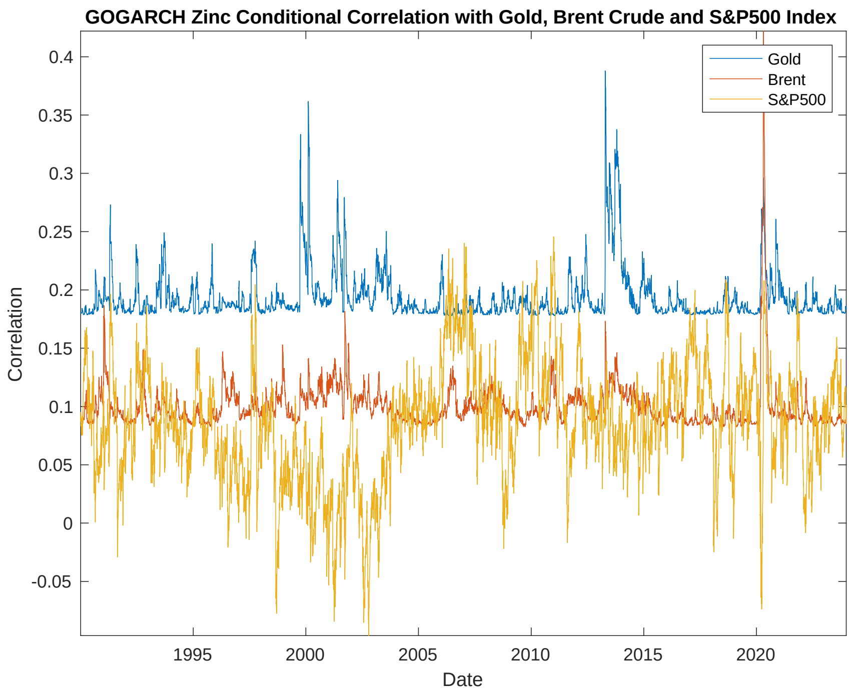


Figure 3.1.29 GOGARCH Tin conditional correlation with LBMA Gold, Brent crude and S&P 500

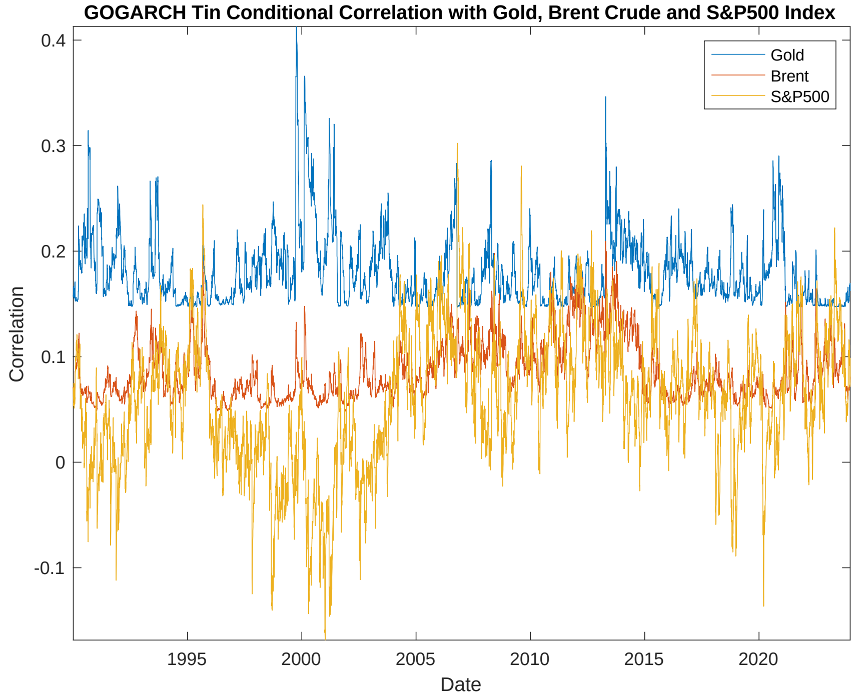


Figure 3.1.30 GOGARCH Nickel conditional correlation with LBMA Gold, Brent crude and S&P 500

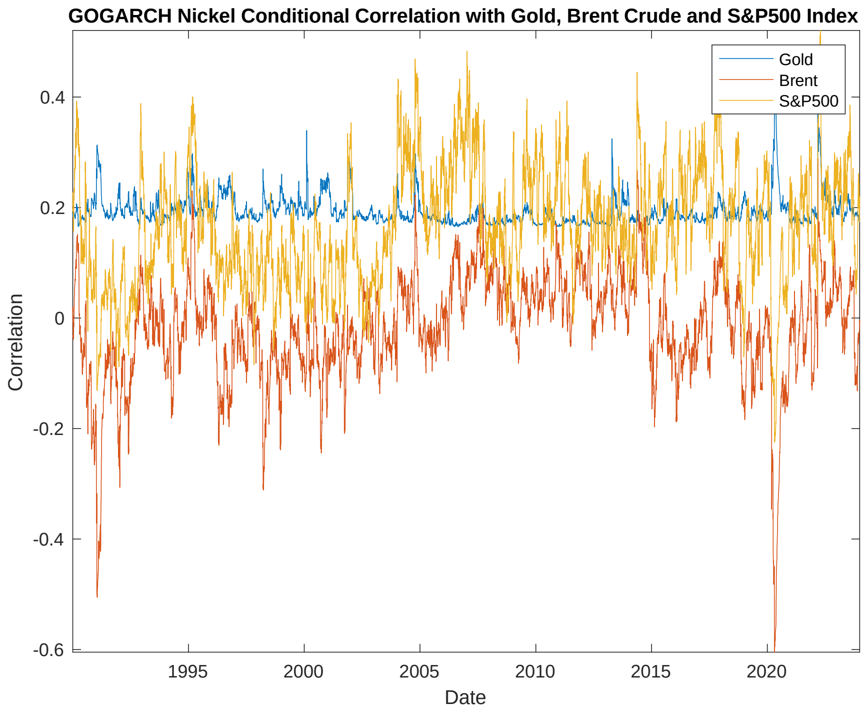


Figure 3.1.31 DCC-MIDAS Copper short run correlation with LBMA Gold, Brent crude and S&P 500 Index

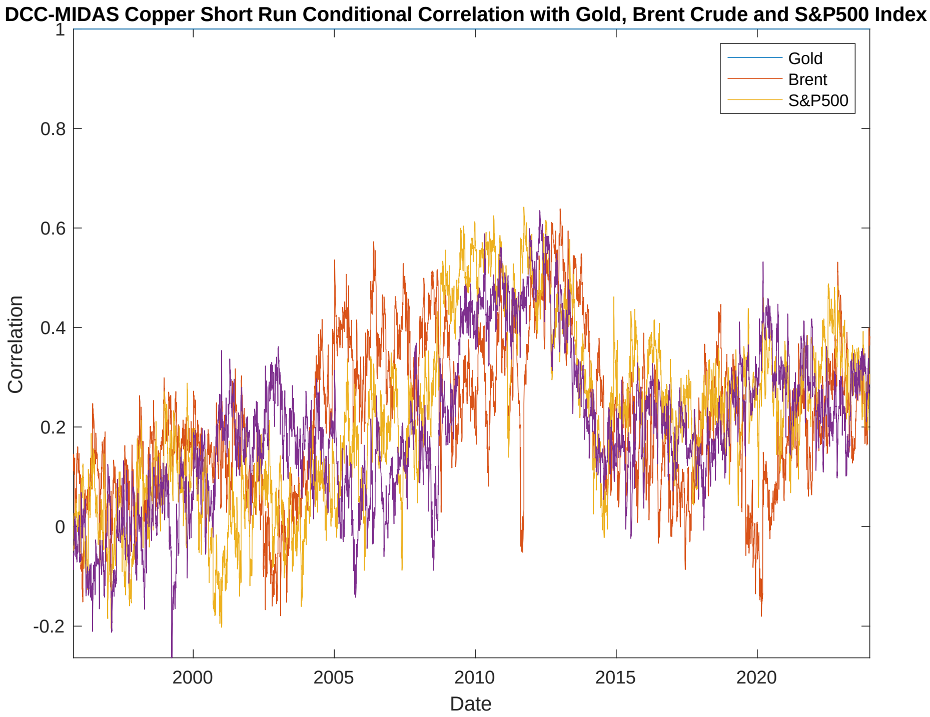


Figure 3.1.32 DCC-MIDAS Aluminium short run correlation with LBMA Gold, Brent crude and S&P 500 Index

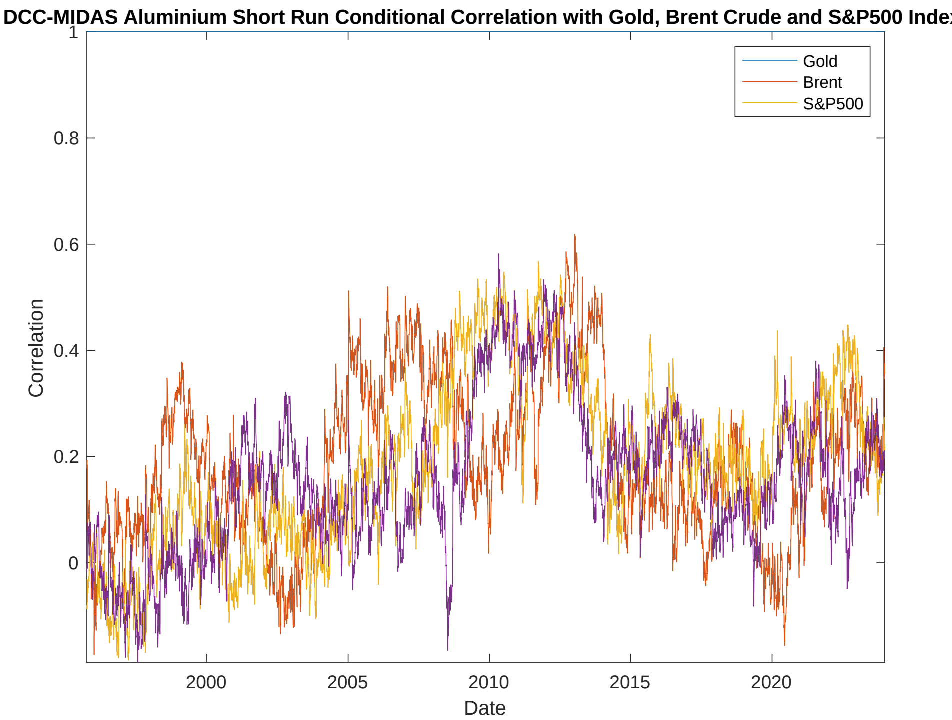


Figure 3.1.33 DCC-MIDAS Zinc short run correlation with LBMA Gold, Brent crude and S&P 500 Index

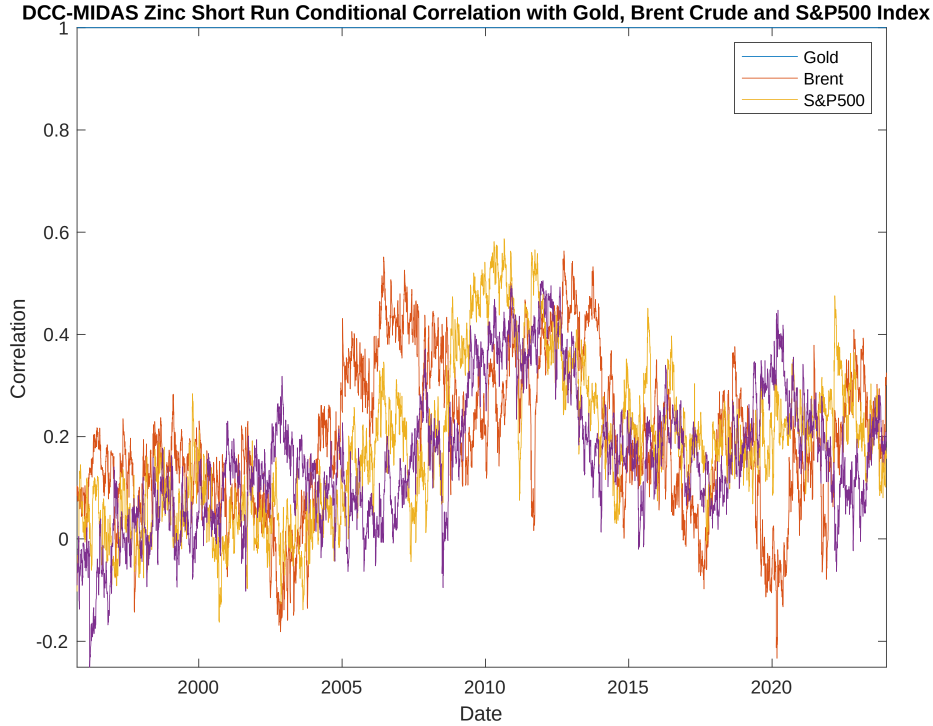


Figure 3.1.34 DCC-MIDAS Tin short run correlation with LBMA Gold, Brent crude and S&P 500

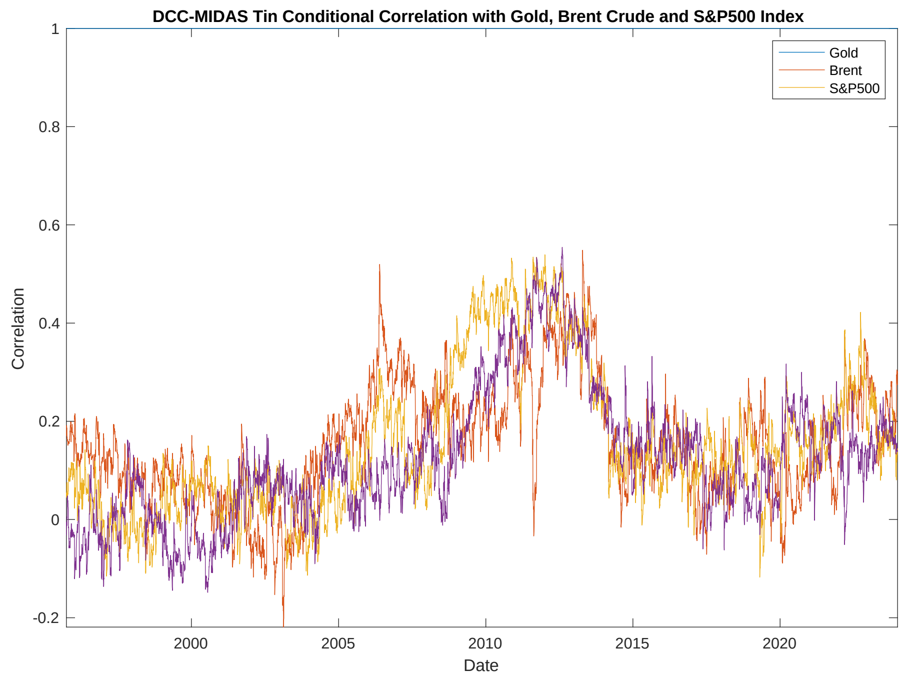


Figure 3.1.35 DCC-MIDAS Nickel short run correlation with LBMA Gold, Brent crude and S&P 500 Index

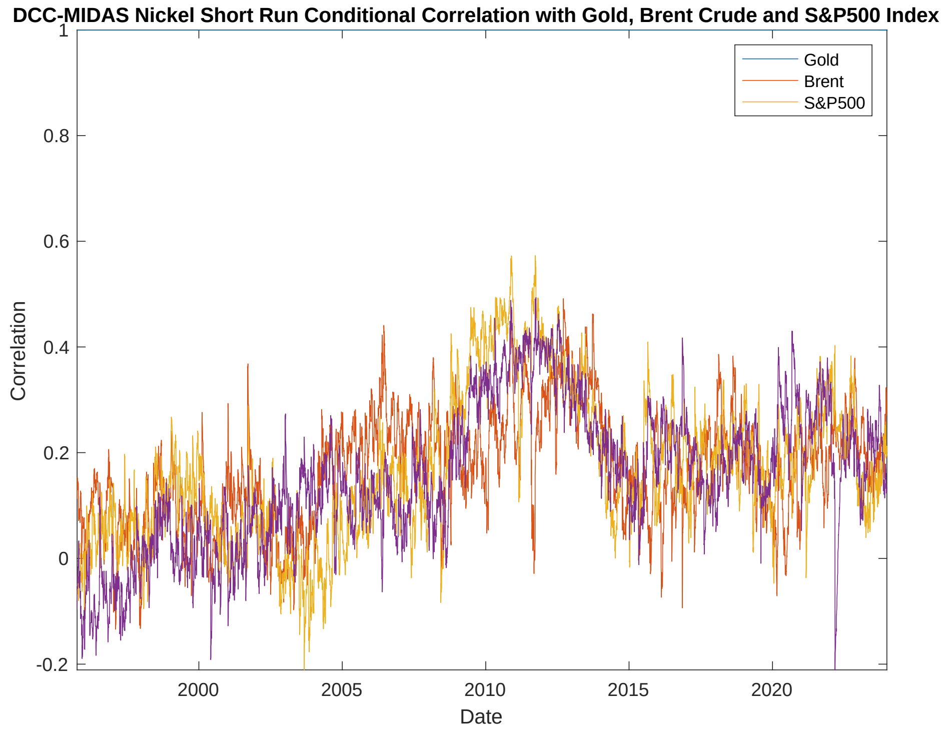


Figure 3.1.36 DCC-MIDAS copper long run correlation with LBMA Gold, Brent crude and S&P 500 Index

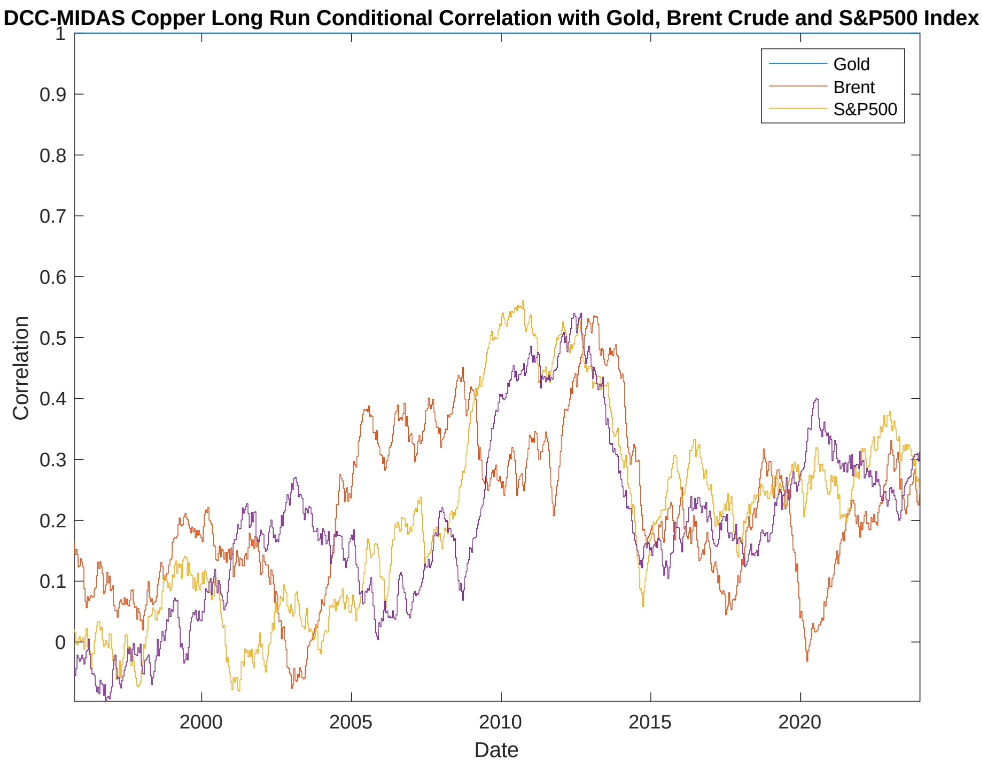


Figure 3.1.37 DCC-MIDAS aluminium long run correlation with LBMA Gold, Brent crude and S&P 500 Index

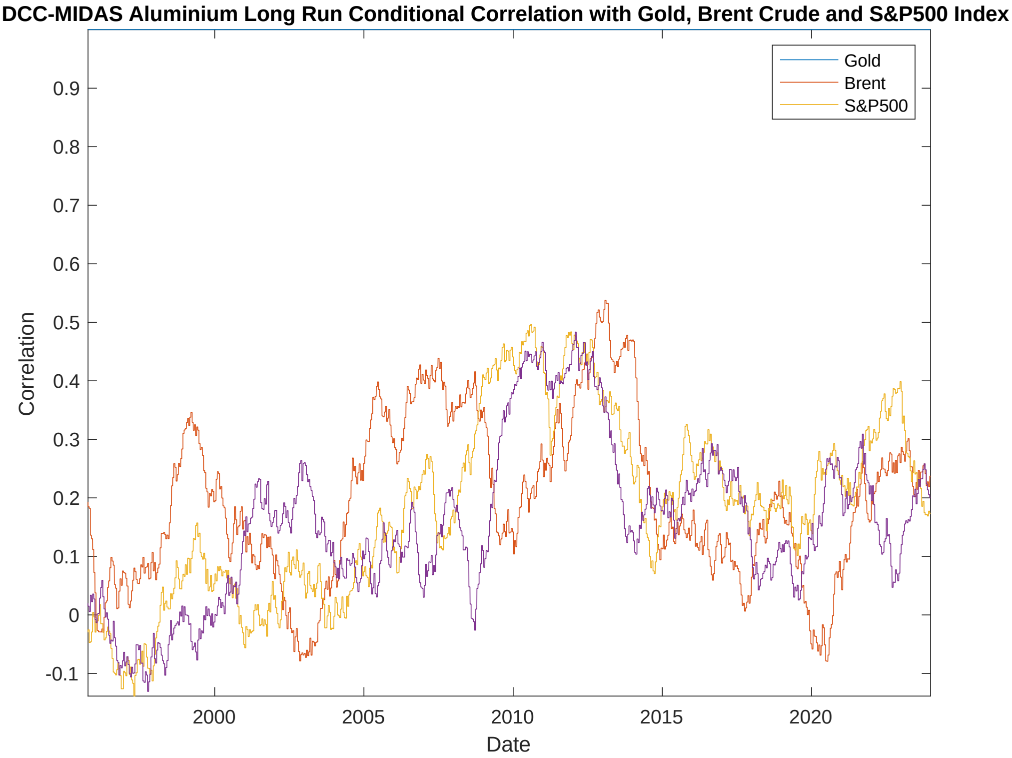


Figure 3.1.38 DCC-MIDAS zinc long run correlation with LBMA Gold, Brent crude and S&P 500 Index

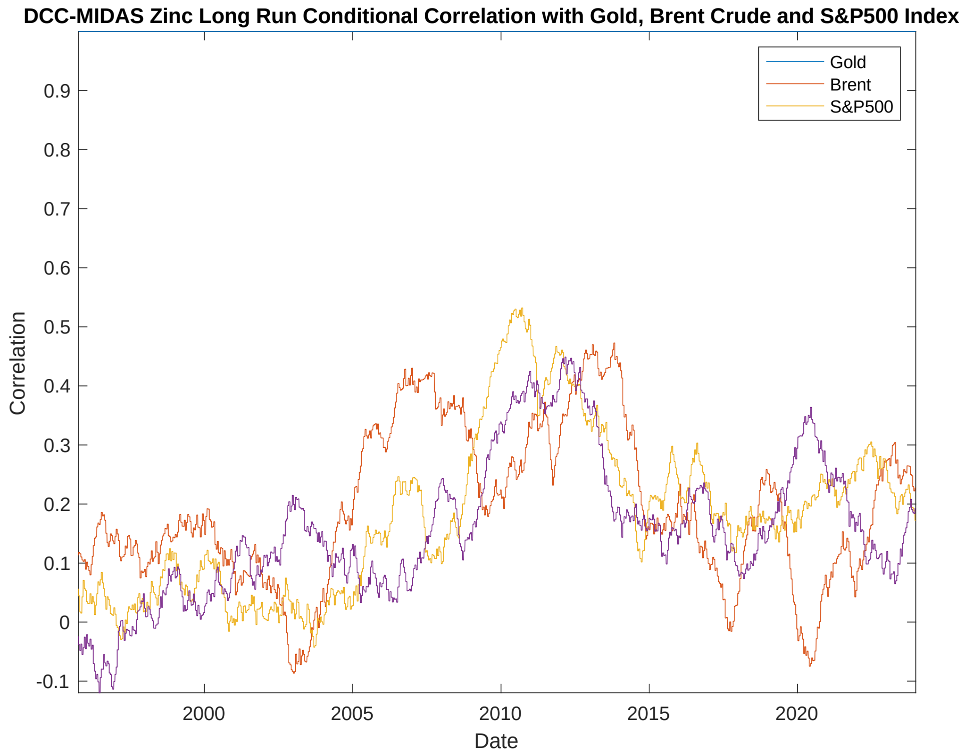


Figure 3.1.39 DCC-MIDAS tin long run correlation with LBMA Gold, Brent crude and S&P 500 Index

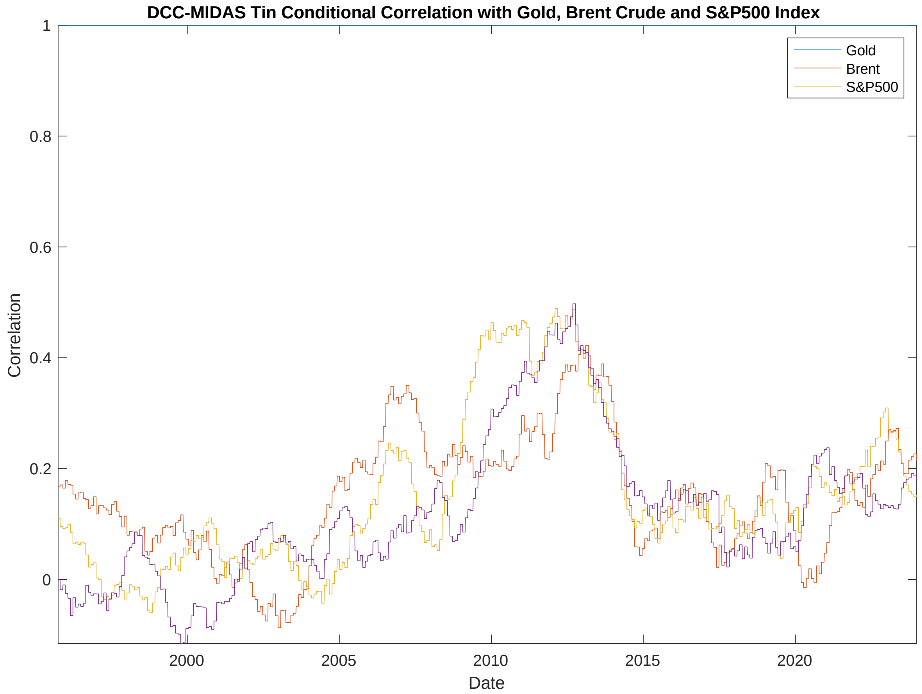


Figure 3.1.40 DCC-MIDAS Nickel long run correlation with LBMA Gold, Brent crude and S&P 500 Index

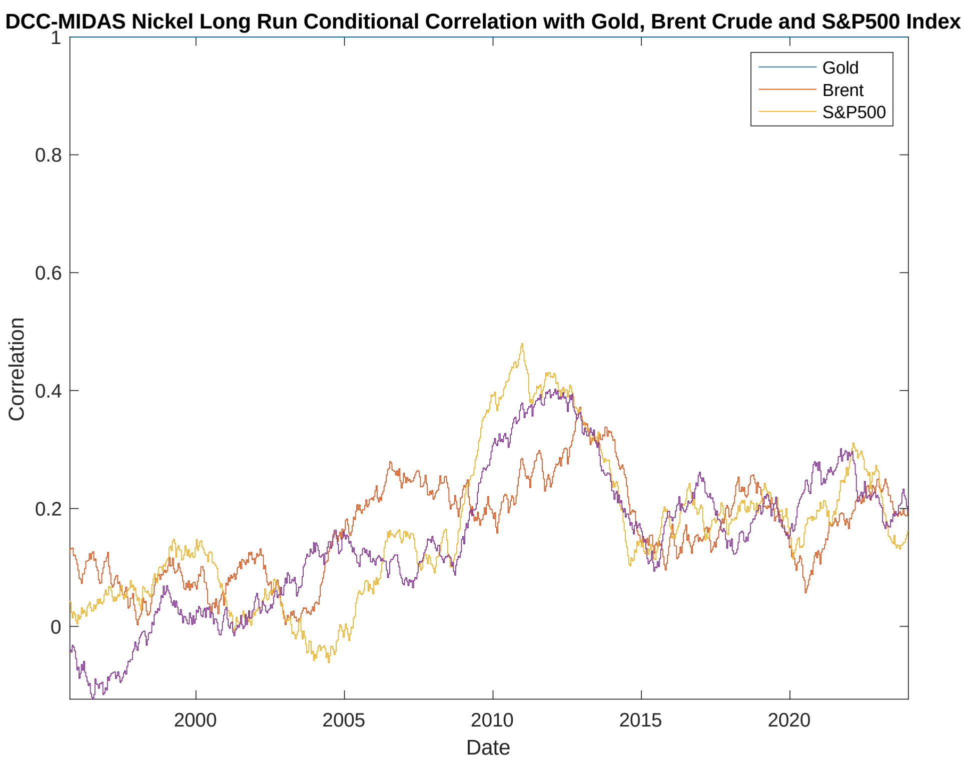


Table 3.2.1 Results from Likelihood ratio test for goodness of fit with CCC-GARCH used as benchmark model. Values in bold indicate rejection of al the null, restricted model in favour of the alternative, unrestricted model at 5% significance level.

Model	DCC Sym	DCC Asym	BEKK Sym	BEKK Asym	OGARCH	GOGARCH	DCC-MIDAS
Copper	0.8627	0.8629	0.946	0.9182	0.5972	0.8068	**1.18E-09**
Aluminium	0.699	0.6977	0.6285	0.6311	0.5449	0.8627	**1.20E-09**
Zinc	0.882	0.885	0.9472	0.9476	0.6492	0.8115	**1.15E-09**
Tin	0.881	0.886	0.9119	0.9201	0.6522	0.8527	**1.23E-09**
Nickel	0.7962	0.7964	0.9036	0.9039	0.6131	0.8319	**1.09E-09**

Results of Likelihood ratio test with CCC-GARCH used as benchmark model. Values in bold indicates rejection of the null, restricted model in favor of the alternative, unrestricted model at 5% significance level.

Figure 3.2.1 Results from Wavelet coherence analysis for LME Copper and LBMA Gold

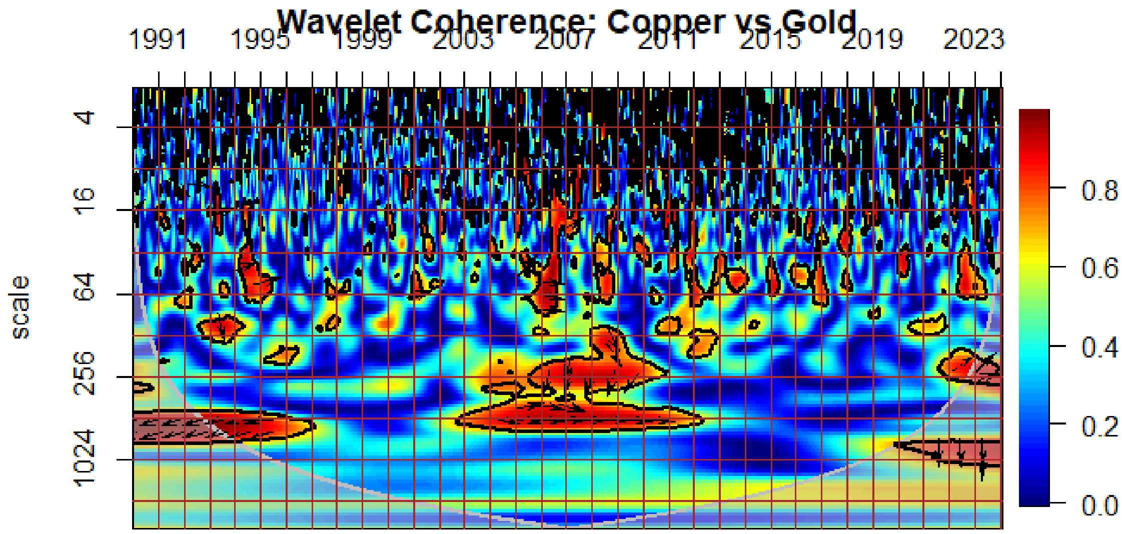


Figure 3.2.2 Results from Wavelet coherence analysis for LME Copper and ICE Brent Crude

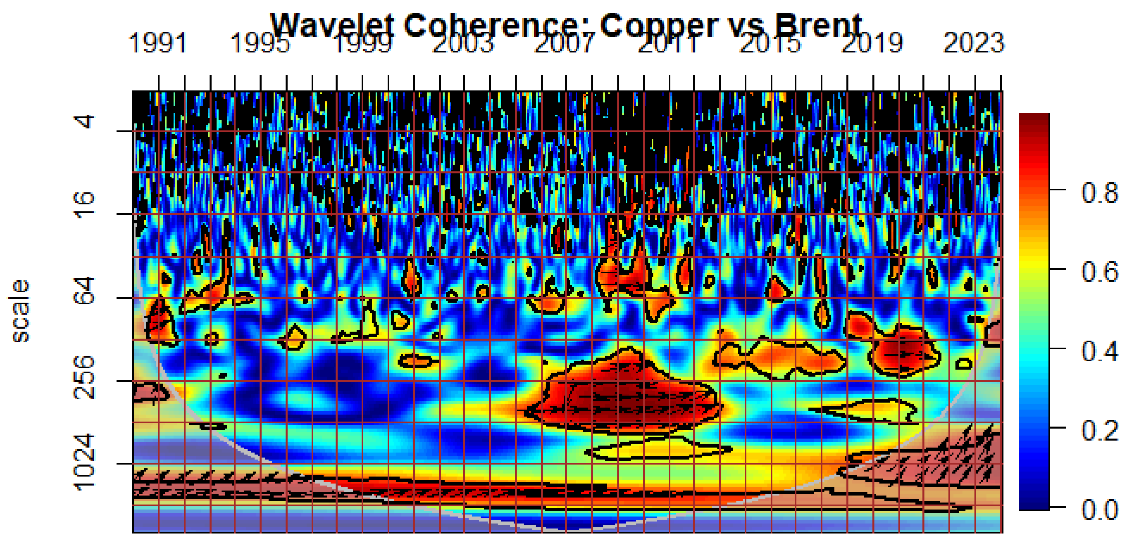


Figure 3.2.3 Results from Wavelet coherence analysis for LME Copper and S&P 500

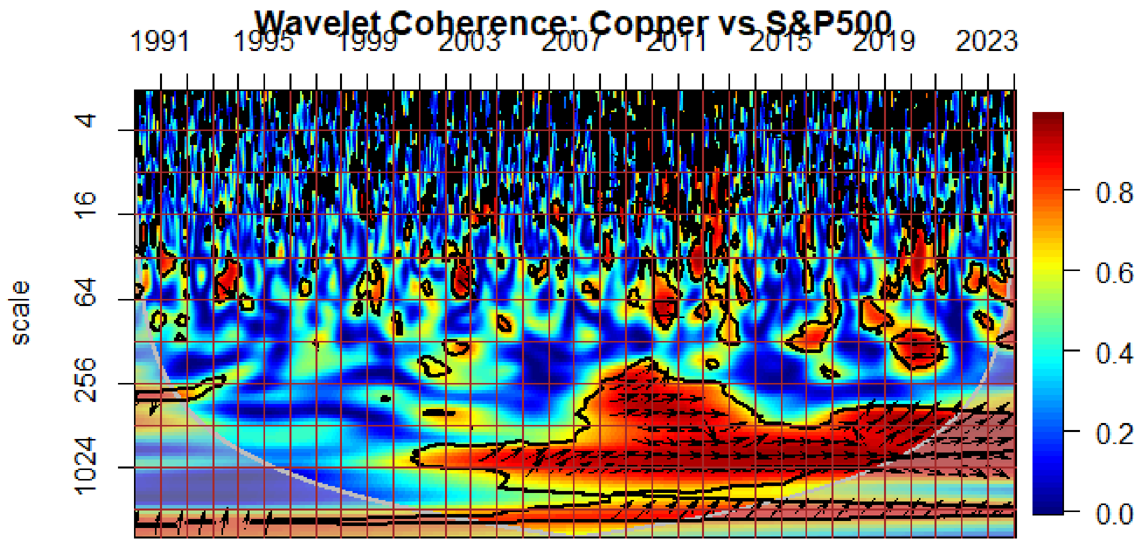


Figure 3.2.4 Results from Wavelet coherence analysis for LME Aluminium and LBMA Gold

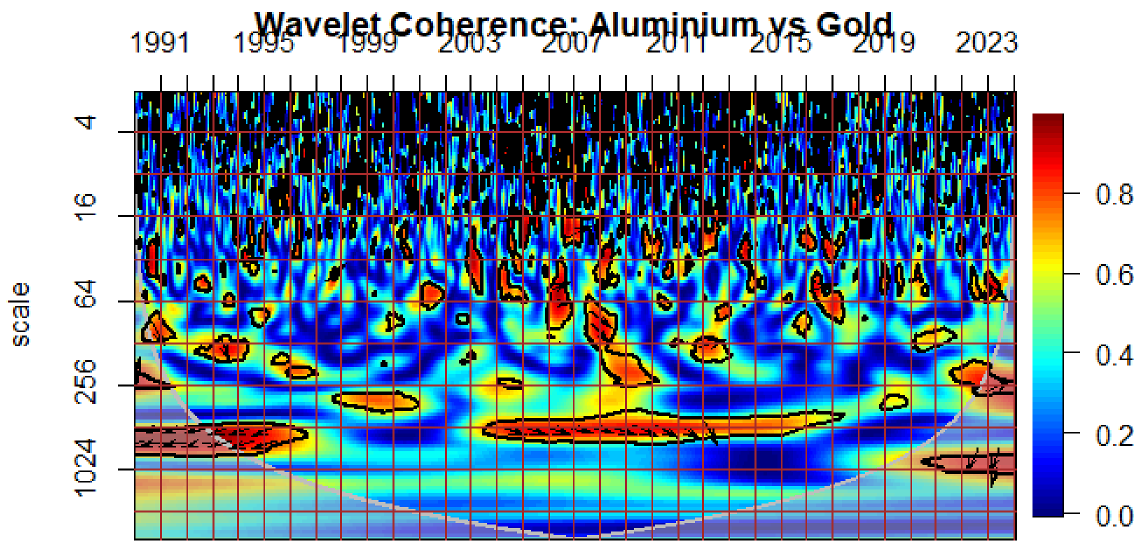


Figure 3.2.5 Results from Wavelet coherence analysis for LME Aluminium and ICE Brent Crude

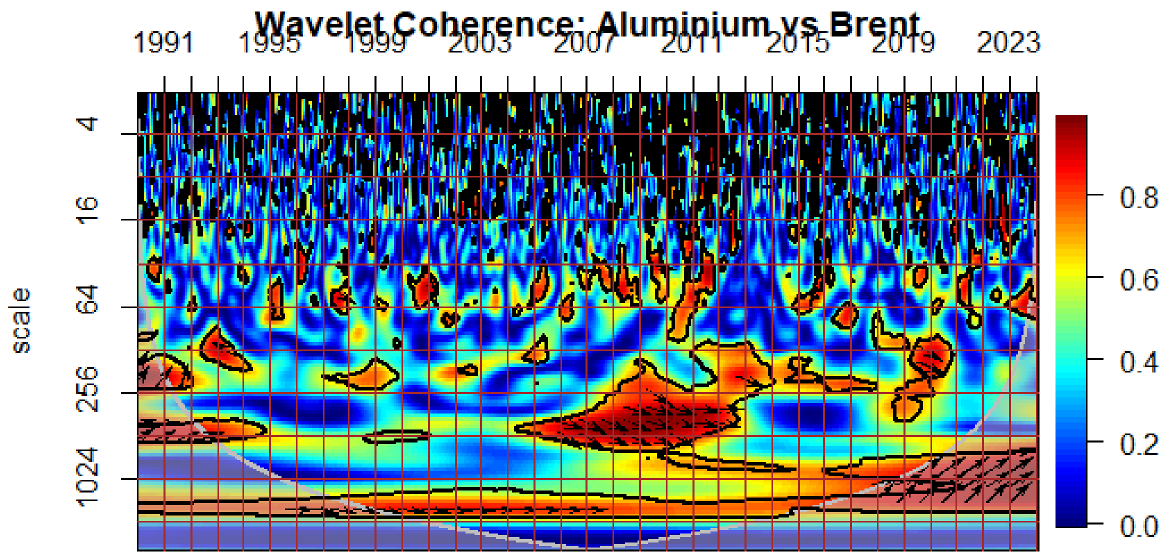


Figure 3.2.6 Results from Wavelet coherence analysis for LME Aluminium and S&P 500

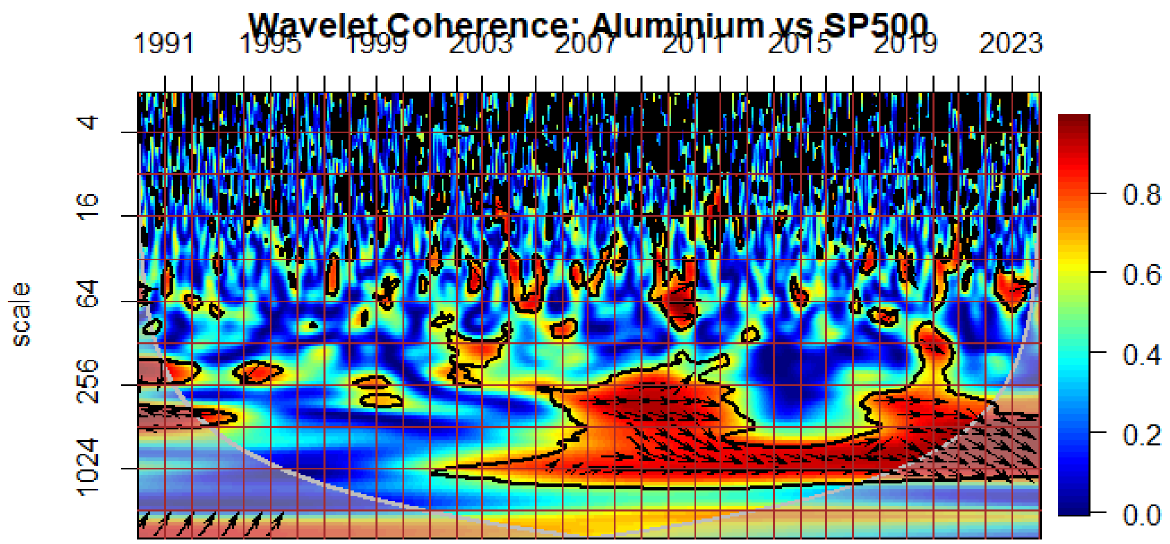


Figure 3.2.7 Results from Wavelet coherence analysis for LME Zinc and LBMA Gold

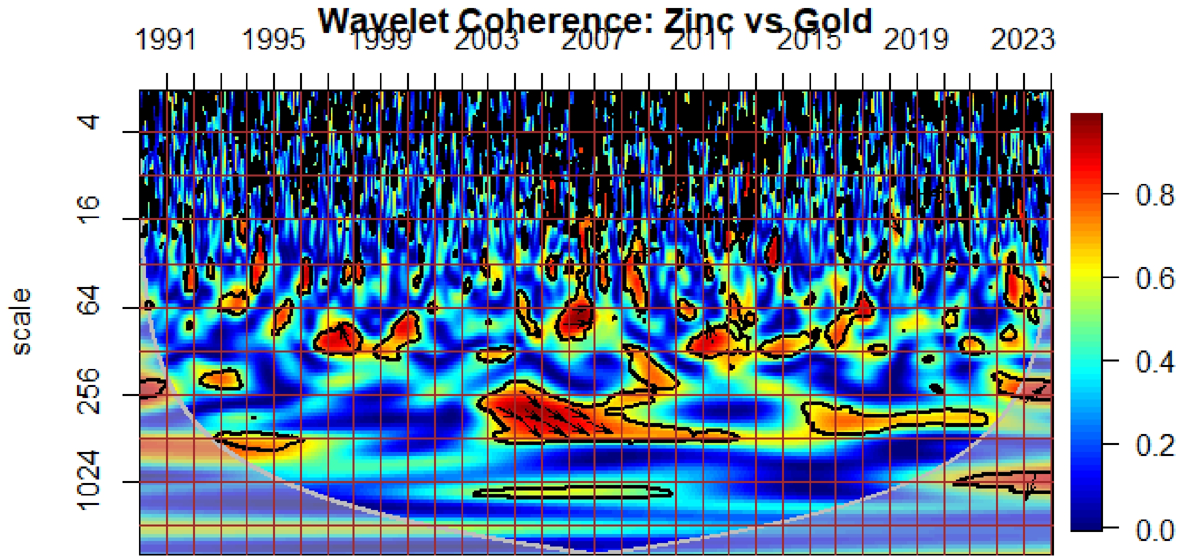


Figure 3.2.8 Results from Wavelet coherence analysis for LME Zinc and ICE Brent Crude

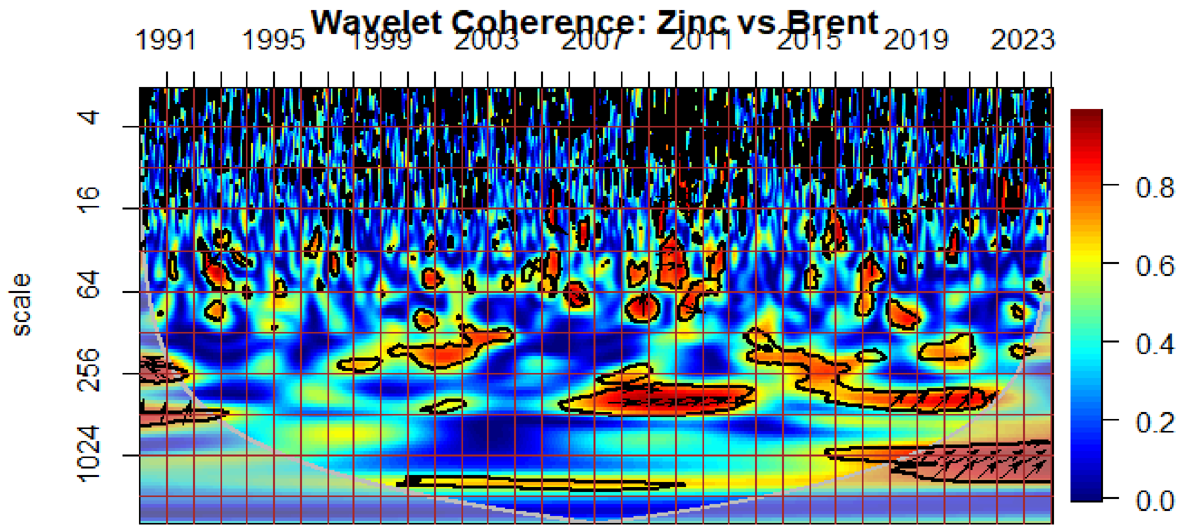


Figure 3.2.9 Results from Wavelet coherence analysis for LME Zinc and S&P500

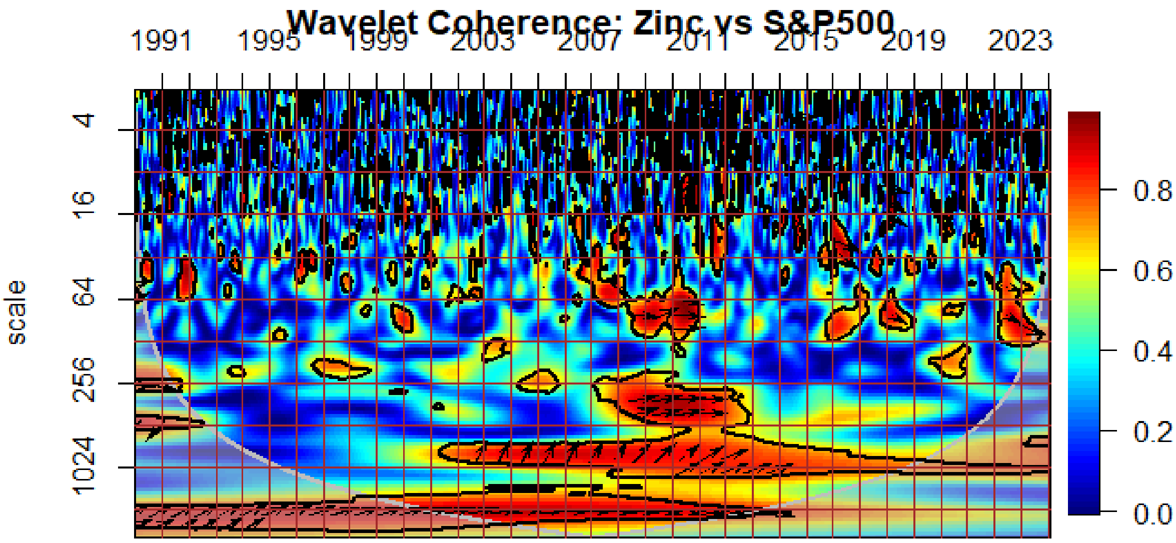


Figure 3.2.10 Results from Wavelet coherence analysis for LME Tin and LBMA Gold

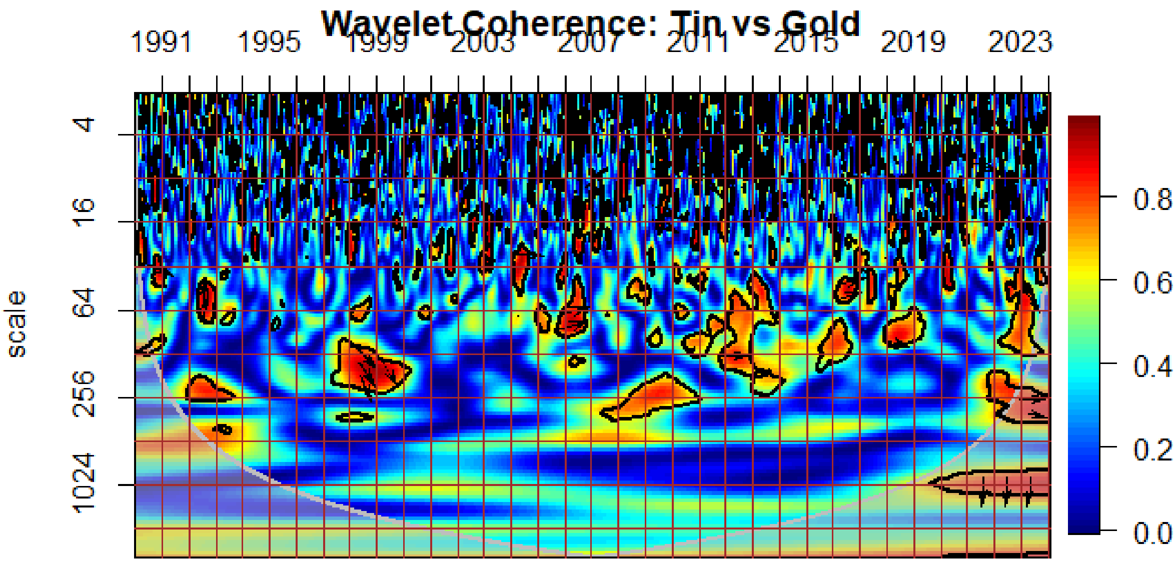


Figure 3.2.11 Results from Wavelet coherence analysis for LME Tin and ICE Brent Crude

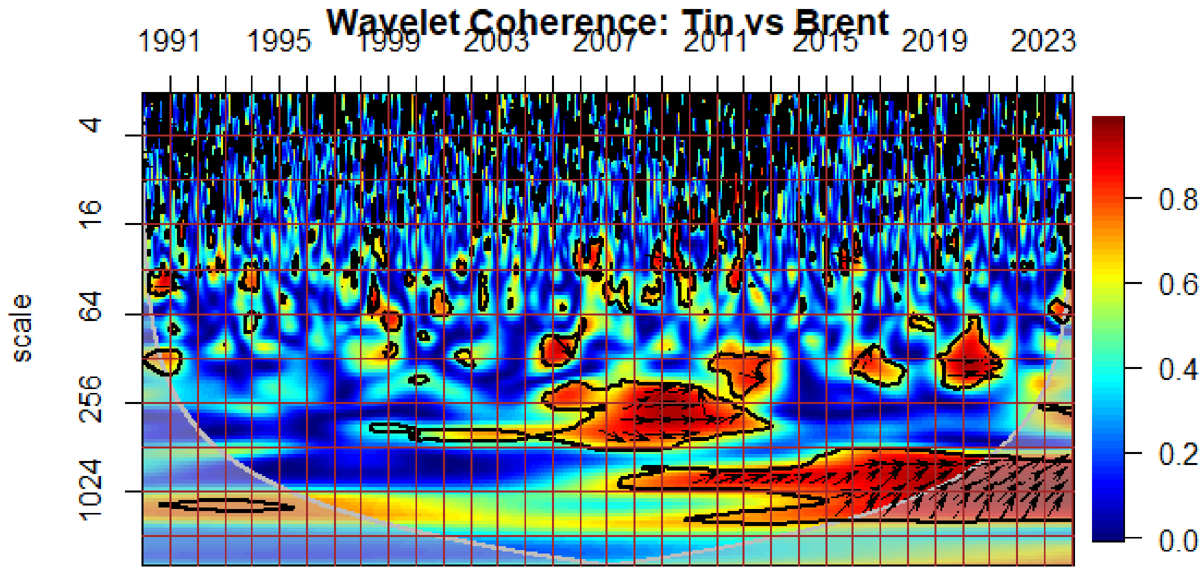


Figure 3.2.12 Results from Wavelet coherence analysis for LME Tin and S&P 500

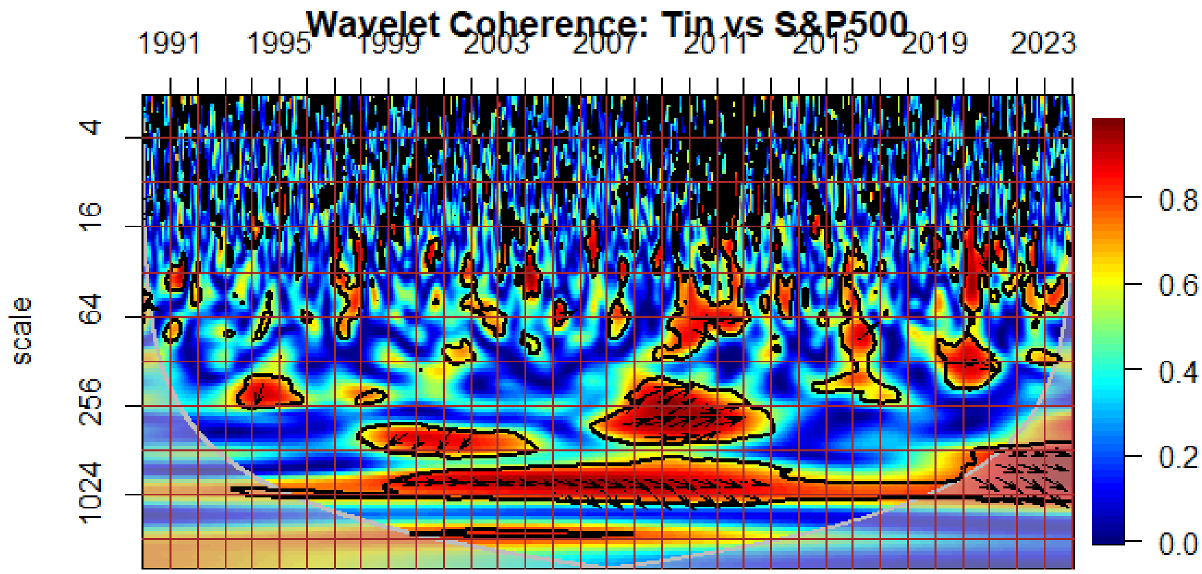


Figure 3.2.13 Results from Wavelet coherence analysis for LME Nickel and LBMA Gold

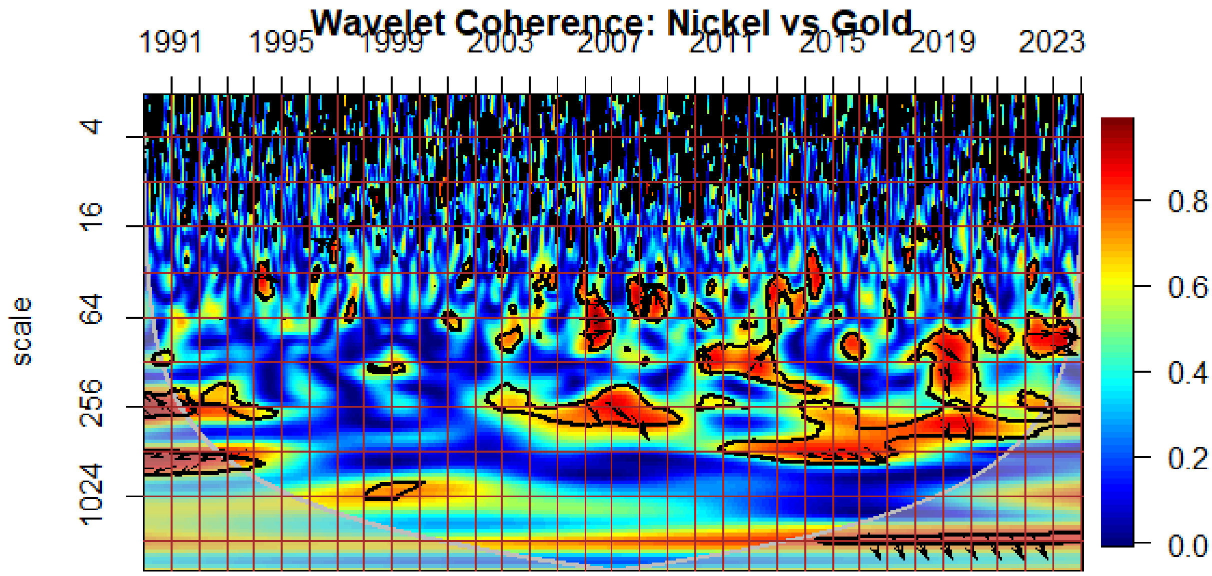


Figure 3.2.14 Results from Wavelet coherence analysis for LME Nickel and ICE Brent Crude

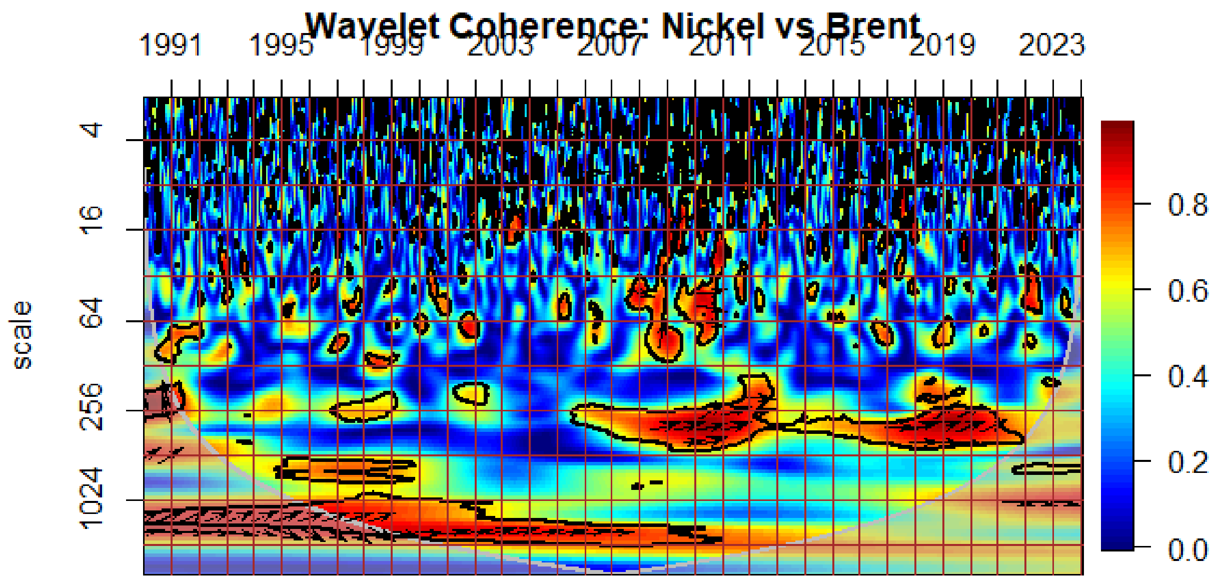


Figure 3.2.15 Results from Wavelet coherence analysis for LME Nickel and S&P 500

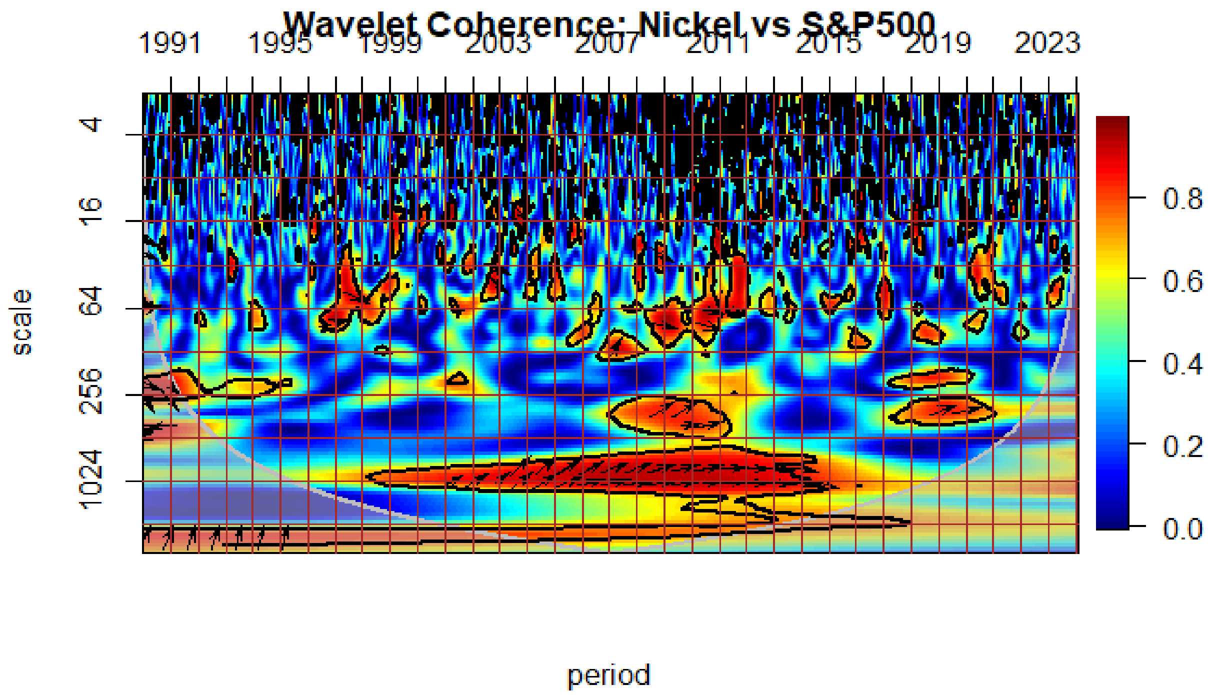


Figure 3.3.1 Dynamic Optimal Hedge Ratio of LME Gold and LBMA Copper

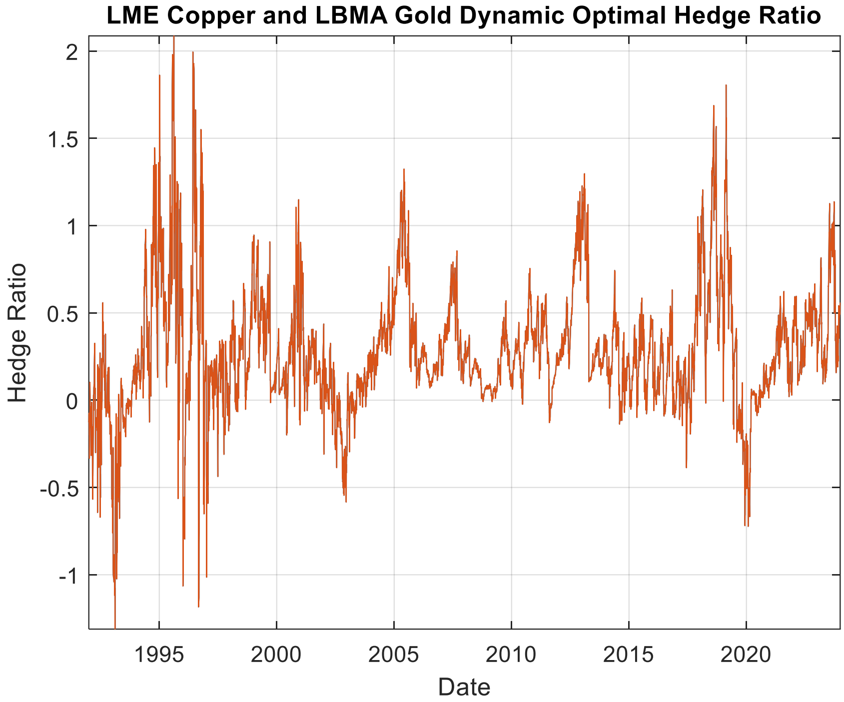


Figure 3.3.2 Dynamic Optimal Hedge Ratio of LME Gold and ICE Brent Crude

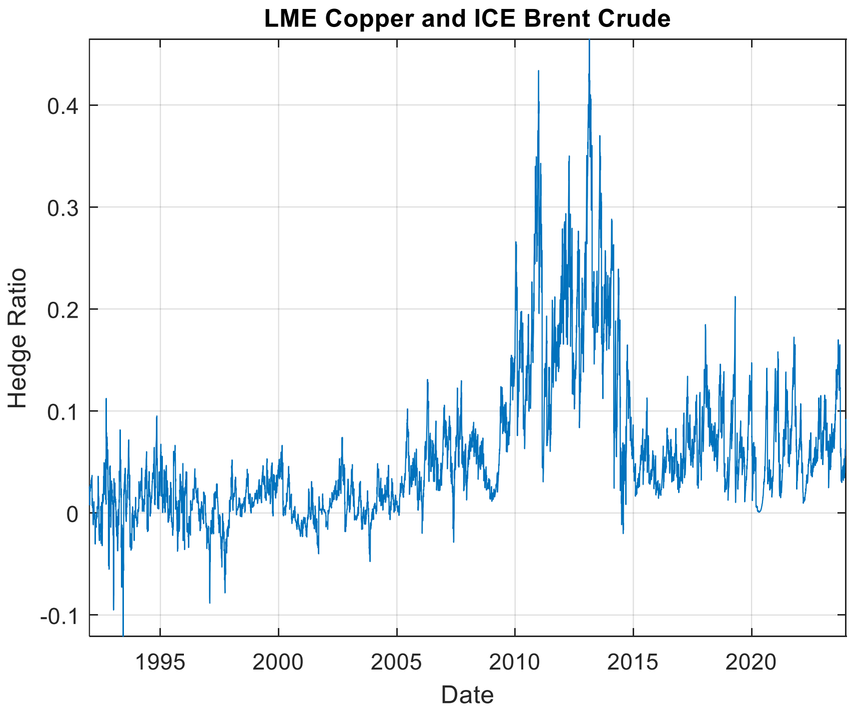


Figure 3.3.3 Dynamic Optimal Hedge Ratio of LME Copper and S&P 500 Index

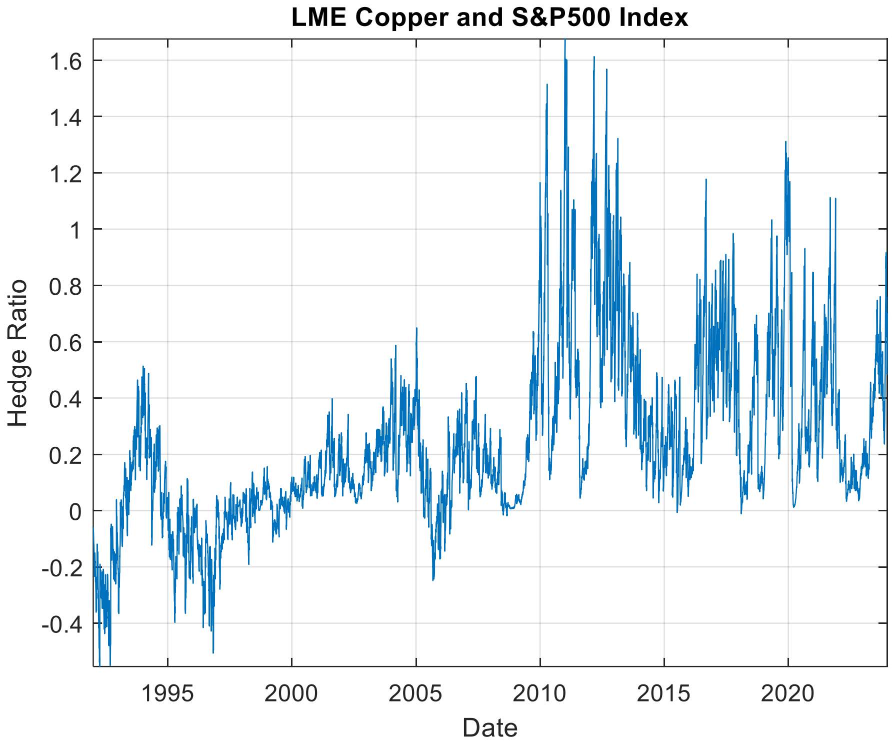


Figure 3.3.4 Dynamic Optimal Hedge Ratio of LME Aluminium and LBMA Gold

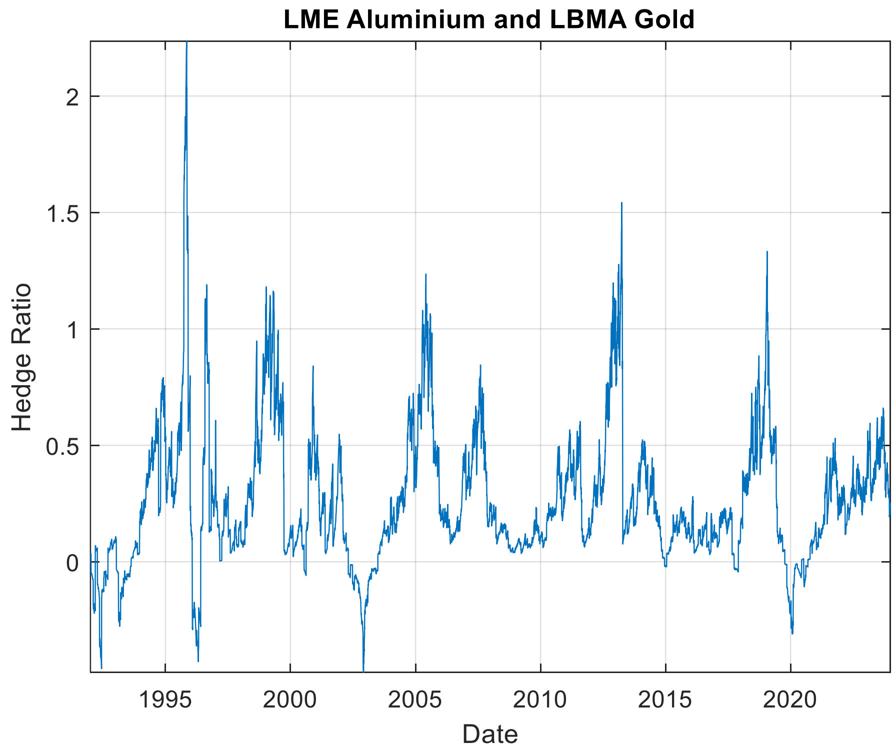


Figure 3.3.5 Dynamic Optimal Hedge Ratio of LME Aluminium and ICE Brent Crude

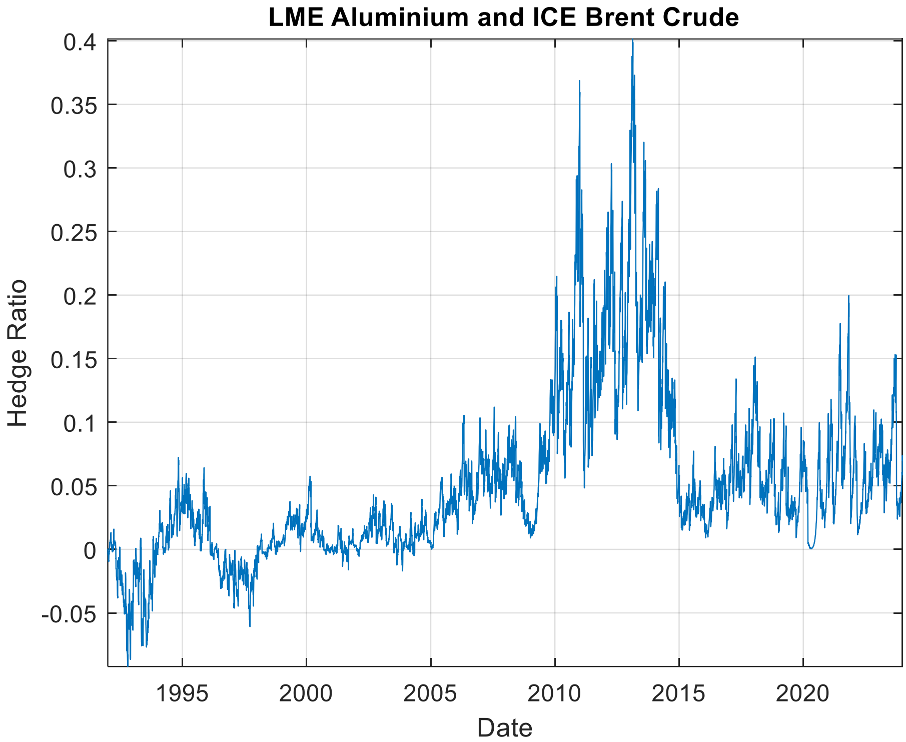


Figure 3.3.6 Dynamic Optimal Hedge Ratio of LME Aluminium and S&P 500 Index

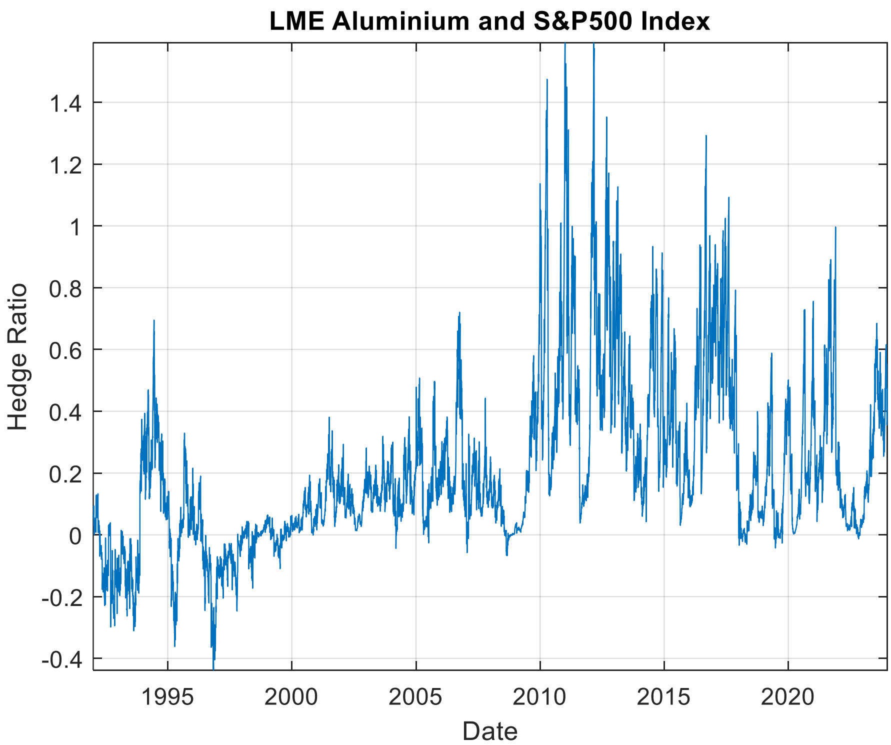


Figure 3.3.7 Dynamic Optimal Hedge Ratio of LME Zinc and LBMA Gold

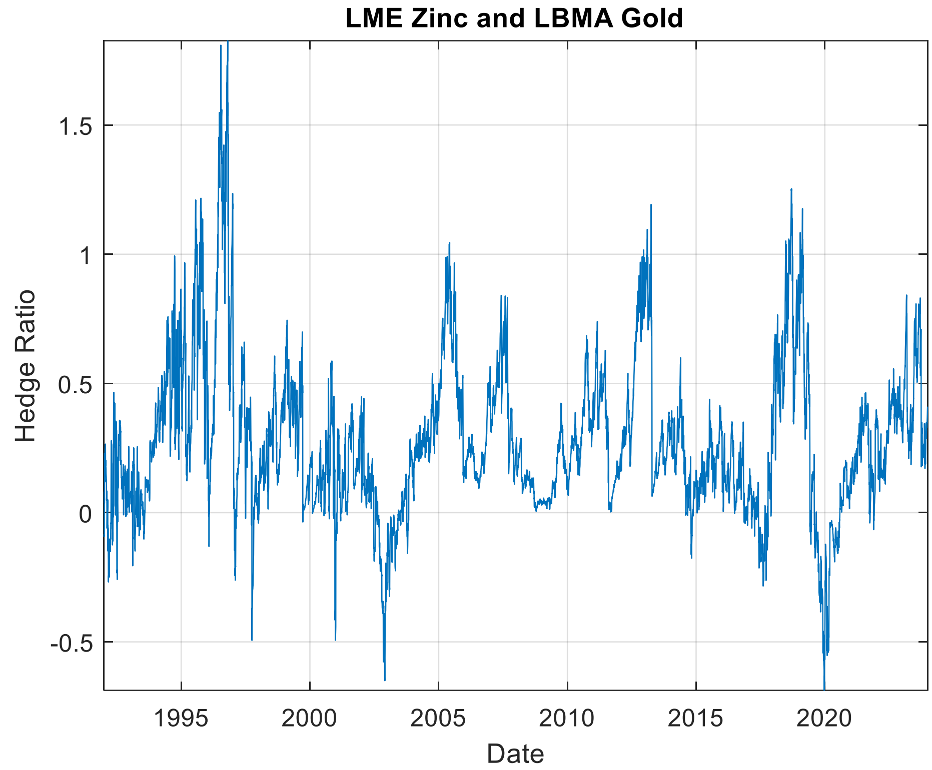


Figure 3.3.8 Dynamic Optimal Hedge Ratio of LME Zinc and ICE Brent Crude

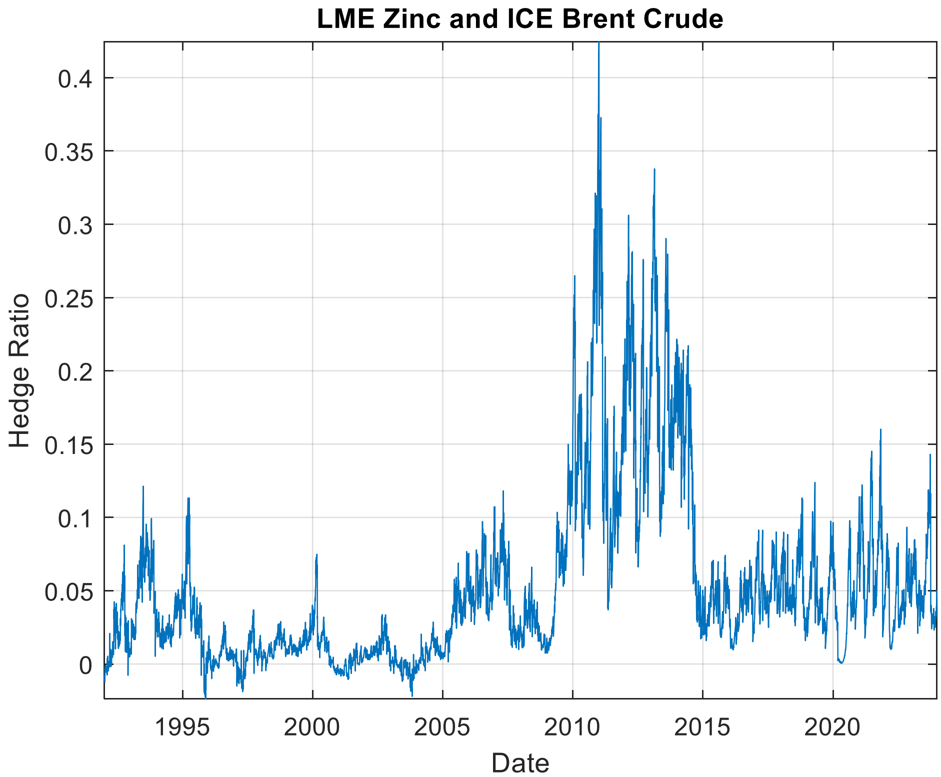


Figure 3.3.9 Dynamic Optimal Hedge Ratio of LME Zinc and S&P500 Index

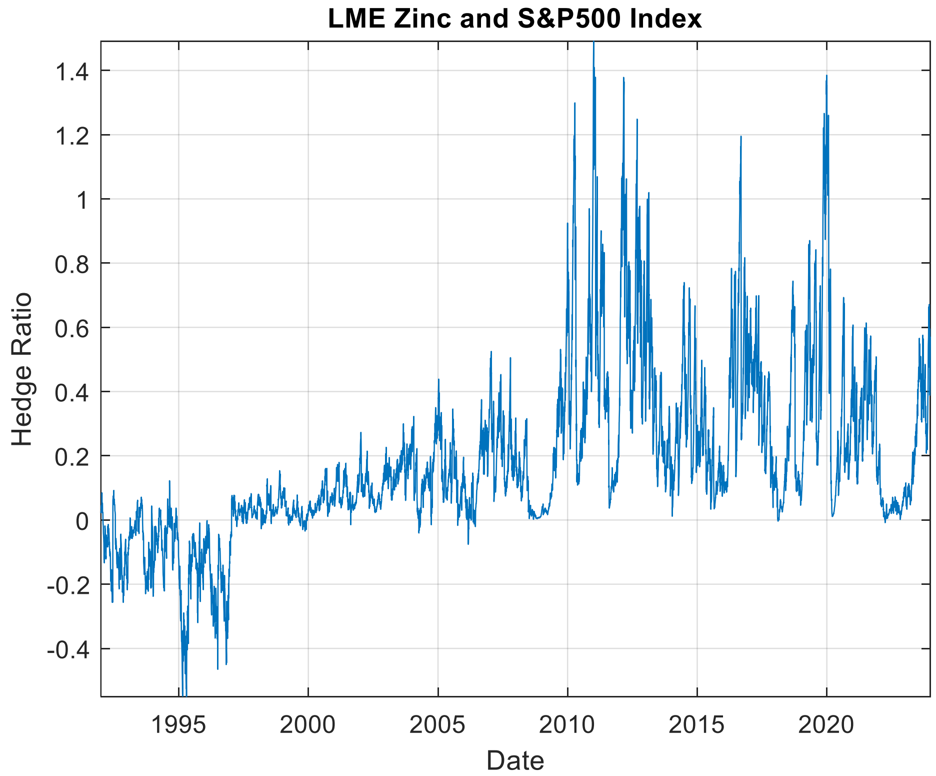


Figure 3.3.10 Dynamic Optimal Hedge Ratio of LME Tin and LBMA Gold

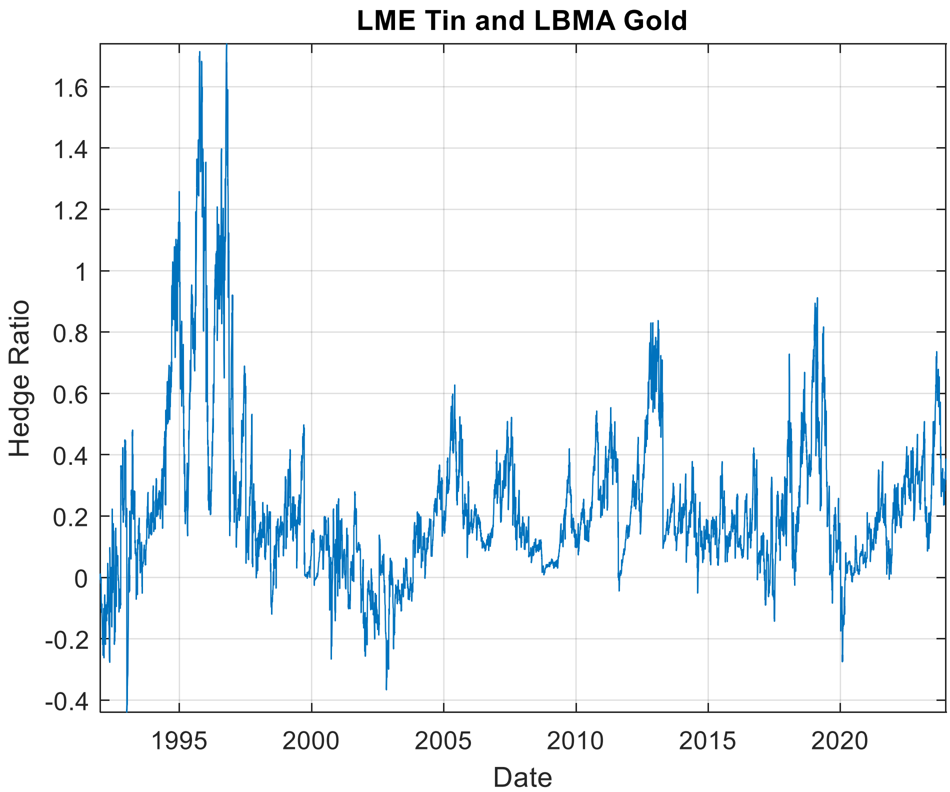


Figure 3.3.11 Dynamic Optimal Hedge Ratio of LME Tin and ICE Brent Crude

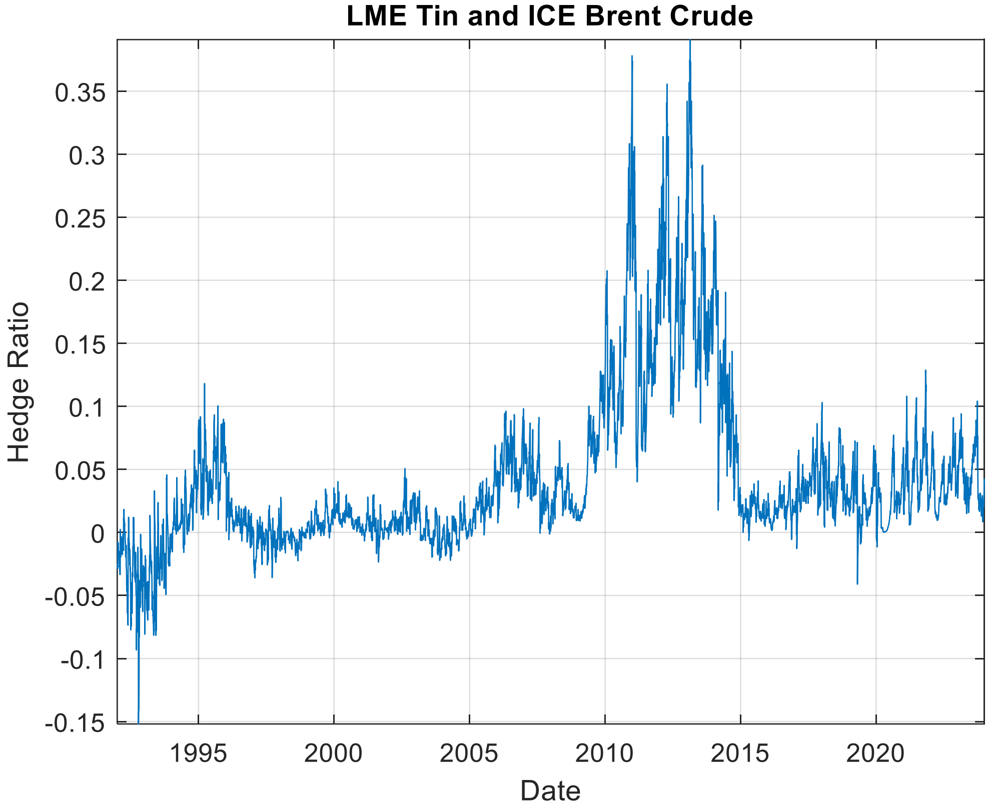


Figure 3.3.12 Dynamic Optimal Hedge Ratio of LME Tin and S&P500 Index

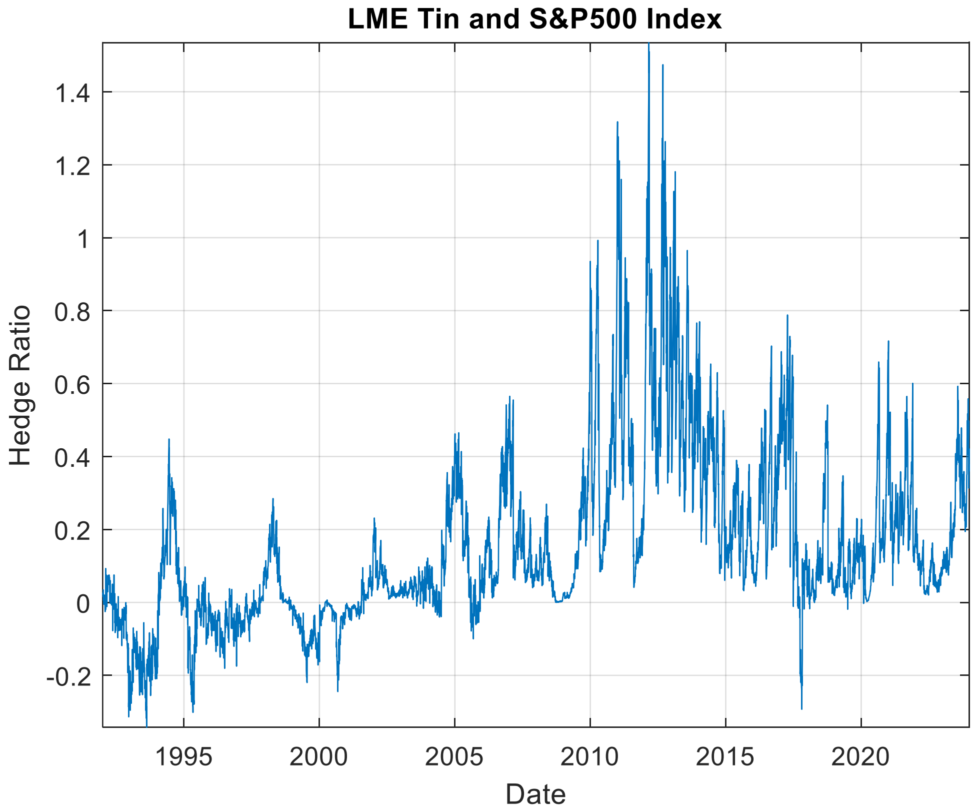


Figure 3.3.13 Dynamic Optimal Hedge Ratio of LME Nickel and LBMA Gold

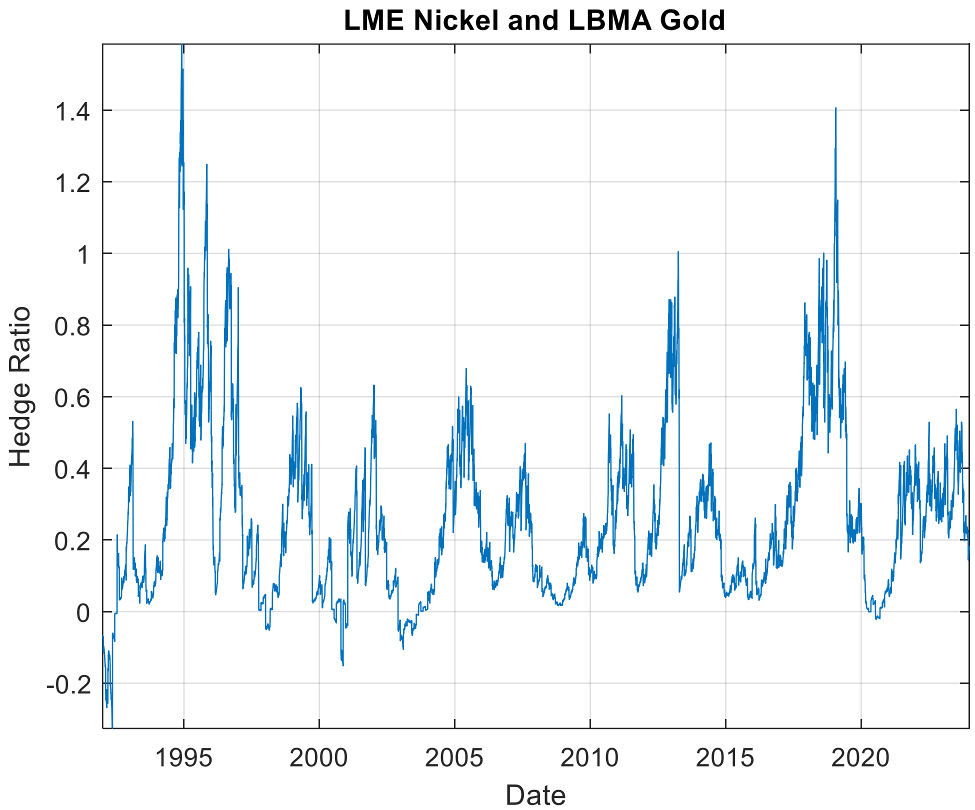


Figure 3.3.14 Dynamic Optimal Hedge Ratio of LME Nickel and ICE Brent Crude

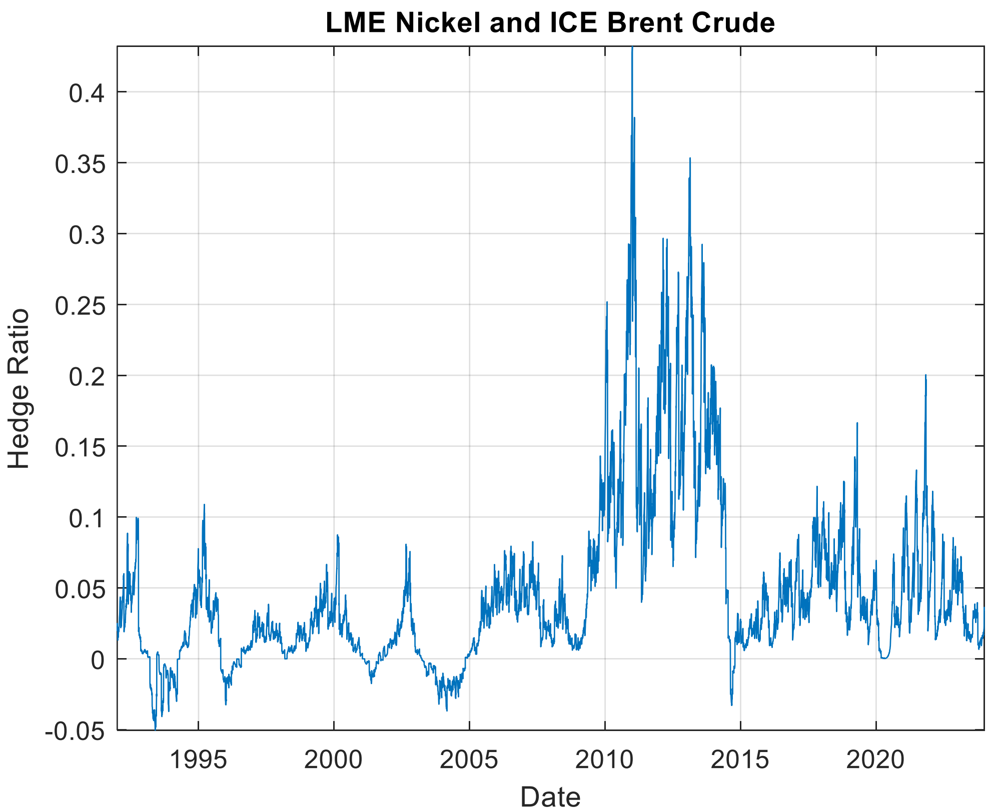
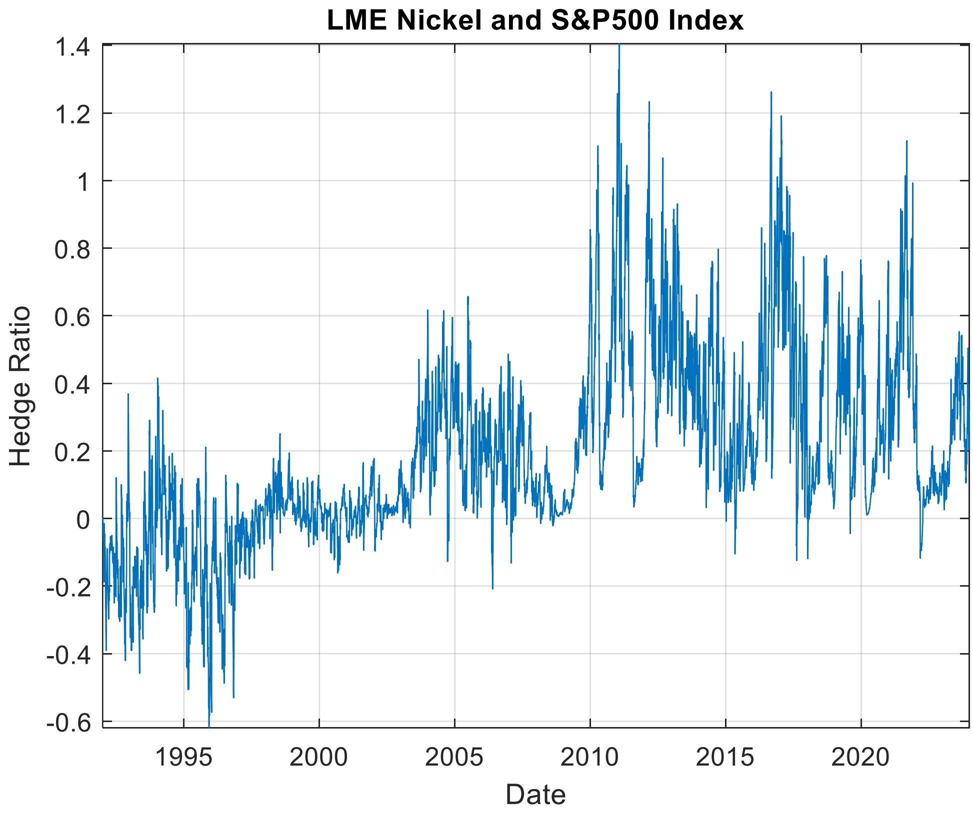


Figure 3.3.15 Dynamic Optimal Hedge Ratio of LME Nickel and S&P500 Index



Chapter 4. The effects of Economic Policy Uncertainty and UK Policy Uncertainty on Non-Ferrous Metals: Evidence Using a TVP-VAR approach

Abstract

We investigate the potential time varying effects of geopolitical risks (GPR) and UK policy uncertainty on non ferrous metal commodity prices by using a vector autoregressive (VAR) model, structural vector autoregressive (SVAR) model, and a time varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV). Following estimation of VAR and SVAR models, geopolitical risks and UK policy shocks are found to have significant and different reactions to GPR and UK policy shocks. Analysis of impulse responses at different time horizons following estimation of TVP-VAR-SV model showcase evidence of both GPR and UK policy shocks having significant positive and negative responses to shocks after major geopolitical events at the one period ahead horizon, with these effects diminishing at longer time horizons, indicating that while GPR and UK policy shocks have dramatic effects on the volatility of non ferrous metals in the short term, these effects are not long lasting.

4.1 Introduction

With the increasing usage of non ferrous metals as an important strategic resource and a widely used industrial resource, they play a significant role in the development of national economies and the operation of various industries, but geopolitical disruptions such as conflicts between nations, rising tensions and policy uncertainty at the national level have caused disruptions to the pattern of global economic stability, with rising costs and bouts of persistent volatility. As world economies still feel the effects of the US subprime mortgage crisis which caused the events of the 2008 financial crisis one and a half decades later, events throughout the 2010s and 2020s such as the 2016 UK Brexit referendum, the COVID crisis and the recent 2024 US Presidential election have additionally thrown stock and commodity markets into periods of upheaval. Geopolitical tensions such as the Russia and Ukraine crisis and the Israel conflict with Palestinian militant groups continue to develop and evolve, and their impacts are hugely felt in various commodity markets, with Brent crude oil prices increasing from $97 per barrel in February 2022 to $117 per barrel in April (Zhao, 2023) being one such example, but both Russia and Ukraine's major roles as importers and exporters of non ferrous metals have additionally played a huge role in extreme price fluctuations for these metals, with LME Nickel futures increasing from $24,558 per tonne in February 2022 to a high of $48,002 in mid March 2022, a record high never previously seen, with a similar story for zinc, with a price of $3582 per tonne reaching a high of $4563 in mid April.

Natural resources such as non ferrous metals and various other types of commodities are heavily driven by geopolitical risk factors and political uncertainty and instability, which have a big influence on available supply and demand of certain commodities, thereby resulting in periods of high volatility and price fluctuations when unforeseen geopolitical events occur. Geopolitical risk is defined by Caldara and Iacoviello (2022) as "the risks associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations". Unpredictable and sudden events are likely to trigger panic among individuals, resulting in large sell offs in volatile assets in the search for safer bets until their previous investments settle at a more stable level (Apergis and Apergis, 2016).

With natural resource production closely linked with geopolitics, changes in the geopolitical landscape may bring about uncertainties in the supply of certain commodities in the international market. However, not all shocks from geopolitical events and economic policy events cause negative reactions in stock and commodity markets. Natural gas prices in Asia, Europe and North America have climbed by as much as 50% in 2024, with prices forecasted to continue rising into 2025 with forecasts for cold weather and high consumer consumption[9].

Geopolitical risks such as conflicts, natural disasters and terrorism play are a notable risk factor in the pricing and supply availability of commodities. The second such risk factor is internal factors such as the policies and decision making of national governments. The role of governmental decision making and policy implementation can have significant effects on global stock and commodity markets. In modern times, natural resources have been inextricably linked with economic competition and these conditions have a profound influence on the supply and availability of these resources (Zhao, 2023), additionally, trade tariffs such as those imposed in the United Kingdom are imposed to restrict the flow of imports and encourage the growth of the economies of their respective nations, with Donald Trump proposing to impose tariffs on imports from foreign nations following his inauguration as United States President in January 2025, with the S&P 500 index climbing 0.88% in response[10]. In this chapter, we use the Vector Autoregressive (VAR) model, structural VAR model and a time varying parameter VAR model with stochastic volatility (TVP-VAR-SV) to explore the effects of geopolitical risks and UK economic policy on non ferrous metal commodity returns. A literature review is conducted, analyzing previous literature in the area of uncertainty shocks, with in depth description of the data and model selection additionally following the literature. The results showcasing impulse responses following VAR and SVAR model estimation are presented, along with impulse responses at different time horizons, which is conducted with the use of the TVP-VAR-SV model.

[9] https://www.reuters.com/business/energy/key-global-natural-gas-prices-set-keep-rising-into-2025-maguire-2024-12-03/

[10] https://www.reuters.com/markets/us/markets-optimistic-trump-returns-white-house-2025-01-20/

4.2 Literature Review

4.2.1 Major Geopolitical events and stock markets

While the linkages between non-ferrous metal markets and major geopolitical events, and their potential long-lasting effects has not been commonly addressed in the literature, there exists numerous such studies have explored the effects of geopolitical events on stock market indices and other types of financial instruments. Geopolitics contains all space-specific components such as geography, energy sources, trade routes, raw materials and food (Lee 2019). Caldara and Iacoviello (2022) define GPR as 'the risks associated with wars, acts of terrorism, and tensions between states that affect the normal and peaceful course of international relations'. Additionally, geopolitical events such as war, foreign policy and terrorism equally play a big role in influencing pricing and decision marking. Among the body of previous literature to address linkages between geopolitical events and stock market indices, Balcilar et al. (2018) seeks to identify a link between geopolitical risks and stock market dynamics of the BRIC economies from January 1985 to April 2016, with data obtained by the work of Caldara and Iacoviello (2022), who construct various GPR indices by counting the occurrence of words related to geopolitical tensions in 11 leading national and international newspapers, additionally using monthly returns data for the BRIC economies. Following nonparametric causality-in-quantile tests, all markets analysed experienced positive mean returns, despite the inclusion of the 2007/08 financial crisis, with Russia having the highest mean returns, along with the highest volatility, while India was the most resilient economy. Their findings across the five markets of Brazil, Russia, India, China and South Africa respectively observe that the effect of GPRs is heterogeneous, suggesting that news regarding geopolitical tensions do not affect return dynamics in these markets in a uniform manner, having a more consistent effect on volatility measures rather than returns, implying possible volatility spillover into these markets as a result of their exposure to geopolitical tension. Bouras et al. (2019) used a more conventional panel GARCH model to examine geopolitical risks, returns and volatility of 18 emerging markets using monthly data over the period spanning November 1998 to June 2017. They find that while country specific geopolitical risks have a positive but statistically weak effect on volatility and no effect on returns, the impact on volatility of global GPRs is both economically and statistically stronger than country specific GPRs, showcasing that global events have broader longer lasting impacts than regional events. Lee (2019) investigates the joint probabilistic behaviours of stock market performances and geopolitical risks over the period from June 1997 to December 2017, attempting to deviate from previous studies by attempting to reveal the joint probability of geopolitics and economy. Results from bivariate copula analysis showcased more discordant relationships with geopolitical acts, with geopolitical uncertainty playing a role with stock market performances in 37 different stock market indices. In a pioneering study, Das et al. (2019) sought to analyse whether geopolitical risk has an impact on precious metal prices, using quantile regression analysis on a sample period from January 1985 to December 1987. In their results, they noted a positive relationship between geopolitical risk within the sample period, with gold returns increasing by 0.0029% when geopolitical risk increases, and higher gold returns were also noted when registering Caldara and Iacoviello's (2018) geopolitical risk index. They furthermore found that negative relationships were noted with other precious metals analysed, namely silver, platinum and palladium, suggesting that these metals were more vulnerable to geopolitical risk. In a similar approach, Baur and Smales (2020) analysed whether precious metals can be used as safe haven assets or act as a hedging mechanism against geopolitical risk. Extending upon the work of Das et al. (2019) they additionally use gold, silver, platinum and palladium precious metals, citing their distinctive supply and demand characteristics, and start their sample period in January 1985 but extend their sample period to October 2018. Corroborating the findings of Das et al. (2019) they noted that the returns of precious metals are closely linked to geopolitical risk, with a stronger relationship found when considering geopolitical threats, however only gold and silver seem to possess the property to consistently hedge in both normal and extreme geopolitical events. They additionally note that commodities appear more closely linked to geopolitical risks rather than geopolitical acts. Cunado et al. (2020) look at the dynamic effects of geopolitical risk on oil prices, finding that GPR has a major effect on crude oil prices, noting that this may be due to decreased demand for oil in periods of global crisis. This research is further examined by Chowdhury et al. (2021) who additionally explore linkages between crude oil and geopolitical risk. Using a quantile regression method, their results find that GPR has a unidirectional effect on crude oil prices. Agnello et al. (2020) investigate the ability of global risk factors such as uncertainty risk, weather conditions and energy prices in explaining the length of commodity price cycles using a continuous time Weibull model. They notice a correlation between commodity price booms with inflation and temperature increases, most notably with agricultural commodities as high temperatures and droughts affect production. Additionally, commodity price busts are shorter global growth, interest rates and violence are higher, but busts are longer in periods of high inflation and rainfall. Increases in oil prices also make commodity booms longer and busts shorter. Abdel-Latif and El-Gamal (2020) study the global relationship of oil prices, financial liquidity, and geopolitical risk with the economic performance of oil export dependent economies using a global vector autoregression model allowing for lag structures for differing variables in countries. They find that oil prices are likely to drop in response to negative shocks in global financial liquidity, however, these effects are. short lived. Heightening of geopolitical risk is also likely to bring periods of higher oil prices. Wang et al. (2022) evaluate the transmission of returns and volatility of oil, agricultural and metal commodity markets in the period leading up to the Ukraine crisis. In relation to the geopolitical risk index of Caldara and Iacoviello (2022), they find that spillovers of returns and volatility are shaped by geopolitical risk, in line with previous research conducted by Gong and Xu (2022). Zhang et al. (2023) explores GPR and stock market volatility using panel data from 32 different countries and regions. Regression results from OLS, fixed effects model (FE) and bias corrected least squares dummy variable (LSDV) estimator show regression coefficients of ΔGPR are positive and statistically significant at the 1% level, indicating that GPR significantly increases stock market volatility from a global perspective. They additionally note that has a greater impact on stock market volatility in countries at peacetime, crude oil exporters and emerging economies. Cheung, Liao and Pan (2023) investigate geopolitical risk premium in the commodity futures market, by estimating the exposure of cross-sectional commodity future excess returns on a historical geopolitical risk index. Upon construction of univariate portfolios and estimating exposure of cross sectional commodity future excess returns, they identify that excess returns of a commodity portfolio decreases as its exposure to GPRH increases, adding that low risk betas generate 9.05% higher annual risk adjusted returns than those with high risk betas, insinuating that low geopolitical risk related commodities require more compensation by risk averse investors. Based on their findings, they suggest that it is difficult to justify the geopolitical risk premium based only on the fundamentals of commodity futures contracts. Eichengreen (2024) explores linkages between trade and capital flows and geopolitical events relating to tensions between the United States and China. They note that the two economies, despite political tensions, remain deeply interdependent on each other.

The effects of weather and climate risk factors on commodity volatility and pricing have also been explored in the literature. Flori et al. (2021) investigate commodity price movements in relation to climate related variables from 1980 to 2017. Comovements among commodity prices and global climate risk factors are noted. Bonato et al (2023) assess whether climate risk factors can be used to predict future realized volatility of commodity currency exchange rates. Using a HAR model with intraday data for 8 major commodity exporting countries, they show that climate risk factors have incremental predictive power for forecasting exchange rate volatility. Faccini et al. (2023) aim to provide evidence on whether physical or transitional climate risks are prices in US stocks. In addition to daily data for all common stocks traded on the NYSE, NASDAQ and AMEX from January 2000 to December 2018, they construct four different measures of environmental risk metrics from mentions of specific key words in 13 million articles published by Reuters, namely international climate change summits, climate policy, global warming and natural disasters. Their findings indicate that government intervention is the main drivers behind US stock pricing rather that physical environmental risk factors, contrary to previous findings from Bonato et al. (2023) that climate risks can be used as a useful tool for forecasting commodity volatility. Climate policy uncertainty and potential links to oil pricing and agricultural commodities are also explored by Wang et al. (2023), using quantile connectedness. Ma, Zhou and Li (2024) explore potential pricing implications for agricultural commodities as a result of extreme climate events such as climate change. The four specific climate risk metrics constructed by Faccini et al. (2023) are used, with monthly data on the agri-commodity price index also used. Both in sample and out of sample show that PCA climate risk index exhibits strong predictability for agricultural commodity returns, citing previous literature from Kotz et al. (2023) noting the adverse effects of climate on agricultural output, and investor attention also playing a potential role.

4.2.2 Macroeconomic and uncertainty shocks

Uncertainty shocks and their effects on asset pricing in different markets have been explored in the literature and have been a subject of considerable empirical research, using varying classes of econometric models. Linkages between macroeconomy and commodity prices movements have previously been documented in Gorton and Rouwenhorst (2006), who showcase evidence that commodity future returns are negatively correlated with equity and bond returns is due in significant part to different behaviour over the business cycle, additionally noting that commodity returns are positively correlated with inflation over long-term horizons. Batten et al. (2010) evaluate the macroeconomic determinants of volatility in precious metal markets, using data covering January 1986 to May 2006. For precious metals, they find only limited evidence that macroeconomic factors jointly influence volatility processes of the precious metals examined. Research from Elder and Serletis (2010) found that uncertainty in crude oil prices causes a decrease in several different measures of investment, durables consumption and output, however, this view is disputed by Jo (2014), who suggests that oil price uncertainty has little effect on output and consumption, based on results obtained using a Vector autoregressive (VAR) model with stochastic volatility in the mean. Common macro uncertainty shocks have effects on par with monetary policy shocks, with macro uncertainty also being strongly countercyclical, with total uncertainty more present in periods of recession than in non-recessions (Jurado, Ludvigson and Ng, 2015). Basak and Pavlova (2016) analyze the financialization of commodities and how investors entering the market affects commodity prices. Utilising comprehensive samples of US and Chinese macroeconomic news announcements, Smales (2017) investigates commodity market volatility in the presence of US and Chinese macroeconomic news. Baseline results showed that in both cases, macroeconomic variables have a well defined relationship with commodity markets, highlighting when investor fear and short term rates are higher, the yield curve is steeper and credit spreads are wider, and volatility increases, although Chinese GDP plays no role in explaining commodity price volatility. Bakas and Triantafyllou (2018) observe the impact of uncertainty shocks on the volatility of agricultural, energy and metal commodity prices over a span of 31 years covering January 1985 to December 2016 using a 6-factor VAR model. Their results show that macroeconomic uncertainty increases volatility in commodity markets, adding that macroeconomic uncertainty is significantly lower after the occurrence of volatility episodes in commodity markets, reaffirming previous research that the impact of potential uncertainty shocks on commodity prices was significant. Prokopczuk, Stancu and Symeonidis (2019) seek to identify the economic drivers of commodity market volatility, using daily data of 25 commodity futures covering 1970 to 2015. Results from comovements analysis showcased evidence that documented pairwise comovements are strongest in periods of recession as compared to economic expansions. Additionally, variables related to credit risk, funding illiquidity, and equity and bond market stress are significant predictors of commodity market volatility, indicating shocks in the real economy affect commodity market volatility. Bakas and Triantafyllou (2020) further explore the effects of macroeconomic uncertainty on commodities, investigating how pandemics have an affect on the sub-indices of crude oil and gold. Using a five factor VAR model, including data for the world pandemic uncertainty index based on Ahir et al. (2019), the world industrial production index on the work of Baumeister and Hamilton (2019) and the GPR index, they find that the broad measure of commodity volatility and volatility in oil markets are reduced when uncertainty about pandemics arises, with contrasting effects for gold but are less significant. Furthermore, they note that pandemic uncertainty shocks reduce commodity price volatility namely through disruptions in global commodity demand in pandemic times. Prokopczuk et al. (2019) analyse relationships between macroeconomic uncertainty and commodity market volatility, using data for 25 commodity futures traded in the US from January 1st 1970 to December 29th 2015. In their analysis, they find a strong relationship between economic uncertainty and volatility in commodity markets. Kassouri and Altintas (2022) look at causal linkages for stock returns of clean and dirty stocks on oil demand and supply shocks. Following a quantile ARDL model approach, they observe a potential decline in the stock price of clean energy companies following demand driven oil shocks in the short run, potentially driven by the prospects of economic growth in China and economic contraction in Europe. Demand oriented oil shocks are therefore found to be positively and significantly correlated with clean energy returns across different market conditions. Chang et al. (2022) study the effects of exchange rate response to economic policy responses in the G7 countries using a nonlinear ARDL model with granger causality and find that positive shocks in economic policy uncertainty has significant effects on exchange rate volatility while negative shocks have no such effect, indicating asymmetric effects. Fernandez et al. (2023) contribute to the literature by exploring the global copper returns and the impact of operational disruptions. Analysing the impact of 109 mining strikes taking place in Chile between 1910 and 2010, regression analysis incorporating dummy variables, they find that the announcement of strikes impact the price of copper before the strike has taken place, suggesting that agents use the information to act in anticipation of the strikes. Additionally, Guo et al. (2023) assess whether climate shocks are connected to agricultural commodity markets. Extreme weather events and climates had the greatest spillover effects, followed by droughts and extreme temperatures, suggesting that these four climate risk factors play a significant role in information transmission between agricultural commodity markets. They additionally suggest future research investigating the impact of climate risk perception on the prices of other climate sensitive resources, such as industrial and mineral resources. In an alternative approach, Triantafyllou et al. (2023) instead examine the impact of price uncertainty in agricultural, precious metal and energy commodity markets on US economic activity using a 8 factor VAR model. Their results show that uncertainty shocks in agricultural and metal markets have potential long lasting effects on economic activity in the US. Obstfeld and Zhou (2023) investigate for potential linkages between the US dollars nominal effective exchange rate on emerging markets and developing economies. They comment that there are alternative factors, namely US monetary policy, US financial conditions and dollar funding stress all contribute to the appreciation or depreciation of the US dollar, which in turn may predict downturns in emerging markets. Glebocki and Saha (2024) assess the response of bilateral exchange rates, exchange rate volatility, market pressure, and nominal and effective interest rates and their effects in emerging and advanced economies, employing monthly data for 28 countries and the euro zone from January 1996 to December 2022. Results obtained using the global vector autoregressive estimation approach show that uncertainty shocks result in depreciation (appreciation) in emerging (advanced) economies in response to policy uncertainty spikes. Additionally, they support the findings of Obstfeld and Zhou (2023) of the impact of dollar cycles on emerging and advanced economies. Bermpei et al. (2024) look to document whether there are linkages between commodity prices and exchange rates of commodity exporting countries. Using a structural vector autoregressive model (SVAR), they show that rising uncertainty in global commodity markets has a negative short run effect on commodity currencies, however, they additionally note that these effects tend to apply to specific commodities, with other benchmark currencies like the euro display neutral effects, while the US dollar appears to be a safe haven, by appreciating in periods of global uncertainty shocks.

4.2.3 Vector Autoregressive Models and alternative models

The literature regarding uncertainty shocks and commodity markets suggests several different approaches to evaluating and analysing the effects of geopolitical risks on markets. Among the relevant literature, Vector Autoregressive models (VAR) and extensions and derivatives of the model are among the most common models used to assess the impact of uncertainty shocks and macroeconomic events and their potential relationships with volatility in commodity markets. Bloom (2009) used a VAR model to assess the impact of uncertainty shocks on prices, showcasing evidence that an uncertainty shock leads to a short run drop and a rebound of interest rates of up to 1.1% points and 0.5% for commodity prices, identifying 17 periods of uncertainty and strong countercyclical between relationship between real activity and uncertainty. An extension of the VAR model, the Structural Vector autoregressive models (SVAR) model, is also employed in the literature to look into linkages between macroeconomic variables and commodity prices and other tradeable financial derivatives. Sousa and Zaghini (2007) uses a SVAR model to explore the effects of global monetary policy shocks in the G5 economies. In their findings, responses of G5 economies to monetary policy shocks are found to be strongly correlated. Furthermore, global price levels rise permanently while real global output temporarily in response to a positive shock to global liquidity. Redl (2015) measure the impact of noisy news on exchange rates using a SVAR model, over a period from 1986 to 2013. Their results show that noisy news is an important driver of variances in exchange rate prices, explaining approximately a fifth of variation. Chen et al. (2016) analyse the impacts of OPEC political risk on the price fluctuation of international crude oil prices including brent crude based on several SVAR models, by using the international country risk guide as a proxy to measure the countries political situation to analyse whether political risk from these countries transmits into brent crude prices from January 1998 to September 2014. In their results, oil demand shocks have significant positive impacts on brent crude prices in the specified period, while supply shocks do not, consistent with previous findings from Kilian (2009). Rant et al. (2024) investigate the impacts of macroeconomic impacts and fiscal policy in the euro area in periods of uncertainty and shifting policy using a SVAR approach, citing the wide use of VAR models and extensions including the SVAR model in the literature is because of their simplicity.

Looking into macroeconomic uncertainty in relation to oil commodity markets, Van Robays (2016) showcase that periods of higher macroeconomic uncertainty have an influence on oil price dynamics, and the elasticity of oil supply and demand using a threshold autoregressive model (TVAR). Among the advantages of the TVAR approach in relation to alternative types of econometric approaches, they note that the TVAR approach is simple in its implementation in comparison to Bayesian VAR models, allowing for the identification of different uncertainty regimes within the model framework. Joëts, Mignon and Razafindrabe (2016) additionally used a TVAR model to tackle the issue of macroeconomic uncertainty affecting the prices of 19 different commodity markets. They note that the sensitivity of uncertainty is dependent on the type of shocks, with not all crude oil shocks following the same pattern. Additionally, the role of macroeconomic uncertainty is countercyclical, with the effects of macroeconomic shocks roughly doubling in importance during periods of recession. Agricultural commodity shocks are also a by product of unexpected increases in demand according to their results. Basu and Bundick (2017) employ a TVAR model to explore uncertainty shocks and monetary policy impacts on stock returns. Increases in uncertainty in the 2008 financial crisis, combined with zero lower bound on nominal interest rates may be a largely important factor in explaining the large decline in economic output. Tan and Ma (2017) analyse the impact of macroeconomic uncertainty on global commodity prices, using a TVAR model to study the impact on 19 different commodity markets. For almost all commodities, after positive two standard deviation macroeconomic uncertainty shock, commodity prices respond negatively, implying positive uncertainty shocks negatively impact commodity prices. Replicating the autoregressive investigation by Bloom (2009), Caggiano, Castelnuovo and Nodari (2020) use the same VAR approach to study uncertainty and monetary policy using S&P 500 stock market data and an uncertainty dummy variable based on the volatility index (VIX). In their replication, they find that an uncertainty shock triggers a temporary fall in prices, although statistically significant in recessions only. Generally, their results are largely line with findings from Bloom (2009), also finding uncertainty and macroeconomic shocks are largely countercyclical. Shaheen (2021) use a TVAR approach to examine energy market dynamics and the impact of fiscal policy in oil-exporting countries. Using GDP growth rate and inflation as macroeconomic response variables, they find evidence that GDP and economic growth rates have a positive relationship with oil output in heavily exporting countries like Saudi Arabia.

The time varying parameter vector autoregressive model (TVP-VAR) augmented by Nakajima (2011) with a stochastic volatility model has additionally been used in the literature to explore the effects of macroeconomic variables on commodity prices. Jebabli, Arouri and Teulon (2014) utilize the TVP-VAR model with stochastic volatility to examine the potential transmission of shocks between food, crude oil and financial markets, noting that the TVP-VAR approach has the advantage over the constant parameter VAR model . Nam (2021) use a time varying factor VAR model with stochastic volatility to investigate the effects of climate uncertainty on global commodity markets. When analysing the effects of the El Nino global climate phenomenon, they find differing levels of shock among the data, with increased impulse responses for agricultural, coal and crude oil futures as a result of decreased power generation and growth of agricultural commodities, with market uncertainty shock causing energy prices to decrease by 0.2% in oil crisis period due to delay in investment decisions. Lyu et al. (2021) analyse impacts of economic policy uncertainty shocks and Chinas commodity future returns market using a TVP-VAR model. Their findings are largely in line with previous literature on developed economies, they find that negative effects on Chinas commodity market, additionally noting that these effects are time varying and are largely countercyclical. Gong and Xu (2022) use a time varying parameter VAR with stochastic volatility (TVP-VAR-SV) approach derived from the approach of Diebold and Yilmaz (2014) to study links between geopolitical risk and dynamic connectedness between commodity markets. In their results, energy precious metal and industrial metal markets were the transmitters of volatility in five different commodity markets in periods of heightened volatility due to geopolitical risk. Wang et al. (2022) evaluate the effects of the war in Ukraine, citing soaring geopolitical risk as a key motivation. Additionally using the TVP-VAR approach, they find that copper, silver, natural gas and gasoline are major net spillover transmitters, whereas lead, sugar and oats are spillover receivers. Additional quantile regression results show that spillovers of returns and volatility are shaped by GPR, in line with the findings of Gong and Xu (2022). Yang, Niu and Gao (2022) employ the TVP-VAR-SV approach to focus on the time varying effects of trade policy uncertainty and geopolitical shocks on commodity market prices, using monthly data from February 2000 to October 2021. They find that TPR and GPU both have significant time varying shocks on the aggregate and commodity markets, with the form being a short term effect before 2006 and a long term effect thereafter. In a similar vein to the research of Lyu et al. (2021), Hu et al. (2023) explore geopolitical uncertainty shocks arising from events such as global conflicts and economic shocks, and their effects on the Chinese commodity market, using a TVP-VAR-SV approach. Their findings are consistent with those of Lyu et al. (2021), stating that Chinas commodity market can be collectively impacted by economic policy uncertainty and geopolitical risk shocks. They further note that the response of the Chinese commodity prices to EPU is more intense than that of GPRC after 2019, with the impact of GPRC on commodity prices is characterized by strong positive response in the 2008 financial crisis, while responses are more pronounced against EPU around the 2022 Russia-Ukraine crisis. Foglia et al. (2023) likewise use a TVPVAR model using a Bayesian framework to disentangle geopolitical risk and its effect on commodities in G8 countries. In their findings, geopolitical risk is more pronounced among countries sharing geographical borders. Additionally, geopolitical risk transmission between G8 countries and commodity markets tend to be uneven. Yin, Chang and Wang (2023) analyze the dynamic impacts of economic uncertainty on commodity and stock prices and any potential linkages combining a stochastic volatility model with a classical vector autoregressive model, which extends the VAR model by employing innovative stochastic walk technique to account for time varying disturbances covariance matrix and coefficient matrix.

Other types of models, such as regime and markov switching models have also been used in the literature to analyse the effects of GPRs with their ability to capture potential nonlinearity in changes to data shocks a primary reason. Bianchi (2016) explains that a key advantage of using Markov switching processes to model parameter instability it that numerical intervention is not required to obtain results. Ahmed and Sarkodie (2021) employ a markov regime switching dynamic model to investigate the effect of COVID-19 and economic policy uncertainty on the prices of eight widely traded commodities. In high volatility regimes, the correlation between corn and soybean returns with COVID 19 cases and economic policy uncertainty is high with a similar such relationship for silver and gold. Alternatively, they note an insignificant such relationship for corn due to the low sensitivity to shocks, with a similar such relationship for gold due to its safe haven potential. One such study from Tiwari et al. (2020) uses a markov switching time varying copula model to examine structural dependence and price dynamics between gold and oil prices and the role of geopolitical risk. They provide evidence of time varying Markov tail dependence and dynamics between gold and oil over the period spanning 1985-2017. Qian, Zeng and Li (2022) use a autoregressive Markov-switching model to explore predictability of GPR on oil market volatility. In their findings, geopolitical risk has a significant impact on oil price volatility over the period January 1986 to May 2018. Abid et al. (2023) used a Markov switching model to analyse the dynamic effects of geopolitical risk shock on five types of commodities (energy, precious metal, industrial metal, agriculture and livestock). The Markov switching model was able to adequately suggest that GPR shocks have a significant impact on commodity returns, also being able to identify different states in relation to GPR, low returns/high volatility and high returns/low volatility. Tang et al. (2024) conduct empirical analysis on the interplay between climate policy uncertainty and commodity future returns in the US using a Markov regime switching approach. When precious and industrial metals returns are low in volatility, they have a positive and significant impact on climate policy uncertainty, for fuel and crude oils, climate policy uncertainty has a significant positive impact in low volatility regimes. They add that the impact of climate policy uncertainty is more pronounced during periods of relatively calm, low volatility market conditions. Dinh et al. (2022) use mixed data sampling to investigate time-varying dynamics of precious metal markets, finding that stock market returns of G7 countries and BRIC economies play an important role in determining both volatility and correlations of precious metals. GARCH-MIDAS analysis also shows GPR has a significant effect on dynamic connectedness between markets (Segnon et al. 2024).

4.3. Data and Methodology

4.3.1 Data

For this chapter, we explore for potential linkages between macroeconomic uncertainty and major geopolitical events, and non-ferrous metals traded on the London Metals Exchange (LME), which is one of the world's largest markets for the exchange of forward and futures contracts for industrial and precious metals. The metals selected in this chapter are namely copper, aluminium, zinc, tin and nickel, which represent some of the most widely traded commodities on the London Metals Exchange and have broad and important uses in industrial applications and are also becoming widely used in portfolio diversification strategies and risk management applications. For the data regarding geopolitical risk and macroeconomic uncertainty, we have a few different measures. Firstly, we select the global Geopolitical Risk Index (GPR) constructed by Caldara and Iacoviello (2022) as a measure of geopolitical events and associated risks. The index uses automated text search results and keyword mentions in the electronic archivers of 10 major global newspapers, with searches organized into eight categories, and is widely used in the literature as a measure of uncertainty and geopolitical risk. Daily UK economic policy uncertainty data is also collected, which is constructed by searching for articles that contain relevant policy terms from over 600 UK newspapers, with relevant terms including 'policy', 'tax', 'spending', 'Bank of England', 'budget' etc. to measure policy related economic uncertainty within the UK. For this chapter, the timespan of the data is from 1st January 2000 to 29th December 2023 due to constraints on the maximum timespan of readily available UK Policy data, but additionally coincides with and allows for the inclusion of major geopolitical tensions and terrorist acts such as the 9/11 terrorist attacks and the 2022 Russian invasion of Ukraine, economic events such as the 2000 dot com bubble, the 2008 financial crisis, the Brexit referendum and the COVID-19 pandemic of 2020-21, political events such as the 2008 and 2016 presidential elections and environmental events such Hurricane Katrina in 2005, the Deepwater Horizon oil spill in 2011 and the 2019-20 Amazon wildfires. The daily data for all the non ferrous metals used in this chapter can be downloaded from Datastream and Bloomberg terminal, while data for the geopolitical risk index and the UK policy uncertainty can be downloaded from https://www.matteoiacoviello.com/gpr.htm and https://www.policyuncertainty.com/index.html respectively. The rationale for selecting daily data in our analysis is so as to ensure each of the respected non ferrous metals, and risk and policy indices capture effectively capture accurate price movements within the sample period.

4.3.2 Vector Autoregresison Model

Vector autoregression (VAR) models have been widely employed in the literature to capture the changes in relationships between multiple variables over time. The seminal work of Sims (1980) was the first to introduce the VAR model as a new approach to granger causality. The VAR model, in essence, illustrates the dynamic relationship between set variables, whereby each variable accounts for its lags and the lags of other variables nested within the model (Jangir et al. 2022). The response of macroeconomic variables to monetary and uncertainty policy can be easily measured using a standard VAR model (Bernanke, Boivin and Eliasz, 2005). Lubik and Matthes (2015) state more specifically, a VAR describes the evolution of a vector of n economic variables at time t as a linear function of its own lags up to order L and a vector of e_t of unforecastable disturbances:

$$y_t = c_t + \sum_{j=1}^{L} A_j y_{t-j} + e_t.$$

The simplest form of VAR model that can be estimated is a bivariate VAR model, where only two variables, γ_{1t} and γ_{2t}, each of whose values depend on combinations of previous k values of both variables and error terms, which can be expressed by Brooks (2014) as:

$$\gamma_{1t} = \beta_{10} + \beta_{11\gamma_{1t}-1} + \cdots + \beta_{1k\gamma_{1t}-k} + \alpha_{11\gamma 2t-1} + \cdots + \alpha_{2k\gamma_{1t}-k} + u_{1t}$$

$$\gamma_{2t} = \beta_{20} + \beta_{21\gamma_{2t}-1} + \cdots + \beta_{2k\gamma_{2t}-k} + \alpha_{21\gamma 2t-1} + \cdots + \alpha_{2k\gamma_{2t}-k} + u_{2t}$$

Where u_{it} represents a white noise disturbance term with $E(u_{It}) = 0, (i = 1,2), E(u_{1t}u_{2t}) = 0$. An important feature of the VAR model is its flexibility and ease of generalization. Instead of only containing two variables, the model can be expanded to include $\gamma_{1t}, \gamma_{2t}, \gamma_{3t}, \dots, \gamma_{it}$ variables, becoming a multivariate VAR model, with each variable having its own equation. Another useful feature of the VAR model is the compactness of which notations can be expressed. In the case above, where k = 1, so that each variable depends upon the immediate previous value of γ_{1t} and γ_{2t} and an error term could alternatively be expressed as:

$$\begin{pmatrix} \gamma_{1t} \\ \gamma_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} + \begin{pmatrix} \gamma_{1t-1} \\ \gamma_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

F-tests and examination of causality in a VAR model can suggest which of the examined macroeconomic variables have statistically significant impacts on the other variables in the model, however, F-tests are not, by construction, able to explain the sign of these relationships and how long these effects take place, or whether a change in the variable has a positive or a negative effect on the alternative variable. We can look for these effects by examining the VAR models impulse responses and variance decompositions. Impulse responses trace the responsiveness of the dependent variables in the VAR equation to shocks to each of the other variables in the equation (Brooks, 2014). In each variable in a VAR equation, a unit shock is applied to the error, and the effects upon the VAR model over time are noted. If there are g variables in a model, a total of g^2 impulse responses can be generated. To illustrate how a VAR model generates impulse responses, lets consider a bivariate VAR(1) model:

$$\gamma_t = A_1 \gamma_{t-1} + u_t$$

$$A_1 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix}$$

Considering the effects at time $t = 0,1 \ldots$, of a unit shock to γ_{1t} at time $t = 0$

$$\gamma_0 = \begin{bmatrix} u_{10} \\ u_{20} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\gamma_1 = A_1 \gamma_0 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix}$$

$$\gamma_2 = A_1 \gamma_1 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix} = \begin{bmatrix} 0.21 \\ 0.04 \end{bmatrix}$$

And so on. The same principles can be applied to VAR equations containing multiple variables or lags. Despite their widespread usage in modelling macroeconomic shocks, VARs can have some issues. One such issue is that they maintain the rather strong assumption that the parameters are constant over time, which may be too restrictive in macroeconomic applications (Koopman and Korobilis, 2009).

4.3.3 Structural Vector Autoregression Model

The structural vector approach to VAR estimation (SVAR) is also widely employed in the literature to explore linkages between macroeconomic shocks and commodity returns. The advantage of the SVAR approach over other forms of vector autoregressive models is because it gives enough restrictions on the contemporaneous structural parameters and allows non-recursive restrictions based on the economic theory (Kim and Roubini, 2000). In the SVAR model, Shokr, Karim and Zaidi (2018) note that the dynamic relationship between the selected variables is given by:

$$BY_t = \left(T_1 L + T_2 L^2 + \cdots + T_k L^k\right) Y_t + \varepsilon_t$$

Where B is a matrix (n x n) which summarizes the relationship between the selected variables, Y_t is a vector (n x 1) of the selected variables, T L is the kth order matrix polynomial in the lag operator (L). ε_t is a vector (n x 1) of structural innovations, where its mean equals zero $E(\varepsilon_t) = 0$. If we multiply the equation with (B^{-1}), the reduced form of the VAR equation is expressed by:

$$Y_t = B^{-1}\left(T_1 L + T_2 L^2 + \cdots + T_k L^k\right) Y_t + \varepsilon_t$$

The estimated residuals ϵ and the structural innovations (ε) are related by: $e_t = B^{-1}$. If Σ_e is the variance-covariance matrix of the structural innovations and Σ_e is the variance covariance matrix of the estimated residuals, the relationship between the two can be expressed as:

$$\sum\nolimits_{\varepsilon} = B \sum\nolimits_{e} B$$

Maximum likelihood estimation of the variance covariance matrix of the estimated residuals Σ_e and the contemporaneous matrix (B) can be obtained through the sample estimation of the variance covariance matrix of the structural innovations. As Σ_e matrix contains $n \times (n + 1)/2$ parameters, at least $n \times (n + 1)/2$ restrictions are needed. However, the contemporaneous matrix (B) needs $n \times (n - 1)/2$ restrictions to achieve identical conditions. In the SVAR model, the contemporaneous matrix can be any structure or form (non-recursive), as long as it has enough restrictions (Kim and Roubini, 2000). We use AIC and BIC information criteria is used to determine the optimal number of lags to be used in the VAR model and its extensions. Information criteria do not require such normality assumptions concerning the distribution of errors.

4.3.4 Time Varying Parameter Vector Autoregression Model with Stochastic Volatility

While VAR and SVAR models are widely employed in the literature in modelling macroeconomic shocks and uncertainty, time varying changes in economic structure make in undesirable to assume constant coefficients and require the incorporation of multivariate stochastic volatility (Koop and Korobilis, 2009). To account for time varying features accurately, we additionally use the time varying parameter vector autoregressive model (TVP-VAR) of Nakajima et al. (2011) is additionally employed alongside the VAR and SVAR models. The TVP-VAR approach allows us to capture the potential time varying nature of the underlying structure in the uncertainty series' in a flexible and robust manner. All of the parameters in the TVP-VAR specification are assumed to follow the first order random walk process, thus allowing both a temporary and permanent shift in the parameters (Nakajima, 2011). The TVP-VAR model preserves the basic structure of the VAR model, that is, it explains the joint evolution of economic variables through its own lags, but in addition, models the coefficients as stochastic processes (Lubik and Matthes, 2015).

Following the procedure of Nakajima (2011), the TVP-VAR-SV model can be introduced with a basic structural VAR model defined as:

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{s-1} + u_{t,} \quad t = s+1, \ldots, n,$$

Where y_t is a k x 1 vector of observed variables, and A, $F_1 \ldots F_S$ and $k \times k$ matrices of coefficients. The disturbance term u_t is a $k \times 1$ structural shock and we assume that $u_t \sim N(0, \Sigma\Sigma)$, where:

$$\Sigma = \begin{bmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k \end{bmatrix}$$

We specify the simultaneous relations of structural shocks by recursive identification, assuming that A is lower triangular,

$$A = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ \alpha_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{k1} & \ldots & \alpha_{k,k-1} & 1 \end{pmatrix}$$

The model can then be rewritten as the following reduced form VAR model:

$$y_t = B_1 y_t + \cdots + B_s y_{t-s} + A^{-1}\Sigma_{\varepsilon t}, \varepsilon_t \sim N(0, I_k)$$

Where $B_i = A^{-1}F_i$, for $i = 1, \ldots, s$. Stacking the elements of the rows of the B_i's to form $\beta(k^2 s\ x\ 1$ vector) and defining $X_t = I_k \otimes (y'_{t-1}, \ldots, y'_{t-s})$, where $\otimes$ denotes a Kronecker product. The model can thus be rewritten as:

$$\mathrm{y}_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t$$

All the parameters in the equation are time invariant. This can be extended to the TVP-VAR model by allowing for the parameters to change over time. Consider the TVP-VAR model stochastic volatility which is specified by:

$$\mathrm{y}_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t,\ \ t = s+1, \ldots, n$$

Where the coefficients β_t and the parameters A_t and Σ_t are all time varying. The procedure of Nakajima (2011) follows that of Primiceri (2005), whereby $\alpha_t = (\alpha_{21}, \alpha_{31}, \alpha_{32}, \alpha_{41}, \ldots, \alpha_{k,k-1})'$ is a stacked vector of lower triangular elements in A_t and $h_t = (h_{1t}, \ldots, h_{kt})'$, with $h_{jt} = log\sigma_{jt}^2$, for $j = 1, \ldots, k, t = s+1, \ldots, n$. The parameters in the above equation follow a random walk process, which can be expressed as follows:

$$\beta_{t+1} = \beta_t + u_{\beta_t}, \qquad a_{t+1} = a_t + u_{a_t},\ \ h_{t+1} = h_t + u_{ht},$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta_t} \\ u_{a_t} \\ u_{h_t} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & O & O & O \\ O & \Sigma_\beta & O & O \\ O & O & \Sigma_a & O \\ O & O & O & \Sigma_h \end{pmatrix} \right),$$

For $t = s+1, \ldots, n$, with $e_t = A_t^{-1}\Sigma_t\varepsilon_t$, where Σ_a and Σ_h are diagonal, $\beta_{s+1} \sim N(u_{\beta_0}, \Sigma_{\beta_t})$, $a_{s+1} \sim N(u_{a_0}, \Sigma_{a_0})$, and $h_{s+1} \sim N(u_{h_0}, \Sigma_{h_0})$. See Nakajima (2011) for more details. Several remarks are required for the TVP-VAR model. Firstly, the assumption of a lower-triangular matrix for A_t is recursive identification for the TVP-VAR model. Second, the parameters of the TVP-VAR model are not assumed to follow a stationary process such as a AR(1) model, but follow a random walk process. As previously mentioned, because the TVP-VAR model has a number of parameters to estimate, the number of parameters is decreased by assuming the random walk process for the innovation of parameters. Additionally, the variance and covariance structure for the innovations of the time-varying parameters are governed by the parameters Σ_β, Σ_a, and Σ_h. It is mostly assumed that Σ_a is a diagonal matrix, however Nakajima (2011) further assumes that Σ_h is a diagonal matrix for simplicity. The state variables of the TVP-VAR model are flexible and can capture both gradual and sudden changes in underlying economic structure. Since the TVP-VAR model forms a nonlinear, maximum likelihood estimation requires heavy computational burden to evaluate the likelihood function of each group of parameters, until we reach the maximum value. Thus, we adopt the approach of Nakajima (2011), which adopts Bayesian approach using MCMC algorithm to effectively estimate a TVP-VAR-SV model.

4.4 Empirical Results

This section presents the results of the estimation of the TVP-VAR-SV model parameters for each set (GPR, UKP, NFM), (GPR, USP, NFM) along with corresponding impulse responses of the VAR and SVAR models, which showcase how non ferrous metals respond to shocks from the GPR index and UK policy uncertainty. Impulse responses at different time horizons from the estimated TVP-VAR-SV model are also presented in this section, which allow us to interpret how non ferrous metals react to changes in GRP, UK policy and US policy uncertainty shocks at different points in time.

4.4.1 Estimation of model parameters

Lag selection the estimation of VAR, SVAR and TVP-VAR models is based in accordance with AIC selection criteria, which penalises the model for the number of parameters and selects the appropriate lag length based on minimises the AIC value. Based on results from AIC procedure, we find that for each of the metals and models, the optimal lag length chosen is 3 periods. Results are obtained by generating 10,000 draws of the posterior, with the first initial 1000 samples discarded for initialization. The parameter estimations for the TVP-VAR-SV model for each non ferrous metal with GPR, UKP and USP can be found within table 4.1 located in the appendix section of this chapter. The findings suggest that the estimated posterior means are included within the 95% confidence interval and that the standard deviations are small. The geweke statistic is less than 1.96 at the 5% confidence level for all estimated models, observing that the Markov chain is considered to have converged and parameters converges to posterior distribution. Inefficiency factors are relatively low, although we note slightly higher inefficiency factors for copper and zinc estimations.

4.4.2 Impulse responses of effects of non ferrous metals on geopolitical risk index and UK policy uncertainty from VAR and SVAR models

Impulse responses are widely used in conjunction with VAR models, with their main purpose being to describe the effects and evolution of a models variables in response to endogenous shocks in one or more variables. Results obtained from VAR impulse responses of select non ferrous metals to GPR shocks can be shown from figure 4.1.1 to figure 4.1.5 within the appendix section, with impulse responses of non ferrous metal to UK policy shocks found in figures 4.1.6 through to figure 4.1.10. In the case of non ferrous metal responses to geopolitical risk index shocks, each metal with the exception of zinc highlight the biggest impact of shocks occurring between the 4th and 6th periods. Additionally, copper, nickel and zinc tend to respond negatively to shocks in the second period, while all metals with the exception of zinc respond positively to shocks in the third period after a GPR shock. Interestingly, all metals respond similarly to UK policy shocks, responding negatively to UK policy shocks after 2 periods, and negatively to shocks after 3 periods, highlighting that the effects of shocks are reflected quickly in metals prices after the shocks occur, rather than persisting for a long period after the shock, as further reflected in the impulse responses, which show no significant positive or negative effects 7 periods after a UK policy shock. It can be noted that in all cases analysed from the VAR model, the most prominent shocks in response to GPR shocks or UK policy shocks occur within 2 to 6 periods of the GPR or UK policy shock, with prices tending to converge fully to the shocks by the 7th period.

Structural Vector Autoregressive models (SVAR) are also used in the literature to assess the impact of macroeconomic shocks on commodity returns. Figure 4.2.1to 4.2.5 showcases the results of impulse responses from SVAR model for select non ferrous metals in response to GPR shocks. Positive impulse responses for copper returns in response to GPR shocks can be noted the 2 and 5 period ahead horizon, with 4 periods ahead showcasing negative response to GPR shocks. Negative shocks for aluminium can also be observed for the 4 and 5 period ahead horizons, which precede positive responses at the 3 period horizon, suggesting that initial positive responses to GPR shocks are subsequently negative once information from the shocks is filtered through to the returns. This trend continues with tin and nickel impulse responses, with a positive response in the second horizon followed by a negative response at the 4 period horizon before levelling out. We note an inverse relationship with zinc, with negative responses to shocks at the 3 and 4 period horizon subsequently followed by positive responses at the 5 and 6 period horizon. Similarly to the standard VAR model, for all metals analysed, no notable positive or negative responses are observed from the 6 period horizon to the 10 period horizon, suggesting that information from shocks are fully reflected in returns by this period. Figures 4.2.6 to 4.2.10 present the results of impulse responses from the SVAR model in response to UK policy shocks. In the case of copper, large positive responses can be noted at the 2 and 5 period horizon, showcasing that responses to UK policy shocks are largely positive. Two negative responses are observable for aluminium after positive responses in the 2 and 5 period horizon respectively, potentially indicating aluminium returns are sensitive to changes in UK policy shocks. Likewise with the case for GPR shocks, most shocks for all metals occur within 5 periods of the initial UK policy shock and return to a baseline after 6 periods, highlighting that while non ferrous metals may exhibit volatility shortly after UK policy shocks, volatility returns to within a normal level after 5 periods. While non ferrous metals may be sensitive to GPR and UK policy shocks, these effects are not persistent and long lasting.

4.4.3 Time-varying effects of economic policy uncertainty and geopolitical risk index on aggregate non-ferrous metal commodity price

To study the effects of geopolitical risk and economic policy uncertainty on non-ferrous metal commodity markets, this chapter employs the standard VAR model, SVAR and TVP-VAR with stochastic volatility to produce time varying impulse responses to analyse the impact of GPR and UK policy shocks on non ferrous metal commodity returns. To compare the impulse responses over time, the value of shocks was set as the mean of random fluctuations of the sample period. For the TVP-VAR-SV model, we set the impulse responses at 1 period, 5 period and 10 periods ahead which, in the case of daily data used in this chapter, corresponds to 1 day, 5 days and 10 day trading periods respectively Impulse response analysis of equal intervals can simulate impulse responses more effectively and reveal the differences among different terms (Zhou et al, 2020). Figures 4.3.1 to 4.3.10 showcase the results of impulses responses estimated using the TVP-VAR-SV model with the impact of geopolitical risk index (GPR) shocks on the respective non ferrous metal markets throughout different time periods. In the 1 period ahead horizon, which is denoted by the bashed green line within the impulse response plots, GPR shocks have significant positive and negative effects on the returns of non ferrous metals. In the cases of copper, these effects are largely negative responses, with downturns in periods such as the 2008 financial crisis and the September 11th attacks, suggesting that copper, zinc and tin returns had large adverse responses to these major geopolitical events. However, these are followed by sharp positive upturns impulse responses, suggesting for these three metals that after an initial shock to a significant geopolitical event, they are likely to rebound. Negative impulses response can also be noted in 2014, potentially coinciding with the annexation of Crimea in February and March 2014, and furthermore in early 2022 with a large prominent negative response in response to the Russian invasion of Ukraine in February 2022. Large positive responses are additionally noted for the three metals from the end of 2022 up the end of the sample period at the end of 2023, which may be due to less volatility in the Russia/Ukraine conflict resulting in a positive upturn. Aluminium and tin 1 period impulse responses showcase far more volatility than other non ferrous metals, with a large negative reaction to GPR shocks in 2014. This may be in turn due to Chile, one of the worlds largest exporters of non-ferrous metals, was struck by a magnitude 8.2 earthquake on April 1st 2014. At the 5 period horizon, showcased by the dashed blue line in the time varying impulse response plots, copper impulse responses are largely the inverse of responses at the 1 period horizon, showcasing properties that after the initial shock the information from the GPR is more accurately reflected in the copper futures. These responses, with notable exceptions coinciding with the aforementioned September 11th attacks and 2008 financial crisis, are largely positive up until 2014. Similar observable patters can be seen in the cases for aluminium and zinc, although in the case of nickel, 5 period response plots follow a similar path to 1 period responses, Additionally, at the 10 period ahead horizon, as denoted by the red line within the impulse response plots, the impacts of GPR shocks on non ferrous metal are close to zero with little amplitude, suggesting that after 10 periods, shocks from GPR have little positive or negative shock on non ferrous metal returns after 5 periods, with their effects on non ferrous metal returns further diminishing at the 10 period ahead horizon. This pattern is observed with all non ferrous metals at the 5 and 10 period ahead horizon

Figures 2.2 showcases the impulse response plots of the impact of UK policy uncertainty on corresponding non ferrous metals at differing time periods. At the 1 period interval, represented by the dashed green line in the impulse response plots, UK policy shocks appear to have positive and negative impacts on non ferrous metal returns at different time periods although not to the same extent as geopolitical risk index shocks for some metals. In the case of copper, large negative responses to UK policy shocks can be observed in 2005, with the re-election of the Labour government in the UK general election in May 2005 and the London Bombings in July 2005 affecting UK markets. Conversely, the 2010 UK general election resulting in the election of David Cameron's conservative government saw positive impulse responses in the copper market at the 1 period ahead horizon. Notable UK policies in the 2010s include the 2016 UK referendum to leave the European Union and the 2017 UK trade bill created in response to the UK referendum to enable the creation of an independent UK trade policy, with Giammetti (2020) noting their design to reduce UK imports and encourage their subsidization by domestic purchases. Copper impulse responses to these policy shocks are initially negative but are positive shortly thereafter and are largely positive for zinc at the 1 period horizon but no identifiable trend can be observed for aluminium and nickel, although negative responses to the aforementioned events are present. At the 5 period and 10 period ahead horizons, denoted by blue and red lines respectively, nickel returns are still particularly sensitive to UK policy shocks throughout the entire sample period, suggesting that the effects of UK policy shocks may have a longer lasting effect on Nickel. Tin returns are similarly sensitive at the 5 period ahead horizon in response to UK policy shocks, although copper, aluminium and zinc showcase less sensitivity to UK policy shocks at the 5 period ahead horizon. Notably, in the case for all metals, at the 10 period ahead horizon, denoted by the red line in the impulse response plots, impulse responses so no significant positive or negative reactions to UK policy shocks. This is consistent with results from impulse responses from the VAR and SVAR model that while non ferrous metals do have significant positive and negative reactions to UK policy shocks, these effects diminish over longer horizons.

4.5 Concluding remarks

In this paper, we study the effects of geopolitical risk and United Kingdom policy uncertainty on returns in the non ferrous metals commodity market, using daily data for non ferrous metals that are widely used for both industrial and portfolio optimization purposes, namely copper, aluminium, zinc, tin and nickel. Daily data from the geopolitical risk index constructed by Caldara and Iacoviello (2022) and the UK policy uncertainty index, covering a span from January 2000 through to December 2023, a period covering numerous geological events and conflicts such as the September 11th attacks in 2001, the 2008 global financial crisis, the ongoing 2022 Russian invasion of Ukraine and the 2023 Israeli conflict with Palestinian back militant groups, along with major UK political events such as the 2005 and 2010 general elections, the 2016 Brexit referendum to leave the European union and the 2017 UK industrial strategy to bolster the UK economy in preparation for its withdrawal from the EU.

We use a vector autoregressive model (VAR), structural vector autoregressive model (SVAR) and a time varying parameter VAR model with stochastic volatility (TVP-VAR-SV) developed by Nakajima (2011) to produce impulse responses to analyse how GPR and UK policy shocks affect non ferrous metal returns. Results from impulse response analysis from VAR and SVAR models showcase evidence of significant and differing reactions to GPR and UK policy shocks, which persist until the 5 period horizon, showcasing that while these effects may be significant, they are not persistent and long lasting. Subsequent impulse response analysis at different time intervals after TVP-VAR-SV estimation shows significant positive and negative responses to major geopolitical events and UK policy events at the 1 period and 5 period ahead response intervals but no significant responses at the 10 period interval, corroborating findings from VAR and SVAR analysis that responses to shocks are more significant at shorter intervals and diminish at longer time horizons. We also note that there is a degree of heterogeneity among the metals analysed, with copper the most resilient to UK policy shocks but amongst the most sensitive to GPR shocks. This adds to the knowledge of how commodity markets respond to shocks and the impact of geopolitical risks on metal markets.

From a decision making viewpoint, the findings in this chapter have implications from a policy perspective, with risk aversion playing an important role among investment decisions and policy makers. Investors can use the findings in this paper to adjust and mitigate their exposure to risk, with geopolitical events and decisions at the UK policy level having significant positive and negative impacts on non ferrous metal commodity returns. Industrial purchasers may also use the findings of this chapter to time bulk purchases of non ferrous metals to save money. With non ferrous metals being natural resources, they are heavily influenced by economic and geopolitical disruptions, and as such are at risk of sudden sharp increases in price and volatility in periods of short supply. While this study has showcased the impacts of geopolitical risk shocks and UK policy shocks on non ferrous metal commodity markets using daily data, there is still work to be done in exploring this area further. Limited by the availability of daily policy uncertainty data regarding individual nations, we encourage the addition of further nations once the daily data for additional economies becomes readily available. Furthermore, with commodities being firmly interlinked with global environments, we encourage the potential future study of the effects of natural disasters, climate policy uncertainty and environmental uncertainty on commodity returns.

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Appendix

Table 4.1 TVP-VAR-SV Estimation for GPR Index, UK Policy Shocks and non ferrous metals

Parameter	Mean	StDev	95%U	95%L	Geweke	Inef.
Estimates for the set (GPR, UKP, Copper)						
sb1	0.0733	0.1601	0.0018	0.4460	0.001	253.12
sb2	0.0159	0.0351	0.0017	0.0957	0.000	251.27
sa1	0.0529	0.0058	0.0395	0.0633	0.000	308.96
sh1	0.1251	0.0153	0.0848	0.1582	0.014	204.30
sh2	0.0207	0.0078	0.0119	0.0412	0.001	315.31
Estimates for the set (GPR, UKP, Aluminium)						
sb1	0.0023	0.0005	0.0018	0.0031	0.115	174.14
sb2	0.0020	0.0002	0.0017	0.0029	0.167	87.69
sa1	0.0080	0.0091	0.0033	0.0361	0.006	262.29
sh1	0.1278	0.0094	0.1101	0.1490	0.635	98.82
sh2	0.1706	0.0127	0.1459	0.1954	0.016	99.38
Estimates for the set (GPR, UKP, Zinc)						
sb1	0.0151	0.0578	0.0020	0.2143	0.056	157.15
sb2	0.0057	0.0163	0.0018	0.0830	0.066	286.45
sa1	0.0716	0.0097	0.0569	0.8990	0.000	339.41
sh1	0.1319	0.0239	0.1099	0.2278	0.028	270.22
sh2	0.0144	0.0127	0.0054	0.4460	0.000	301.13
Estimates for the set (GPR, UKP, Tin)						
sb1	0.0025	0.0010	0.0019	0.0044	0.229	191.33
sb2	0.0021	0.0002	0.0017	0.0026	0.015	197.77
sa1	0.0126	0.0246	0.0035	0.0853	0.002	254.17
sh1	0.1273	0.0094	0.1106	0.1465	0.191	99.49
sh2	0.1765	0.0163	0.1497	0.2090	0.135	118.24
Estimates for the set (GPR, UKP, Nickel)						
sb1	0.0023	0.0002	0.0020	0.0028	0.051	163.32
sb2	0.0021	0.0002	0.0019	0.0026	0.154	101.32
sa1	0.0071	0.0087	0.0035	0.0397	0.004	273.49
sh1	0.1274	0.0091	0.1104	0.1444	0.179	85.04
sh2	0.1730	0.0130	0.1498	0.2003	0.211	110.14

Figure 4.1.1 VAR Impulse responses of Copper to GPR shocks

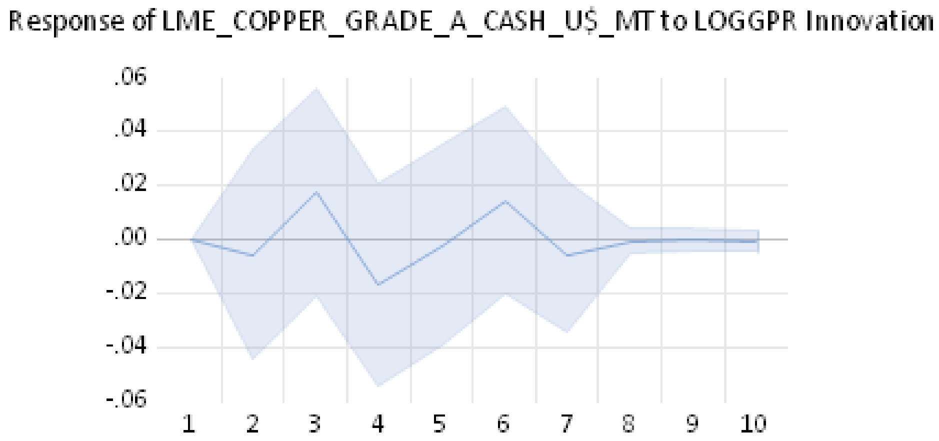


Figure 4.1.2 VAR Impulse responses of Aluminium to GPR shocks

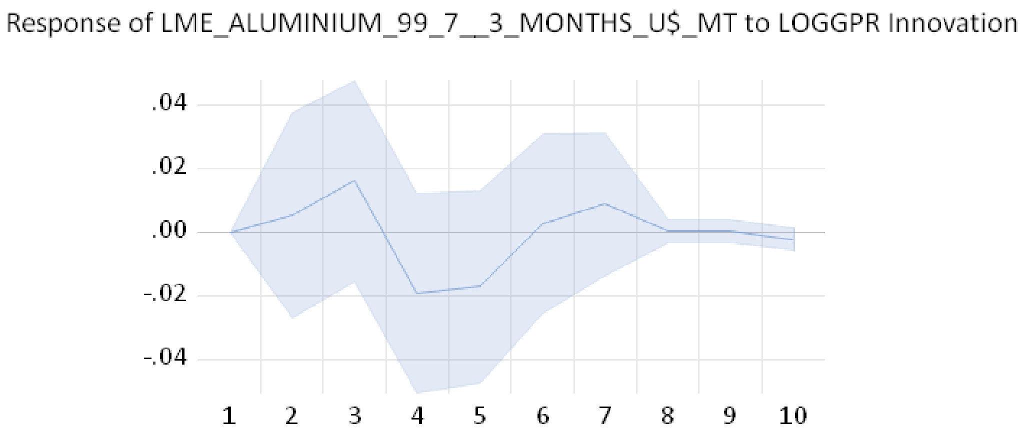


Figure 4.1.3 VAR Impulse responses of Zinc to GPR shocks

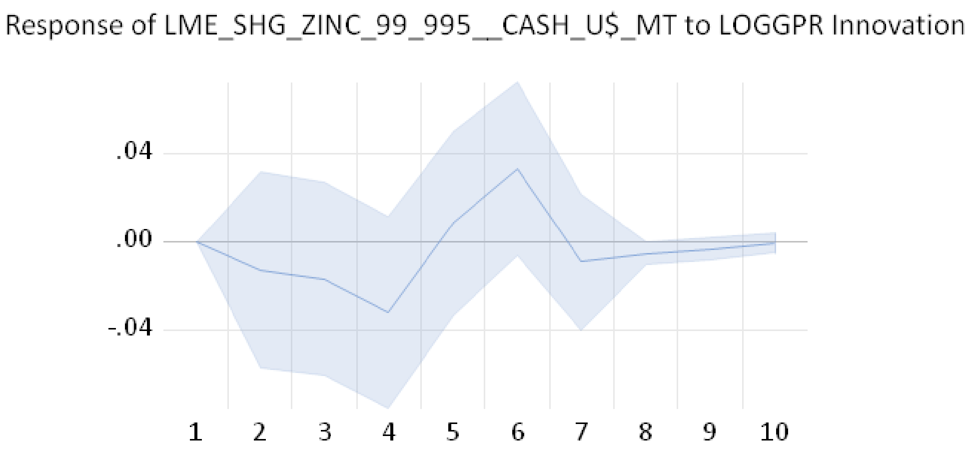


Figure 4.1.4 VAR Impulse responses of Tin to GPR shocks

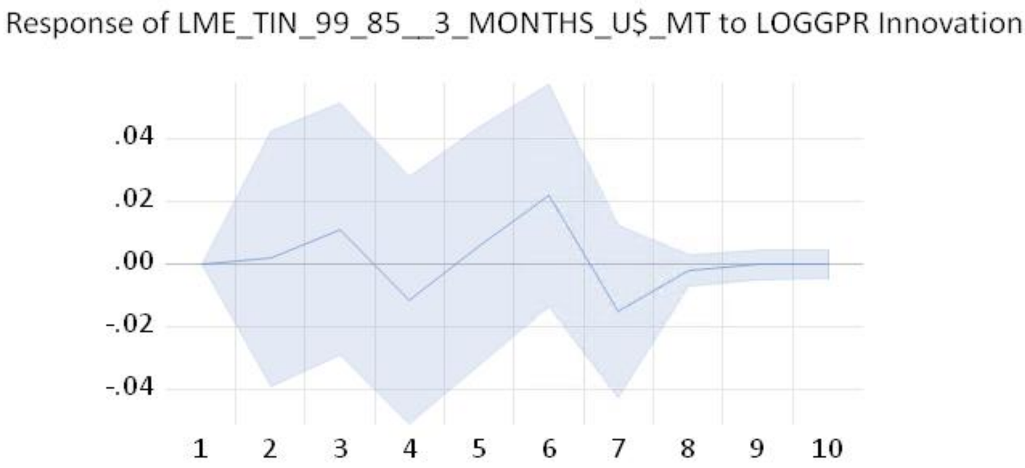


Figure 4.1.5 VAR Impulse responses of Nickel to GPR shocks

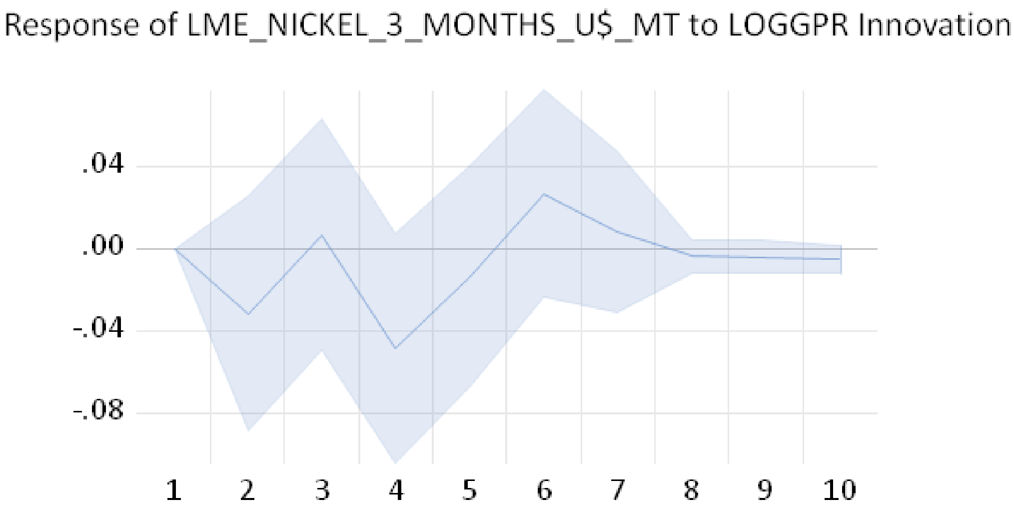


Figure 4.1.6 VAR Impulse responses of LME Copper to UK Policy Shocks

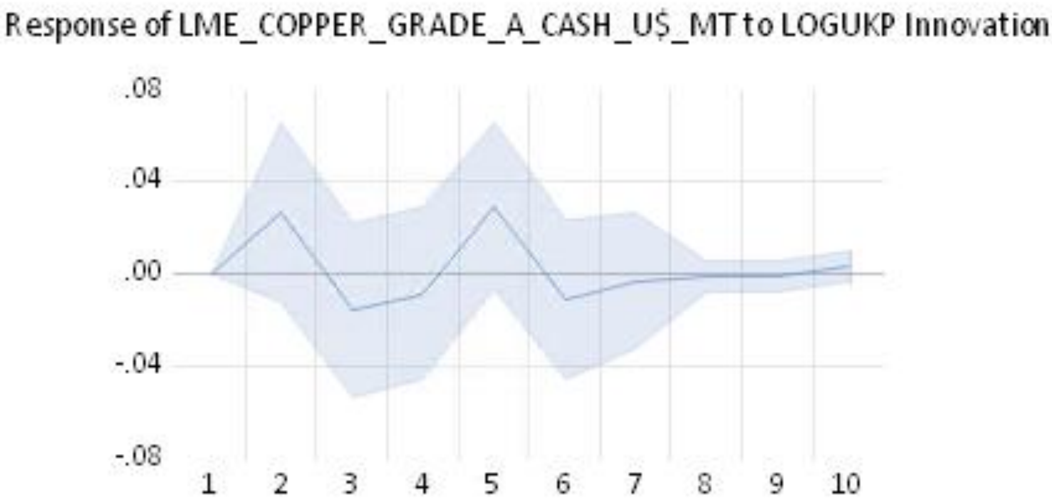


Figure 4.1.7 VAR Impulse responses of LME Aluminium to UK Policy Shocks

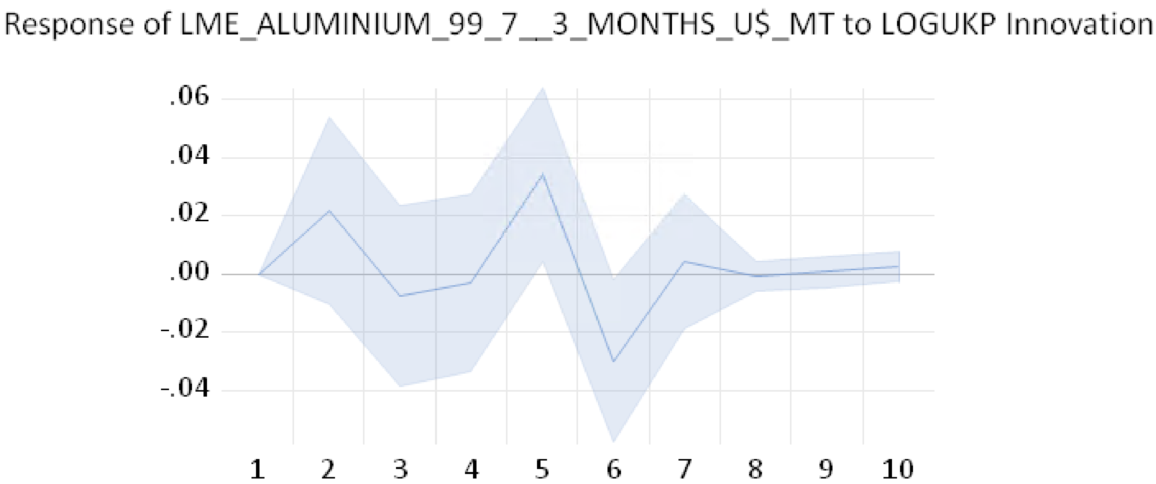


Figure 4.1.8 VAR Impulse responses of LME Zinc to UK Policy Shocks

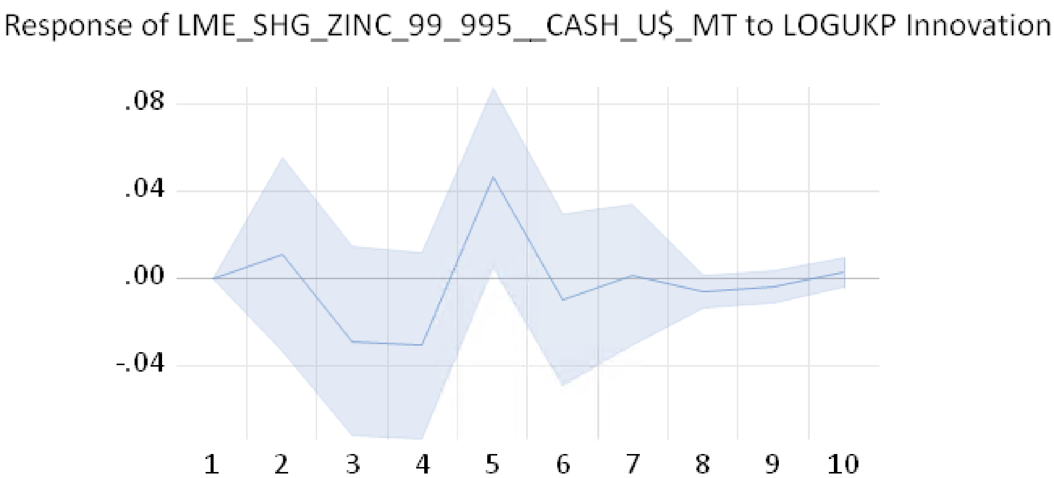


Figure 4.1.9 VAR Impulse responses of LME Tin to UK Policy Shocks

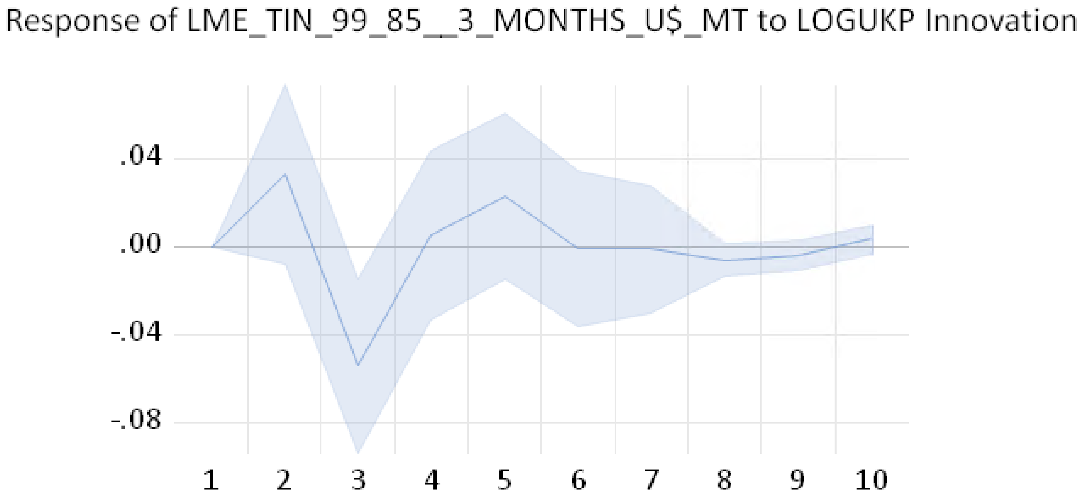


Figure 4.1.10 VAR Impulse responses of LME Nickel to UK Policy Shocks

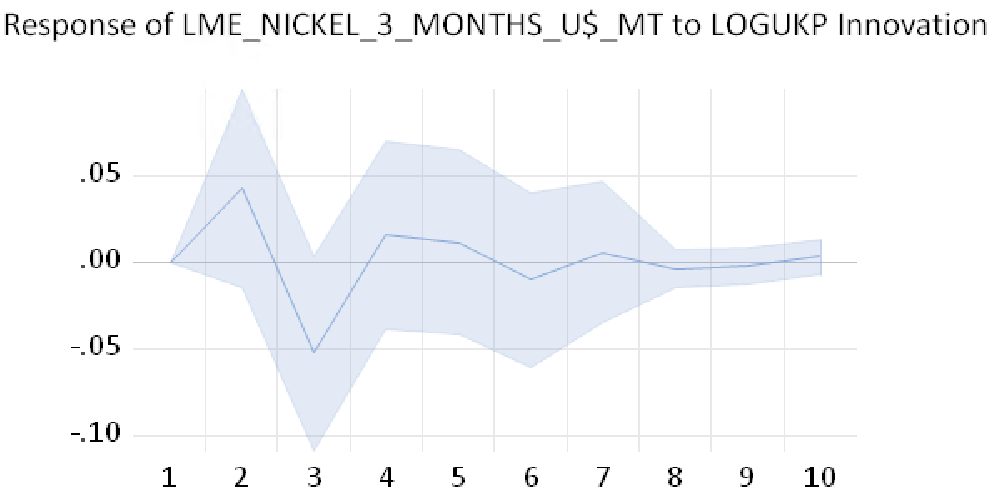


Figure 4.2.1 SVAR impulse responses of LME Copper to GPR shocks

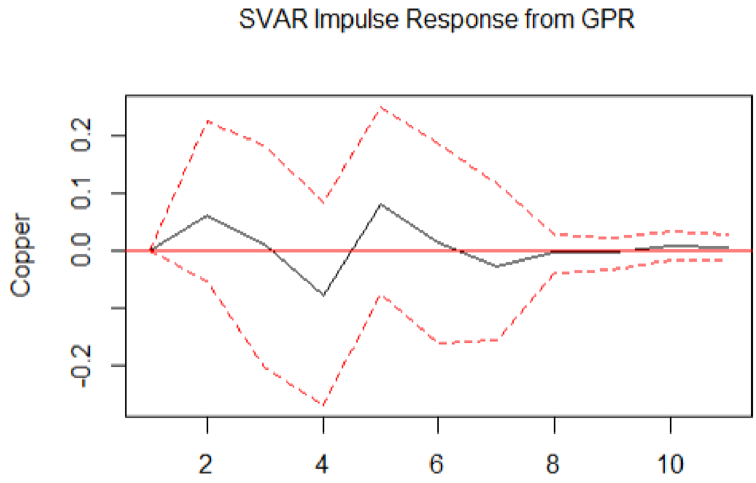


Figure 4.2.2 SVAR impulse responses of LME Aluminium to GPR shocks

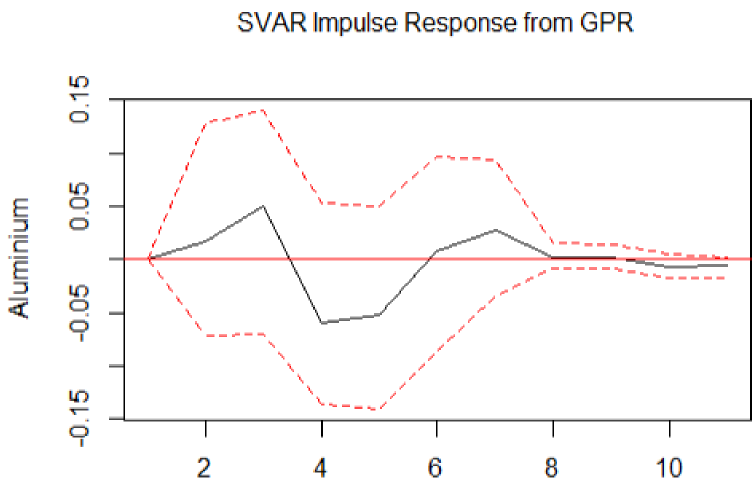


Figure 4.2.3 SVAR impulse responses of LME Zinc to GPR shocks

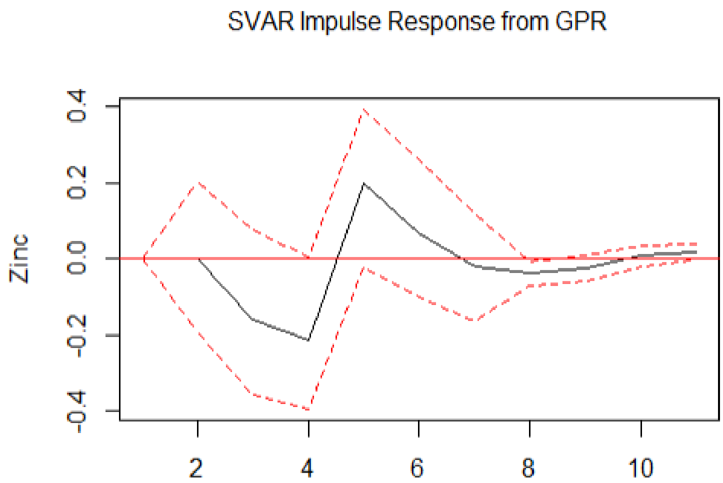


Figure 4.2.4 SVAR impulse responses of LME Tin to GPR shocks

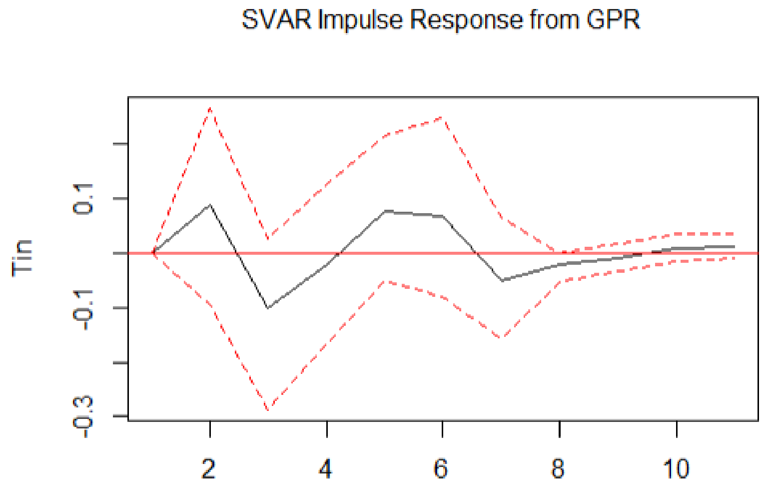


Figure 4.2.5 SVAR impulse responses of LME Nickel to GPR shocks

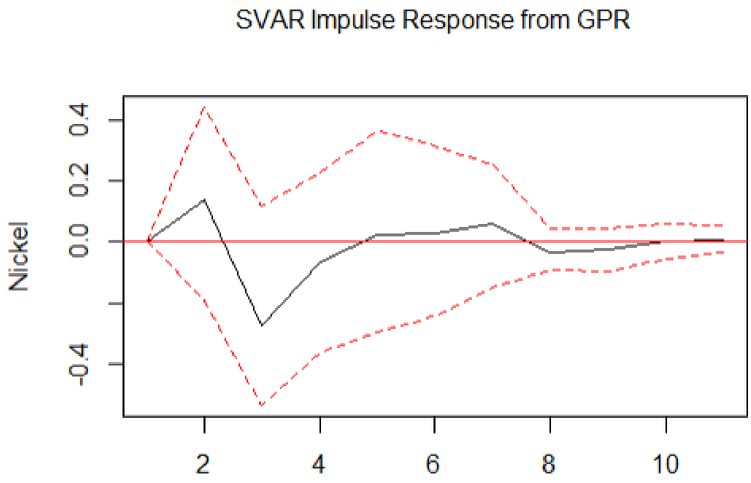


Figure 4.2.6 SVAR impulse responses of LME Copper to UK Policy shocks

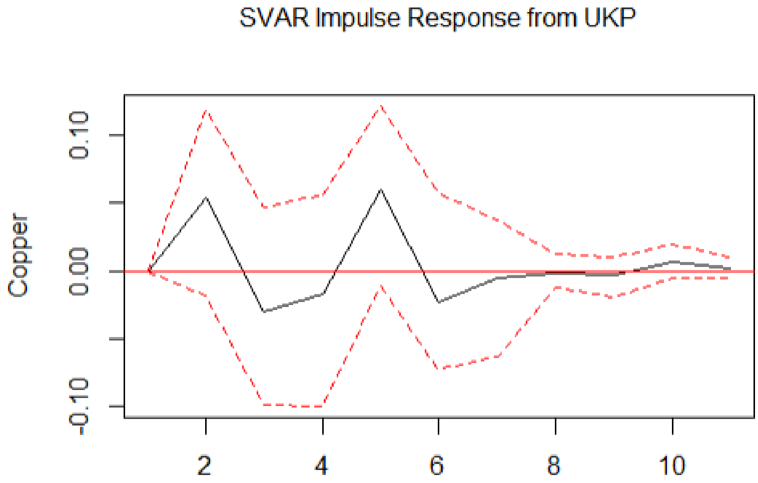


Figure 4.2.7 SVAR impulse responses of LME Copper to UK Policy shocks

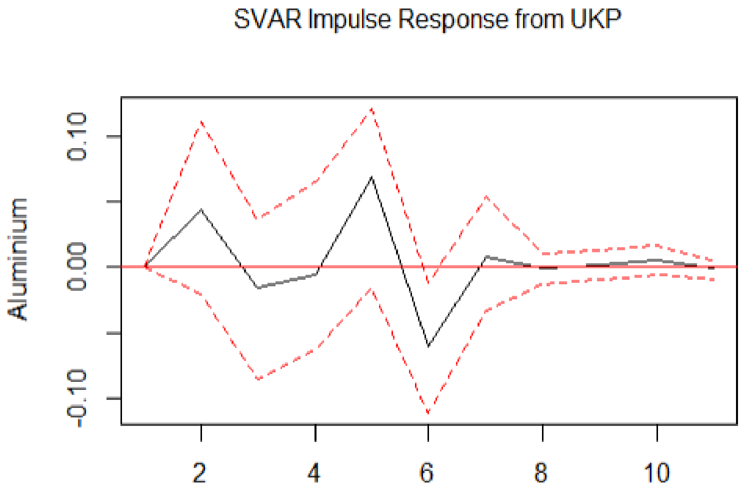


Figure 4.2.8 SVAR impulse responses of LME Copper to UK Policy shocks

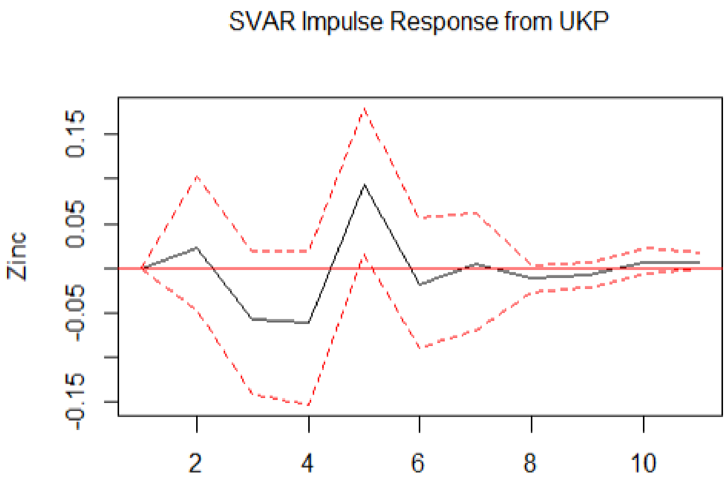


Figure 4.2.9 SVAR impulse responses of LME Tin to UK Policy shocks

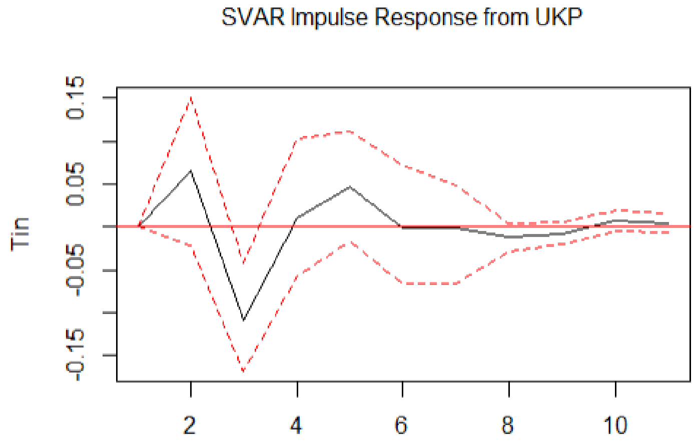


Figure 4.2.10 SVAR impulse responses of LME Nickel to UK Policy shocks

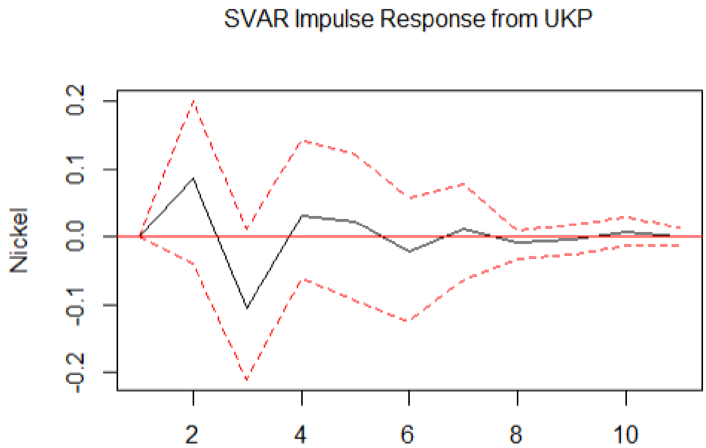


Figure 4.3.1 TVP-VAR Impulse responses of LME Copper to GPR shocks at different time periods

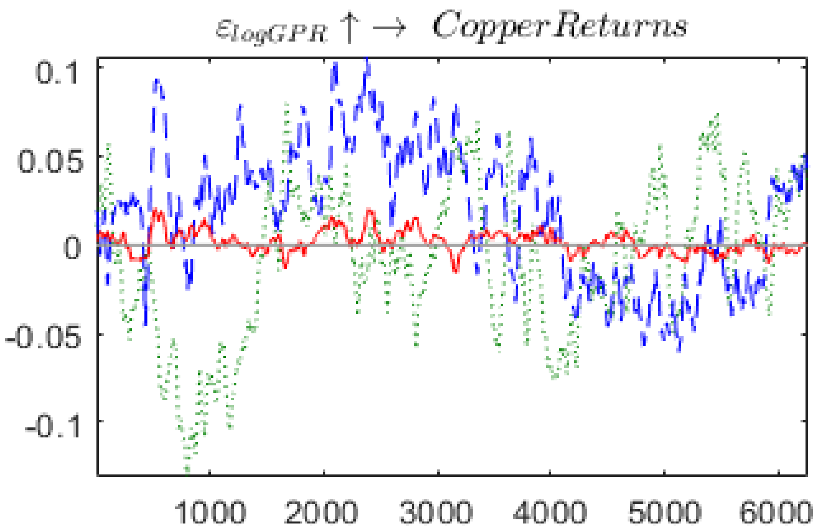


Figure 4.3.2 TVP-VAR Impulse responses of LME Aluminium to GPR shocks at different time periods

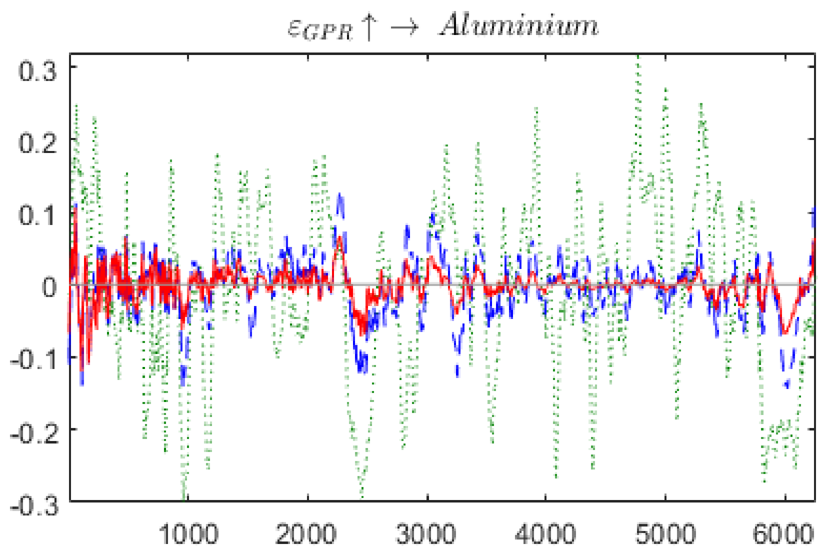


Figure 4.3.3 TVP-VAR Impulse responses of LME Zinc to GPR shocks at different time periods

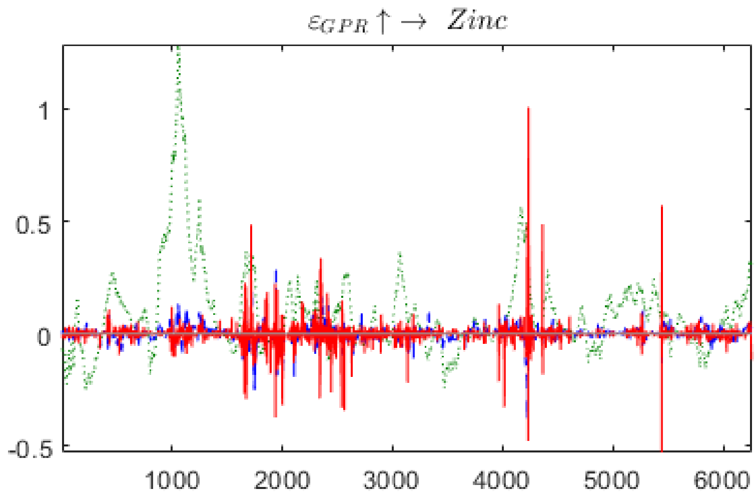


Figure 4.3.4 TVP-VAR Impulse responses of LME Tin to GPR shocks at different time periods

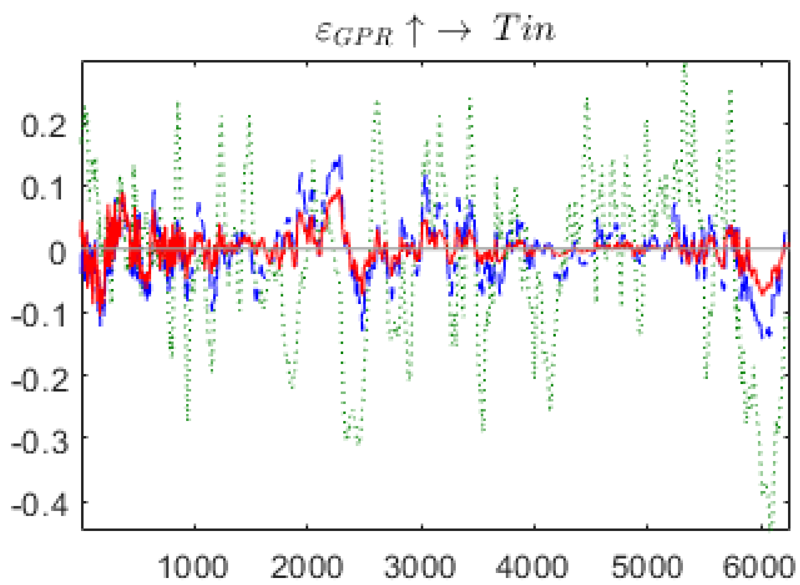


Figure 4.3.5 TVP-VAR Impulse responses of LME Nickel to GPR shocks at different time periods

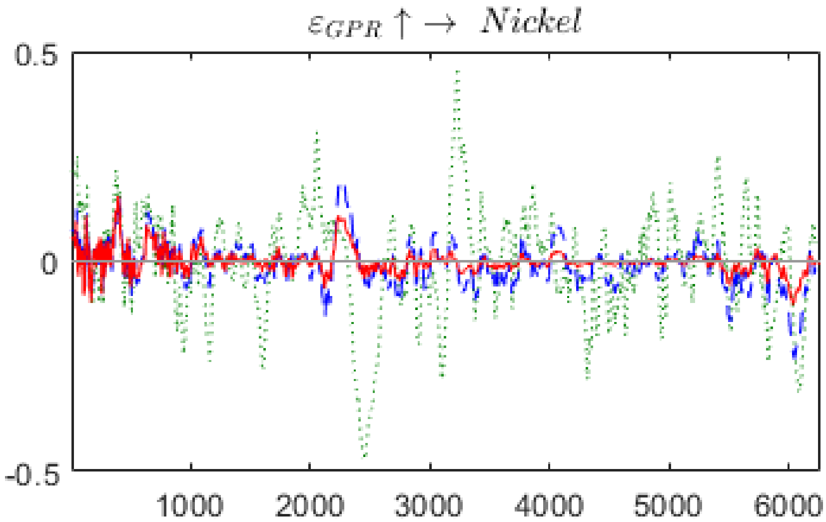


Figure 4.3.6 TVP-VAR Impulse responses of LME Copper to UK Policy Shocks at different time periods

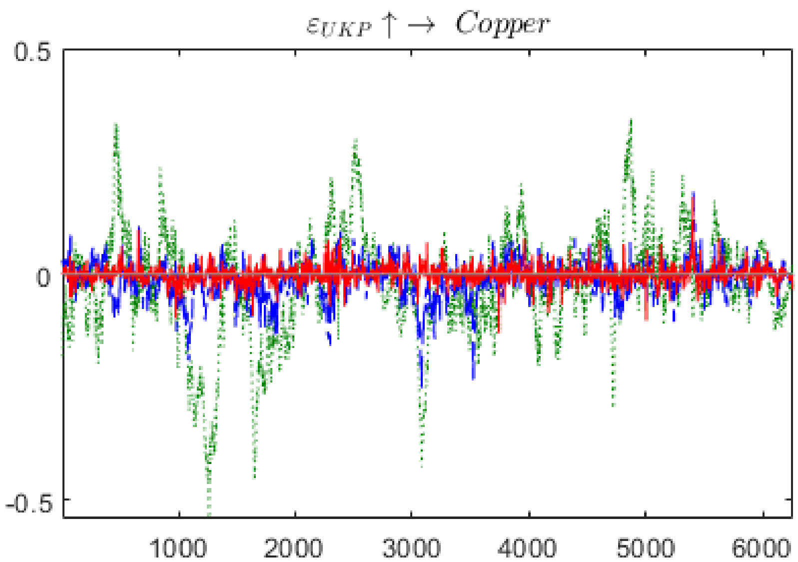


Figure 4.3.7 TVP-VAR Impulse responses of LME Copper to UK Policy Shocks at different time periods

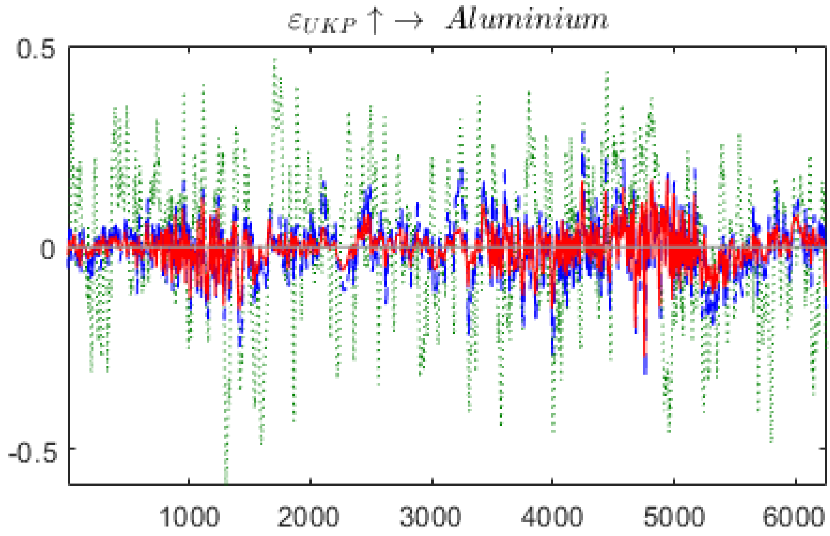


Figure 4.3.8 TVP-VAR Impulse responses of LME Zinc to UK Policy Shocks at different time periods

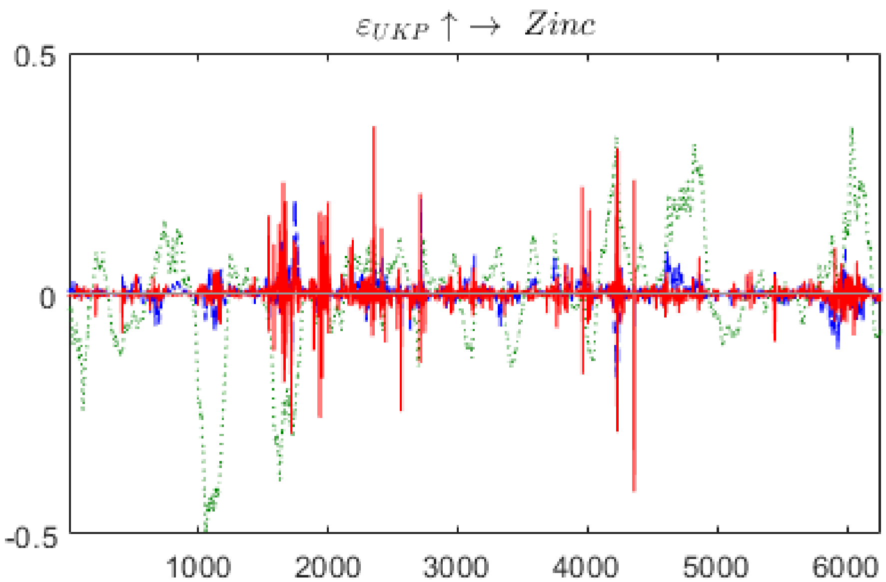


Figure 4.3.9 TVP-VAR Impulse responses of LME Tin to UK Policy Shocks at different time periods

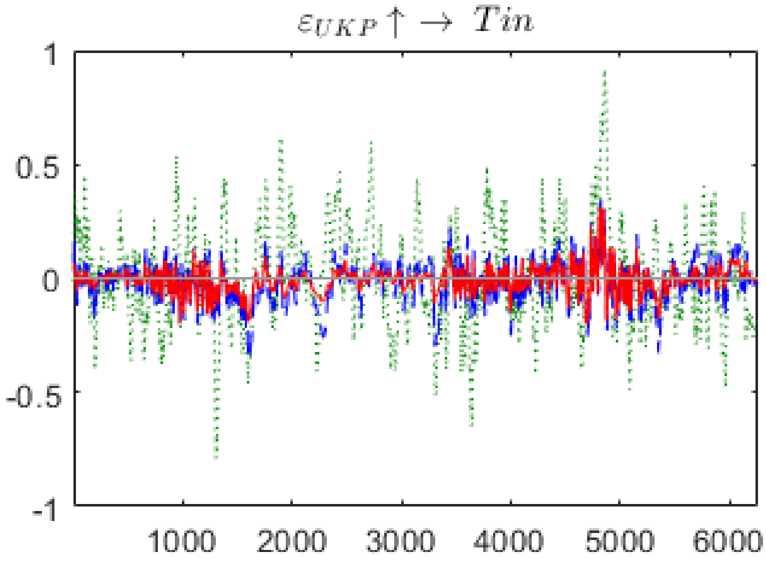
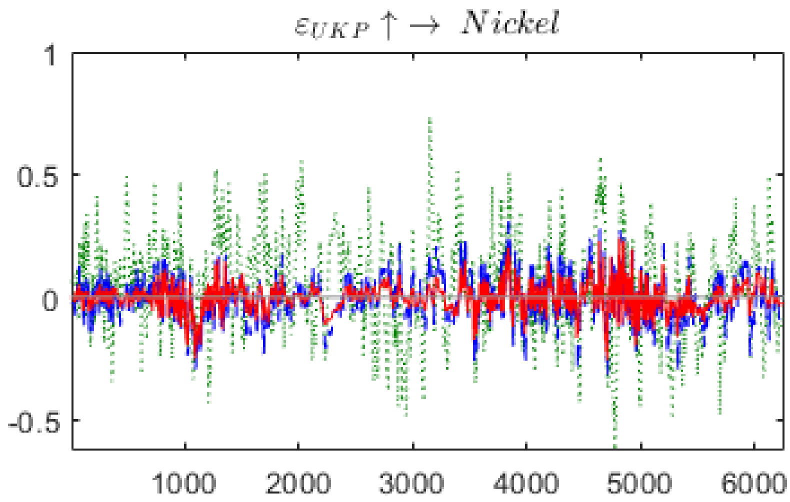


Figure 4.3.10 TVP-VAR Impulse responses of LME Nickel to UK Policy Shocks at different time periods



5.0 Concluding Remarks

This thesis focuses on an array of areas within the finance literature regarding the estimation of volatility, namely volatility forecasting, conditional correlations and uncertainty shocks, within the contexts of the non ferrous metals market, estimated using various types of volatility models to obtain our findings.

In chapter 2, we explore the forecasting ability of various models using the daily data of five non ferrous metals traded on the London Metals Exchange (LME). Several GARCH family models are employed, namely: GARCH, EGARCH and GJR-GARCH using gaussian and students-t distributions, the GARCH-MIDAS model and the GAS model using gaussian and students-t distributions. We additionally incorporate trading volume as a macroeconomic predictor variable into the GARCH-MIDAS model in an attempt to improve forecasting performance. Forecasting performance is assessed using various loss functions and MCS test of Hansen (2011) to determine the best fitting models. To backtest the models, we conduct VaR analysis using the procedures of Kupiec (1995) and Christoffersen (1998). The out of sample forecasting comparison presents the standard GARCH model following the students-t distribution to produce the most accurate forecasts in most scenarios, beating out the GAS model and GARCH-MIDAS models. Additionally, trading volume is not found to improve forecasting performance for the GARCH-MIDAS model. The results of Kupiec (1995) and Christoffersen (1998) VaR tests confirm the robustness of our findings.

Chapter 3 shifts the focus to the conditional correlation framework, with a further emphasis on the hedging effectiveness of non ferrous metals. This chapter uses various multivariate GARCH models, notably, symmetric and asymmetric DCC and BEKK GARCH models, OGARCH, GOGARCH and the DCC-MIDAS model, with CCC-GARCH used as a benchmark, to investigate conditional correlations between non ferrous metals and LBMA gold, ICE Brent crude oil and the S&P 500 index, representing 3 of the most widely traded financial instruments. In our results, we present evidence of all metals exhibiting positive and negative spikes in conditional correlation in periods of economic instability, such as the 2008 financial crisis, with copper having strong correlations with gold in periods with low correlations with brent crude and the S&P500 and vice versa. Likelihood ratio test results determine the DCC-MIDAS model to be the model with the highest goodness of fit of the models chosen. Extracting the conditional variances and conditional covariance matrices of the DCC-MIDAS model to compute dynamic optimal hedge ratios, we find that non ferrous metals have a mixed ability to serve as a optimal hedge, being a potential hedge to the S&P500, but having limited ability to hedge against brent crude oil.

Chapter 4 focuses on the impacts of uncertainty shocks on the non ferrous metals market utilizing daily data of the geopolitical risk index of Caldara and Iacoviello (2022) and UK policy uncertainty in conjunction with the standard vector autoregressive (VAR) model, structural VAR and the TVP-VAR-SV approach. Following impulse response analysis, our results show that GPR and UK policy shocks have significant positive and negative impacts on non ferrous metal returns up to a 5 period ahead horizon with diminishing effects up to the 10 period ahead horizon. Evidence from impulse response analysis at different time periods shows non ferrous metals react positively and negatively to GPR shocks and UK policy shocks at significant geopolitical events, such as the September 11th attacks, the 2008 financial crisis and the 2016 UK Brexit referendum, at the 1 period ahead horizon, although the effects of shocks diminish at longer time horizons, indicating effects of shocks on non ferrous metal returns are not persistent.

This thesis makes a few notable contributions to the literature. Firstly, it adds to the literature regarding non ferrous metals, of which few such empirical studies exist (Todorova et al. 2014). As previously mentioned throughout this thesis, non ferrous metals play an important role in economic development, as widely traded commodities and important industrial resources and, as such, it is important for fund managers and industrial consumers to know the price dynamics of non ferrous metals and their volatilities. Chapter 2 helps in this regard by informing practitioners not to arbitrarily select a forecasting model based on empirical findings, rather how to select their own models to evaluate forecasting performance. Accurate volatility forecasting enables effect risk management, portfolio selection and policy implementation, providing them with an insight into accurate volatility forecasting, while additionally contributing to the literature surrounding the debate of whether trading volume improves forecasting accuracy. Chapter 3 showcases how non ferrous metals can be potentially implemented in a hedging strategy, with conditional correlations and wavelet coherence analysis identifying the short and long run behavioural characteristics of non ferrous metals and their linkages to popularly traded financial instruments. It is important for fund managers to diversify financial portfolios to optimize returns and minimize exposure to risk by selecting a basket of assets with opposing correlations to create beta neutral portfolios. It is also important for buyers and consumers, who will want to ensure the best possible price and hedge against negative market movements. Chapter 4 finally contributes by applying the TVP-VAR-SV approach to the non ferrous metals literature using a daily data approach, displaying evidence of how geopolitical risks and policy uncertainty at the national level impact non ferrous metal returns in the short run.