DYNAMIC INTERACTIONS OF COMMODITIES AND POLICY UNCERTAINTY: A VARX-ADCC-EGARCH APPROACH

Jyväskylä University
School of Business and Economics

Master's Thesis

2023

Author: Anssi Kallio
Subject: Banking and International Finance
Supervisors: Heikki Lehkonen and Juha-Pekka Junttila

ABSTRACT

Author Anssi Kallio	
Title Dynamic interactions of commodities and policy uncertainty: a VARX-ADCC-EGARCH approach	
Subject Banking and International Finance	Type of work Master's Thesis
Date 12/2023	Number of pages 90

Abstract

In this study, I focused on three essential food staples: wheat, corn, and rice. Unfortunately, food prices are unstable, which can cause troubles in different economies in different economic cycles. As price stability is vital for so many, this research sought ways of decreasing price instability.

Financial models and analysis have developed new accounting methods for economic policy uncertainty. The study used the VARX-ADCC-EGARCH model to investigate the return and volatility relationships between the selected assets. The model included the uncertainty indexes as exogenous variables and acting as shocks outside the system. The primary research was done on daily data to see the changes and evolution of the relationship and the risks between the variables. A simple ARX model was used to analyze the impact of the policy uncertainty on wheat, corn, and rice.

Because the VARX-ADCC-EGARCH model gave conditional covariances and conditional variances of the assets as results, these results were used to build a minimum variance portfolio. The results revealed that the S&P 500 CI leads the returns on food staples, and the copper and gold futures influence the returns of foods. Interestingly, corn interactions are overall more frequent than wheat, and silver futures returns influence wheat, but corn and rice influence silver futures.

21-day rolling average portfolios were all long positions on S&P 500 CI, but other than that, the optimal portfolios varied a lot from each other from period to period and reflected the changing risks and interactions between the selected assets.

Keywords
Dynamic conditional correlation, dynamic hedging, agricultural commodities, multivariate GARCH, minimum variance portfolio, policy uncertainty

Place of storage
Jyväskylä University Library

TIIVISTELMÄ

Tekijä Anssi Kallio	
Työn nimi Hyödykkeiden dynaaminen vuorovaikutus ja järjestelmän epävarmuus: VARX-ADCC-EGARCH-lähestymistapa	
Oppiaine Banking and International Finance	Työn laji Pro gradu -tutkielma
Päivämäärä 12/2023	Sivumäärä 90

Tiivistelmä

Tässä tutkimuksessa keskityin kolmeen välttämättömyyshyödykkeeseen: vehnään, maissiin ja riisiin. Epävakaa ruoan hinta voi aiheuttaa ongelmia eri talouksissa eri suhdanteissa. Koska hintavakaus on monille elintärkeää, tässä tutkimuksessa etsittiin tapoja vähentää hintaepävakautta.

Taloudellisten mallien ja analyysien avulla on kehitetty uusia laskentamenetelmiä talouspolitiikan epävarmuuteen. Tutkimuksessa käytettiin VARX-ADCC-EGARCH-mallia tutkimaan valittujen omaisuuserien tuotto- ja volatiliteettisuhteita. Malli sisälsi epävarmuusindeksit eksogeenisina muuttujina, jotka toimivat shokkina järjestelmän ulkopuolella. Ensisijainen tutkimus tehtiin päivittäisillä tiedoilla, jotta voidaan nähdä muuttujien välisen suhteen ja riskien muutokset ja kehitys. Yksinkertaista ARX-mallia käytettiin analysoimaan politiikan epävarmuuden vaikutusta vehnään, maissiin ja riisiin.

Koska VARX-ADCC-EGARCH-malli antoi tuloksina omaisuuserien ehdollisia kovariansseja ja ehdollisia variansseja, näitä tuloksia käytettiin vähimmäisvarianssisalkun rakentamiseen. Tulokset paljastivat, että S&P 500 CI johtaa peruselintarvikkeiden tuottoja ja kuparin ja kullan futuurit vaikuttavat elintarvikkeiden tuottoon. Mielenkiintoista on, että maissin vuorovaikutus on yleisempää kuin vehnällä, ja hopea futuurien tuotto vaikuttaa vehnään, mutta maissin ja riisin tuotot vastaavasti vaikuttavat hopea futuureihin.

21 päivän liukuvat keskiarvosalkut olivat kaikki pitkiä positioita S&P 500 CI:ssä, mutta optimaaliset salkut vaihtelivat paljon jaksoittain ja heijastivat muuttuvia riskejä ja vuorovaikutuksia valittujen omaisuuserien välillä.

Asiasanat Dynaaminen korrelaatio, dynaaminen suojaus, maataloushyödykkeet, monimuuttuja GARCH, minimivarianssi portfolio, epävarmuustekijät
Säilytyspaikka Jyväskylän Yliopisto

Acknowledgments

I want to express my sincere gratitude to my guiding supervisors, Juha-Pekka Junttila, Heikki Lehkonen, and Juhani Raatikainen, for their valuable feedback, expertise, and mentorship throughout my academic journey and thesis project.

I would also like to thank Raahentienoon Osuuspankki, my employer, for allowing me to focus on my studies and giving me the time and space, I needed to complete them.

Lastly, my utmost gratitude goes to my spouse and my family for giving me the much-needed support, understanding, and patience during these years of study.

"An investment in knowledge pays the best interest."
-Benjamin Franklin

CONTENTS

LIST OF TABLES AND FIGURES

FIGURES

TABLES

1 INTRODUCTION

1.1 Research background

You might not think about it when filling up your shopping cart, but the price of wheat, corn, and rice has far-reaching implications for the global economy. In this thesis, we will take a deep dive into the time series of these vital commodities and examine the factors that influence their prices. Understanding the factors influencing the price of food is crucial not only for the farmers but investors and policymakers alike. The wheat, corn, and rice prices can also impact inflation rates in many countries. These staple foods are essential in formulating the consumer price index (CPI), which measures the average price change over time for a basket of goods and services. If the prices of these foods increase, it can lead to higher CPI and potentially impact monetary policy decisions made by central banks. Also, in a larger context, stable food prices and price fluctuations are crucial elements for well-functioning societies.

Formally, the price of goods forms through supply and demand. Price is increased if the demand exceeds the supply, and the decrease of the supply is greater than the demand. When the supply and demand are in sync, the market is in equilibrium. However, the pricing mechanism is far more complex. The commodities market has evolved, and different factors can affect the price. The commodities market consists of at least these products: spots, futures, forward contracts, and swaps. Settlements are either in cash or physical deliveries. There are also options on futures and micro and mini contracts for smaller investors. Different market participants with different agendas can access these products. Agendas can vary from simply buying the goods at a spot price for production purposes to buying the futures for speculative purposes. Moreover, there are components outside of the markets that affect the prices. According to Headey (2010), big factors impacting food prices during the food crisis in 2007-2008 were export restrictions and import increases among the countries, as well as weathers such as droughts and floods and the high price of oil.

The financialization of commodities is believed to be one of the forces affecting price formation. This financialization of commodities means that financial actors such as banks and hedge funds have been trading the commodities futures, affecting the demand. It has been argued that this financialization has adversely affected price stability as the speculators can distort the markets by targeting specific commodity futures prices. Especially the 2008 Great Financial Crisis substantially affected commodity futures by increasing price volatility. A big factor was the collapse of the Lehman Brothers since the company was one of the largest derivatives market participants. Another big event was when COVID-19 started to affect the economy. The price of West Texas Intermediate (WTI) went negative. Market participants holding the front-month May 2020 WTI futures contracts, were willing to pay for the new buyer to get rid of their contracts so that the physical products would not be delivered in May 2020 and would not need to be stored. These kinds of swings are thought not to be related solely to the supply and demand of the commodity.

While there is no denying the potential risks associated with financialization, it is also essential to recognize its positive impact on commodity markets. The financialization of commodities has significantly impacted the liquidity of commodity markets. By allowing a broader range of market participants to enter and exit these markets, financialization has increased the depth and breadth of trading, leading to improved liquidity. This increased liquidity has allowed for more efficient price discovery, with prices more accurately reflecting the supply and demand of the underlying commodities. Price discovery is the price information transferred from futures to the spot market. This price discovery and increased liquidity through futures increases allow the market participants to manage their risk and improve their financial performance.

This thesis focuses on improving financial performance through hedging with other assets than food staples futures. According to IEA (2022), clean energy products are becoming increasingly important, and copper and silver are among the most critical metals in their production. These two metals are treated in this study as clean energy metals. The fight against climate change has seen more concrete actions through changes in legislation such as the Paris Climate Agreement 2015 and Green Deal in Europe and the forming of a national climate change task force in the U.S. The fight against climate change is a significant factor in the future demand for these metals.

Copper is a particularly vital commodity in this climate change task, as it is utilized in all clean energy products, including wind, solar, and hydropower. On the other hand, silver is valued for its high electrical conductivity and is mainly used in solar power, and demand for solar power is rising fast year by year (IEA, 2022). In contrast, non-clean energy, such as crude oil, is still needed during this transitioning process and is used as an input in agricultural products. Gold is historically known for its safe haven performance and is selected to reveal possible hedging abilities against these selected food staples. The S&P composite index is chosen to bring another dimension, and the financial channel and the structural changes in correlations against food staples are in the interest of many market participants as they affect the performance of diversified portfolios.

Additionally, growing research on uncertainty indexes and the increased accuracy in measuring uncertainties will be considered in this research, and these uncertainties are taken as exogenous variables affecting the system. Since the war began in Ukraine, geopolitical uncertainty has risen, and Ukraine and Russia are both critical wheat producers. The conflict started in Crimea as early as 2014. Food has been used as a weapon throughout history, and wars often disrupt the supply lines and affect the world, as reported by The World Bank (2023). The importance and measuring methods of different kinds of uncertainties are covered in chapter 3.

1.2 Research aim, objectives, and structure

This study mainly focuses on staple food correlations with clean energy metals, non-clean energy, gold, and the stock market. The interest is in hedging these food staples prices and seeing if hedging possibilities exist. The dynamic hedging ratio and hedging effectiveness are examined to ensure an adequate study of the hedging abilities. The secondary objective is to research the immediate impact of various exogenous variables, such as the CBOE volatility index (VIX), geopolitical risk (GPR), climate policy uncertainty (CPU), and economic policy uncertainty (EPU), on food prices and returns. Understanding and anticipating the effects of uncertainties will help investors, policymakers, and food producers in risk management when they can assume the initial impact on stable food prices in times of rising or falling uncertainty. Thirdly, as there is a selection of 5 assets together with wheat, corn, and rice, the VARX-ADCC-EGARCH method is used to produce minimum variance portfolios using these assets. This study will also add to the cross-commodity literature by providing information on volatility spillovers and price behavior.

Overall, this master's thesis aims to contribute to understanding food prices and price fluctuations and their relationship to other variables. Furthermore, to help understand how the food staples are affected by various external factors, providing insights that can inform decision-making and risk management in the agricultural and financial sectors when forming an efficient portfolio.

The research questions can be as follows:

- Is there a way for a hedge for the food producers with commodities?
- How do different uncertainty factors initially affect food prices on a daily and monthly frequency?
- How would the 21-day rolling average minimum variance portfolio look like when combining wheat, corn, and rice with S&P 500 CI, crude oil futures, copper futures, silver futures, and gold futures, when uncertainty factors such as VIX index and geopolitical risk are added to the equation?

This master's thesis is structured as follows. After the introduction, chapters 2 and 3 are about the theoretical framework, chapter 4 is about data and methodology, chapter 5 is for the results and analysis section, and chapter 6 concludes the research.

2 PREVIOUS STUDIES

According to World Atlas (2019) data, the world's three most important food staples are wheat, corn, and rice. The spot prices of these staples are crucial for policymakers, including the Federal Reserve (FED) and other central banks like the European Central Bank (ECB), as the change in the price of food is factored into the CPI numbers released by such institutions as the Bureau of Labor Statistics, U.S. Department of Labor. Price stability is the most important part of the central bank's mandate, and they rely on this data to make informed monetary policy decisions. For example, when CPI numbers remain high for an extended period, central banks tend to tighten their policy by increasing interest rates in an attempt to adjust inflation.

Food price stability is particularly significant for low-income countries, as a significant proportion of their population's income is spent on food (Bogmans, Kearns, Pescatori & Prifti, 2022). Low-income countries are often so-called food-deficit countries and rely on food imports. Rising food costs can reduce expenditure on other essential goods and services like healthcare and education, which can have broader implications on economic growth. Global food programs like the World Food Program can offer acute aid during severe natural disasters or conflicts. Food programmes assisted over 100 million people during the food crisis in 2008 and 158 million in 2022 (The World Bank, 2008; World Food Programme, 2023).

Cereal banking can effectively stabilize prices by ensuring food and nutrition when crop yields are lean (Jatta, 2016). Jatta reports that food price variability and the food gap would be reduced by 25% if communities in import-dependent Gambia stored the excess food at harvest instead of selling it at a lower price. Selling prices at harvest were 16% lower in control villages when the surplus was sold right after the harvest. His study also confirms the speculative behavior of intermediaries exploiting the prices inter-seasonally, confirming the findings of Oguoma et al. (2011). These findings are signs of market inefficiencies and inadequate knowledge of risk management tools and their capacities (Dana, 2013).

For a farmer of these food staples, stable prices are essential for income and profitability, like for any other business. Unpredictable price development can impact investment decisions, leading to necessary investments being postponed. The commodity market is especially challenging because of its price volatility (Dana, 2013). Supply and demand times can be lengthy as crops need to be harvested seasonally, and processing and logistics will take their time before the commodity is delivered. This seasonality will lead to different price risks during the process and needs to be considered in risk management operations among the market participants. It is important to have integrated and well-working supply lines through commercial trade markets to have a proper forward market for commodities. A well-established supply chain reduces hoarding and opportunistic behavior, bringing price security while securing the supply (Williams, 2013).

In times of uncertain food price development and economic stress, farmers needing credit may also find it difficult to access financing from lenders. Governments should establish adequate safety nets for consumers and farmers. However, if the private sector has invested in the supply chain, it gives more resilience against price changes (Dana, 2013). Governments should intervene in times of uncertainty but let market participants fill their roles and put their stake in the process. Bellemare, Barrett & Just (2013) used panel data to study the effects of food price intervention on rural Ethiopian households. They reported that price stabilizing attempts increased household incomes, and the interventions work as a regressive government policy tool. However, they reported that this intervention was more beneficial for wealthier households in a progressive fashion. If a policy tool aims to reduce poverty and inequality, policymakers may need to consider additional measures to ensure that the benefits of price stabilization interventions are distributed more equally across different socioeconomic groups.

The U.S. dollar (USD) dominated world trade has its own unique effect. The general belief has been that if the USD strengthens or weakens, it is felt worldwide. The change in the USD exchange rate affects domestic food imbalances and causes variations in the price of the foods. Reboredo & Ugando (2014) used copula functions to study dependency structures between the USD and wheat, corn, soybeans, and rice. The authors reported positive and weak dependence between food and the USD and increased hedging effectiveness. A severe USD depreciation was, perhaps surprisingly, not causing the spikes in rapid food price changes. Confirming that market participants should keep an eye open for changes in the USD exchange rate as currency moves result in volatility in food prices but to seek other ways of hedging in case of a more significant dollar depreciation.

The financialization of commodities has led to non-energy commodity futures correlating more with oil prices (Tang & Xiong, 2012). This co-movement is due to the indexing of commodity markets and can be problematic for commodity producers' hedging strategies and countries implementing specific food and energy policies. This increased cointegration between commodities is shown to result from high crude oil prices, which led to a surge in finding alternative energy sources away from fossil fuels (Serra, Zilberman & Gil, 2011). Biofuels such as ethanol are substitutes for fossil fuels, and biofuels are mainly produced from food crops. Different countries produce ethanol and biofuel from different foods and sugars depending on their primary agricultural production. After the financial crisis, there is a significant link between fossil fuels, biofuels, and agricultural commodities among the countries that produce biofuel from their crops (Reboredo, 2012; Thenmozhi & Maurya, 2020). This link was found to work already after 2005, when the Renewable Fuel Programme started (Roberts & Schlenker, 2013).

On the positive side, this financialization of commodities is argued to contribute to more extensive price risk sharing as index investors are believed to be investing in a more diversified portfolio, leading to lower risk premiums and higher prices for producers. The financialization and rise of commodities in portfolios are argued to follow from low returns from bonds and stocks (Thenmozhi & Maurya, 2020).

Changes in commodity futures prices were found to affect spot prices mainly in the first four days of a volatility shock (Duc Huynh, Burggraf & Nasir, 2020). The study also found that commodity futures were affecting spot prices more than the spot prices on the underlying derivatives. This finding suggests that the futures market plays a crucial role in transmitting the price movement to the spot market in the short term. Reboredo (2012) reported using copulas that wheat, corn, and soybean move together with oil. Reboredo further reports that considerable rises in oil prices do not cause unsuspected and sizeable price changes in food. However, there is evidence of increased co-movement between foods and oil after the great financial crisis.

The correlations between commodities, stocks, and bonds were lower at the beginning of the 1990s and increased and peaked during the great financial crisis (Silvennoinen & Thorp, 2013). Ali & Gupta (2011) found with Johansen's cointegration test that there is no cointegration between wheat and rice spot and futures markets and suggested that the futures market is leading the spot price, and the market is inefficient for these two. Chen et al. (2023) reported no cointegration in the Chinese wheat and corn spot and futures market. This market inefficiency is believed to be a result of government market interventions to regulate the price of food. Overall, these studies provide insights into the dynamics of commodity prices and their relationships with other financial markets. They highlight the importance of considering short-term effects, the role of futures markets, the comovement of commodities with oil, and the changing correlations between commodities, stocks, and bonds in different market conditions.

In light of these findings, farmers need to implement effective hedging strategies to ensure price stability and mitigate the risks associated with commodity price fluctuations. One way to approach this hedging is by the use of futures contracts. Bernard & Frecka (1987) did a study on effectively setting up a hedge against price inflation on consumption-based commodities focusing on food, shelter, and transportation. Surprisingly, according to Bernard & Frecka, the futures provided little help against the unexpected rise in inflation, but common stocks worked well. The use of futures helps the farmer ensure the price of crops to be sold at a predetermined price but offers no help for investors who want to shelter their portfolio against inflation. Jebabli & Roubaud (2018) used a time-varying Hurst rolling exponent and threshold vector error correction model on commodities markets. They found that spot and futures prices are long-time efficient and short-time inefficient, and economic conditions could explain their results.

Cross-commodity analysis has revealed weak spot market volatility dynamics (Thenmozhi & Maurya, 2020). They found that crude oil and wheat volatility is affected by volatility in corn in the long and short run. Crude oil and wheat have been reported to have primarily positive correlations using DCC-

GARCH, ADCC-GARCH, and GO-GARCH models (Pal & Mitra, 2019). The authors found an average hedge ratio of 0.3656 between crude oil and corn using GO-GARCH. The correlation mean for crude oil and wheat was, on average, 0.1661. DCC-GARCH worked the best for the hedging effectiveness of these models, and the ADCC-GARCH model was the worst among these three GARCH models. Declerck (2014) explored the hedging possibilities of companies processing food commodities. 9 of 49 companies' stock returns showed heightened sensitivity to wheat returns. As for wheat, no such significant hedging functions were coming from wheat processing companies as gold mining companies' stock returns have with gold returns.

To ensure price stability, farmers have different options, including using futures prices for their crop sales or employing hedging strategies. Liu & Pietola (2005) researched the optimal hedge ratio for Finnish spring wheat producers. Finnish spring weather is particularly volatile, and the yields differ from spring to spring. The volatility in yields is found to be the dominant factor affecting the price of wheat. This has implications for optimal hedging ratios, as correlation estimates are negative. Liu & Pietola suggest a natural hedge existing in the process and working for the farmer since farmers' income does not vary yearly. Hedging effectiveness declined further as yield volatility increased, indicating that forward contracts would not work as well in Finland as in other countries with more stable yields.

Another approach to increasing price stability for farmers is to diversify their crops. By growing a variety of crops, farmers can reduce their reliance on a single commodity and spread their risks across different markets. Diversification can help protect against price shocks that may occur in a specific market or commodity. There needs to be more than this crop diversification to deliver stability. Climate change will affect agriculture through extreme weather events, decreased crop production and failures due to pests and diseases, decreased land production from soil degradation, and changes in the availability and quality of water resources (Dasgupta 2021).

In conclusion, price stability is essential for farmers and policymakers, as it can have far-reaching implications for economic growth and stability. While there are various strategies that farmers can implement to increase price stability, policymakers could also take a more active role by helping small-scale farmers with incentives and subsidiaries to make them less affected by price shocks (Kibris & Tapki, 2014). However, this intervention increases market inefficiency between spot and futures prices. Understanding the effects of policies and uncertainties can help with risk management, and the next chapter will cover four different uncertainty indexes.

3 IMPORTANCE OF UNCERTAINTY INDEXES

3.1 Understanding the uncertainty indexes

In simple terms, policy-related uncertainty has been measured by searching specific keywords from written text such as newspaper articles. The more hits these searched words give, the higher the index number is. Then, these daily index numbers can be reformed into monthly, quarterly, and yearly data points if desired. Then, these uncertainty data points can be regressed, for example, against price and return data of the financial markets to find the signs of possible price shocks.

Price impacts can originate from myriad sources, including fluctuations in commodity prices, shifts in interest rates, and geopolitical events (Bloom, 2009; Hove, Touna Mama & Tchana Tchana, 2015). It is vital to acknowledge that policy uncertainty can serve as a pivotal catalyst for price shocks, subsequently instigating market instability and unpredictability for longer (Jurado, Ludvigson, Ng, 2015; Benhabib, Liu, Wang 2019).

One way for policymakers to reduce uncertainty is to provide clear and unwavering policy guidance. Governments and central banks can contribute significantly by articulating their policy intentions with utmost clarity, enabling businesses and investors to make well-judged decisions (Bloom, 2009). Additionally, businesses can manage uncertainty by diversifying their portfolios, hedging against risk, and investing in research and development to create new opportunities. Overall, comprehending the ramifications of uncertainty on food staples and taking steps to control it can be crucial for promoting more profound economic growth and mitigating the vulnerability to price shocks. In this thesis, the focus is on four uncertainty series, each encapsulating diverse facets of uncertainty.

3.2 CBOE Volatility Index (VIX)

The Chicago Board Options Exchange Volatility Index (VIX) measures the expected or implied volatility of the S&P 500 index, which is widely used to gauge investor sentiment and market risk. The input includes the market prices of SPX options, SPXW options, and U.S. Treasury yield curve rates (Cboe Global Indices, 2023). This stock market volatility has increased correlations in commodity markets (Tang, Wang, 2023). It is noteworthy that VIX and EPU indexes are found to be frequently moving together in different crises, such as the global financial crisis and the Euro debt crisis, with a correlation of 0.58, as discerned by

Baker, Bloom & Davis (2016) when the authors formulated the EPU index and examined the uncertainties affecting different asset classes.

During the crisis periods characterized by elevated VIX levels, the correlations between different asset classes became more pronounced, diminishing the effects of diversification as a risk-mitigating strategy (Silvennoinen & Thorp, 2013). This observation is a compelling indication of the increasing integration of financial markets, with the elevated VIX levels also portending heightened volatility within the commodities markets.

3.3 Geopolitical Risk (GPR)

The GPR index was formed by Caldara & Iacoviello (2022). Their method involved aggregating news articles from the electronic archives of ten news magazines to formulate daily and monthly GPR indexes. Their study yielded compelling evidence that increased geopolitical risk significantly heightens the likelihood of economic crises, dampens investment activity, and negatively impacts employment levels.

The importance and effect of geopolitical risk are addressed by different institutions such as the International Monetary Fund (IMF), the Federal Reserve (FED), the European Central Bank (ECB), and the Bank of England. These institutions also follow the geopolitical risk index (Caldara & Iacoviello, 2022).

The GPR index has been explored by Tiwari, Boachie, Suleman & Gupta (2021), who studied the linkages between energy and agricultural commodities and the changes in their co-movements affected by the GPRs. The main natural link between energy and agricultural products is that energy commodities serve as a pivotal input for agricultural production, but this connection is negatively disrupted by the GPRs. Dependence and tail dependence are more pronounced in a bear market when correlations are particularly robust. They also found that wheat and corn can hedge the energy downturns. Tiwari et al. (2021) underscore the importance for commodity traders to maintain vigilant oversight over all commodities and keep an eye open for geopolitical risks that may influence their portfolio performance.

3.4 Economic Policy Uncertainty (EPU)

Economic policy uncertainty (EPU) refers to the uncertainty surrounding government policies and their potential economic ramifications. It has become an increasingly important research topic in recent years as policymakers worldwide have grappled with various economic challenges, including economic recession, financial crises, and political instability.

One of the most well-known studies on the EPU is by Baker et al. (2016), who developed a comprehensive gauge of policy uncertainty based on news articles from prominent U.S. newspapers. They found that the EPU significantly impacts economic activity, leading to declines in investment and hiring and increases in stock market volatility. The authors suggest that mitigating policy uncertainty could effectively promote economic growth and ensure stability.

Another study authored by Bernanke (1983) underscores the critical role of comprehending uncertainty in economic decision-making. Bernanke argues that uncertainty about future economic conditions can impede investment and hiring decisions as firms wait for more information before committing to long-term projects. This can result in economic deceleration, and in more extreme scenarios, trigger recessions.

The unintended consequences of these policies, such as inflationary pressures and trade conflicts, economic wars, and capital wars, further add to policy uncertainty. Investors and businesses are uncertain about how governments and central banks would respond to these challenges, creating additional uncertainty and eroding confidence in the global economy's long-term stability.

3.5 Climate Policy Uncertainty (CPU)

The CPU index is based on a study by Gavriilidis (2021), which refers to the lack of clarity and consistency in climate policies and regulations. The CPU index is brought together from numerous articles published in eight leading newspapers. The index aims to capture events related to climate policy and events such as legislative changes and presidential statements concerning climate matters. Gavriilidis found a strong correlation between the CPU and CO^2 emissions.

The CPU strongly affects the performance of green energy stocks over non-green stocks (Dutta, Bouri, Rothovius & Uddin, 2023). This observation carries consequential implications for strategic asset allocation during times of crisis. Furthermore, the study finds that policy measures, such as feed-in tariffs and renewable energy targets, can further enhance the positive relationship between climate risk and green investments. Threats coming from climate-related uncertainty influence corporations' motivation for new investments Engle et al. (2020).

In conclusion, addressing climate policy uncertainty is crucial for transitioning to a low-carbon economy. Effective mitigation necessitates policymakers to furnish lucid and unwavering signals regarding the trajectory of climate policy. Such clarity mitigates investment risk and fosters an environment conducive to innovation, expediting the transition toward a sustainable future. The results from the studies emphasize the need to consider climate-related factors when evaluating the performance of green energy stocks and making informed investment decisions. Additionally, the studies highlight the influence of climate uncertainties on corporations' investment behavior.

4 DATA AND METHODOLOGY

In this thesis, endogenous data (food prices, futures, and S&P CI) is gathered via the Refinitiv Datastream platform. The dataset comprises daily price series of wheat spot (wheat no.2, soft red u$/bushel), corn spot (corn no.2 yellow u$/bushel), rice price (CSCB rough rice tr - return index), S&P 500 composite index, copper futures (CMX-high grade copper cont. - sett. price), crude oil futures (NYM-light crude oil continuous - sett. price), silver Futures (CMX-silver 5000 oz continuous - sett. price), gold Futures (CMX-gold 100 oz continuous - sett. price).

Uncertainty data, which is considered exogenous data, are gathered from different sources. The VIX index is obtained from the FRED database, and the other uncertainty (GPR, EPU, and CPU) data are from policy uncertainty websites. The geopolitical risk index in daily and monthly format can be accessed at https://www.matteoiacoviello.com/gpr.htm, and EPU and CPU data are retrievable from https://www.policyuncertainty.com/.

The daily price series starts in May 2002 and ends in August 2021. Daily prices consist of 4869 data points; return data are natural log returns calculated from the daily prices using equation 1 and have 4868 data points. Natural logarithmic returns are calculated using the following:

$$\boldsymbol{r_t = [ln(P_t) - ln(P_{t-1})\,] * 100}, \tag{1}$$

where the r_t denotes the returns and $\ln(P_t)$ and $\ln(P_{t-1})$ represent the natural log differences between the price at time t and the day before. This specific data point has been excluded from our dataset due to an extraordinary event in the spring of 2020, where the price of light crude oil futures turned negative, resulting in a computational anomaly in the natural logarithmic return calculation.

The primary analysis is done using daily data, but as the EPU and the CPU of the uncertainty datasets are in monthly format, a secondary dataset is needed. The daily dataset is transformed into monthly data by aggregating financial returns data by month, grouping the data by year and month, and then summing the returns for each group. The resulting data frame contains the aggregated returns for each month. Additionally, as the policy uncertainty dataset is aggregated from daily data, the monthly data in this thesis is aggregated from daily returns. Overall, the monthly data has 231 data points, starting in June (returning from May) and ending in August 2021.

Appendix A provides a visual presentation of the daily price and return series for wheat, corn, and rice spot series. The plots show significant spot price fluctuations between 2005 and 2010 for each series. Notable observations include the doubling of wheat prices and the tripling of corn prices during this period. Corn made new highs in the summer of 2008 but peaked even higher in 2012. COVID-19 temporarily affected prices of corn and rice, as the volatility of rice peaked earlier and corn in the following months. Wheat returns were the most volatile at the end of 2018. Rice prices deflated after 2011 and made no significant price changes after that.

Appendix B plots the daily prices and returns for light crude oil, copper, and silver futures. Copper futures exhibit dissimilar price movements compared to wheat, whereas crude oil futures display some intriguing similarities. This includes a peak in 2008 and the lower levels after 2015. Silver futures exhibit partial resemblances in prices to the wheat spot after 2015. Likewise, corn and copper futures share similarities in their price movements after 2015. With crude oil futures, the co-movement has a more extended history—the price pattern with silver futures shares similar traits with corn spot, and even the volatility clustering looks similar but not identical. The only things that go well together with rice prices and crude oil futures are the peak during 2008 and volatility clustering during 2016. Silver futures again look different from rice price movements.

Appendix C plots the daily price and returns of gold futures, S&P CI, and CBOE VIX index series. A noteworthy observation is that wheat spot and gold futures prices exhibit limited correlation, except during the tumultuous period of 2008. Volatility patterns also diverge, further emphasizing their distinct behaviors.

Over the long term, the S&P CI has made a substantial increase in price. In stock market downturns, the wheat price has tended to decline. Increased VIX levels seem to have led to a decrease in wheat prices on many occasions. On steadier VIX levels, the wheat price looks to have had gains.

Turning to gold futures and corn spot prices, they reached peak values between 2010 and 2015, with gold futures experiencing a subsequent peak after 2020. In contrast, corn prices did not reach new highs. Similarly to wheat spot prices, corn also declines in S&P CI downturns. Furthermore, there was volatility clustering at the same time in 2008, at the end of 2015, and COVID-19. High VIX levels seem to affect corn spot prices negatively, and lower VIX levels strengthen the prices.

Rice and gold futures, however, appear to have different price trends. Significant S&P CI downturns have co-movement with rice levels going down. Higher VIX levels typically lead to lower rice prices, but COVID-19 did not have a sustained effect on rice prices, distinguishing it from other observed events.

Heightened geopolitical risk levels can be seen in the early part of the data. It provides a straightforward narrative of significant events impacting the index, such as the Iraq war in 2003, the London bombings in July 2005, and the Russian military aggression in Crimea in 2014.

Level series reverts to the mean and has some variance in the series, but the change series of GPRD looks like it has a white noise process with a few more extensive changes. Furthermore, observing that some volatility spikes in the GPR change series align with wheat spot volatility, particularly after 2015, is a valuable insight for understanding potential correlations or influences. The note that corn, rice, and the GPR index do not seem to share common traits when plotted suggests that there may not be a direct relationship between these commodities and geopolitical risk, which is an important finding.

The descriptive statistics of daily returns are given in Table 1. We can observe that futures prices have higher means than the food spot series, except crude oil futures mean returns are lower than corn mean returns. The rice spot mean is slightly negative.

Crude oil futures and wheat spot have the highest standard deviations. The skewness of rice returns is positive when the other series is left-skewed, indicating that rice spot returns have more values below the mean than above the mean. Crude oil futures have heavy left skewness, indicating possibly fat tails, and the mean might not be a good measure of central tendency. In cases of high skewness, it might be suitable to adjust for the skewness with non-parametric statistical methods or transformations.

Excess kurtosis is moderate for corn spot and copper futures. In the case of crude oil futures, the value is extreme and highly unusual. Excess kurtosis value over 12 indicates a distribution of heavy peakedness, and these could be considered as "outliers". Partly because EPU and CPU are monthly values and partly because of the high skewness and kurtosis of the return series, monthly values of the daily return series will be taken, and the results are shown in Table 3**.**

Table 1. Descriptive statistics of the daily return series

N=4868	Start	02/05/2002	End	31/08/2021
	Mean	SD	Skewness	Kurtosis
Wheat Spot	0.0182	2.5316	-0.1773	8.3524
Corn Spot	0.0225	1.9383	-0.1263	4.7254
Rice Spot	-0.0013	1.4309	0.0943	13.2923
Light Crude Futures	0.0193	2.6706	-1.1794	31.3483
Copper Futures	0.0368	1.7215	-0.2145	4.1926
Silver Futures	0.0342	2.0509	-0.8913	7.0998
Gold Futures	0.0363	1.1321	-0.3695	5.2749
S&P 500 CI	0.0293	1.2331	-0.4642	12.5867
VIX	-0.0040	7.2472	1.0389	6.6084
GPRD	0.0091	38.8543	0.0561	1.9900

Furthermore**,** the Jarque-Bera statistical test results in Table 2 indicate that none of the daily return series follow the normal distribution. The results from augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests show robust unit root tests for the null hypothesis, which is that there is a unit root. All the return series are stationary at a 1% confidence level, allowing the use of dynamic conditional correlation analysis. The ARCH-LM test hypothesis is that there is no ARCH effect, and with 1% confidence, this null hypothesis is rejected. With high confidence, the return series variance of the error term in a regression model varies over time, and from this result, it can be concluded that the GARCH-based models are appropriate models to be used.

Table 2. Unit root test results of the daily returns.

N=4868	Start	02/05/2002	End	31/08/2021
	J-B stat.	ADF with intercept (10)	PP test	ARCH-LM test
Wheat	14191.56 ***	-23.1038 ***	-77.0598 ***	493.5530 ***
Corn	4548.19 ***	-21.1345 ***	-70.3567 ***	366.5081 ***
Rice	35880.89 ***	-21.6372 ***	-67.4255 ***	1126.5197 ***
Crude O F	200635.96 ***	-21.9521 ***	-72.6013 ***	926.6065 ***
Copper F	3607.79 ***	-20.4230 ***	-75.0217 ***	771.1676 ***
Silver F	10881.19 ***	-21.9857 ***	-71.2420 ***	308.7858 ***
Gold F	5761.83 ***	-22.2985 ***	-70.3879 ***	261.0650 ***
S&P CI	32341.60 ***	-22.1107 ***	-80.0213 ***	1492.5304 ***
VIX	9744.72 ***	-25.1313 ***	-79.0419 ***	255.5167 ***
GPRD	807.48 ***	-33.2871 ***	-187.8517 ***	526.6403 ***

Notes: J-B statistics refer to Jarque-Bera normal distribution, ADF with intercept refers to the augmented Dickey-Fuller test with intercept and 10 lags. The hypothesis in the ADF test is that the series contains a unit root. PP test refers to the Phillips-Perron test with the null hypothesis of non-stationary. ARCH-LM with the null hypothesis of heteroscedasticity at lag 10. *, **, and *** indicate the significance of reported statistics at 10, 5, and 1% risk levels, respectively.

Table 3 gives the monthly returns of the daily series and the GPRM, with the addition of the CPU and the EPU indexes. From this table, we can observe that most of the series have positive mean, with the rice monthly series being the exception and resulting negative mean, as well as the VIX and the GPRM indexes.

The lowest standard deviations are in the SPCI and gold futures series, and crude oil futures have the highest volatility of the assets. The exogenous variable CPU has the highest standard deviation, having a value slightly over 68, which means that if the data followed a normal distribution, about 68 % of the data falls within one standard deviation of the mean, 95% within two standard deviations, and 99.7% within three standard deviations.

Skewness results indicate that all the assets have more observations on the left side, and the uncertainty variables have more observations on the right side of the curve. Kurtosis values are the highest for crude oil futures, which was the case also for the daily return series. Copper futures also have heavier and more extreme values on a monthly basis. Most of the series have kurtosis under 3, which indicates that most of the monthly series have shorter tails and fewer extreme values than a normal distribution.

Table 3. Descriptive statistics of the monthly returns.

N=231	Start	01/06/2002	End	31/08/2021
	Mean	SD	Skewness	Kurtosis
Wheat Spot	0.3709	10.6183	-0.4528	1.8093
Corn Spot	0.4400	9.1836	-0.5086	0.9961
Rice Spot	-0.0808	6.6949	-0.3923	0.9369
Light Crude Futures	0.4310	11.3935	-0.9968	12.6545
Copper Futures	0.7554	7.7699	-0.7989	5.3704
Silver Futures	0.6761	9.1681	-0.1914	0.8862
Gold Futures	0.7426	4.9285	-0.2873	0.8239
S&P 500 CI	0.6252	4.2744	-0.8787	2.1030
VIX	-0.0834	21.2434	0.5334	1.4260
GPRM	-0.2608	18.7345	0.4136	1.5244
CPU	0.7745	68.2220	0.4245	2.4319
EPU	0.4260	17.6943	0.4509	1.1563

Table 4 reports the goodness of the monthly data. The Jarque-Bera test results in every monthly series indicate that the returns are not normally distributed. The ADF and PP tests are passed at a 1% confidence level. ARCH-LM test shows that the monthly return series are not heterogeneous enough for most of the series. In other words, the residuals are likely autocorrelated. This autocorrelation indicates that only a few series are heterogeneous enough for GARCH-type analysis. The autoregressive integrated moving average (ARIMA) model (1,0,0) is used to research the initial effect on monthly food series from the selected exogenous variables.

Table 4. Unit root test results of the monthly returns.

N=231		Start 01/06/2002	End 31/08/2021	
	J-B stat.	ADF with intercept (10)	PP test	ARCH-LM test
Wheat	40.9801 ***	-5.2045 ***	-15.7075 ***	22.11 **
Corn	20.3192 ***	-5.2816 ***	-15.1312 ***	6.3517
Rice	15.081 ***	-5.2203 ***	-16.2195 ***	42.4281 ***
Crude O F	1613.4658 ***	-4.9588 ***	-13.2152 ***	10.8372
Copper F	310.0796 ***	-5.3054 ***	-12.2398 ***	58.0385 ***
Silver F	9.577 ***	-5.0988 ***	-15.7657 ***	26.2382 ***
Gold F	10.2918 ***	-5.0216 ***	-17.3227 ***	18.2979 *
S&P CI	74.5027 ***	-4.8894 ***	-13.8815 ***	48.165 ***
VIX	31.7407 ***	-5.6115 ***	-18.597 ***	12.4704
GPRM	30.2136 ***	-8.9981 ***	-23.1275 ***	10.0022
CPU	66.1922 ***	-7.597 ***	-26.6666 ***	11.1069
EPU	21.618 ***	-5.8514 ***	-19.5077 ***	16.5154 *

Notes: See Table 2.

The econometric methodology for daily return series is a vector autoregressive model with exogenous variables (VARX), an asymmetric dynamic conditional correlation (aDCC), and an exponential generalized autoregressive conditional heteroskedastic model (eGARCH). The abbreviated model is the VARX-aDCC-eGARCH model, typically used in financial time series analysis.

This variation of the model can be used for volatility and correlation dynamics analysis, and it can capture the effect on the mean equation coming from exogenous variables such as uncertainty shocks from outside the system. With the help of the asymmetric models, it is possible to capture the adverse effects impacting the volatility or the correlation more than the positive shocks, which often occurs in economics where negative shocks have a steeper impact on returns.

4.1 The VARX-model

The VAR model helps to understand the relationships between different variables, and adding exogenous variables allows one to capture the effect of changes from unmodeled variables or uncertainties. The exogenous variables restrict the equation on the right-hand side, and it is not in the spirit of the true VAR process to impose restrictions, but it is used in this thesis to research the initial impact of the uncertainty on the selected assets. Using the VARX model reduces the number of parameters to be estimated, answering overparameterization concerns raised by Bernanke et al. (2004). This thesis has exogenous variables as changes from the levels, which allows the capture of the short-term effects when uncertainties change. Therefore, the memory process is different compared to the levels approach. The VARX approach can be decomposed in matrix notation as:

$$\boldsymbol{y_t} = \boldsymbol{c} + \sum_{i=1}^{p} \boldsymbol{\Phi_i y_{t-i}} + \sum_{j=0}^{q} \boldsymbol{\varphi_j X_{t-j}} + \boldsymbol{u_t}, \tag{2}$$

where y_t is a vector of endogenous variables at time t, c is a vector of constants, Φ_i and φ_j are the k×k coefficient matrices of the lagged endogenous variables and exogenous variables X_t, respectively. u_t is the k-dimensional vector of residuals. The initial effect from exogenous variables is considered, and no lags will be allowed.

4.2 Asymmetric Dynamic Conditional Correlation (aDCC)

The basic dynamic conditional correlation model is built on the generalized autoregressive conditional heteroscedasticity (GARCH) model proposed by

Bollerslev (1986). Engle (2002) added a time-varying conditional correlation process, and this standard DCC-GARCH model has been widely used in time series analysis to research risk correlations in financial markets. From the return vector y_t is assumed that it follows a conditional normal distribution with zero mean and covariance matrix H_t. $y_t|\Im_{t-1} \sim N(0, H_t)$, where $\Im_{t-1}$ is lagged time information set.

Cappiello et al. (2006) introduced a modification to the original DCC-GARCH model by allowing dynamic asymmetries or the "leverage effect". With the new model configuration, positive and negative shocks are allowed to have different effects on the correlation dynamics between different assets.

The DCC-GARCH model is a two-part model. The first part estimates the univariate GARCH and the second part proceeds to the multivariate GARCH process to allow the cross-correlations between assets to be estimated. DCC-GARCH model assumes that conditional variance/covariance matrix can be formulated as:

$$\boldsymbol{H_t = D_t P_t D_t}, \tag{3}$$

where D_t is a k × k diagonal matrix $diag\left[\sqrt{h_{i,t}^2}\right]$ of time-varying standard deviations and P_t denotes the conditional correlation matrix holding the time-varying correlations of the standardized returns.

Nelson (1991) modified the standard GARCH model from Bollerslev (1986) into exponential GARCH. Allowing the asymmetries of the conditional variance of the residuals to be both negative and positive by adding the absolute value and, therefore, capturing the leverage effect. The equation for EGARCH can be decomposed as:

$$\boldsymbol{log\left(h_{i,t}^2\right) = \omega_i + \sum_{l=1}^{s} \beta_{i,l}\, log\left(h_{i,l,t-1}^2\right) + \sum_{k=1}^{r} \alpha_{i,k} \frac{\varepsilon_{i,k,t-1}}{\sqrt{h_{i,k,t-1}^2}} +}$$

$$\boldsymbol{\sum_{n=1}^{m} \gamma_{i,n} \left(\frac{\left|\varepsilon_{i,n,t-1}\right|}{\sqrt{h_{i,n,t-1}^2}} - \sqrt{2/\pi}\right)}, \tag{4}$$

where $\log(h_{i,t}^2)$ is the conditional variance of the ith series residual at time t. ω_i is the constant for the long-term average variance, $\alpha_{i,k}$ is the coefficient for the absolute values of lagged residuals, which captures the impact of earlier shocks on volatility, $\beta_{i,l}$ is the coefficient for the logarithms of the lagged time-varying variance, which gives the long-term effect of volatility and $\gamma_{i,n}$ is the parameter for the standardized residuals tuned by $2/\pi$, which captures the leverage effect, $\varepsilon_{i,t}$ is the vector of standardized residuals at time t. These standardized residuals are used to estimate the correlation parameters in $\varepsilon_{i,t} = \frac{r_{i,t}}{\sqrt{h_{i,t}}}$.

P_t or the conditional correlation matrix in the $H_t = D_t P_t D_t$ equation can be decomposed as,

$$\boldsymbol{P_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}}, \tag{5}$$

where Q_t is the order of the asymmetric DCC model and is defined by Cappiello et al. (2006) as a scalar ADCC model:

$$\boldsymbol{Q_t = (\bar{P} - a^2\bar{P} - b^2\bar{P} - g^2\bar{N}) + a^2\varepsilon_{t-1}\varepsilon'_{t-1} + g^2n_{t-1}n'_{t-1} + b^2Q_{t-1}}, \tag{6}$$

For Q_t to be positive, the matrix $(\bar{P} - a^2\bar{P} - b^2\bar{P} - g^2\bar{N})$ needs to be positive, semi-definitive, and $a^2 + b^2 + \delta g^2$ <1, where δ = maximum eigenvalue $[\bar{P}^{-½}\bar{N}\bar{P}^{-½}]$, which can be evaluated on the data sample and taken during the conditional correlation estimation.

Parameters in the model can be estimated using maximum likelihood estimation. This form of model estimation finds the most likely values of the parameters regarding the given dataset. This type of estimation is needed because the model is not in linear form, and OLS cannot be used. Normal distribution of disturbances is assumed.

$$\boldsymbol{L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + log|H_t| + y_t'H_t^{-1}y_t)} \tag{7}$$

After applying the maximum likelihood function and obtaining the optimal parameters, the next step is to calculate the dynamic conditional correlations between assets using the equation:

$$\boldsymbol{\rho_{i,j,t} = \frac{h_{i,j,t}}{\sqrt{h_{ii,t}h_{jj,t}}}}, \tag{8}$$

where $h_{i,j,t}$ is the covariance of assets i and j at time t. $h_{ii,t}$ and $h_{jj,t}$ are the diagonal elements of the variance-covariance matrix Q_t and represent the conditional variances of the assets i and j.

4.3 Optimal hedge ratio

For the optimal hedge ratio, the Kroner & Sultan (1993) method is used.

$$\boldsymbol{\beta_t = \frac{h_t^{sf}}{h_t^{ff}}}, \tag{9}$$

where h_t^{sf} is for the conditional covariance between a food staple and other assets such as futures and S&P CI data at time t. h_t^{ff} is for the conditional variance of the other than food variable at time t. Bivariate or multivariate GARCH models are frequently applied for modelling time-varying conditional covariance and variance. A negative optimal hedge ratio would mean that the investor should take a short position in the futures contract to offset the possible risk in the spot price. If the ratio is small, only a partial hedge is given, and more contracts would be needed to buy to hedge the position entirely. Perfect hedge ratios are considered 1 and -1, from which -1 is an inverse relationship between the returns.

4.4 Hedge effectiveness

Following Dutta et al. (2021) process, the hedge effectiveness (TVHE) is calculated by using the formula:

$$\boldsymbol{TVHE_t = \beta_t^2 \frac{h_t^{ff}}{h_t^{ss}}}, \tag{10}$$

Note that now, the conditional variance of the futures data at time t is divided by the conditional variance of the food staple at time t. This formula gives a result of how effective hedging is. The squared optimal hedge ratio obtained from equation 9 is used in the formula. If $TVHE_t$ is exactly 1, it gives the perfect hedge for that situation, and a result of 0 indicates that there is no hedging effectiveness.

4.5 Minimum variance portfolio weights

Because there is a multi-dimensional model for asset returns, an optimal minimum variance portfolio of assets can be created with optimal weights, Junttila et al. (2018) method is followed in creating the portfolio.

$$\boldsymbol{\min_{\omega_t} \omega_t' H_t \omega_t \;\; st. \textstyle\sum_{i=1}^{6} \omega_i = 1}, \tag{11}$$

where $\omega_t = \begin{pmatrix} \omega_{1,t} \\ \omega_{2,t} \\ \omega_{3,t} \\ \omega_{4,t} \\ \omega_{5,t} \\ \omega_{6,t} \end{pmatrix}$ is a vector of the minimum variance portfolio weights at time t and H_t is the variance-covariance matrix obtained from the ADCC-EGARCH model. Here, Lagrangian style is used by adding λ as a coefficient, and the following formula is formed. Certain conditions need to be met for this solution.

$$\boldsymbol{\mathcal{L}_t = \omega'_t H_t \omega_t + \lambda\left(\textstyle\sum_{i=1}^{6} \omega_i - 1\right)}, \tag{12}$$

where the conditions are:

$$\boldsymbol{2\omega_t' H_t + \Upsilon = 0}$$

$$\boldsymbol{\omega_{1,t} + \omega_{2,t} + \omega_{3,t} + \omega_{4,t} + \omega_{5,t} + \omega_{6,t} = 1}, \tag{13}$$

where $\Upsilon = \begin{pmatrix} \lambda \\ \lambda \\ \lambda \\ \lambda \\ \lambda \\ \lambda \end{pmatrix}$, is the risk aversion or Lagrangian multiplier. ϒ can be further written as:

$$\boldsymbol{\Omega_t \omega_t = z}, \tag{14}$$

where $\Omega_t = \begin{pmatrix} 2h_{1,1,t} & 2h_{1,2,t} & 2h_{1,3,t} & 2h_{1,4,t} & 2h_{1,5,t} & 2h_{1,6,t} & 1 \\ 2h_{2,1,t} & 2h_{2,2,t} & 2h_{2,3,t} & 2h_{2,4,t} & 2h_{2,5,t} & 2h_{2,6,t} & 1 \\ 2h_{3,1,t} & 2h_{3,2,t} & 2h_{3,3,t} & 2h_{3,4,t} & 2h_{3,5,t} & 2h_{3,6,t} & 1 \\ 2h_{4,1,t} & 2h_{4,2,t} & 2h_{4,3,t} & 2h_{4,4,t} & 2h_{4,5,t} & 2h_{4,6,t} & 1 \\ 2h_{5,1,t} & 2h_{5,2,t} & 2h_{5,3,t} & 2h_{5,4,t} & 2h_{5,5,t} & 2h_{5,6,t} & 1 \\ 2h_{6,1,t} & 2h_{6,2,t} & 2h_{6,3,t} & 2h_{6,4,t} & 2h_{6,5,t} & 2h_{6,6,t} & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{pmatrix}$, $\omega_t = \begin{pmatrix} \omega_{1,t} \\ \omega_{2,t} \\ \omega_{3,t} \\ \omega_{4,t} \\ \omega_{5,t} \\ \omega_{6,t} \\ \lambda \end{pmatrix}$,

and $z = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$, and $h_{i,j,t} (i = 1,2,3,4,5,6, j = 1,2,3,4,5,6)$ are the elements of the conditional variance-covariance matrix H_t based on ADCC estimations. Lastly, weights for the minimum variance portfolio for each time period are given by:

$$\boldsymbol{\omega_t = \Omega_t^{-1} z}. \tag{15}$$

4.6 ARX model

The ARMA model is widely used in financial research. This research follows a model by Brockwell & Davis (1991). The ARIMA model can be expressed as

$$\boldsymbol{r_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i \, x_{t-i}}, \tag{16}$$

where p refers to the autoregressive (AR), q to the moving average (MA), and b to the exogenous input terms. r_t is the food series return at time t and r_{t-1} is the lagged value. ε_t or the error term is considered white noise, η_i are the coefficient of the exogenous variables x_{t-1}.

This thesis analyzes the monthly return series using the ARX model, which allows for omitting the moving average part,

$$\boldsymbol{r_t = \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{i=0}^{b} \eta_i \, x_{t-i} + \varepsilon_t}. \tag{17}$$

Akaike Information Criterion (AIC) is used as a penalty function statistic and further utilized to determine the optimal lag structure for the model. However, the Bayesian Information Criterion has a more substantial penalty function for model complexity. With a sample size of 231 observations, these two information criteria tend to converge toward the same model selection.

5 RESULTS AND ANALYSIS

5.1 VARX results

The model estimation strategy first explores the daily return relationships between commodities futures, the S&P 500 composite index, and wheat, corn, and rice spot prices. The VARX part of the model explores the relationships of returns, and the VIX and the GPR indexes are added to the equation as exogenous variables to see the initial impact of the uncertainty index on the assets and to keep the number of parameters lower. The VARX part of the model results are provided in Appendix I, Appendix J, and Appendix K.

The optimal lag structure for each VARX model is 16 lags, and the optimal lag is given by AIC. The optimal lag structure in this thesis is noted to be long but used in building the model as the data tells to do and to seek possible deeper relationships between commodities.

In a larger context, interpreting long VARX process results can be challenging due to the a-theoretic nature of the model, a higher number of parameters, and lower degrees of freedom. Especially the changing signs of the coefficients of the variables across the lags can cause problems when forecasting the future values of the system. This thesis does not try to attempt forecasts. Nevertheless, the selected variables seem to have statistically significant longer-lasting relationships.

5.1.1 Wheat VARX results

Appendix I shows that the impact from wheat lags is highest in the beginning and continues to decay and rise to positive until the 13^{th} trading day when the impact turns negative. The Granger causality is not strong between SPCI and wheat-lagged returns. There is a bidirectional relationship, but the effect from lagged SPCI is stronger than wheat lags, and this supports the idea of financialization of the commodity markets that the stock market is driving commodity returns. There is a consistent but weak relationship between copper futures and wheat lags. The relationship with lagged copper futures is strong and turns the results negative as the results from wheat lagged returns are primarily positive. The relationship between crude oil futures lags and wheat is not statistically strongly significant, but the sign is negative. Crude oil futures do not substantially impact wheat returns, as the economic assumption is that changes in oil prices would lead to increased commodity prices because of the changes in transportation and production costs. The impact of silver futures lags is more substantial and seems to be leading the wheat returns. Gold futures are not strongly affected by wheat spot lags. Gold one lag is affecting the returns with 5% significance by 0,1081. It can be concluded that the gold futures lagged values strongly influenced the wheat spot price. It seems that gold futures and wheat spot prices have something more going on that is not showing in the VARX model because the initial move is positive, and after six trading days, the relationship turns negative. However, this relationship is only weakly statistically significant. The initial "fear gauge" rise is affecting the wheat spot price negatively, and the geopolitical risks are not affecting significantly, but the sign is negative. The GPR contains many different styles of information about geopolitics, so it might deliver more robust results if the news focuses on fewer categories, as this GPR index dataset now consists of eight different categories.

Another interesting finding from the VARX results is that the impact of one-day lagged SPCI return Granger causes positive returns on gold futures with high statistical significance and does not support the idea that gold futures would be acting as a safe haven asset against stock market moves.

5.1.2 Corn VARX results

For the corn series, the results found in Appendix J show that the moves coming from the lagged corn spot are not strong but are positive and have statistical significance after two and three trading weeks. The lagged values of corn do not strongly affect the SPCI but have some statistical significance after ten trading days. Wheat returns are strongly and positively influenced by moves in SPCI, again indicating towards the financialization of the commodities. With copper futures and corn, the relationship does not seem to be significant, and neither is it constant. The high oil prices affecting corn prices as a substitute for energy demand are not confirmed in this model; the changes in returns do not confirm this. The relationship between silver and corn lags grows stronger later in the lags. Gold futures are Granger caused by the move in corn. The sign is changing from positive to negative and back to positive. Similarly, as did silver futures and corn, the relationship between gold lags and corn grows statistically more robust while deeper in the lags. As were the results with wheat, the corn spot price is affected by gold lags rather strongly but with weak statistical significance, and the sign changes between positive to negative during the 16 trading days. VIX has negative -0,0289 Granger causality with 1% confidence. This relationship sign is slightly negative for GPR, but the result falls out of statistical significance.

5.1.3 Rice VARX results

The rice VARX-model results can be found in Appendix K. For the rice series, the effect of own-lagged returns is not strong in statistical terms; the coefficient is positive and does not revert to the mean. Between rice lagged values and SPCI, only the later lags seem statistically significant, and the sign is negative, but the causality is weak. The relationship between rice and SPCI is significantly weaker than between wheat and corn. Lack of return dynamics can affect rice portfolio compositions more than wheat and corn portfolios when optimizing the minimum variance portfolio. Causality is not strong, but there is weak bidirectional statistical significance among copper futures and rice. Crude oil futures seem not to be Granger caused by any rice lags in statistical terms. This result was the same with corn spot, but the relationship is different with wheat spot lags and crude oil futures. The relationship between lagged crude oil futures and rice is weak compared to wheat and corn. A weakly statistically significant relationship exists between rice lagged returns and silver futures, but the effects are not drastic. Silver futures lags do not have any Granger causality over rice in terms of statistical significance. Compared to wheat and corn, this relationship between rice and gold futures lagged returns is weaker. VIX seems to be Granger causing negative moves in rice returns by -0,0126 at a 1% confidence level. This relationship is less strong than with wheat and corn. GPR has a positive initial response and indicates a positive relationship with a rise in geopolitical risk, but the result is not statistically significant.

5.2 aDCC-eGARCH model results

Tables 5, 6, and 7 show the aDCC-eGARCH model results using Equation 4. Overall, most of the results are conventional at significant levels, with the exception of rice model results. For crude oil futures, the selected model does not seem to deliver so well for modelling volatility and leverage effect. Adding the uncertainty indexes seems to have had an unwanted effect on the SPCI results. Perhaps the VIX as a measure of expected volatility could have impacted the results.

5.2.1 Wheat aDCC-eGARCH model results

From Table 5, the ω or the long-term volatility of the returns is at a 1% level for wheat spot returns, copper futures, and silver futures. For gold futures, this relationship is statistically significant. The SPCI coefficient is negative -0,0099 with 5% confidence; a negative coefficient for volatility persistence does not have a meaningful interpretation in the world of finance. This indicates that the selected model might not be the best suite for the data, or the data might have something aberrant.

Crude oil futures and silver futures show statistically significant longer-lasting effects of α or the past volatility shocks to future volatility. For crude oil futures, the negative coefficient means that when volatility clustering and time of high volatility are experienced, they are followed by lower volatility. For silver futures, this is self-reinforcing and indicates persistent volatility in the series, but the effect is low.

β is significant and high for all the series, indicating that the impact of past conditional variance on the conditional variance is strong. Furthermore, adverse shocks substantially impact volatility more than positive ones.

γ is strongly statistically significant for all the series except crude oil futures. SPCI is reported to have almost 0,1964 gamma, and wheat spot is 0,1798. Copper futures gamma is lowest at 0,0868 and is the sign of the weakest leverage effect. The impact of past standardized error terms on conditional variance is positive for every time series in the model, indicating leverage effects. The leverage effect is captured from the mean equation and allows for the asymmetric response of the mean equation to past shocks.

DCC A is reported to be highly statistically significant in each of Table 5, Table 6, and Table 7. The models and the conditional correlation at time t depend on the past conditional correlations relatively little. DCC B is high with high statistical significance and indicates that the conditional variance of each variable at time t depends highly on the own past conditional variance on every model. DCC G specifies how the conditional variance at time t depends on the past conditional variances and the past conditional correlations, but the coefficient is not statistically significant in either of the reported results.

Table 5. Wheat aDCC-eGARCH model results

Parameters 636	AIC 20.121		LL -48176.77		Avg LL -9.93	
	Wheat	S&P CI	Copper F	Crude Oil F	Silver F	Gold F
ω	0.0516	-0.0099	0.0093	0.0303	0.0218	0.0072
P-value	0.0000	0.0235	0.0000	0.2293	0.0000	0.0143
α	0.0036	-0.0029	-0.0046	-0.0791	0.0186	0.0090
P-value	0.7995	0.8130	0.5259	0.0000	0.0693	0.4363
β	0.9749	0.9801	0.9933	0.9827	0.9891	0.9881
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ	0.1798	0.1964	0.0868	0.1478	0.1244	0.0986
P-value	0.0000	0.0000	0.0000	0.5185	0.0000	0.0006
Joint estimates						
DCC A	0.0071					
P-value	0.0000					
DCC B	0.9873					
P-value	0.0000					
DCC G	0.0007					
P-value	0.2669					

Notes: This table reports the outcomes for the VARX-aDCC-eGARCH model for the wheat spot model. ω measures the long-term volatility of the returns, α is the past squared error term on the conditional variance, β is the past conditional variance, γ is the impact of past standardized error term on conditional variance, i.e., and P-value corresponds to the probability value of the result.

5.2.2 Corn aDCC-eGARCH model results

Results from Table 6 are consistent with the results in Table 5. The long-term volatility has the highest effect on corn returns with high statistical significance. The SPCI is again negative, and copper and gold coefficients are positive with high statistical significance. Longer lasting effects of past volatility shocks to future volatility are not statistically significant for corn spot. For crude oil futures, the coefficient is -0,0766, with a high probability. For silver futures, this coefficient is 0,0189 with a 5% probability. Beta and gamma results are almost as reported in Table 5.

Table 6. Corn aDCC-eGARCH model results

Parameters 636	AIC 19.609		LL -46934.33	Avg LL -9.67		
	Corn Spot	S&P CI	Copper F	Crude Oil F	Silver F	Gold F
ω	0.0434	-0.0102	0.0094	0.0303	0.0227	0.0071
P-value	0.0000	0.0208	0.0000	0.1016	0.0000	0.0123
α	-0.0002	-0.0019	-0.0053	-0.0766	0.0189	0.0078
P-value	0.9903	0.8752	0.4824	0.0000	0.0682	0.4848
β	0.9707	0.9801	0.9931	0.9827	0.9885	0.9881
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ	0.1653	0.1994	0.0905	0.1495	0.1286	0.0983
P-value	0.0000	0.0000	0.0000	0.3801	0.0000	0.0004
Joint estimates						
DCC A	0.0075					
P-value	0.0000					
DCC B	0.9866					
P-value	0.0000					
DCC G	0.0003					
P-value	0.6041					

Notes: See Table 5.

5.2.3 Rice aDCC-eGARCH model results

The long-term volatility coefficient for the rice series is not statistically significant. Other omega coefficients are similar to the results in Tables 5 and 6. Only the crude oil futures coefficient differs from other results and is 0,0303 with a low 10% probability reported in Table 7.

The impact of past squared error terms on the conditional variance for crude oil futures is -0,0768 with 1% significance, consistent with the results in Tables 5 and 6. This negative coefficient indicates that crude oil futures short-term volatility tends to decrease. Beta for rice spot, this coefficient is the lowest compared to wheat and corn. Beta is 0,9485 for rice, which is the lowest of the food staples, but still indicates a high level of persistence for the shocks or fluctuation continuation in the future. Gamma for rice is 0,1286, which is lower than wheat and corn spot, indicating a lower leverage effect.

Table 7. Rice aDCC-eGARCH model results

Parameters 636	AIC 19.08		LL -45652.7	Avg LL -9.41		
	Rice Spot	S&P CI	Copper F	Crude Oil F	Silver F	Gold F
ω	0.0386	-0.0108	0.0097	0.0303	0.0216	0.0070
P-value	0.3124	0.0243	0.0000	0.0711	0.0000	0.0343
α	0.0177	-0.0007	-0.0054	-0.0768	0.0161	0.0072
P-value	0.1871	0.9559	0.4672	0.0000	0.1134	0.5406
β	0.9485	0.9786	0.9928	0.9827	0.9892	0.9882
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ	0.1286	0.2067	0.0899	0.1489	0.1240	0.0968
P-value	0.0021	0.0000	0.0000	0.3321	0.0000	0.0090
Joint estimates						
DCC A	0.0069					
P-value	0.0000					
DCC B	0.9879					
P-value	0.0000					
DCC G	0.0005					
P-value	0.4228					

Notes: See Table 5.

5.3 The effect on correlations from having and not having exogenous variables in the model

Dynamic conditional correlations between wheat spot and other assets are shown in Figure 1. Figure 2 plots the same correlations without the exogenous variables in the system, and Figure 3 plots the difference between the time series. If the correlation in Figure 3 is negative, it means that the presence of exogenous variables reduces the correlations between assets, and if the correlation is positive, then having the exogenous variables in the system increases the correlations between assets.

Two selected events are added to the timeline as vertical dotted lines. The lines on the figures represent the dates for Lehman Brothers bankruptcy (2008-09-15) and invasion in Crimea on the eve of Russian troops taking over the Crimean parliament building (2014-02-26).

5.3.1 Wheat correlations

From Figure 1, we can observe that the correlations vary over time, mainly being positive. None of the assets have a constant negative correlation with the wheat spot series. The correlation with wheat spot is negative several times regardless of the wheat pair. There is a specific time when the correlations with wheat narrow very close to each other to 0,1 level, and this is when Crimea was occupied. As the conditional correlations vary significantly over time, corrections in the hedging positions are needed to protect the portfolio more efficiently. The lowest overall conditional correlation looks to be in the pair wheat-SPCI, and wheat-crude oil futures have the broadest range for the correlation. This finding is confirmed in the summary statistics of the correlations in Table 8.

In Figure 2, the correlations are close to the VARX-aDCC-eGARCH model. The most significant difference is between the correlation pair Wheat-SPCI. Further plotting the differences in Figure 3, we can see that the W minus W/O gives a visualization of the effects of having exogenous variables in the model. Exogenous variables seem to decrease the correlations of the wheat-SPCI, especially after the Euro crisis, when the deviations from 0 are more considerable. Other wheat-paired correlations are quite firmly inside the range of 0.1 and -0.1, as seen in Table 8.

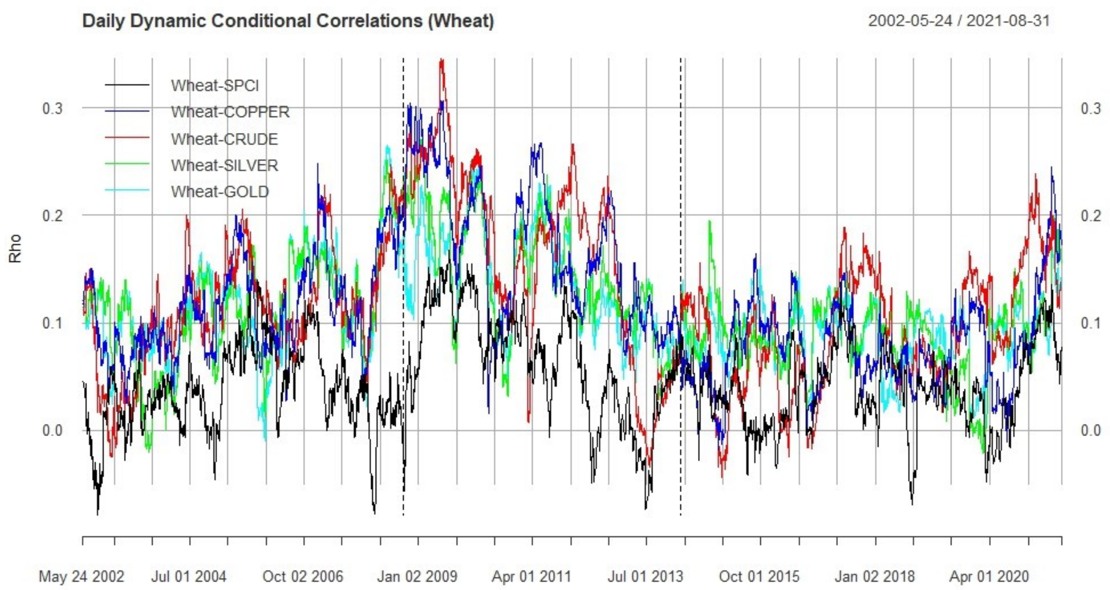


Figure 1. Daily Dynamic Conditional Correlations (Wheat)

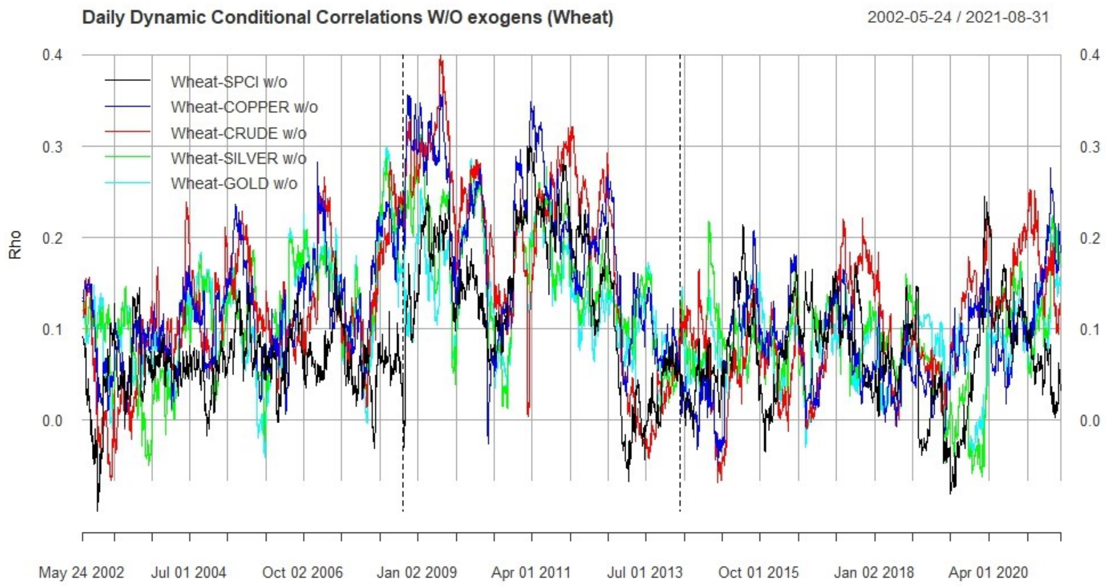


Figure 2. Daily DCC without exogenous variables (Wheat)

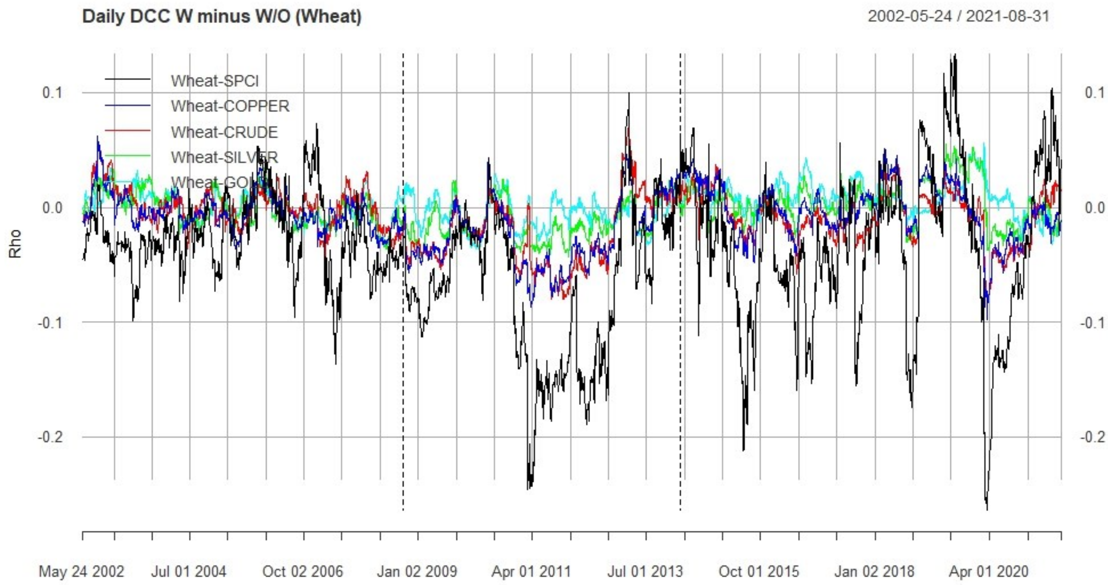


Figure 3. Daily DCC with exogenous minus without exogenous variables (Wheat)

Table 8. Summary statistics for Wheat DCC models

	Mean	SD	Maximum	Minimum
Wheat/SPCI	0.0446	0.0438	0.1675	-0.0785
Wheat/Copper	0.1159	0.0632	0.3068	-0.0182
Wheat/Crude Oil	0.1201	0.0719	0.3460	-0.0432
Wheat/Silver	0.1123	0.0525	0.2709	-0.0251

Wheat/Gold	0.1102	0.0480	0.2648	-0.0097
	Wheat DCC w/o			
	Mean	SD	Maximum	Minimum
Wheat/SPCI	0.0868	0.0689	0.2998	-0.1071
Wheat/Copper	0.1250	0.0809	0.3567	-0.0513
Wheat/Crude Oil	0.1294	0.0882	0.4002	-0.0705
Wheat/Silver	0.1145	0.0675	0.3129	-0.0602
Wheat/Gold	0.1080	0.0603	0.2991	-0.0535
	Wheat DCC w minus w/o			
	Mean	SD	Maximum	Minimum
Wheat/SPCI	-0.0422	0.0628	0.1340	-0.2640
Wheat/Copper	-0.0091	0.0253	0.0618	-0.1012
Wheat/Crude Oil	-0.0093	0.0250	0.0696	-0.0850
Wheat/Silver	-0.0022	0.0181	0.0553	-0.0457
Wheat/Gold	0.0022	0.0153	0.0564	-0.0381

Notes: This table reports the summary statistics of conditional correlations obtained from the VARX-aDCC-eGARCH model and the VAR-aDCC-eGARCH model and the subtraction of the models.

5.3.2 Corn correlations

Figures 4, 5, and 6 plot the conditional correlations of the corn spot paired assets. In Figure 4, the corn-SPCI pair has the lowest correlations again, and the correlation is often negative, and this negative correlation is persistent before the selected events. This relatively steady negative correlation could give some information about how investors are anticipating more significant market movements or geopolitical changes that are about to happen. After the event, there is some relief or rise in covariances where the correlation increases again. COVID-19 seems to have briefly affected the correlation pairs corn-silver futures, corn-copper futures, and corn-crude oil futures in the Spring of 2020. However, in Figure 5, which contains no exogenous variables, an increased correlation of the corn-SPCI pair can be seen at the start of the COVID-19 period.

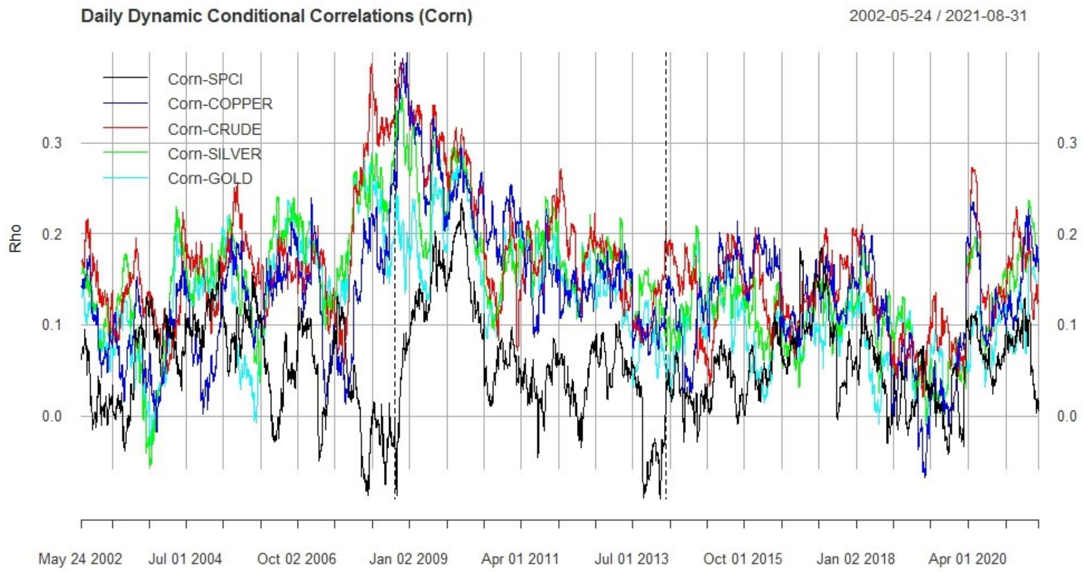


Figure 4. Daily Dynamic Conditional Correlations (Corn)

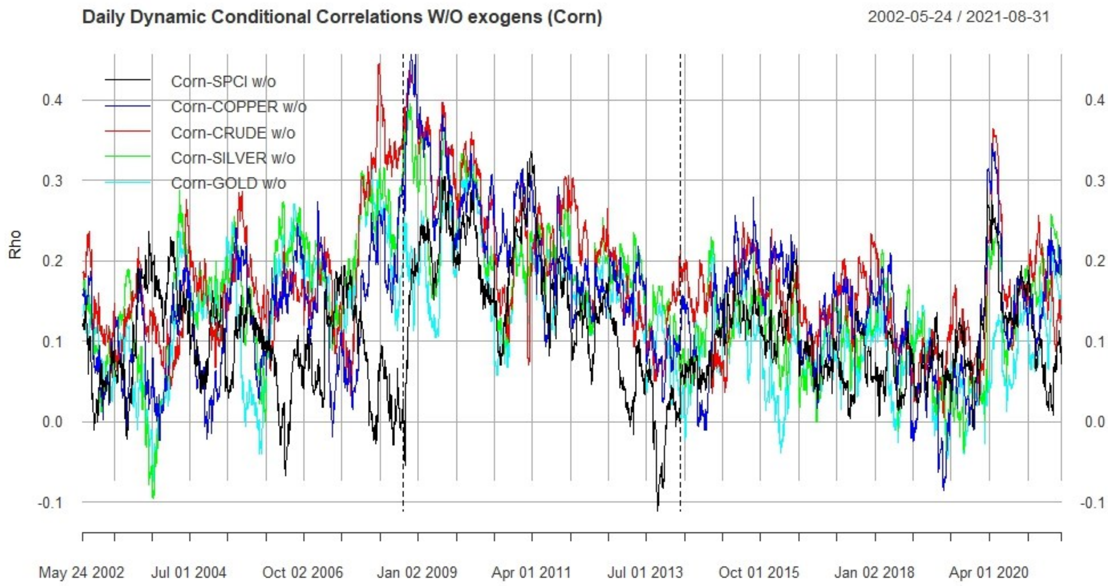


Figure 5. Daily DCC without exogenous variables (Corn)

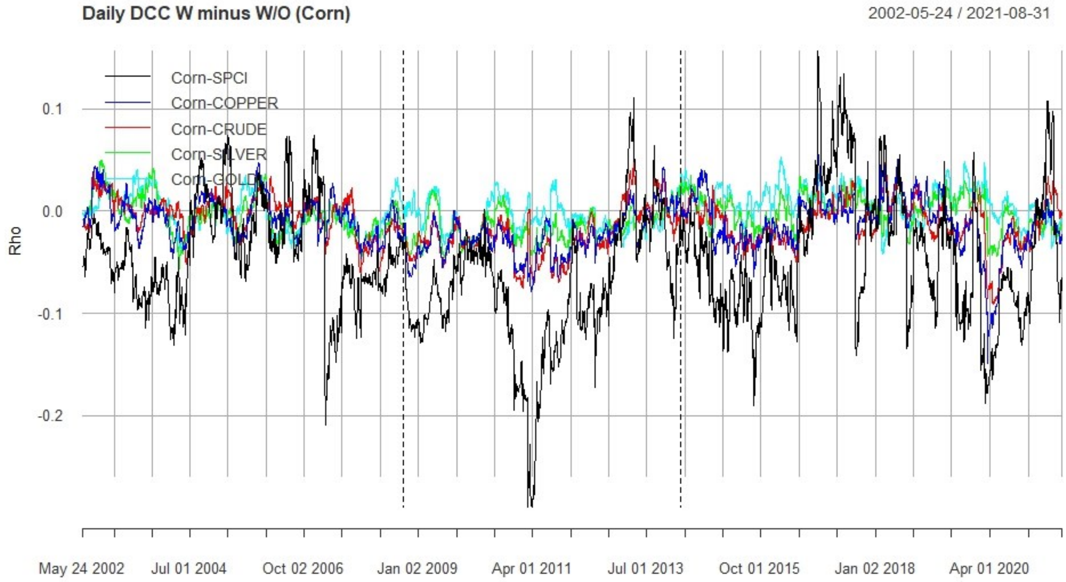


Figure 6. Daily DCC with exogenous minus without exogenous variables (Corn)

Figure 6 plots the differences between having the exogenous variables in the model. Exogenous variables in the model seem to affect the correlation pair corn-SPCI, but the differences are not as significant as in Figure 3.

March 16, 2011, was the event of the Fukushima nuclear meltdown in Japan, and the correlation difference in corn aDCC w minus w/o shows a steep negative correlation of the corn-SPCI pair. The difference comes from the correlation going up in the basic VAR model. Either the VIX, geopolitical risk, or they jointly impacted the correlation.

Looking at the corn DCC w minus w/o results in Table 9, we can see negative means in all the other series than the corn-gold futures pair. The value indicates slightly stronger correlations when the exogenous variables are included in the model. Also, the standard deviation is the smallest for corn-gold futures, meaning that the overall correlation differences are the smallest. This result is in line with the VARX model parameters, as gold futures are unaffected by the VIX index changes or geopolitical risks.

Table 9. Summary statistics for Wheat DCC models

Summary statistics	Corn aDCC			
	Mean	SD	Maximum	Minimum
Corn/SPCI	0.0571	0.0541	0.2390	-0.0909
Corn/Copper	0.1370	0.0722	0.3990	-0.0675
Corn/Crude Oil	0.1645	0.0706	0.3905	0.0207
Corn/Silver	0.1486	0.0666	0.3528	-0.0545
Corn/Gold	0.1235	0.0617	0.2988	-0.0323
	Corn aDCC w/o			

	Mean	SD	Maximum	Minimum
Corn/SPCI	0.1083	0.0708	0.3353	-0.0960
Corn/Copper	0.1503	0.0882	0.4563	-0.0863
Corn/Crude Oil	0.1768	0.0837	0.4455	-0.0285
Corn/Silver	0.1543	0.0810	0.3953	-0.1144
Corn/Gold	0.1225	0.0754	0.3337	-0.0861
	Corn aDCC w minus w/o			
	Mean	SD	Maximum	Minimum
Corn/SPCI	-0.0512	0.0622	0.1566	-0.3045
Corn/Copper	-0.0133	0.0250	0.0596	-0.1745
Corn/Crude Oil	-0.0123	0.0232	0.0556	-0.1110
Corn/Silver	-0.0057	0.0184	0.0497	-0.0596
Corn/Gold	0.0011	0.0181	0.0532	-0.0609

Notes: This table reports the summary statistics of conditional correlations obtained from the VARX-aDCC-eGARCH model and the VAR-aDCC-eGARCH model and the subtraction of the models.

5.3.3 Rice correlations

Figures 7, 8, and 9 plot the rice conditional correlation pairs with and without the exogenous variables in the system, and the last plot shows the changes between the two models. Figure 7 plots the paired conditional correlations for rice. The rice-SPCI pair correlation is behaving differently from wheat and corn. In Figure 7, ex-ante the GFC, the correlation of the pair is often negative. Figure 8 shows that the correlation pair is mainly positive during the same period. From Figure 9 ex-post GFC, the mean correlation of the rice-SPCI pair is lower and at the lowest when the Fukushima event in Japan happened. Furthermore, the correlation difference is 0.2 on two occasions ex-post Crimea and a few other times close to 0.2 and repeatedly positive, indicating that having exogenous variables in the system increases correlation. A few times, the difference between correlations reached -0,1 during the year 2015 and the end of summer 2021.

Figures 7 and 8 show that the rice-silver and rice-gold futures pairs relationship changed after 2015, and the correlation is repeatedly lower and negative. Rice-copper and rice-crude oil futures pairs are not behaving much differently from each other. In Figure 9, after the event in Crimea, the rice-SPCI correlation is negative and different from the other series; as in Figure 7, all of the correlation pairs narrow together close to 0.1.

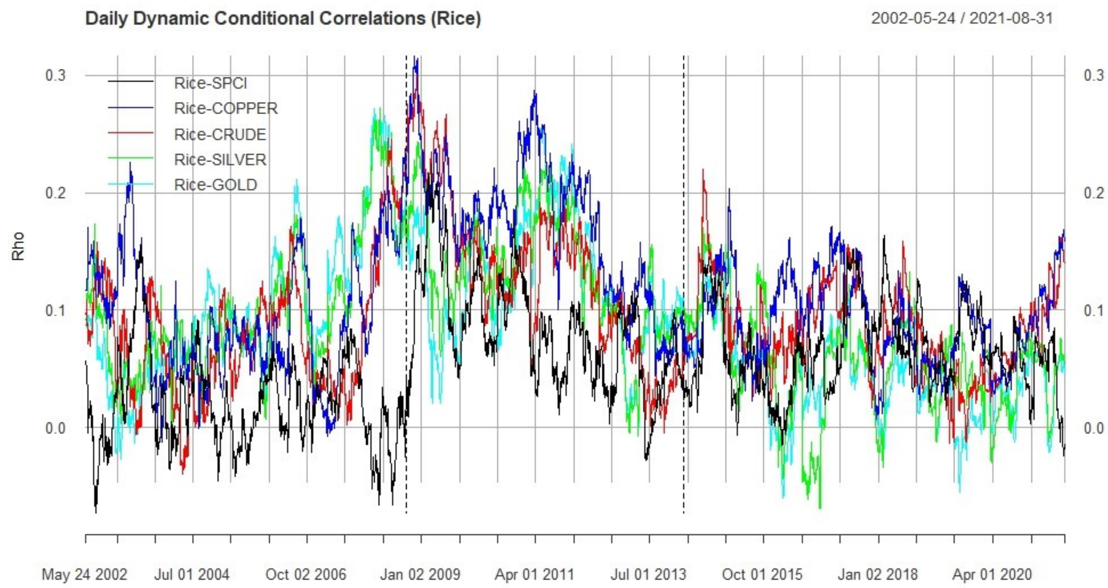


Figure 7. Daily Dynamic Conditional Correlations (Rice)

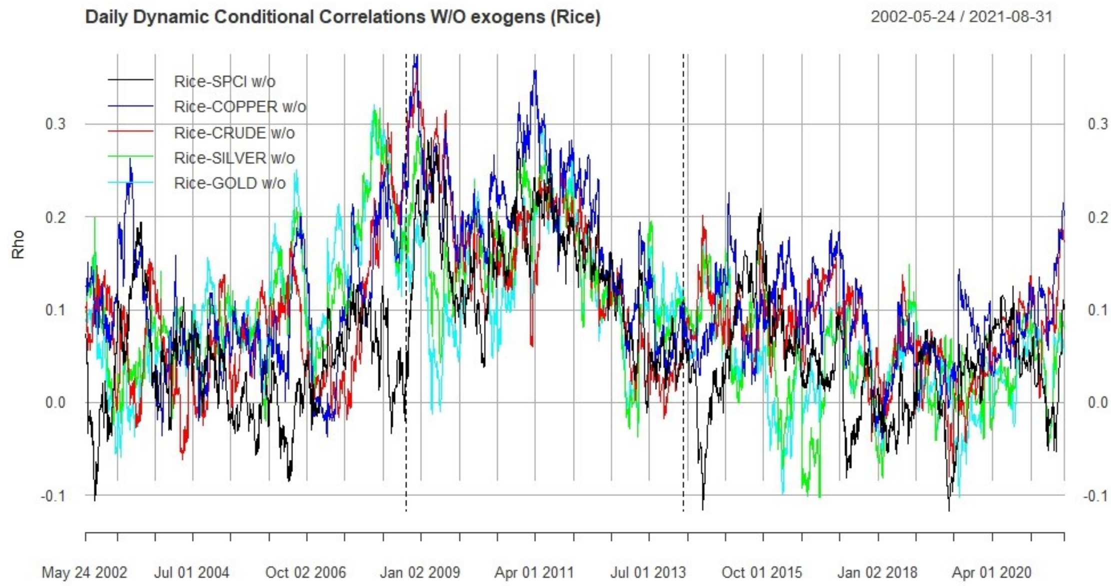


Figure 8. Daily Dynamic Conditional Correlations without exogenous (Rice)

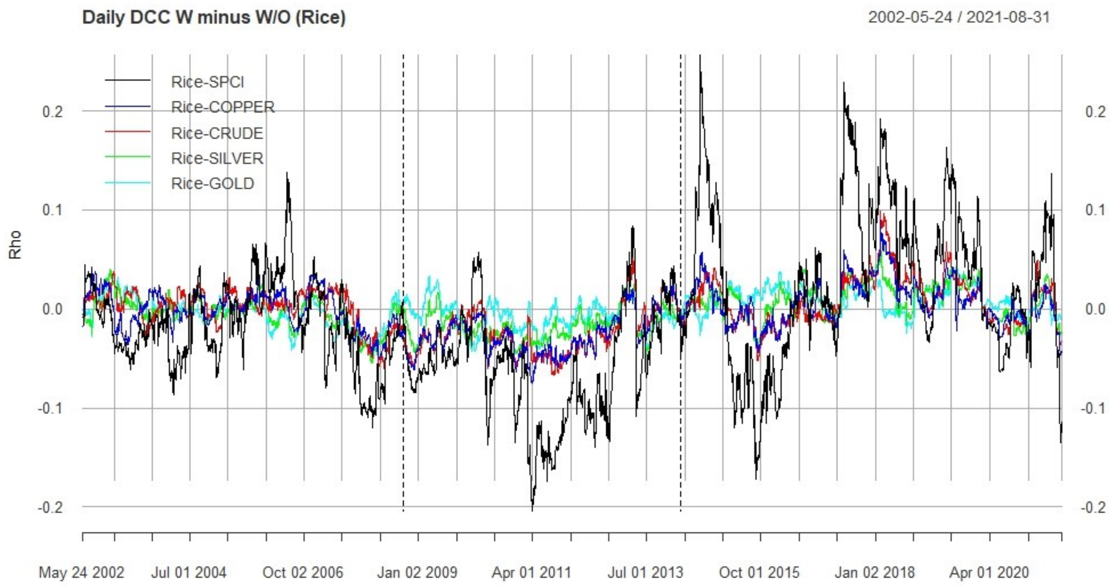


Figure 9. Daily DCC with exogenous minus without exogenous variables (Rice)

From Figure 9, it can be concluded that having the exogenous variables in the system positively affected the correlations of the selected series, but there seems to have been a regime shift among the rice correlation pairs after the event in Crimea. The most significant change is in the correlation pair rice-SPCI, which behaves differently from wheat-SPCI and corn-SPCI pairs. When looking at the summary statistics of the correlations in Table 10, it can be further concluded that the standard deviation in the rice-SPCI series containing the exogenous variables brings consistency for all the pairs except the rice-gold series, which is almost unaffected by the presence of the exogenous variables.

Table 10. Summary statistics for Wheat DCC models

Summary statistics	Rice DCC			
	Mean	SD	Maximum	Minimum
Rice/SPCI	0.0551	0.0477	0.2249	-0.0724
Rice/Copper	0.1151	0.0612	0.3162	-0.0118
Rice/Crude Oil	0.0955	0.0582	0.3070	-0.0398
Rice/Silver	0.0916	0.0609	0.2713	-0.0686
Rice/Gold	0.0864	0.0624	0.2727	-0.0602
	Rice DCC w/o			
	Mean	SD	Maximum	Minimum
Rice/SPCI	0.0660	0.0753	0.2855	-0.1318
Rice/Copper	0.1200	0.0806	0.3750	-0.0469
Rice/Crude Oil	0.0984	0.0756	0.3652	-0.0726
Rice/Silver	0.0944	0.0773	0.3171	-0.1348
Rice/Gold	0.0863	0.0759	0.3202	-0.1299

Rice DCC w minus w/o

	Mean	SD	Maximum	Minimum
Rice/SPCI	-0.0108	0.0717	0.2569	-0.2326
Rice/Copper	-0.0049	0.0250	0.0900	-0.0937
Rice/Crude Oil	-0.0029	0.0265	0.0990	-0.0913
Rice/Silver	-0.0027	0.0196	0.0647	-0.0642
Rice/Gold	0.0001	0.0163	0.0472	-0.0635

Notes: This table reports the summary statistics of conditional correlations obtained from the VARX-aDCC-eGARCH model and the VAR-aDCC-eGARCH model and the subtraction of the models.

Overall, the food staples share similarities with correlations with SPCI, but differences remain. Before the occupation of Crimea, the correlation between corn and SPCI behaved differently from wheat and rice. This can be because Ukraine and Russia are big wheat exporters for the whole world, and the dispute would affect food prices significantly, and there would be increased demand for corn as a substitute.

5.4 Optimal hedge ratio and hedging effectiveness.

With the results from the DCC analysis, the optimal hedge ratio can be calculated by using the formula:

$$\boldsymbol{\beta_t = \frac{h_t^{sf}}{h_t^{ff}},} \tag{9}$$

This optimal hedge ratio is further processed into hedging effectiveness by using the formula:

$$\boldsymbol{TVHE_t = \beta_t^2 \frac{h_t^{ff}}{h_t^{ss}},} \tag{10}$$

Hedge ratios and hedging effectiveness results for the VARX and VAR models are presented in Tables 11, 12, and 13. Decreased mean hedge ratios are reported for every correlation pair in every table except for the wheat-gold futures pair. However, this increased hedge ratio in the wheat-gold futures pair does not lead to an increase in mean hedging effectiveness. Wheat variance is either increased in the non-exogenous model, or the presence of exogenous variables in the system lowers the variance of the wheat spot.

5.4.1 Wheat hedge ratio and hedging effectiveness

Figure 10 plots the daily hedge ratio for the wheat-paired assets with the exogenous variables in the system. From here, it is seeable that the daily hedge ratio for wheat-SPCI varies from profoundly negative values to profoundly positive values. The wheat-gold futures pair also receives high values; the mean values are the highest among the pairs. As can be noted from Table 11, the mean values are positive. Figure 11 plots the wheat-paired assets without the exogenous variables. Wheat-SPCI has the most prominent standard deviations, but wheat-silver futures are the least affected pair. Earthquake events in Fukushima seem to be causing wheat-copper differences between the models in March 2011. The most significant difference between the wheat-gold pairs is around the Haiti earthquake in January 2010. The wheat-silver pair difference is at its largest gap at the beginning of January 2009 when Israel attacked the Gaza Strip, and another large gap happened in August 2011 when the crackdown in Syria started.

Table 11. Wheat Average Hedge Ratio and Hedging Effectiveness

N=4852	Hedge Ratio	Hedging Effectiveness
Wheat-SPCI	0.1846	0.0039
Wheat-COPPER	0.1801	0.0174
Wheat-CRUDE	0.1454	0.0196
Wheat-SILVER	0.1478	0.0154
Wheat-GOLD	0.2544	0.0144
Wheat-SPCI w/o	0.2384	0.0067
Wheat-COPPER w/o	0.1877	0.0208
Wheat-CRUDE w/o	0.1542	0.0236
Wheat-SILVER w/o	0.1485	0.0173
Wheat-GOLD w/o	0.2500	0.0152

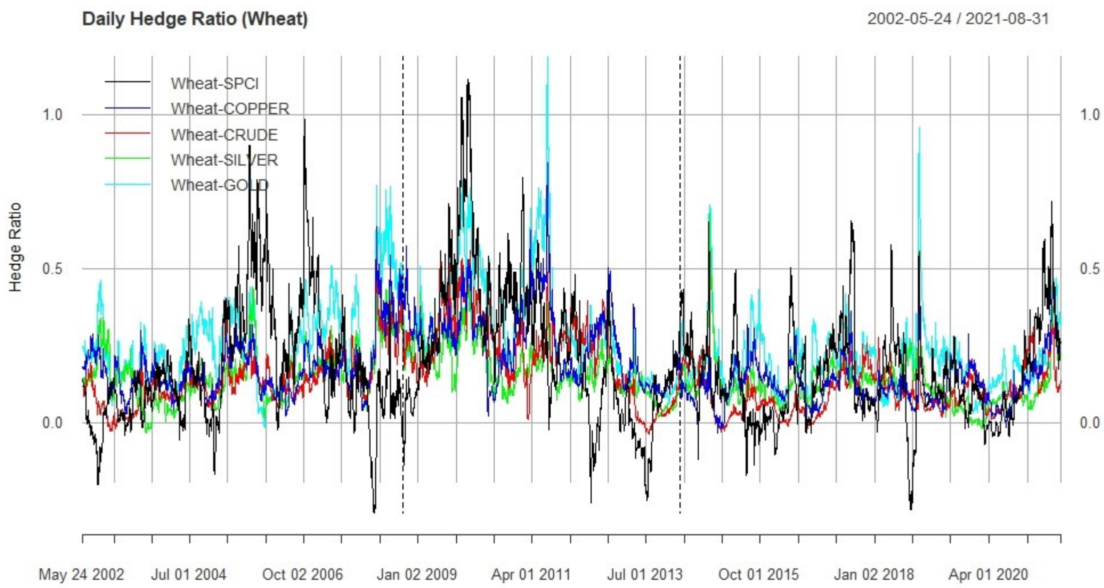


Figure 10. Hedge Ratio (Wheat)

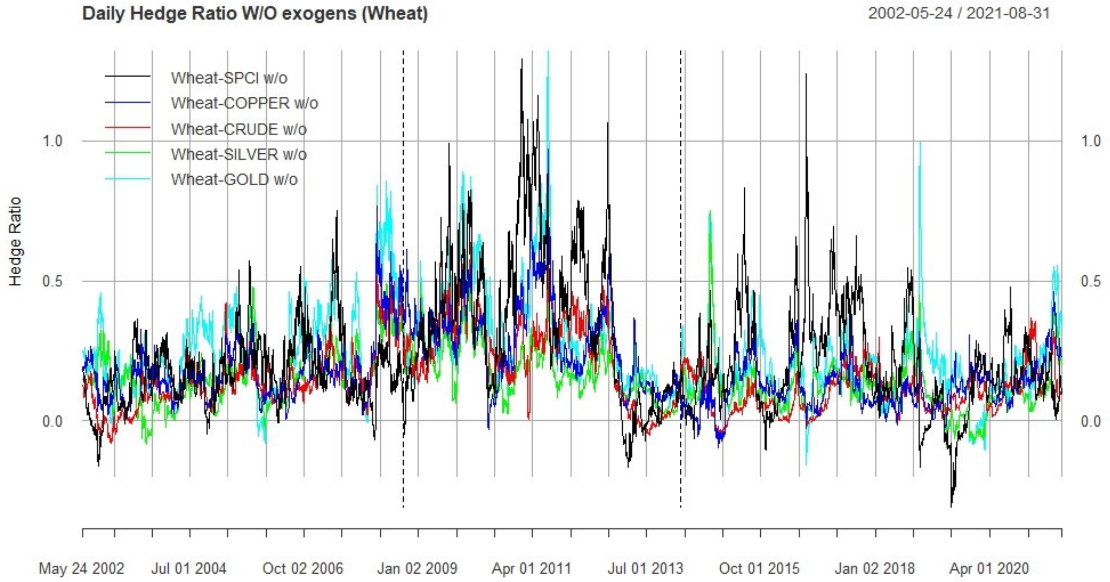


Figure 11. Hedge Ratio without exogenous variables (Wheat)

The hedging effectiveness of the assets suffers when the exogenous variables are added to the system. Only the wheat-gold futures pair hedge ratio is improved, but does not increase the hedging ratio mean. Hedging effectiveness ratios are plotted for the wheat pairs in Figure 12 and Figure 13. Wheat-crude oil and wheat-copper futures pairs seem to have the highest hedging effectiveness in both plots, confirmed in Table 11. The wheat-SPCI pair has only a few occurrences where the hedging effectiveness has been higher in Figure 12 than in Figure 13. Those are 2005-2006, 2014, and 2021; more often, the inclusion of the exogenous variables in the system seems to be decreasing hedging effectiveness.

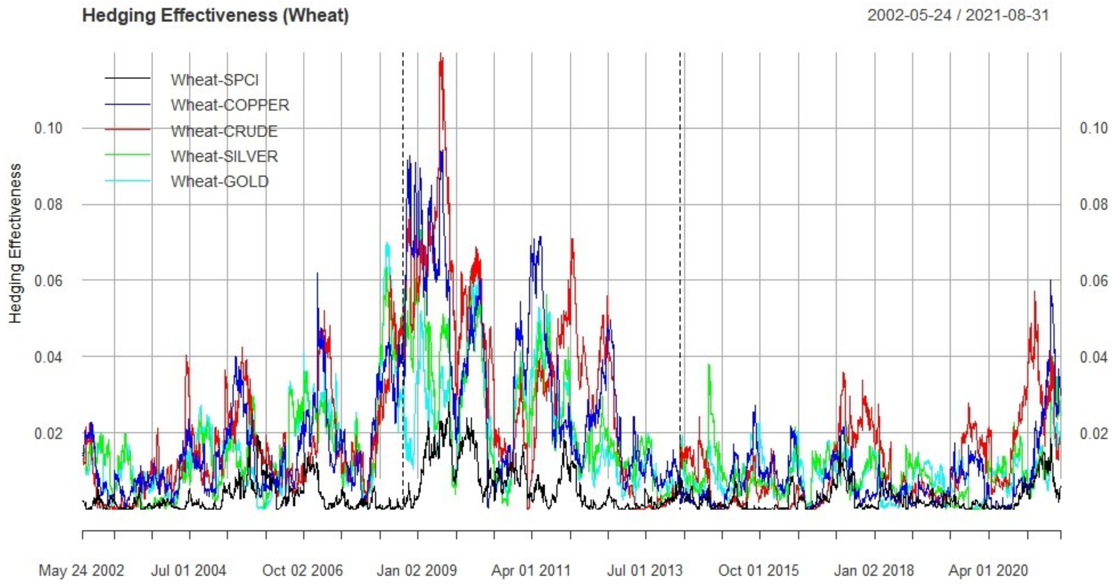


Figure 12. Hedging Effectiveness (Wheat)

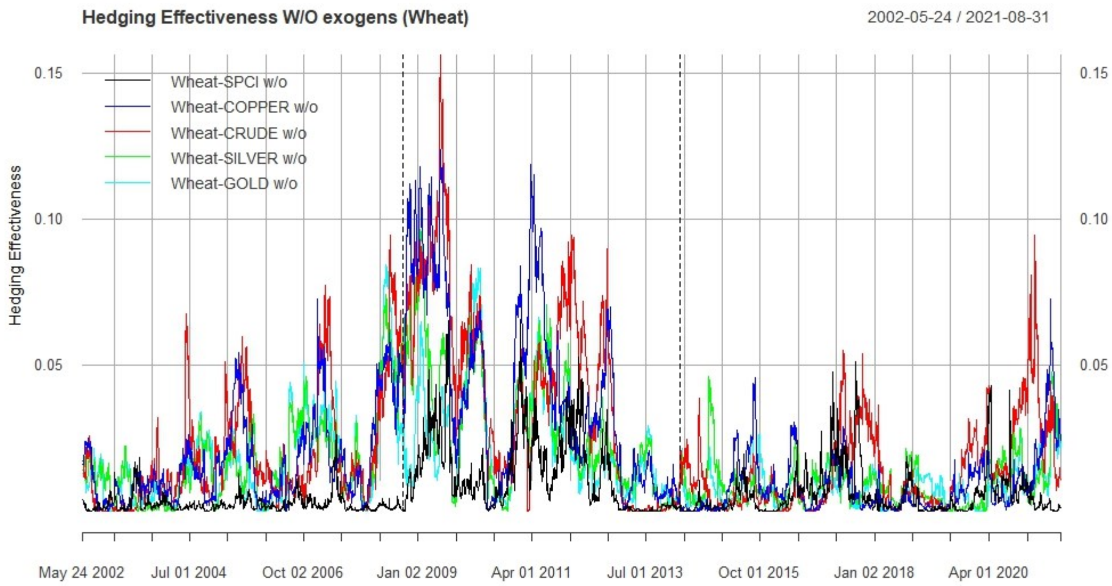


Figure 13. Hedging Effectiveness without exogenous variables (Wheat)

5.4.2 Corn hedge ratio and hedging effectiveness

Corn-paired hedge ratios are reported in Table 12. The results are similar to the results in Table 11. The corn-gold futures pair has increased the average hedge ratio, but it does not lead to increased hedging effectiveness. Corn-SPCI w/o has the highest average hedge ratio, but the hedging effectiveness is the best for the corn-CRUDE w/o pair.

Table 12. Corn Average Hedge Ratio and Hedging Effectiveness

N=4852	Hedge Ratio	Hedging Effectiveness
Corn-SPCI	0.1785	0.0062
Corn-COPPER	0.1634	0.0240
Corn-CRUDE	0.1513	0.0320
Corn-SILVER	0.1493	0.0265
Corn-GOLD	0.2208	0.0191
Corn-SPCI w/o	0.2301	0.0167
Corn-COPPER w/o	0.1749	0.0304
Corn-CRUDE w/o	0.1609	0.0383
Corn-SILVER w/o	0.1535	0.0304
Corn-GOLD w/o	0.2202	0.0207

Notes: This table reports the average hedge ratio and hedging effectiveness for VARX-aDCC-eGARCH and VAR-aDCC-eGARCH models.

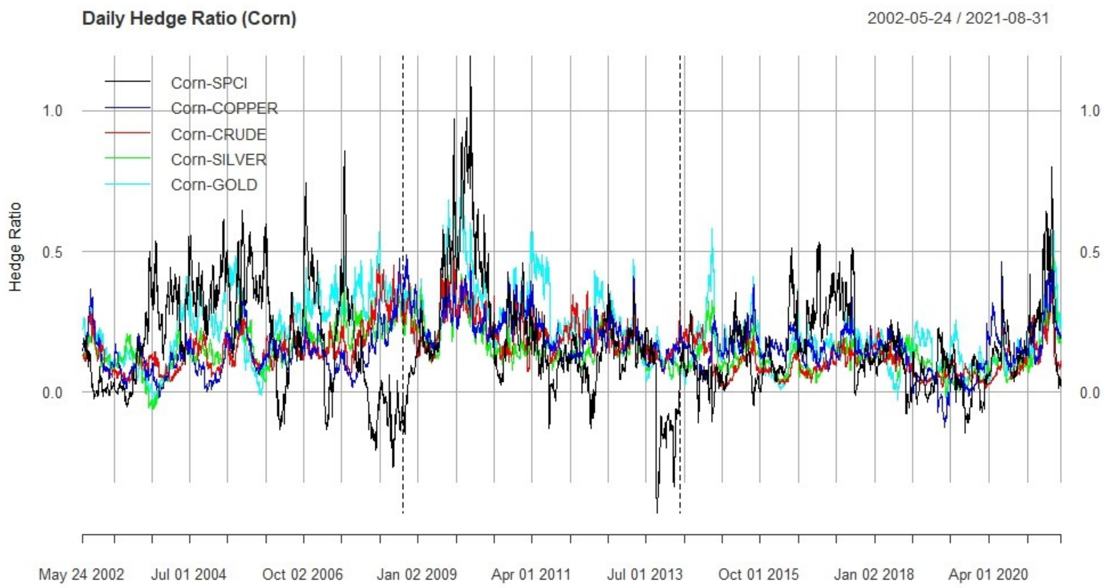


Figure 14. Hedge Ratio (Corn)

Figures 14 and 15 shows the different models, and from here, it is visible that corn-SPCI pairs in both plots have the highest variance in the hedge ratio. The corn-gold futures hedge ratio increases every now and then and reverts to the mean. Corn-gold futures w/o decreases often to briefly negative after the event in Crimea, and the mean is lower than after the event of the GFC.

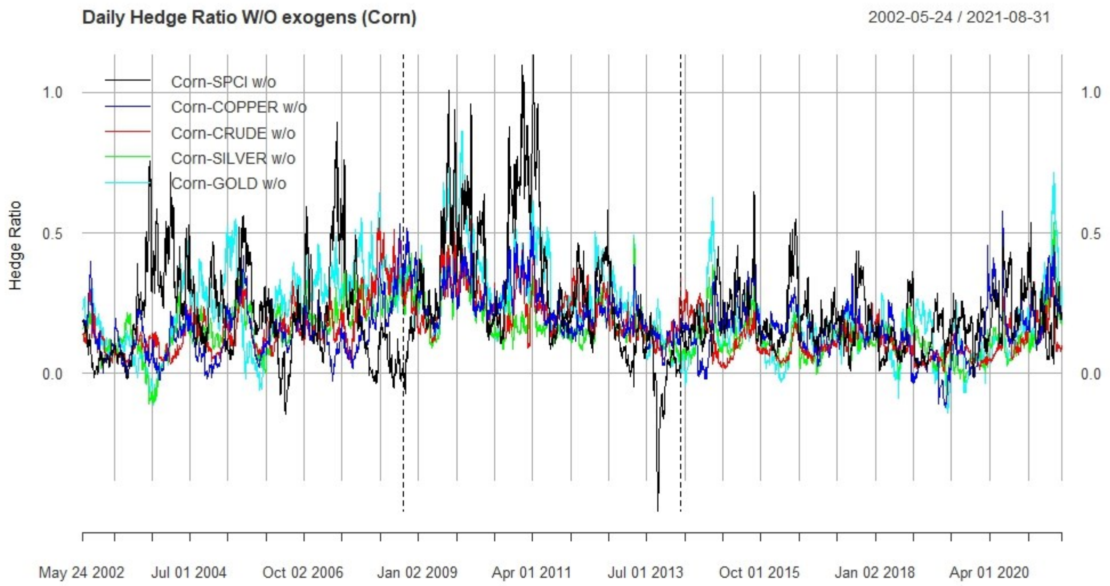


Figure 15. Hedge Ratio without exogenous variables (Corn)

Figures 16 and 17 plot the hedging effectiveness for corn pairs. Crude oil futures seem to be the most effective in hedging for corn spot. Copper, crude oil, and silver futures appear to be working as hedge assets for corn. Corn-SPCI peaks are shorter than corn-SPCI w/o. Around 2019, it looks to be a lengthy period when none of the selected assets have increased hedging effectiveness. COVID-19 marks a higher peak hedging effectiveness in the Spring of 2020, but gold futures do not seem very effective in hedging during that time. Also, during COVID-19, the corn-SPCI pairs behave differently, as the model with exogenous variables has lower highs. The most significant negative difference between corn-copper futures hedging effectiveness is around the second week of March 2020, and the biggest positive difference is 1st April 2013, a day after North Korea declared that it was in a state of war with South Korea.

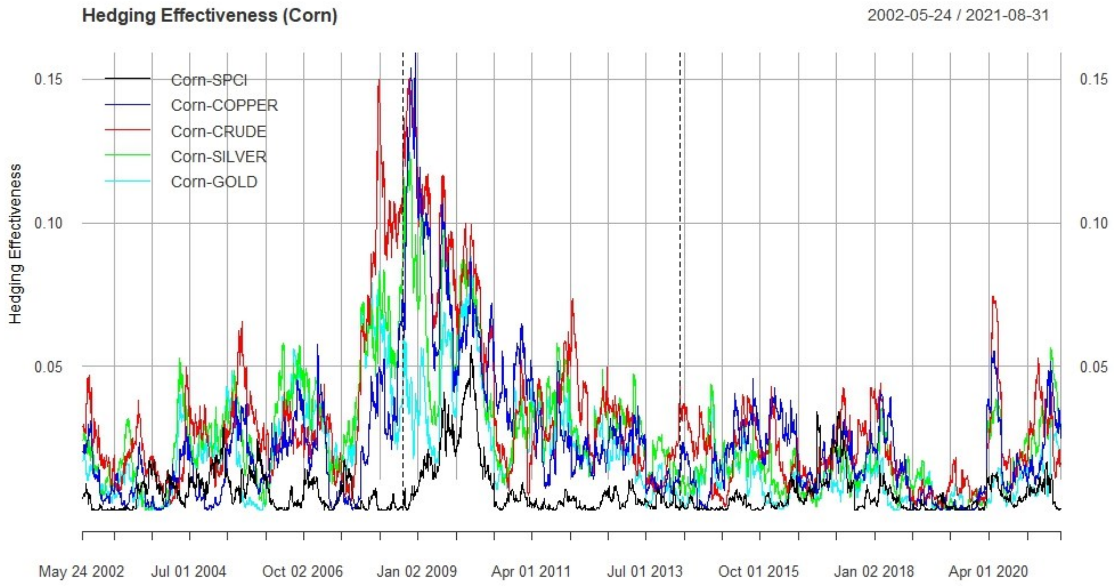


Figure 16. Hedging Effectiveness (Corn)

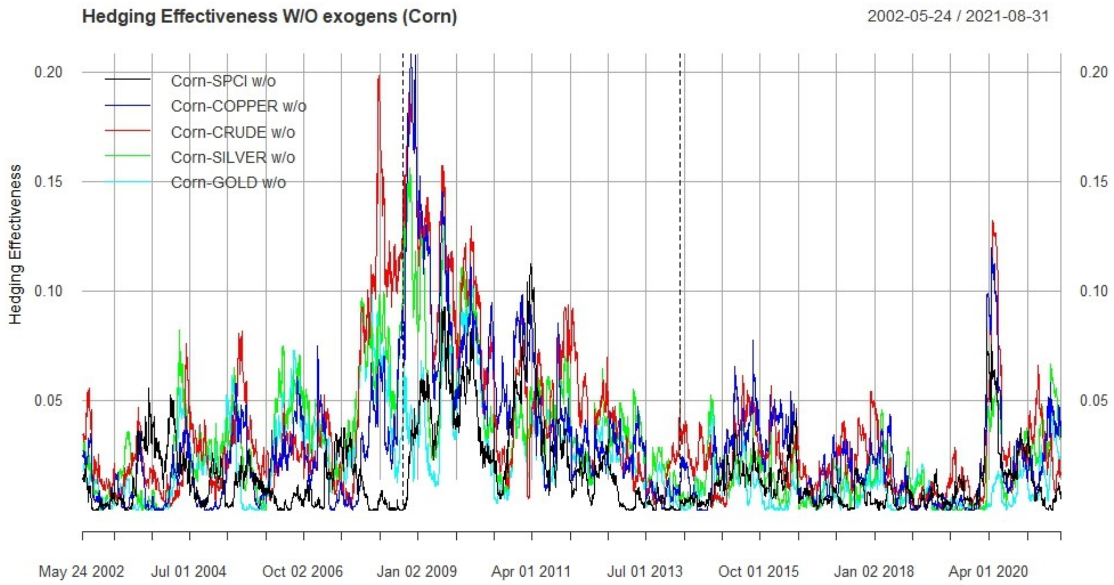


Figure 17. Hedging Effectiveness without exogenous variables (Corn)

5.4.3 Rice hedge ratio and hedging effectiveness

The results in Table 13 are different than in Tables 11 and 12. Rice-SPCI hedge ratio increases, but it does not increase the hedging effectiveness. Average hedge ratios are not much affected by the presence of exogenous variables in the system. The results in Table 13 show a difference in the hedging effectiveness of the financial assets compared to the wheat and corn pairs without the exogenous variables. Overall, the hedging effectiveness is low. 10% effectiveness would mean that the portfolio's variance would be reduced by the hedge. The perfect hedging effectiveness would be 1.

Financialization of commodity markets may well be an essential factor in affecting the hedging ratios for wheat and corn, and the uncertainties coming from Western financial markets are not affecting rice pairs. For rice, other explaining factors might be affecting the correlations among the financial assets. Perhaps the rice prices are heavily regulated by government entities. According to USDA Foreign Agricultural Service (2023), the top rice-producing countries, China and India, aggregated over 50% of the world's rice production. These two countries have high populations, and food price stability would be a key feature in maintaining social stability. This thesis leaves the Chinese and Indian stock markets out of the model and could be a factor affecting the rice price.

Table 13. Rice Average Hedge Ratio and Hedging Effectiveness

N=4852	Hedge Ratio	Hedging Effectiveness
Rice-SPCI	0.1175	0.0053
Rice-COPPER	0.1061	0.0170
Rice-CRUDE	0.0650	0.0125
Rice-SILVER	0.0673	0.0121
Rice-GOLD	0.1116	0.0114
Rice-SPCI w/o	0.0960	0.0100
Rice-COPPER w/o	0.1063	0.0209
Rice-CRUDE w/o	0.0659	0.0154
Rice-SILVER w/o	0.0676	0.0149
Rice-GOLD w/o	0.1107	0.0132

Notes: This table reports the average hedge ratio and hedging effectiveness for VARX-aDCC-eGARCH and VAR-aDCC-eGARCH models.

From Figure 18, it is visible that optimal hedge ratios change after the bankruptcy news of Lehman Brothers. The hedge ratio mean increased, and the rice-SPCI hedge ratio remained elevated afterward. The first positive difference between rice-SPCI models was seen in mid-late August 2014 when WHO reported more Ebola outbreaks. The largest positive difference was recorded after the Dow Jones index selloff of 4.6% on the 5th of February 2018.

Figure 19 shows that the hedge ratio behavior for rice-SPCI changes after the event in Crimea. The hedge ratios plunge to negative often instead of increasing.

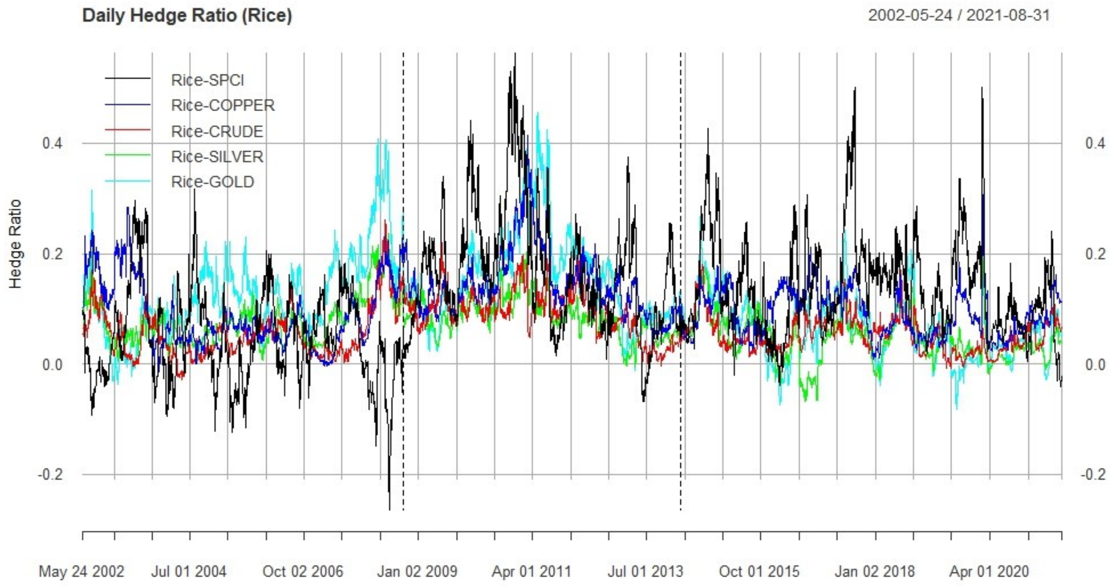


Figure 18. Hedge Ratio (Rice)

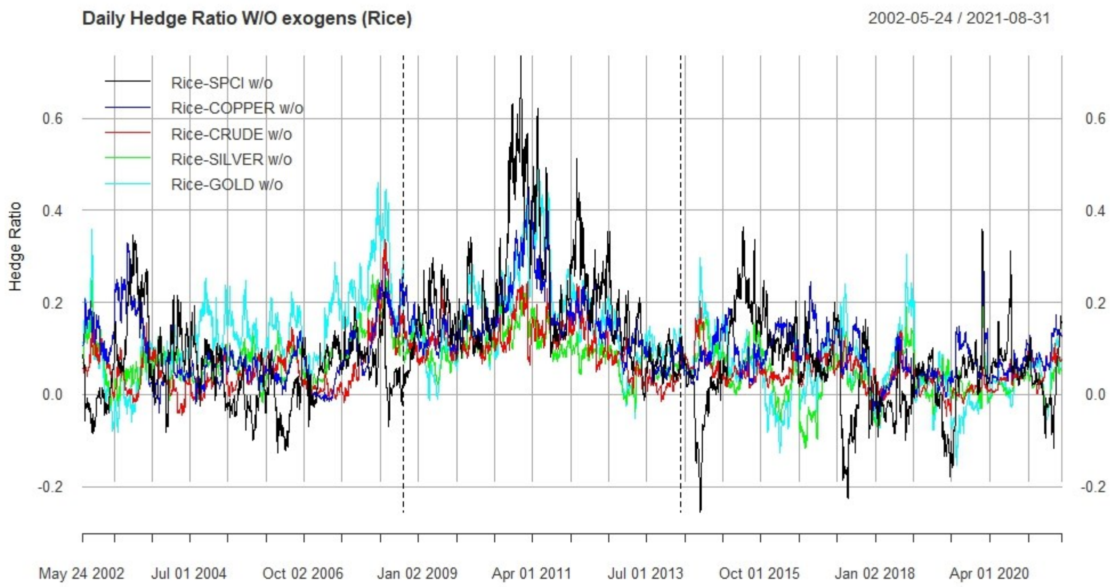


Figure 19. Hedge Ratio without exogenous variables (Rice)

Figures 20 and 21 continue the story of rice hedging effectiveness. Crude oil, copper, silver, and sometimes gold bring effective hedging. Rice-SPCI's increased hedging effectiveness is now visible, and this increased efficiency seems to be better after the event in Crimea. The peaks are not sizeable for rice pairs after the event in Crimea and the aftermath of the Euro debt crisis.

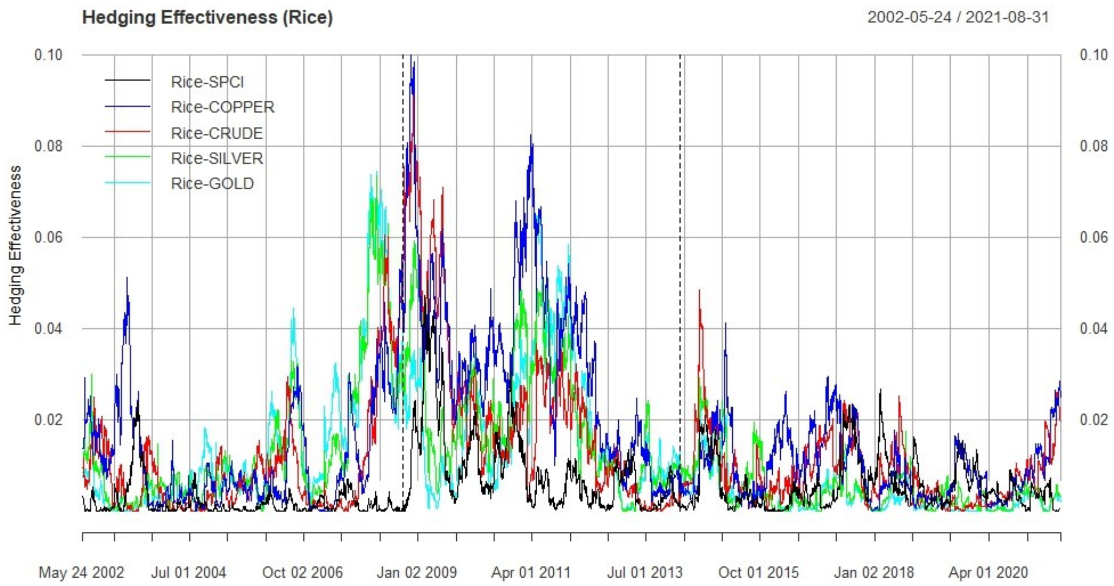


Figure 20. Hedging Effectiveness (Rice)

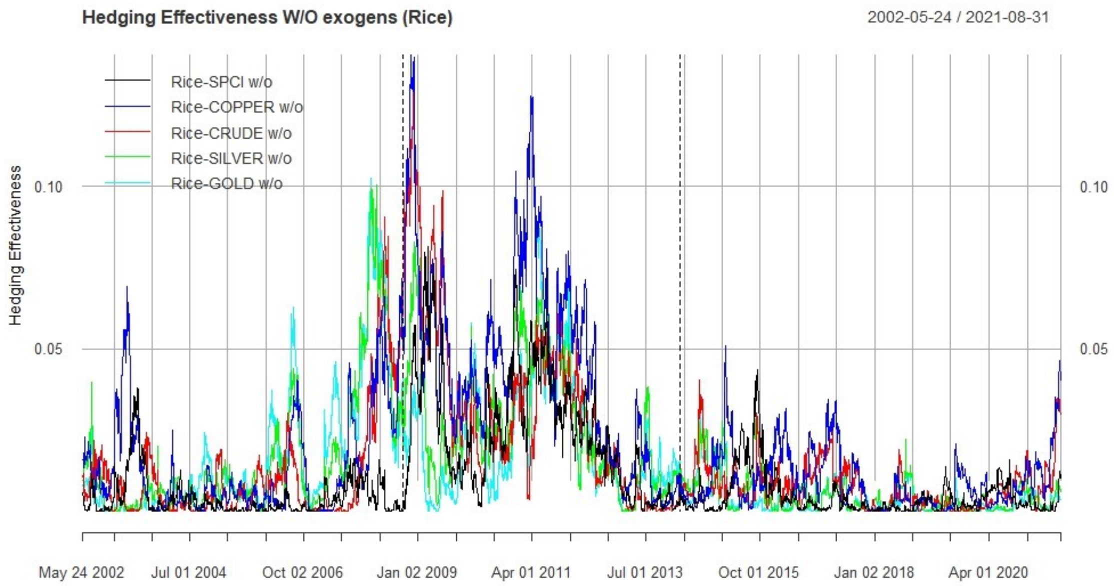


Figure 21. Hedging Effectiveness without exogenous variables (Rice)

5.5 Minimum variance portfolios

Risk-aversive investors seek to create diversified portfolios with assets that have low or negative correlations. A diversified portfolio can help spread the risk and minimize the variance of the portfolio. Time-varying minimum variance portfolios are constructed by using Formulas 11-15. The weight of an individual asset can be either positive or negative, but the sum of weights must be equal to one for every t to meet the second portfolio constraint. Because the one-day optimal portfolio varies a lot, the minimum variance portfolios were formed with 21-day rolling average weights. Three portfolios are constructed for each of the food staples. This portfolio construction will reveal the changes in risks as the optimal asset weights will evolve.

5.5.1 Wheat minimum variance portfolio

The portfolio contains the weights for wheat spot, S&P CI, copper futures, crude oil futures, silver futures, and gold futures. Table 14 gives the mean portfolio weights for three different periods. The SPCI weights in the first and last periods are considerable. In the first period, the weight of SPCI exceeded one, meaning that silver and copper futures needed to be sold short. In the second period, the SPCI average weight in the portfolio was 30%, and the weight was mainly replaced by copper futures and wheat longs.

Wheat is another asset among SPCI that had a positive mean weight in every period. Wheat spot average weight was 13.5%, the highest in the second period. Copper futures were to be shorted in the first period, and in the second period, it took the position from the SPCI; the mean weight was 41%, and the mean weight was reduced to 7.5% in the third measuring period. Crude oil futures had a 25% mean weight in the first period and were to be shorted for the second and third periods. Silver futures were shorted in the first period with an average weight of -60%; in the second period, the weight was -1.5%; in the third period, the short was reversed to long 7%. Gold futures average weight was 20% and 22% in the first and second periods and turned into a short position of -14% of the weight. During all the periods, gold had brief but deep short positions. Figure 22 plots the optimal weight for each asset for the minimum variance portfolio. From here, it is visible that the gold futures position is to be shorted during every period. Also, copper futures were to be shorted, especially at the end of the summer of 2011.

Table 14. Wheat Minimum Variance Portfolio Weights During Different Periods

Period	Wheat	S&P CI	Copper	Crude Oil	Silver	Gold
I	0.0547	1.1513	-0.0664	0.2482	-0.5938	0.2060
II	0.1347	0.3000	0.4132	-0.0485	-0.0167	0.2173
III	0.0259	0.9921	0.0758	-0.0230	0.0719	-0.1426

Note: Selected periods I: 24/05/2002-15/09/2008;
II: 16/09/2008-26/02/2014; III: 27/02/2014-31/08/2021

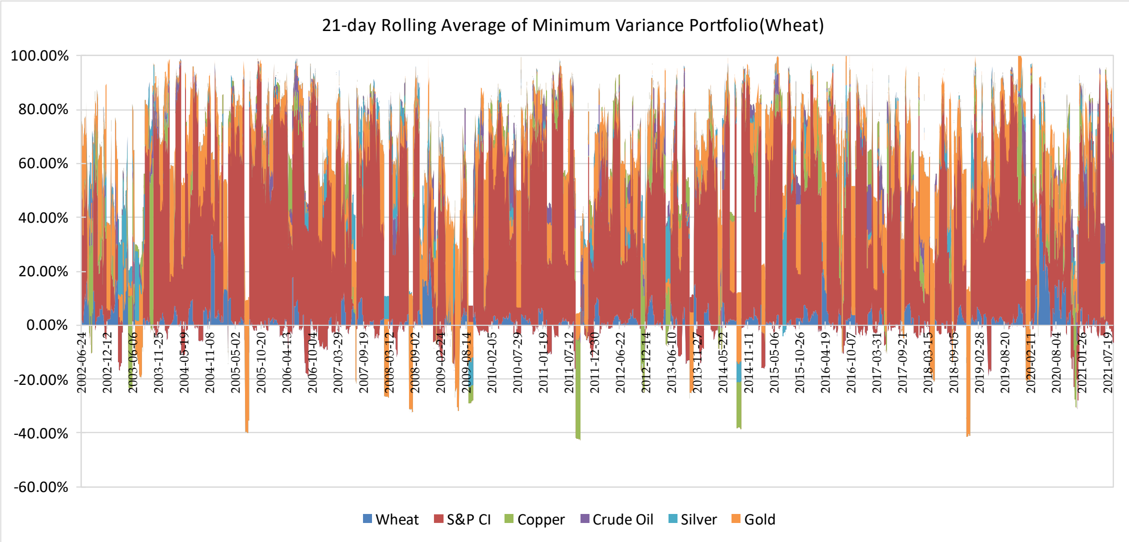


Figure 22. Wheat Minimum Variance Portfolio

5.5.2 Corn minimum variance portfolio

Table 15 gives the results of optimal mean weights for the selected three time periods. SPCI weights are over one in the first and the third (145%); in the second period, the average weight dropped to 44%. Corn weight was close to zero in the first period; for the second period, the average weight was 37%, and it turned into a negative weight of -13% for the third period. Copper futures first-period average weight was close to zero, but in the second period, the weight was -62% and rose to -16% in the third period. Copper futures weight differs significantly from the wheat portfolio. Crude oil futures average weight in the first period was close to 5%, grew to 27% in the second, and was close to zero in the third period. Silver futures weight swung from 45% in the first period to -29% in the second and rose to 53% in the third. Gold futures swings were reversed with silver as the first-period weight was -54%. In the second, it rose to 82%; in the third, the optimal mean weight dropped to -70%. Figure 23 plots the optimal minimum variance portfolio weights for the corn model. Gold futures short positions are infrequent compared to the wheat model, but the short positions are deep. 2014 short position in copper futures is noticeable.

Table 15. Corn Minimum Variance Portfolio Weights During Different Periods

Period	Corn	S&P CI	Copper	Crude Oil	Silver	Gold
I	0.0117	1.0208	0.0017	0.0482	0.4423	-0.5247
II	0.3761	0.4442	-0.6167	0.2672	-0.2908	0.8200
III	-0.1311	1.4687	-0.1583	-0.0051	0.5316	-0.7058

Note: Selected periods I: 24/05/2002-15/09/2008;
II: 16/09/2008-26/02/2014; III: 27/02/2014-31/08/2021

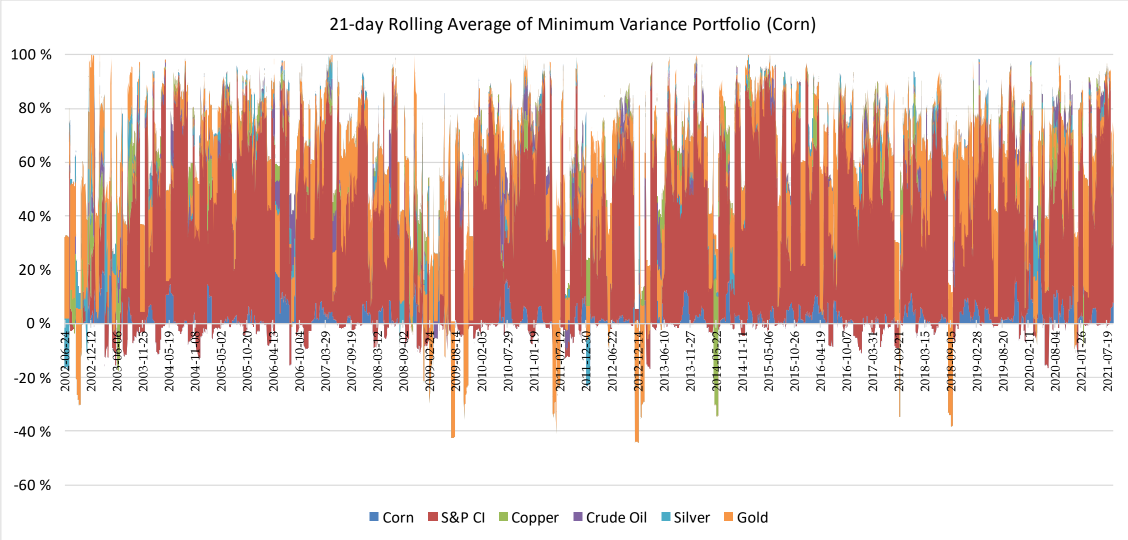


Figure 23. Corn Minimum Variance Portfolio

5.5.3 Rice minimum variance portfolio

The mean weights for selected periods are found in Table 16. The SPCI mean weight was 46% in the first period; in the second period, the weight rose to 151% and dropped to 75% in the third. In the first and second periods, rice had average weights of 1.5% and 5%; in the third period, it turned negative -4%. The average copper weight in the first period was -1 %; second, the short weight continued to be 38%, and during the third, it rose to 23%. The mean weight of crude oil futures in period one was 33%; the second was negative, closer to -3%, and rose to positive 4% in the third period. The silver futures first-period mean weight was -28%, followed by a rise to 45% and 10% in the second and third periods, respectively. Like in the corn portfolio, gold and silver futures were countering each other; the gold futures mean weight was 48% during the first period, turning into -61% and -8.5% weights during the second and third periods. The minimum variance portfolio for the rice model is plotted in Figure 24.

Table 16. Rice Minimum Variance Portfolio Weights During Different Periods

Period	Rice	S&P CI	Copper	Crude Oil	Silver	Gold
I	0.0177	0.5335	-0.0393	0.3115	-0.2859	0.4625
II	0.0516	1.5180	-0.3819	-0.0243	0.4530	-0.6164
III	-0.0402	0.7479	0.2315	0.0411	0.1035	-0.0837

Note: Selected periods I: 24/05/2002-15/09/2008;
II: 16/09/2008-26/02/2014; III: 27/02/2014-31/08/2021

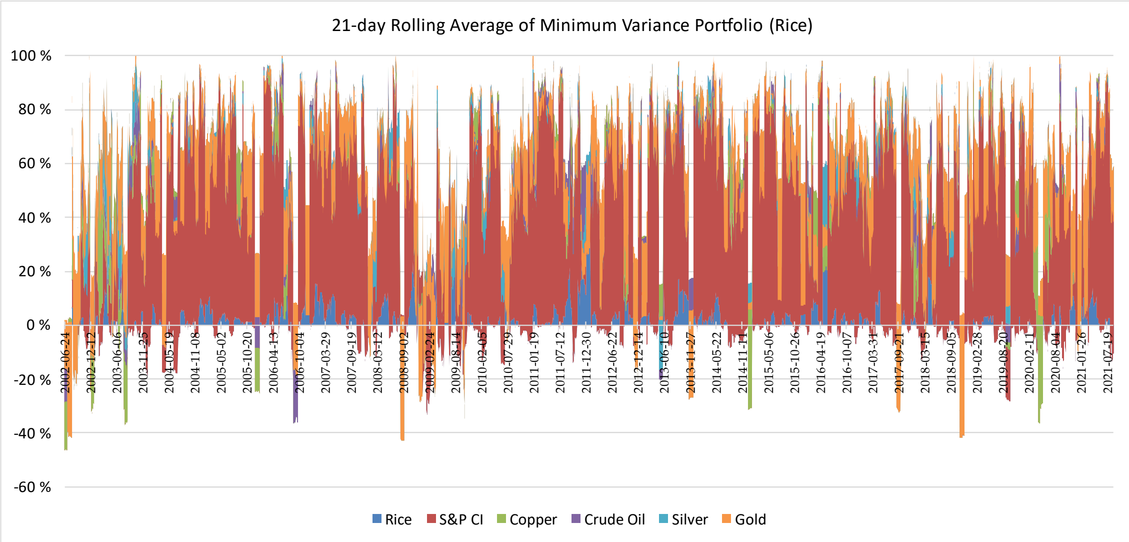


Figure 24. Rice Minimum Variance Portfolio

5.6 ARX model results for monthly returns

Results for the wheat, corn, and rice ARX models are found in Appendix L. The model can only be implemented on univariate time series. All the selected exogenous variables statistically significantly influence the food staples.

VIX negatively impacts wheat, corn, and rice at 5% statistical significance, and this confirms the finding by (Gozgor et al., 2016). The coefficient for wheat and corn is almost the same at -0,05; for the rice series, this effect is at -0,005. These negative coefficients mean that when the stock market is in a downturn, the food staples go down also. This result further supports the idea of financialization of commodities used as portfolio assets to bring diversification.

The rising geopolitical risk has a positive coefficient with wheat and corn returns at 0,037 and 0,036, respectively, but interestingly, a decreasing effect on rice returns by -0,019. Micallef et al., 2023) did not find statistically significant results between corn and rice and GPR. The authors divided the geopolitical risk into acts and threats. All the GPR coefficients have 5% statistical significance. These coefficients mean that when a geopolitically important event like an earthquake or tsunami happens, or there are rising tensions and even conflicts between countries that reach the news headlines, the returns of wheat and corn tend to increase, but rice returns tend to lower. Wheat and corn might be viewed as safe-haven assets, or the demand is expected to rise because a natural disaster disrupts the supply chain and causes a lack of food in the area. For rice, this inverse move could happen because of investors' risk aversion away from commodities or government interventions.

Economic policy uncertainty has the most significant negative impact on corn returns, with the coefficient nearing -7%. This is in line with findings made by (Long et al., 2023). Wheat and rice coefficients are low (-0,0014 and -0,0022), but all the coefficients have 5% statistical significance. This move could be explained by investor risk aversion away from riskier commodities such as corn. The standard deviation for corn is higher than the S&P CI on daily and monthly timespan, but wheat has even higher standard deviations than corn but is not moved by the EPU. Furthermore, EPU is an indicator of an increase or decrease in economic activity. Changes in economic activity further affect the usage of biofuels and livestock feeding. Changes in demand for corn may be induced by speculators making changes in their portfolio holdings. For wheat and rice, this low coefficient could be explained by diversified production as there are many regions in the world where wheat and rice are grown in different policy environments and how the crops are consumed regardless of the economic policy uncertainty.

Climate policy uncertainty has a negative coefficient with corn (-0,0017), but wheat and rice are reported positive (0,0041 and 0,0031). Statistical significance is 1% for corn and rice and 5% for wheat. The effect of CPU on food staples is very pronounced. The small coefficients could be further analyzed by comparing different time frames, for example, before and after the Paris Climate Agreement 2015, when climate-related issues gained more popularity through scientific research.

6 CONCLUSIONS

I used the VARX-ADCC-GARCH model on three different portfolios that included six different assets that included food commodities (wheat, corn, and rice) with S&P 500 CI, copper futures, crude oil futures, silver futures, and gold futures. These were considered as endogenous variables. I also added VIX and geopolitical risk indexes in the equation as exogenous variables. The primary analysis was done on daily returns and volatility, and the ARX model was used to briefly study the effects of the uncertainty indexes on the food staples. On the ARX analysis, I analyzed two more uncertainty indexes: climate policy uncertainty and economic policy uncertainty.

On a return level, there were some interesting findings from the VARX-model. S&P 500 CI has a bidirectional relationship with wheat and corn and a weak relationship with rice. S&P 500 CI is the leader in moving the corn and rice from the first lag, but wheat is moved stronger later in the lags. Foods Granger cause moves in the S&P 500 CI later in the lags. Copper futures and wheat returns have a frequent bidirectional relationship. Copper futures return leads the interactions between the food staples. Corn and rice interaction is less frequent, but the relationship is bidirectional. Crude oil futures have a bidirectional relationship with wheat but are unidirectional with corn and rice, and crude oil is causing mostly negative market moves on the food staples. This means that food prices go down if non-renewable energy goes up. Silver futures relationship is unidirectional with wheat. With corn, it is bidirectional, and corn influences the returns more, and interestingly, unidirectional from the rice side later in the lags. Gold futures are almost unidirectional with wheat, and gold strongly leads the returns on wheat. Strongly bidirectional with corn, but gold leading the interaction, and with rice, weakly bidirectional but gold leading.

ADCC-EGARCH results brought a few upsetting results, as S&P 500 CI results on omega were negative and likely influenced by the VIX index in an unwanted way. Crude oil futures data did not seem to fit in the selected model. Past volatility shocks to the future seemed to be statistically insignificant. Other than these, the model seemed to deliver statistically significant results.

Bringing the uncertainty factors into the data influenced the dynamic conditional correlations between the assets by mostly bringing the correlations down for every food-paired asset except gold futures. For gold futures and its food pairs, the correlations averaged higher. The presence of uncertainty indexes was shown, especially in the S&P500 CI correlations, bringing the average correlations down significantly.

Because of the lower overall correlations between the food staples and assets, the average hedge ratios were influenced negatively with few exceptions. The gold futures hedge ratio was improved by the presence of the uncertainty indexes. Interestingly, for the Rice-S&P 500 CI pair, there was an improvement, but the mean ratio was 11,75%. For neither of these pairs, including the gold futures, the hedging effectiveness was improved but, in fact, worsened. This could be because of the complexity of the model, as there was a long lag effect taken into the system of equations. Perhaps the model would deliver better results with shorter lags. The VIX and GPR data were calculated as log differences, and the GPR changes were constantly high on a daily level.

Even with the 21-day rolling average filter on the minimum variance portfolio, the portfolio asset weights were to be changed often, from being short to being long with the assets. The S&P 500 was to be long in every portfolio, with changing weights. No portfolio looked otherwise the same. The portfolio weights were unrestricted, which resulted in considerable long and short positions, and some weight constraints might have delivered different results. This result shows that there is a need for an investor to be aware of the changes between asset correlations and covariances to protect the portfolio from shortfalls.

According to ARX-model results, the VIX index negatively influences food prices and, therefore, moves together with the stock market. This supports the financialization of commodities and is consistent with findings from (Basak & Pavlova, 2016). Economic policy uncertainty influences mostly corn spot returns with negative response. Interestingly, the rise of geopolitical risk seems to cause lower rice returns but higher returns in wheat and corn. Most of the findings are in line with the earlier literature.

Dividing geopolitical risks into acts and threats could bring interesting results in the future, as in this study, the geopolitical risk was given as it is. Future studies could focus more on the monthly interaction between the assets, but I would keep the uncertainty indexes in the equations.

REFERENCES

Ali, J., & Gupta, K. B. (2011). Efficiency in agricultural commodity futures markets in India: Evidence from cointegration and causality tests. *Agricultural Finance Review*, *71*(2), 162–178. https://doi.org/10.1108/00021461111152555

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Basak, S., & Pavlova, A. (2016). A Model of Financialization of Commodities. *The Journal of Finance*, *71*(4), 1511–1556. https://doi.org/10.1111/jofi.12408

Bellemare, M. F., Barrett, C. B., & Just, D. R. (2013). The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics*, *95*(4), 877–899. https://doi.org/10.1093/ajae/aat018

Benhabib, J., Liu, X., & Wang, P. (2019). Financial Markets, the Real Economy, and Self-Fulfilling Uncertainties. *The Journal of Finance*, *74*(3), 1503–1557. https://doi.org/10.1111/jofi.12764

Bernanke, B. (1983). Non-Monetary Effects of the Financial Crisis in the Propagation of the Great Depression. *NBER Working Paper Series*, *1054*, Art. 1054. https://doi.org/10.3386/w1054

Bernanke, B., Boivin, J., & Eliasz, P. (2004). *Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach*. https://doi.org/10.3386/w10220

Bernard, V. L., & Frecka, T. J. (1987). Commodity Contracts and Common Stocks as Hedges against Relative Consumer Price Risk. *The Journal of Financial and Quantitative Analysis*, *22*(2), 169. https://doi.org/10.2307/2330711

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), 623–685. https://doi.org/10.3982/ECTA6248

Bogmans, C., Kearns, J., Pescatori, A., & Prifti, E. (2022, March 16). *War-Fueled Surge in Food Prices to Hit Poorer Nations Hardest*. IMF Chart of the Week. https://www.imf.org/en/Blogs/Articles/2022/03/16/war-fueled-surge-in-food-prices-to-hit-poorer-nations-hardest

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Brockwell, P. J., & Davis, R. A. (1991). *Time Series: Theory and Methods* (P. J. Brockwell, R. A. J. Davis, & R. A. Davis, Eds.). Springer New York. https://doi.org/10.1007/978-1-4419-0320-4

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics*, *4*(4), 537–572. https://doi.org/10.1093/jjfinec/nbl005

Cboe Global Indices. (2023). *Volatility Index® Methodology: Cboe Volatility Index®*. https://cdn.cboe.com/api/global/us_indices/governance/Volatility_Index_Methodology_Cboe_Volatility_Index.pdf

Chen, Z., Yan, B., Kang, H., & Liu, L. (2023). Asymmetric price adjustment and price discovery in spot and futures markets of agricultural commodities. *Review of Economic Design*, *27*(1), 139–162. https://doi.org/10.1007/s10058-021-00276-1

Dana, J. (2013). Market-based approaches for governments of food-importing countries to manage food security risks. *Global Food Security*, *2*(3), 182–187. https://doi.org/10.1016/j.gfs.2013.06.001

Dasgupta, P. (2021). *The Economics of Biodiversity: The Dasgupta Review*.

Declerck, F. (2014). Do Agricultural Commodity Firm Stock Price and Agricultural Commodity Price Move Together? *Int. J. Food System Dynamics*, *5*(3), 120–129. https://doi.org/https://doi.org/10.18461/ijfsd.v5i3.532

Duc Huynh, T. L., Burggraf, T., & Nasir, M. A. (2020). Financialisation of natural resources & instability caused by risk transfer in commodity markets. *Resources Policy*, *66*. https://doi.org/10.1016/j.resourpol.2020.101620

Dutta, A., Bouri, E., & Noor, M. H. (2021). Climate bond, stock, gold, and oil markets: Dynamic correlations and hedging analyses during the COVID-19 outbreak. *Resources Policy*, *74*(January), 102265. https://doi.org/10.1016/j.resourpol.2021.102265

Dutta, A., Bouri, E., Rothovius, T., & Uddin, G. S. (2023). Climate risk and green investments: New evidence. *Energy*, *265*. https://doi.org/10.1016/j.energy.2022.126376

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *Review of Financial Studies*, *33*(3). https://doi.org/10.1093/rfs/hhz072

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3847388

Gozgor, G., Lau, C. K. M., & Bilgin, M. H. (2016). Commodity markets volatility transmission: Roles of risk perceptions and uncertainty in financial markets. *Journal of International Financial Markets, Institutions and Money*, *44*, 35–45. https://doi.org/10.1016/j.intfin.2016.04.008

Headey, D. (2011). Rethinking the global food crisis: The role of trade shocks. *Food Policy*, *36*(2), 136–146. https://doi.org/10.1016/j.foodpol.2010.10.003

Hove, S., Touna Mama, A., & Tchana Tchana, F. (2015). Monetary policy and commodity terms of trade shocks in emerging market economies. *Economic Modelling*, *49*, 53–71. https://doi.org/10.1016/j.econmod.2015.03.012

IEA. (2022, December). *Renewables 2022*. IEA Report. https://www.iea.org/reports/renewables-2022/executive-summary

Jatta, R. (2016). Hedging seasonal food price risks: The impact of cereal banking in the Gambia. In *Food Price Volatility and Its Implications for Food Security and Policy* (pp. 583–601). Springer International Publishing. https://doi.org/10.1007/978-3-319-28201-5_22

Jebabli, I., & Roubaud, D. (2018). Time-varying efficiency in food and energy markets: Evidence and implications. *Economic Modelling*, *70*, 97–114. https://doi.org/10.1016/j.econmod.2017.10.013

Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. *Journal of International Financial Markets, Institutions and Money*, *56*, 255–280. https://doi.org/10.1016/j.intfin.2018.01.002

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177–1216. https://doi.org/10.1257/aer.20131193

Kang, W., Tang, K., & Wang, N. (2023). Financialization of commodity markets ten years later. *Journal of Commodity Markets*, *30*, 100313. https://doi.org/10.1016/j.jcomm.2023.100313

Kibris, Ö., & Tapki, I. G. (2014). A mechanism design approach to allocating central government funds among regional development agencies. *Review of Economic Design*, *18*(3), 163–189. https://doi.org/10.1007/s10058-014-0160-7

Kroner, K. F., & Sultan, J. (1993). Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures. *The Journal of Financial and Quantitative Analysis*, *28*(4), 535. https://doi.org/10.2307/2331164

Liu, X., & Pietola, K. (2008). Forward hedging under price and production risk of wheat. *Agricultural and Food Science*, *14*(2), 123. https://doi.org/10.2137/145960605774826028

Long, S., Li, J., & Luo, T. (2023). The asymmetric impact of global economic policy uncertainty on international grain prices. *Journal of Commodity Markets*, *30*, 100273. https://doi.org/10.1016/j.jcomm.2022.100273

Micallef, J., Grima, S., Spiteri, J., & Rupeika-Apoga, R. (2023). Assessing the Causality Relationship between the Geopolitical Risk Index and the Agricultural Commodity Markets. *Risks*, *11*(5). https://doi.org/10.3390/risks11050084

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*(2), 347. https://doi.org/10.2307/2938260

Oguoma, O., Nkwocha, V., & Ibeawuchi, I. (2011). Implications of middlemen in the supply chain of agricultural products. *Journal of Agriculture and Social Research (JASR)*, *10*(2). https://doi.org/10.4314/jasr.v10i2.67575

Pal, D., & Mitra, S. K. (2019). Correlation dynamics of crude oil with agricultural commodities: A comparison between energy and food crops. *Economic Modelling*, *82*, 453–466. https://doi.org/10.1016/j.econmod.2019.05.017

Reboredo, J. C. (2012). Do food and oil prices co-move? *Energy Policy*, *49*, 456–467. https://doi.org/10.1016/j.enpol.2012.06.035

Reboredo, J. C., & Ugando, M. (2014). US dollar exchange rate and food price dependence: Implications for portfolio risk management. *North American Journal of Economics and Finance*, *30*, 72–89. https://doi.org/10.1016/j.najef.2014.08.005

Roberts, M. J., & Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate. *American Economic Review*, *103*(6), 2265–2295. https://doi.org/10.1257/aer.103.6.2265

Serra, T., Zilberman, D., & Gil, J. (2011). Price volatility in ethanol markets. *European Review of Agricultural Economics*, *38*(2), 259–280. https://doi.org/10.1093/erae/jbq046

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*(1), 42–65. https://doi.org/10.1016/j.intfin.2012.11.007

Tang, K., & Xiong, W. (2012). Index Investment and the Financialization of Commodities. *Financial Analysts Journal*, *68*(6), 54–74. https://doi.org/10.2469/faj.v68.n6.5

The World Bank. (2023). *Food Security Update*.

Thenmozhi, M., & Maurya, S. (2020). Crude Oil Volatility Transmission Across Food Commodity Markets: A Multivariate BEKK-GARCH Approach. *Journal of Emerging Market Finance*, *20*(2), 131–164. https://doi.org/10.1177/0972652720927623

Tiwari, A. K., Boachie, M. K., Suleman, M. T., & Gupta, R. (2021). Structure dependence between oil and agricultural commodities returns: The role of geopolitical risks. *Energy*, *219*. https://doi.org/10.1016/j.energy.2020.119584

USDA Foreign Agricultural Service. (2023). *World Agricultural Production 2023*. https://apps.fas.usda.gov/psdonline/circulars/production.pdf

Williams, J. (2013). Agricultural Supply Chains and the Challenge of Price Risk. In *Agricultural Supply Chains and the Challenge of Price Risk*. Routledge. https://doi.org/10.4324/9780203525265

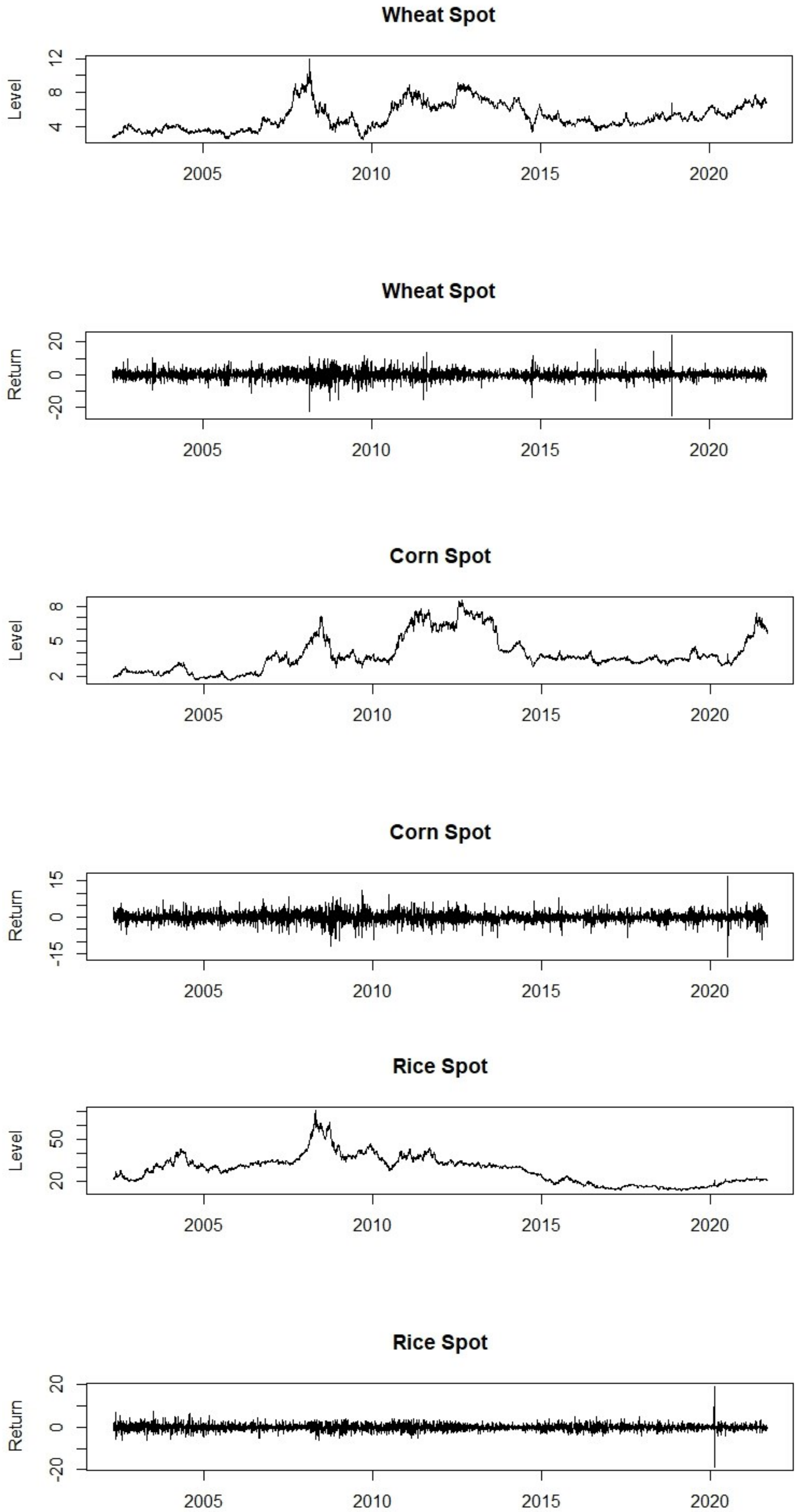
World Atlas. (2019, June). *What Are The World's Most Important Staple Foods?* Environment. https://www.worldatlas.com/articles/most-important-staple-foods-in-the-world.html

World Bank. (2008). *Rising food and fuel prices: Addressing the risks to future generations*. http://documents.worldbank.org/curated/en/701151468339092400/Rising-food-and-fuel-prices-addressing-the-risks-to-future-generations

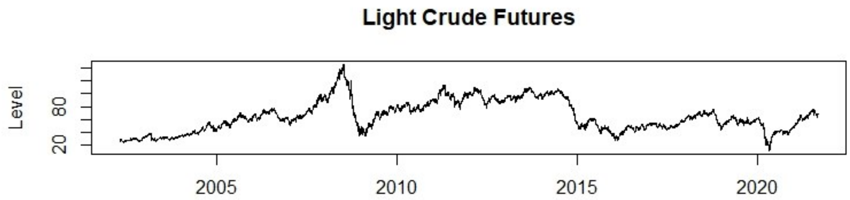
World Food Programme. (2023). *WFP Global Operational Response Plan 2023*. https://www.wfp.org/publications/wfp-global-operational-response-plan-update-7-february-2023

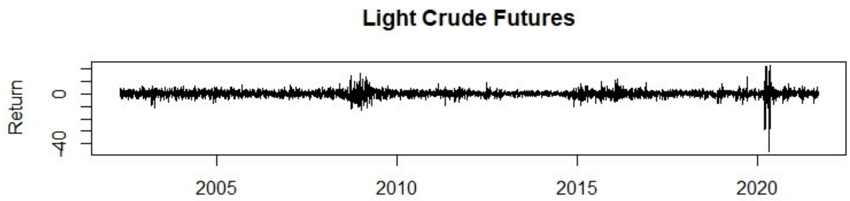
APPENDIX

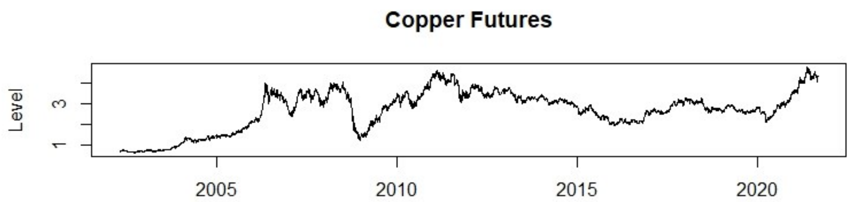
Appendix A. The daily price and return of wheat, corn, and rice spot series.

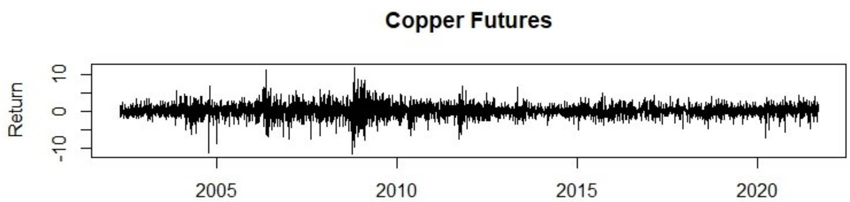


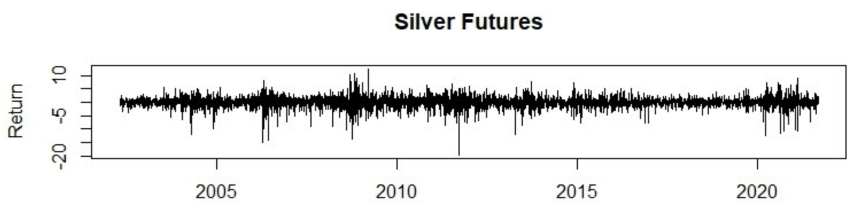
Appendix B. The daily price and return of crude oil, copper, and silver futures.



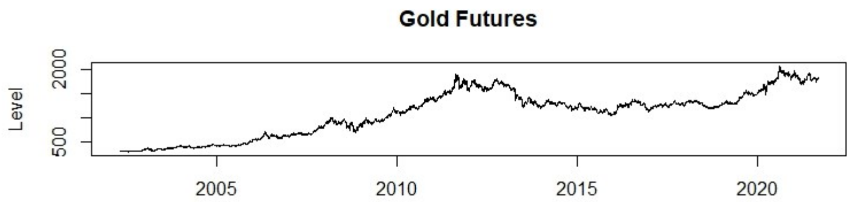


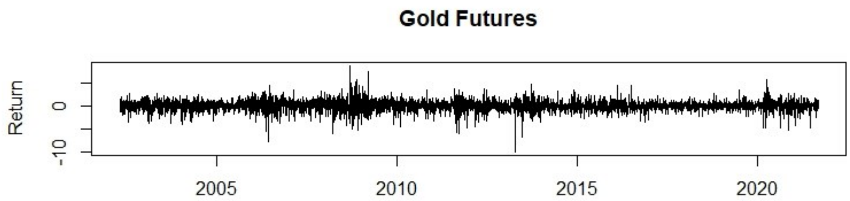


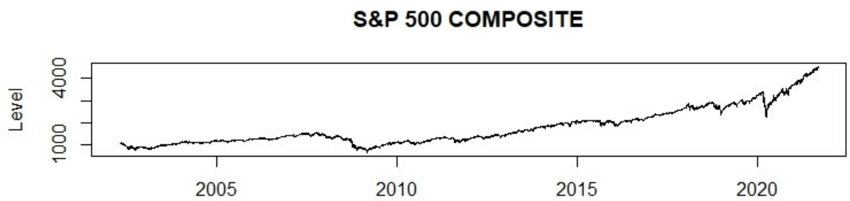


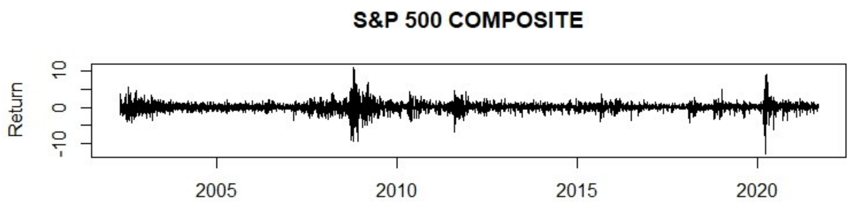


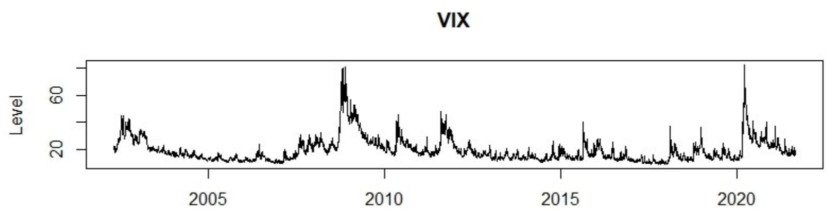
Appendix C. The daily price and return of gold futures, S&P 500 CI, and VIX.

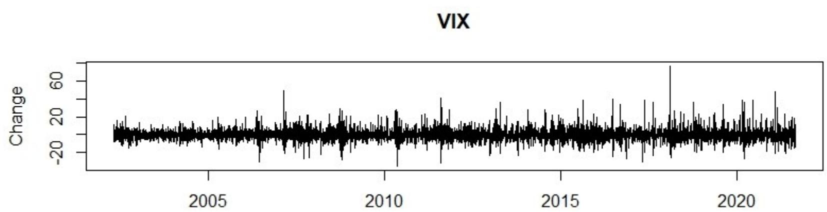




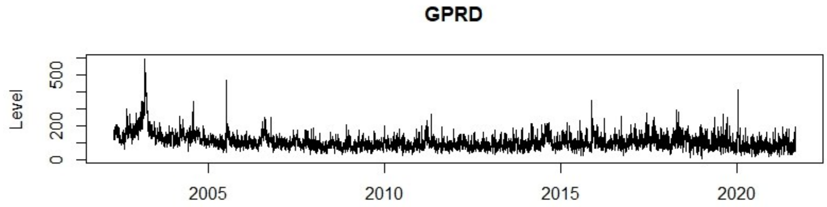


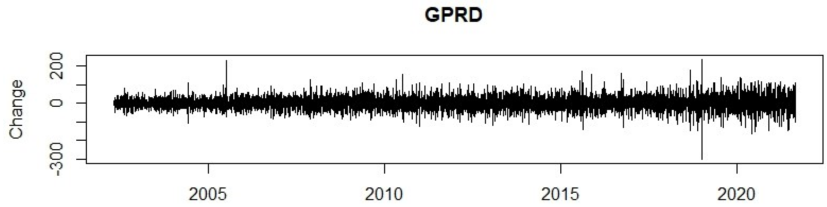




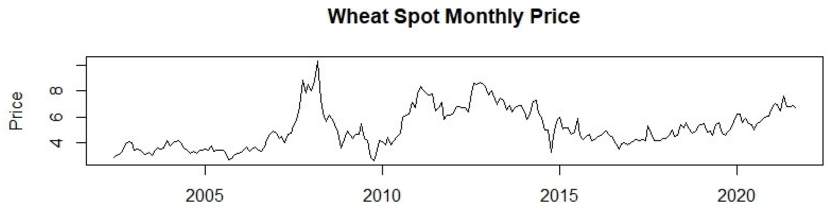


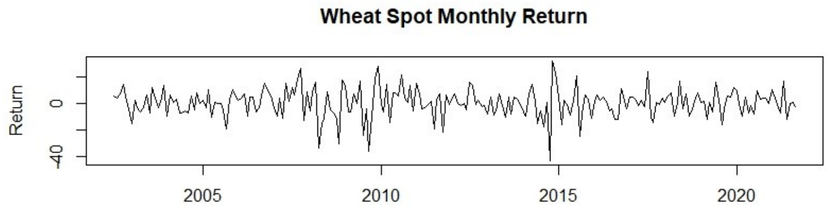
Appendix D. The daily level and change of GPR.

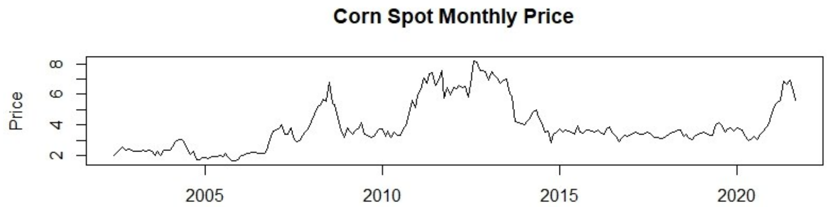


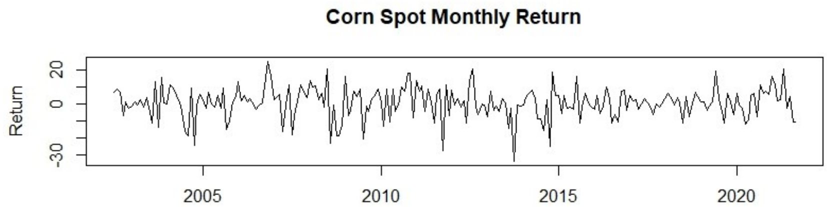


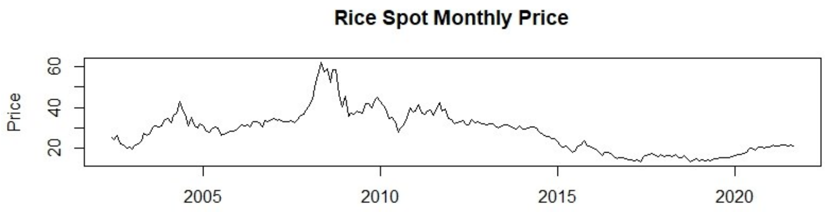
Appendix E. The monthly price and return of wheat, corn, and rice spot series.

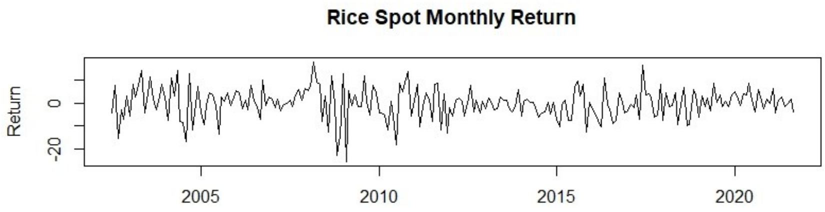




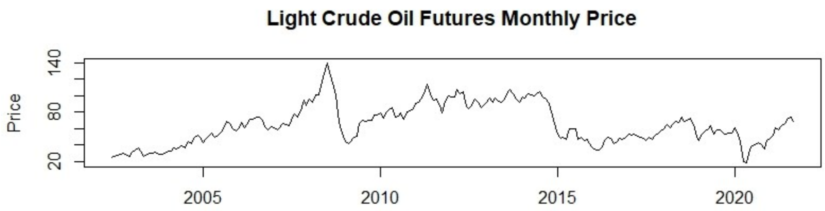


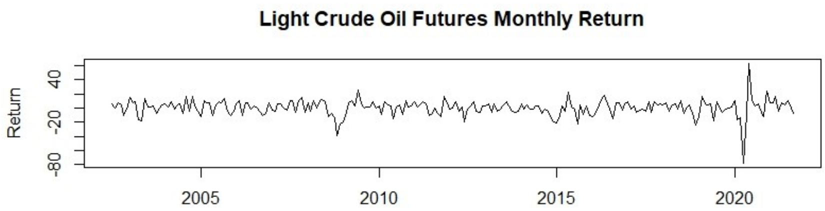


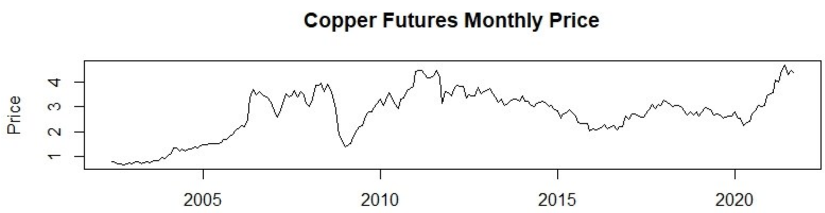


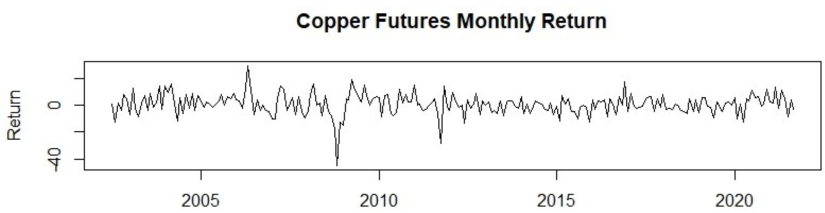


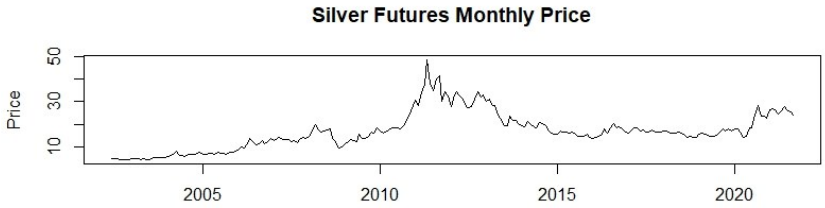
Appendix F. Monthly price and return of crude oil, copper, and silver futures.

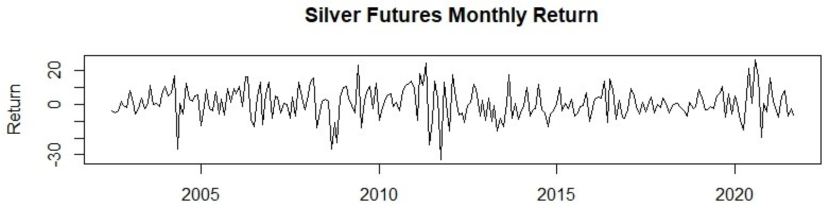




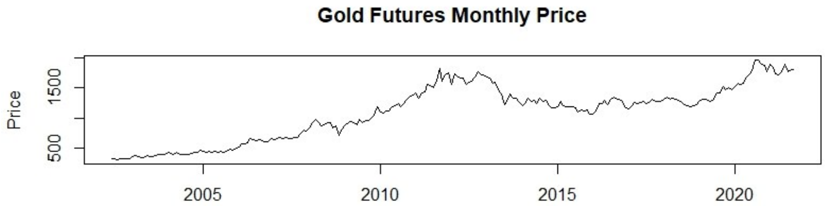


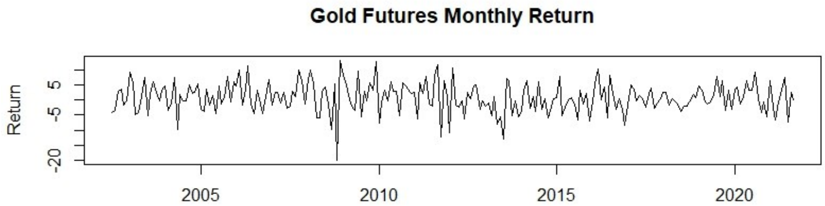


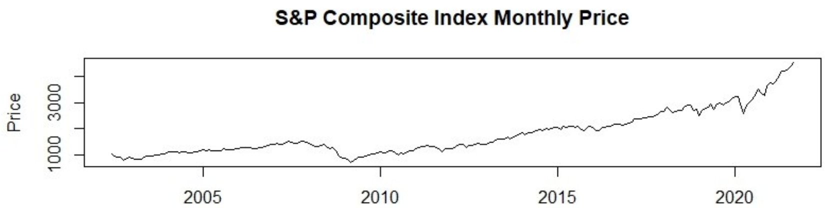


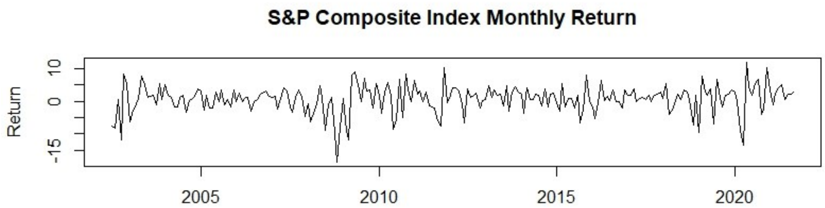


Appendix G. The monthly price and return of gold futures, S&P 500CI, and VIX.

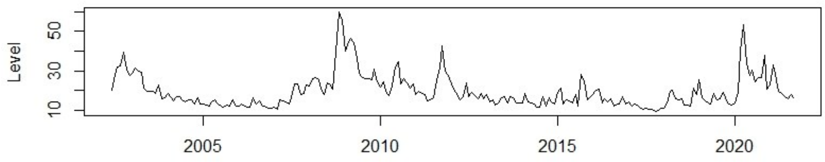




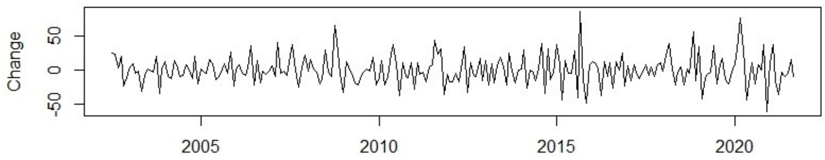




CBOE Volatility Index Monthly Level

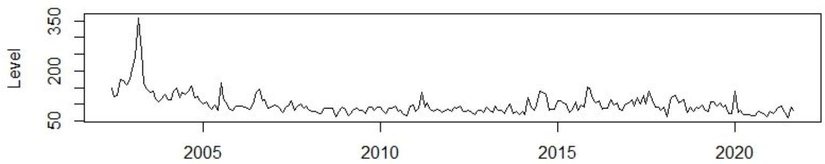


CBOE Volatility Index Monthly Change

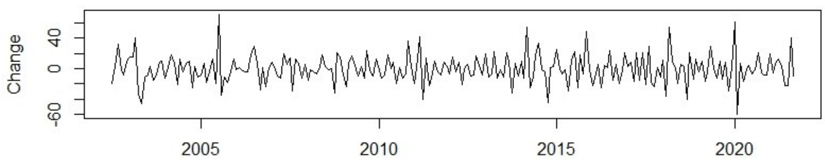


Appendix H. Monthly level and change of GPR, EPU and CPU index's.

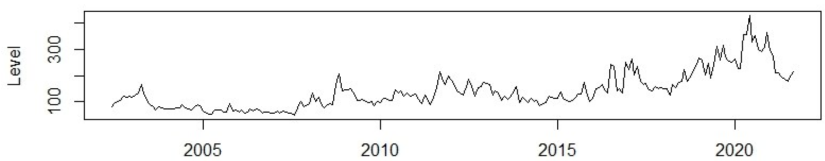
Geopolitical Risk Monthly Level



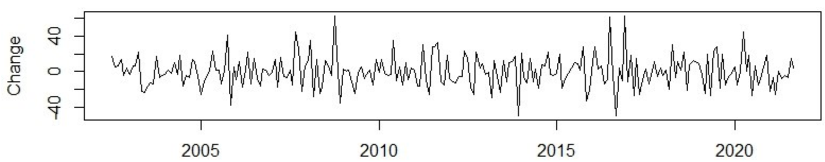
Geopolitical Risk Monthly Change

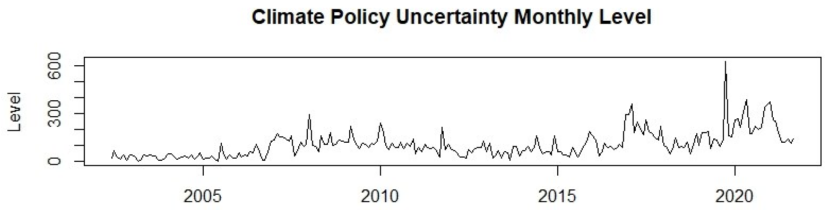


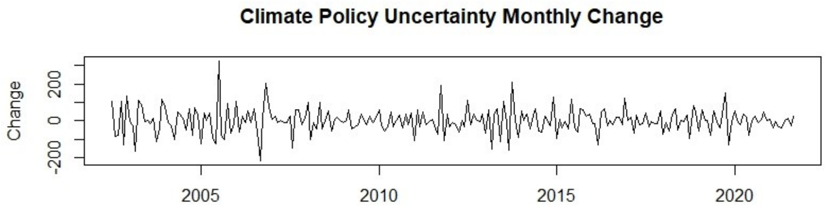
Economic Policy Uncertainty Monthly Level



Economic Policy Uncertainty Monthly Change







Appendix I. Wheat VARX-model results.

	LWHEAD.l1	LSPCID.l1	LCOPPFD.l1	LCRUDFD.l1	LSILVFD.l1	LGOLDFD.l1
LWHEAD	-0.0885	0.0528	-0.0505	-0.0308	-0.0223	0.1081
	0 ***	0.1067	0.043 **	0.0393 **	0.4703	0.0447 **
LSPCID	-0.0013	-0.0424	-0.0017	0.0003	-0.0098	0.0297
	0.7914	0.0001 ***	0.8366	0.9453	0.3356	0.093 *
LCOPPFD	0.0168	0.2011	-0.1004	-0.0144	-0.0240	0.0645
	0.083 *	0 ***	0 ***	0.1448	0.2386	0.0693 *
LCRUDFD	-0.0098	0.0817	-0.0283	-0.0337	-0.0096	0.0595
	0.5176	0.0154 **	0.2722	0.0289 **	0.7622	0.2835
LSILVFD	0.0109	0.2346	-0.0497	0.0049	-0.0654	0.1074
	0.3585	0 ***	0.0138 **	0.6836	0.0088 ***	0.0136 **
LGOLDFD	0.0096	0.0540	-0.0302	0.0003	-0.0139	0.0239
	0.1477	0.0003 ***	0.0073 ***	0.9613	0.3183	0.3248
	LWHEAD.l2	LSPCID.l2	LCOPPFD.l2	LCRUDFD.l2	LSILVFD.l2	LGOLDFD.l2
LWHEAD	0.0133	-0.0220	0.0103	0.0044	-0.0262	0.0461
	0.3674	0.5084	0.6797	0.7709	0.3965	0.3921
LSPCID	0.0067	0.0457	-0.0003	-0.0070	-0.0098	0.0600
	0.1672	0 ***	0.9706	0.1548	0.3331	0.0007 ***
LCOPPFD	0.0227	0.0218	-0.0096	0.0028	0.0093	0.0026
	0.0201 **	0.3205	0.5594	0.7759	0.649	0.9427
LCRUDFD	0.0038	0.0596	-0.0006	-0.0596	0.1026	-0.0477
	0.8041	0.0829 *	0.9803	0.0001 ***	0.0013 ***	0.3898
LSILVFD	-0.0061	0.0412	-0.0055	-0.0223	0.0173	0.0159
	0.6095	0.126	0.7861	0.065 *	0.4893	0.7145
LGOLDFD	-0.0012	0.0246	-0.0028	-0.0082	-0.0075	0.0027

	0.8585	0.1011	0.8062	0.2218	0.5892	0.9108
	LWHEAD.l3	LSPCID.l3	LCOPPFD.l3	LCRUDFD.l3	LSILVFD.l3	LGOLDFD.l3
LWHEAD	-0.0113	0.0533	0.0064	-0.0027	-0.0638	0.0625
	0.4453	0.109	0.7967	0.858	0.0384 **	0.2448
LSPCID	0.0120	0.0256	-0.0095	0.0262	0.0094	-0.0121
	0.0138 **	0.0194 **	0.246	0 ***	0.3552	0.4933
LCOPPFD	0.0143	-0.0129	-0.0012	0.0233	-0.0268	0.0067
	0.1411	0.5582	0.94	0.018 **	0.1867	0.851
LCRUDFD	0.0271	-0.0891	-0.0155	0.0015	-0.0200	0.0187
	0.0753 *	0.0094 ***	0.5462	0.9233	0.5279	0.7355
LSILVFD	0.0255	0.0001	-0.0128	0.0041	-0.0099	0.0403
	0.0327 **	0.9975	0.526	0.7366	0.6913	0.3541
LGOLDFD	0.0109	-0.0188	-0.0127	0.0010	0.0039	0.0146
	0.1027	0.2114	0.259	0.887	0.7803	0.5457
	LWHEAD.l4	LSPCID.l4	LCOPPFD.l4	LCRUDFD.l4	LSILVFD.l4	LGOLDFD.l4
LWHEAD	-0.0219	0.0075	0.0073	0.0182	-0.0003	-0.0355
	0.137	0.8216	0.7713	0.2227	0.9921	0.5088
LSPCID	-0.0061	-0.0262	0.0213	0.0043	-0.0069	-0.0157
	0.2058	0.0168 **	0.0095 ***	0.3854	0.4978	0.3727
LCOPPFD	0.0183	0.0258	0.0015	-0.0014	0.0384	-0.0931
	0.0601 *	0.2394	0.9257	0.8868	0.0586 *	0.0086 ***
LCRUDFD	-0.0235	0.0556	0.0579	0.0678	-0.0207	-0.1206
	0.1229	0.1056	0.0245 **	0 ***	0.5141	0.0294 **
LSILVFD	0.0008	-0.0410	0.0124	0.0177	-0.0249	-0.0344
	0.9467	0.1277	0.5384	0.1429	0.3176	0.4278
LGOLDFD	0.0033	0.0009	0.0037	-0.0029	-0.0127	0.0064
	0.618	0.9528	0.7424	0.6703	0.3617	0.7904
	LWHEAD.l5	LSPCID.l5	LCOPPFD.l5	LCRUDFD.l5	LSILVFD.l5	LGOLDFD.l5
LWHEAD	-0.0029	0.0346	0.0034	-0.0035	-0.0005	-0.0012
	0.8456	0.2991	0.8909	0.8132	0.986	0.9827
LSPCID	0.0075	0.0106	-0.0291	-0.0015	0.0273	-0.0029
	0.1244	0.3334	0.0004 ***	0.7618	0.007 ***	0.8713
LCOPPFD	0.0068	0.0297	-0.0219	-0.0013	-0.0095	0.0530
	0.4875	0.1765	0.1832	0.8966	0.6397	0.1338
LCRUDFD	-0.0041	-0.0409	-0.0484	0.0286	0.0016	-0.0155
	0.7885	0.2328	0.0601 *	0.0639 *	0.9586	0.7794
LSILVFD	0.0156	0.0112	0.0373	0.0090	-0.0094	-0.0069
	0.1922	0.677	0.0649 *	0.4589	0.7069	0.8731
LGOLDFD	0.0055	0.0090	0.0207	0.0034	-0.0010	-0.0132
	0.4113	0.5485	0.0662 *	0.6178	0.9443	0.5854
	LWHEAD.l6	LSPCID.l6	LCOPPFD.l6	LCRUDFD.l6	LSILVFD.l6	LGOLDFD.l6
LWHEAD	-0.0259	-0.0901	0.0317	-0.0118	0.0907	-0.0905

	0.0788 *	0.0068 ***	0.2038	0.4314	0.0031 ***	0.0899 *
LSPCID	-0.0041	-0.0019	-0.0142	-0.0042	0.0109	-0.0137
	0.3997	0.8608	0.0844 *	0.3937	0.2794	0.4346
LCOPPFD	0.0046	-0.0129	-0.0132	0.0121	-0.0119	0.0270
	0.6343	0.5555	0.4221	0.2194	0.5555	0.4436
LCRUDFD	-0.0009	0.0269	-0.0045	-0.0074	0.0267	-0.0311
	0.9535	0.4325	0.8619	0.6299	0.3996	0.5726
LSILVFD	-0.0071	0.0514	-0.0028	-0.0010	-0.0294	0.0348
	0.5514	0.0565 *	0.8914	0.9342	0.2357	0.4198
LGOLDFD	0.0032	-0.0057	-0.0014	-0.0051	-0.0216	0.0011
	0.6312	0.7034	0.9032	0.4473	0.1195	0.962
	LWHEAD.l7	LSPCID.l7	LCOPPFD.l7	LCRUDFD.l7	LSILVFD.l7	LGOLDFD.l7
LWHEAD	-0.0259	-0.0559	0.0106	-0.0119	0.0548	-0.1245
	0.079 *	0.0939 *	0.6721	0.4282	0.0745 *	0.0198 **
LSPCID	-0.0011	0.0422	0.0146	0.0012	-0.0166	-0.0056
	0.8184	0.0001 ***	0.0744 *	0.8151	0.0996 *	0.75
LCOPPFD	-0.0001	0.0476	0.0370	0.0074	0.0028	-0.0255
	0.995	0.0304 **	0.0244 **	0.4546	0.8887	0.4692
LCRUDFD	-0.0032	0.1261	-0.0008	-0.0199	0.0308	-0.0722
	0.8331	0.0002 ***	0.9765	0.1973	0.3309	0.1896
LSILVFD	-0.0029	-0.0021	0.0353	0.0067	0.0182	-0.0807
	0.8108	0.9376	0.0801 *	0.5817	0.4638	0.0618 *
LGOLDFD	-0.0001	-0.0051	0.0217	-0.0050	0.0138	-0.0476
	0.9935	0.7331	0.054 *	0.4584	0.3208	0.0482 **
	LWHEAD.l8	LSPCID.l8	LCOPPFD.l8	LCRUDFD.l8	LSILVFD.l8	LGOLDFD.l8
LWHEAD	0.0104	0.0189	0.0091	-0.0207	-0.0018	-0.0371
	0.4786	0.5708	0.7148	0.1678	0.9538	0.4879
LSPCID	0.0043	0.0157	-0.0130	-0.0092	-0.0109	-0.0014
	0.3765	0.1532	0.1134	0.0629 *	0.2792	0.9342
LCOPPFD	0.0172	-0.0187	0.0371	0.0000	0.0012	-0.0343
	0.0759 *	0.396	0.0242 **	0.9997	0.9532	0.3308
LCRUDFD	0.0053	-0.0344	0.0423	0.0148	-0.0208	0.0198
	0.7287	0.3171	0.1003	0.3378	0.5113	0.719
LSILVFD	0.0083	-0.0487	0.0197	-0.0067	0.0090	-0.0455
	0.4848	0.0711 *	0.3291	0.5786	0.7162	0.292
LGOLDFD	-0.0019	-0.0490	0.0203	-0.0026	-0.0149	0.0121
	0.7779	0.0011 ***	0.0717 *	0.7029	0.2827	0.6144
	LWHEAD.l9	LSPCID.l9	LCOPPFD.l9	LCRUDFD.l9	LSILVFD.l9	LGOLDFD.l9
LWHEAD	0.0137	0.1165	-0.0556	-0.0262	0.0104	-0.0105
	0.3531	0.0005 ***	0.0258 **	0.0805 *	0.7359	0.8441
LSPCID	-0.0010	0.0428	-0.0095	0.0164	-0.0161	0.0166
	0.8306	0.0001 ***	0.2463	0.0009 ***	0.1116	0.3448

LCOPPFD	0.0020	0.0103	-0.0143	0.0205	-0.0201	0.0204
	0.8402	0.6403	0.3862	0.0374 **	0.3206	0.5618
LCRUDFD	0.0039	0.0192	-0.0438	0.0043	0.0650	-0.0757
	0.7992	0.5756	0.0889 *	0.7793	0.04 **	0.1687
LSILVFD	0.0079	-0.0025	-0.0202	-0.0078	0.0607	-0.0428
	0.5061	0.9259	0.3163	0.52	0.0145 **	0.3212
LGOLDFD	0.0049	0.0065	-0.0046	-0.0132	0.0212	0.0025
	0.4583	0.6633	0.6802	0.0511 *	0.1263	0.9168
	LWHEAD.l10	LSPCID.l10	LCOPPFD.l10	LCRUDFD.l10	LSILVFD.l10	LGOLDFD.l10
LWHEAD	-0.0099	0.0692	-0.0281	-0.0239	0.0140	-0.0336
	0.5005	0.0381 **	0.2607	0.1112	0.6488	0.5294
LSPCID	-0.0053	0.0034	0.0072	0.0104	-0.0158	0.0185
	0.2766	0.7535	0.3803	0.0355 **	0.1187	0.2915
LCOPPFD	-0.0072	0.0419	0.0283	0.0091	-0.0232	0.0610
	0.4604	0.0567 *	0.0861 *	0.3599	0.2531	0.0832 *
LCRUDFD	-0.0050	0.0194	0.0583	-0.0407	0.0341	-0.0764
	0.7408	0.5724	0.0234 **	0.0084 ***	0.2819	0.1649
LSILVFD	-0.0052	-0.0240	0.0065	0.0005	0.0106	-0.0008
	0.663	0.3732	0.7479	0.9676	0.6709	0.9854
LGOLDFD	-0.0038	0.0173	-0.0005	-0.0006	0.0100	-0.0029
	0.5714	0.2503	0.9646	0.9271	0.4698	0.9048
	LWHEAD.l11	LSPCID.l11	LCOPPFD.l11	LCRUDFD.l11	LSILVFD.l11	LGOLDFD.l11
LWHEAD	0.0325	-0.0443	-0.0314	-0.0039	-0.0198	0.0665
	0.0267 **	0.1844	0.2088	0.7934	0.5189	0.2119
LSPCID	0.0134	-0.0282	0.0200	-0.0087	-0.0006	-0.0182
	0.0057 ***	0.0103 **	0.0149 **	0.0792 *	0.9544	0.2988
LCOPPFD	0.0042	0.0265	-0.0129	-0.0081	-0.0284	0.0369
	0.6673	0.2281	0.434	0.4101	0.1601	0.2941
LCRUDFD	0.0355	-0.0132	0.0143	-0.0402	0.0204	-0.0739
	0.0191 **	0.7011	0.5798	0.0093 ***	0.5191	0.1784
LSILVFD	-0.0008	-0.0021	-0.0222	0.0003	0.0210	-0.0609
	0.9465	0.9383	0.2723	0.9793	0.3981	0.1581
LGOLDFD	0.0157	0.0348	-0.0040	-0.0023	0.0105	-0.0519
	0.0178 **	0.0208 **	0.7224	0.7311	0.4494	0.0309 **
	LWHEAD.l12	LSPCID.l12	LCOPPFD.l12	LCRUDFD.l12	LSILVFD.l12	LGOLDFD.l12
LWHEAD	0.0116	-0.0358	0.0561	-0.0221	-0.0101	-0.0379
	0.4295	0.284	0.0248 **	0.1407	0.7421	0.4779
LSPCID	0.0009	0.0238	0.0071	0.0039	-0.0099	-0.0198
	0.8492	0.0304 **	0.3846	0.4276	0.3279	0.2604
LCOPPFD	0.0248	0.0272	0.0279	0.0108	-0.0069	-0.0102
	0.0106 **	0.2168	0.0906 *	0.2749	0.733	0.7715
LCRUDFD	0.0201	0.0135	0.0480	0.0239	-0.0738	0.0786

	0.1866	0.6952	0.0627 *	0.1214	0.0196 **	0.1531
LSILVFD	0.0129	-0.0303	0.0513	0.0102	0.0293	-0.0613
	0.2795	0.2622	0.0112 **	0.4001	0.2388	0.1559
LGOLDFD	-0.0010	-0.0139	0.0189	0.0013	0.0464	-0.0883
	0.8805	0.3549	0.0944 *	0.8511	0.0008 ***	0.0002 ***
	LWHEAD.l13	LSPCID.l13	LCOPPFD.l13	LCRUDFD.l13	LSILVFD.l13	LGOLDFD.l13
LWHEAD	-0.0550	0.0172	-0.0521	-0.0058	0.0322	-0.0601
	0.0002 ***	0.6072	0.0367 **	0.699	0.2938	0.2602
LSPCID	-0.0032	-0.0145	0.0176	-0.0006	0.0095	-0.0252
	0.5143	0.1867	0.0321 **	0.9056	0.3447	0.1507
LCOPPFD	-0.0061	0.0487	0.0198	0.0024	-0.0452	0.0835
	0.53	0.0269 **	0.2298	0.811	0.0257 **	0.0177 **
LCRUDFD	-0.0289	0.0839	-0.0002	0.0333	-0.0856	0.1764
	0.0575 *	0.0148 **	0.9927	0.0306 **	0.0068 ***	0.0014 ***
LSILVFD	0.0009	0.0360	0.0043	0.0082	-0.0756	0.1000
	0.9372	0.1832	0.8313	0.4953	0.0023 ***	0.0206 **
LGOLDFD	0.0014	0.0160	0.0016	-0.0046	-0.0313	0.0518
	0.8282	0.2896	0.8887	0.495	0.0239 **	0.0314 **
	LWHEAD.l14	LSPCID.l14	LCOPPFD.l14	LCRUDFD.l14	LSILVFD.l14	LGOLDFD.l14
LWHEAD	0.0202	-0.0210	-0.0452	0.0139	-0.0381	0.0786
	0.1715	0.5294	0.0704 *	0.352	0.2145	0.1417
LSPCID	-0.0030	0.0021	0.0041	-0.0058	-0.0070	0.0373
	0.539	0.8488	0.6158	0.2353	0.4863	0.0338 **
LCOPPFD	0.0082	-0.0274	-0.0043	0.0163	0.0190	-0.0528
	0.3974	0.2122	0.7917	0.0981 *	0.3473	0.1346
LCRUDFD	-0.0109	-0.0313	0.0105	0.0295	0.0039	-0.0044
	0.475	0.362	0.6819	0.0552 *	0.9016	0.9363
LSILVFD	0.0019	0.1108	-0.0270	-0.0093	0.0069	-0.0372
	0.8745	0 ***	0.1814	0.4393	0.7821	0.3902
LGOLDFD	-0.0028	0.0462	-0.0221	0.0067	-0.0169	0.0412
	0.6738	0.0021 ***	0.0497 **	0.3195	0.2223	0.0873 *
	LWHEAD.l15	LSPCID.l15	LCOPPFD.l15	LCRUDFD.l15	LSILVFD.l15	LGOLDFD.l15
LWHEAD	0.0093	-0.0024	0.0122	0.0126	-0.0265	0.0736
	0.5295	0.9424	0.6264	0.399	0.3886	0.1693
LSPCID	0.0037	-0.0290	0.0078	0.0063	-0.0066	0.0379
	0.4459	0.0084 ***	0.344	0.196	0.5155	0.0314 **
LCOPPFD	-0.0244	0.0255	-0.0001	-0.0133	-0.0266	0.1225
	0.0123 **	0.2475	0.9942	0.1775	0.1895	0.0005 ***
LCRUDFD	-0.0171	-0.0228	0.0737	-0.0120	-0.0254	0.0426
	0.2607	0.5086	0.0042 ***	0.4339	0.4218	0.4404
LSILVFD	-0.0142	0.0067	-0.0156	0.0130	-0.0382	0.0811
	0.2357	0.8054	0.4411	0.2815	0.1244	0.0611 *

LGOLDFD	-0.0065	0.0025	-0.0163	0.0100	-0.0050	0.0284
	0.3267	0.866	0.1475	0.1386	0.7207	0.2397

	LWHEAD.l16	LSPCID.l16	LCOPPFD.l16	LCRUDFD.l16	LSILVFD.l16	LGOLDFD.l16
LWHEAD	-0.0098	0.0302	0.0149	0.0024	0.0169	-0.0614
	0.5066	0.3608	0.5479	0.8731	0.5776	0.249
LSPCID	-0.0083	0.0493	-0.0174	0.0170	-0.0036	-0.0151
	0.087 *	0 ***	0.0331 **	0.0005 ***	0.7201	0.3881
LCOPPFD	-0.0080	0.0165	0.0184	0.0154	0.0118	-0.0688
	0.4063	0.4483	0.2606	0.1185	0.5569	0.0503 *
LCRUDFD	-0.0181	0.0287	0.0191	0.0115	0.0217	-0.0808
	0.2311	0.3996	0.4536	0.4536	0.4875	0.1411
LSILVFD	0.0062	0.0308	-0.0082	0.0036	0.0159	-0.0132
	0.604	0.25	0.6825	0.7672	0.5166	0.7597
LGOLDFD	0.0030	0.0246	-0.0053	-0.0059	0.0167	-0.0270
	0.6497	0.0984 *	0.6324	0.3823	0.2224	0.261

	const	LVIX	LGPRD
LWHEAD	0.0250	-0.0278	-0.0023
	0.4922	0 ***	0.0151 **
LSPCID	0.0234	-0.1225	0.0005
	0.051 *	0 ***	0.074 *
LCOPPFD	0.0183	-0.0549	-0.0001
	0.4463	0 ***	0.9312
LCRUDFD	0.0109	-0.0775	-0.0004
	0.7725	0 ***	0.6798
LSILVFD	0.0224	-0.0329	0.0002
	0.4475	0 ***	0.8116
LGOLDFD	0.0334	0.0000	-0.0001
	0.0425 **	0.983	0.7624

Notes: VARX model daily results are based on a formula in section 4.1. Row names correspond to the values of the series at time t, and in the column section, the names correspond to the t-i values of the series. In the last section, the values for constant, VIX, and geopolitical risk are estimated. The first estimation corresponds to the parameter value, and the second value under it corresponds to the p-value, and its statistical significance is highlighted with * (10%), ** (5%) and *** (1%) to help to find the most statistically significant values.

Appendix J. Corn VARX-model results.

	LCORND.l1	LSPCID.l1	LCOPPFD.l1	LCRUDFD.l1	LSILVFD.l1	LGOLDFD.l1
LCORND	-0.0064	0.1183	-0.0408	-0.0228	-0.0020	0.0663
	0.6681	0 ***	0.0334 **	0.0478 **	0.9318	0.1094
LSPCID	-0.0062	-0.0433	-0.0003	0.0009	-0.0114	0.0328
	0.3336	0.0001 ***	0.9755	0.8562	0.2604	0.0638 *
LCOPPFD	0.0072	0.2026	-0.0972	-0.0128	-0.0291	0.0746
	0.5719	0 ***	0 ***	0.196	0.1533	0.0355 **

LCRUDFD	-0.0026	0.0800	-0.0289	-0.0340	-0.0155	0.0670
	0.8978	0.0179 **	0.2625	0.0281 **	0.627	0.228
LSILVFD	0.0278	0.2345	-0.0477	0.0022	-0.0733	0.1140
	0.0752 *	0 ***	0.018 **	0.8562	0.0033 ***	0.0087 ***
LGOLDFD	0.0135	0.0541	-0.0287	-0.0010	-0.0168	0.0251
	0.1214	0.0002 ***	0.0106 **	0.8803	0.2265	0.3007
	LCORND.l2	LSPCID.l2	LCOPPFD.l2	LCRUDFD.l2	LSILVFD.l2	LGOLDFD.l2
LCORND	-0.0056	-0.0281	0.0223	0.0008	-0.0124	-0.0310
	0.706	0.274	0.2469	0.9429	0.6024	0.4545
LSPCID	0.0014	0.0462	-0.0002	-0.0065	-0.0093	0.0607
	0.8228	0 ***	0.9819	0.185	0.3632	0.0006 ***
LCOPPFD	0.0083	0.0216	-0.0059	0.0034	0.0059	0.0117
	0.5152	0.3253	0.7225	0.7302	0.771	0.7424
LCRUDFD	-0.0009	0.0577	-0.0012	-0.0590	0.1038	-0.0452
	0.9653	0.0937 *	0.9623	0.0001 ***	0.0012 ***	0.4156
LSILVFD	0.0028	0.0399	-0.0062	-0.0226	0.0135	0.0249
	0.8587	0.139	0.7608	0.0624 *	0.5889	0.5669
LGOLDFD	-0.0041	0.0256	-0.0034	-0.0082	-0.0090	0.0091
	0.6403	0.0874 *	0.7658	0.2241	0.5192	0.707
	LCORND.l3	LSPCID.l3	LCOPPFD.l3	LCRUDFD.l3	LSILVFD.l3	LGOLDFD.l3
LCORND	0.0190	-0.0088	0.0009	0.0045	-0.0405	0.0780
	0.2008	0.7303	0.9632	0.6984	0.0879 *	0.0589 *
LSPCID	0.0104	0.0262	-0.0086	0.0261	0.0093	-0.0141
	0.1008	0.0167 **	0.293	0 ***	0.3583	0.4252
LCOPPFD	0.0110	-0.0094	-0.0023	0.0231	-0.0266	0.0091
	0.3891	0.6682	0.8883	0.0196 **	0.1914	0.7974
LCRUDFD	0.0017	-0.0843	-0.0158	0.0040	-0.0146	0.0159
	0.9327	0.0142 **	0.5402	0.7956	0.6479	0.7739
LSILVFD	0.0147	0.0032	-0.0120	0.0051	-0.0107	0.0481
	0.3458	0.9052	0.5516	0.6762	0.6685	0.2671
LGOLDFD	0.0055	-0.0174	-0.0114	0.0016	0.0037	0.0185
	0.5277	0.245	0.3124	0.8165	0.7914	0.4446
	LCORND.l4	LSPCID.l4	LCOPPFD.l4	LCRUDFD.l4	LSILVFD.l4	LGOLDFD.l4
LCORND	-0.0131	0.0395	-0.0032	0.0098	0.0116	-0.0392
	0.378	0.1229	0.8667	0.3941	0.6237	0.3419
LSPCID	0.0089	-0.0277	0.0201	0.0025	-0.0109	-0.0121
	0.1626	0.0115 **	0.0145 **	0.6072	0.282	0.4942
LCOPPFD	0.0383	0.0248	0.0024	-0.0051	0.0344	-0.0935
	0.0027 ***	0.2598	0.8843	0.609	0.0909 *	0.0082 ***
LCRUDFD	0.0132	0.0505	0.0532	0.0634	-0.0227	-0.1260
	0.5073	0.1417	0.0391 **	0 ***	0.4762	0.0229 **
LSILVFD	0.0275	-0.0435	0.0094	0.0138	-0.0238	-0.0397

	0.0781 *	0.1063	0.6425	0.2544	0.339	0.36
LGOLDFD	0.0192	0.0004	0.0017	-0.0049	-0.0139	0.0064
	0.0276 **	0.9806	0.8824	0.4645	0.3174	0.7898
	LCORND.l5	LSPCID.l5	LCOPPFD.l5	LCRUDFD.l5	LSILVFD.l5	LGOLDFD.l5
LCORND	0.0117	0.0389	-0.0503	-0.0044	-0.0107	0.0541
	0.4325	0.1292	0.0088 ***	0.7058	0.6506	0.1898
LSPCID	0.0068	0.0095	-0.0286	-0.0010	0.0271	-0.0031
	0.2888	0.3849	0.0005 ***	0.845	0.0077 ***	0.8594
LCOPPFD	0.0082	0.0282	-0.0211	-0.0018	-0.0110	0.0548
	0.52	0.1989	0.2004	0.8573	0.5893	0.1214
LCRUDFD	0.0060	-0.0470	-0.0471	0.0289	0.0002	-0.0200
	0.7657	0.172	0.0677 *	0.0629 *	0.995	0.7173
LSILVFD	0.0000	0.0075	0.0403	0.0114	-0.0064	-0.0101
	0.9976	0.7795	0.0456 **	0.3465	0.7968	0.8147
LGOLDFD	0.0063	0.0054	0.0222	0.0036	-0.0004	-0.0165
	0.4694	0.7185	0.0475 **	0.5964	0.9781	0.4945
	LCORND.l6	LSPCID.l6	LCOPPFD.l6	LCRUDFD.l6	LSILVFD.l6	LGOLDFD.l6
LCORND	-0.0155	-0.0032	-0.0101	0.0015	0.0387	-0.0736
	0.2986	0.9006	0.5999	0.8962	0.1025	0.0733 *
LSPCID	-0.0008	0.0002	-0.0156	-0.0050	0.0098	-0.0104
	0.9055	0.9851	0.0574 *	0.3096	0.3339	0.5523
LCOPPFD	-0.0181	-0.0119	-0.0088	0.0136	-0.0104	0.0292
	0.1562	0.589	0.5924	0.1692	0.6097	0.4073
LCRUDFD	-0.0024	0.0310	-0.0063	-0.0080	0.0274	-0.0322
	0.9044	0.3674	0.8075	0.6044	0.3881	0.5597
LSILVFD	-0.0315	0.0546	0.0006	0.0006	-0.0270	0.0314
	0.044 **	0.0425 **	0.9755	0.9616	0.2769	0.4674
LGOLDFD	-0.0087	-0.0039	0.0003	-0.0045	-0.0190	-0.0015
	0.3196	0.7954	0.9775	0.5053	0.169	0.9509
	LCORND.l7	LSPCID.l7	LCOPPFD.l7	LCRUDFD.l7	LSILVFD.l7	LGOLDFD.l7
LCORND	-0.0060	0.0097	0.0031	-0.0078	0.0089	-0.0486
	0.6882	0.7066	0.8697	0.4983	0.7056	0.2376
LSPCID	0.0016	0.0410	0.0153	0.0008	-0.0157	-0.0076
	0.8025	0.0002 ***	0.0626 *	0.8776	0.1214	0.6675
LCOPPFD	-0.0173	0.0514	0.0393	0.0069	0.0049	-0.0237
	0.1758	0.0196 **	0.017 **	0.4876	0.8084	0.5025
LCRUDFD	0.0056	0.1264	-0.0031	-0.0216	0.0304	-0.0720
	0.7811	0.0002 ***	0.9041	0.1634	0.3384	0.192
LSILVFD	-0.0013	-0.0009	0.0340	0.0061	0.0181	-0.0804
	0.9352	0.9738	0.0918 *	0.6151	0.4675	0.0629 *
LGOLDFD	-0.0163	-0.0040	0.0224	-0.0045	0.0159	-0.0487
	0.0611 *	0.7911	0.0465 **	0.5094	0.2496	0.0428 **

	LCORND.l8	LSPCID.l8	LCOPPFD.l8	LCRUDFD.l8	LSILVFD.l8	LGOLDFD.l8
LCORND	0.0136	-0.0345	0.0061	-0.0038	0.0142	-0.0758
	0.3612	0.1781	0.7507	0.743	0.548	0.0651 *
LSPCID	0.0020	0.0155	-0.0113	-0.0089	-0.0104	-0.0016
	0.7515	0.1569	0.1678	0.0721 *	0.3035	0.9255
LCOPPFD	0.0167	-0.0238	0.0396	-0.0010	0.0035	-0.0382
	0.1925	0.2797	0.016 **	0.9185	0.8638	0.2784
LCRUDFD	0.0083	-0.0343	0.0446	0.0150	-0.0241	0.0268
	0.6792	0.3191	0.0832 *	0.3332	0.4485	0.6277
LSILVFD	0.0005	-0.0477	0.0228	-0.0065	0.0057	-0.0412
	0.9739	0.0766 *	0.2589	0.5936	0.8197	0.3408
LGOLDFD	0.0027	-0.0481	0.0193	-0.0029	-0.0160	0.0140
	0.7604	0.0013 ***	0.0857 *	0.673	0.2475	0.5607
	LCORND.l9	LSPCID.l9	LCOPPFD.l9	LCRUDFD.l9	LSILVFD.l9	LGOLDFD.l9
LCORND	0.0269	0.0399	-0.0353	0.0036	0.0078	-0.0126
	0.0707 *	0.1198	0.0659 *	0.7529	0.7404	0.7595
LSPCID	-0.0021	0.0396	-0.0091	0.0165	-0.0140	0.0129
	0.7392	0.0003 ***	0.2675	0.0008 ***	0.1653	0.4625
LCOPPFD	0.0000	0.0063	-0.0125	0.0208	-0.0177	0.0166
	0.9997	0.7735	0.4474	0.0357 **	0.3815	0.6368
LCRUDFD	0.0172	0.0133	-0.0426	0.0042	0.0671	-0.0791
	0.3896	0.7	0.0985 *	0.7877	0.0344 **	0.1515
LSILVFD	0.0077	-0.0033	-0.0168	-0.0081	0.0598	-0.0356
	0.6235	0.9039	0.4045	0.5068	0.0161 **	0.41
LGOLDFD	0.0027	0.0048	-0.0005	-0.0131	0.0183	0.0068
	0.7605	0.7477	0.9676	0.0522 *	0.1859	0.7782
	LCORND.l10	LSPCID.l10	LCOPPFD.l10	LCRUDFD.l10	LSILVFD.l10	LGOLDFD.l10
LCORND	0.0298	0.0499	0.0071	-0.0080	-0.0206	-0.0177
	0.0456 **	0.0514 *	0.7112	0.4885	0.3843	0.6669
LSPCID	-0.0108	0.0050	0.0079	0.0108	-0.0152	0.0176
	0.0906 *	0.648	0.3376	0.0291 **	0.1324	0.3172
LCOPPFD	-0.0217	0.0420	0.0310	0.0095	-0.0223	0.0607
	0.0893 *	0.056 *	0.0594 *	0.339	0.2729	0.0848 *
LCRUDFD	-0.0043	0.0162	0.0600	-0.0409	0.0331	-0.0807
	0.8286	0.6378	0.0199 **	0.0084 ***	0.2968	0.1433
LSILVFD	0.0099	-0.0271	0.0071	-0.0016	0.0105	-0.0030
	0.5251	0.314	0.7238	0.8929	0.6717	0.9446
LGOLDFD	0.0086	0.0156	-0.0003	-0.0024	0.0099	-0.0036
	0.3256	0.2979	0.9809	0.7183	0.4759	0.8813
	LCORND.l11	LSPCID.l11	LCOPPFD.l11	LCRUDFD.l11	LSILVFD.l11	LGOLDFD.l11
LCORND	0.0144	0.0396	-0.0288	-0.0041	0.0040	-0.0261
	0.3344	0.1226	0.1339	0.7221	0.8656	0.5239

LSPCID	0.0079	-0.0265	0.0212	-0.0088	-0.0019	-0.0136
	0.2153	0.0158 **	0.0099 ***	0.0757 *	0.8545	0.4376
LCOPPFD	0.0162	0.0309	-0.0167	-0.0101	-0.0286	0.0375
	0.2054	0.1603	0.3105	0.3105	0.1577	0.2866
LCRUDFD	0.0214	-0.0093	0.0145	-0.0390	0.0195	-0.0685
	0.2849	0.7865	0.5724	0.0119 **	0.539	0.213
LSILVFD	0.0086	-0.0039	-0.0238	-0.0006	0.0237	-0.0640
	0.5844	0.8836	0.2375	0.9592	0.34	0.1371
LGOLDFD	0.0173	0.0345	-0.0047	-0.0026	0.0120	-0.0541
	0.0468 **	0.0216 **	0.6778	0.697	0.386	0.024 **
	LCORND.l12	LSPCID.l12	LCOPPFD.l12	LCRUDFD.l12	LSILVFD.l12	LGOLDFD.l12
LCORND	-0.0037	0.0292	0.0301	0.0024	-0.0078	-0.0087
	0.8061	0.2557	0.1173	0.8359	0.741	0.833
LSPCID	-0.0149	0.0263	0.0074	0.0051	-0.0084	-0.0192
	0.0191 **	0.0166 **	0.3663	0.3063	0.4048	0.275
LCOPPFD	0.0072	0.0264	0.0280	0.0111	-0.0075	-0.0073
	0.5725	0.2298	0.0892 *	0.2638	0.7128	0.8346
LCRUDFD	-0.0191	0.0171	0.0471	0.0267	-0.0707	0.0807
	0.3389	0.6191	0.0681 *	0.0855 *	0.0259 **	0.1431
LSILVFD	-0.0061	-0.0306	0.0517	0.0110	0.0321	-0.0633
	0.6967	0.2563	0.0105 **	0.3673	0.1965	0.1422
LGOLDFD	-0.0052	-0.0141	0.0167	0.0007	0.0473	-0.0885
	0.5523	0.3496	0.1369	0.9117	0.0006 ***	0.0002 ***
	LCORND.l13	LSPCID.l13	LCOPPFD.l13	LCRUDFD.l13	LSILVFD.l13	LGOLDFD.l13
LCORND	-0.0021	0.0220	-0.0142	0.0131	0.0041	-0.0156
	0.8888	0.3919	0.4607	0.2554	0.8626	0.7039
LSPCID	0.0108	-0.0153	0.0160	-0.0023	0.0077	-0.0228
	0.0895 *	0.1646	0.0513 *	0.6407	0.4441	0.1942
LCOPPFD	-0.0022	0.0470	0.0168	-0.0001	-0.0446	0.0841
	0.8661	0.0326 **	0.3071	0.9902	0.0278 **	0.017 **
LCRUDFD	-0.0276	0.0824	-0.0037	0.0332	-0.0861	0.1795
	0.1673	0.0167 **	0.8864	0.0317 **	0.0066 ***	0.0011 ***
LSILVFD	-0.0239	0.0363	0.0048	0.0088	-0.0726	0.1014
	0.1274	0.1788	0.8134	0.4661	0.0034 ***	0.0188 **
LGOLDFD	-0.0062	0.0143	0.0012	-0.0044	-0.0291	0.0509
	0.48	0.3427	0.915	0.5166	0.0354 **	0.0341 **
	LCORND.l14	LSPCID.l14	LCOPPFD.l14	LCRUDFD.l14	LSILVFD.l14	LGOLDFD.l14
LCORND	-0.0017	-0.0134	-0.0288	0.0062	0.0223	-0.0014
	0.9099	0.6022	0.1329	0.5917	0.3448	0.9719
LSPCID	-0.0021	0.0005	0.0047	-0.0055	-0.0068	0.0359
	0.7364	0.965	0.5711	0.2676	0.5026	0.0412 **
LCOPPFD	0.0245	-0.0331	-0.0078	0.0138	0.0199	-0.0563

	0.0557 *	0.1318	0.634	0.1629	0.3264	0.1104
LCRUDFD	0.0116	-0.0330	0.0098	0.0297	-0.0004	-0.0034
	0.5637	0.3379	0.7035	0.0543 *	0.9907	0.9511
LSILVFD	-0.0166	0.1097	-0.0270	-0.0080	0.0075	-0.0327
	0.2894	0 ***	0.1806	0.5059	0.7631	0.4485
LGOLDFD	-0.0171	0.0470	-0.0217	0.0074	-0.0174	0.0439
	0.0501 *	0.0017 ***	0.0533 *	0.2687	0.2073	0.0677 *

	LCORND.l15	LSPCID.l15	LCOPPFD.l15	LCRUDFD.l15	LSILVFD.l15	LGOLDFD.l15
LCORND	0.0294	-0.0110	0.0129	-0.0004	-0.0518	0.1368
	0.0487 **	0.6694	0.5014	0.9718	0.0283 **	0.0009 ***
LSPCID	0.0011	-0.0303	0.0073	0.0061	-0.0052	0.0372
	0.8677	0.0059 ***	0.3739	0.2128	0.605	0.0345 **
LCOPPFD	-0.0139	0.0213	-0.0040	-0.0145	-0.0275	0.1193
	0.2761	0.3347	0.8058	0.1406	0.1742	0.0007 ***
LCRUDFD	0.0199	-0.0270	0.0727	-0.0150	-0.0290	0.0351
	0.3209	0.4345	0.0048 ***	0.3315	0.3599	0.5247
LSILVFD	0.0116	0.0048	-0.0162	0.0100	-0.0430	0.0794
	0.4601	0.8591	0.4224	0.409	0.0832 *	0.0662 *
LGOLDFD	0.0116	0.0009	-0.0176	0.0083	-0.0076	0.0273
	0.1827	0.9529	0.1175	0.2154	0.5831	0.2562

	LCORND.l16	LSPCID.l16	LCOPPFD.l16	LCRUDFD.l16	LSILVFD.l16	LGOLDFD.l16
LCORND	0.0169	0.0116	0.0179	0.0051	-0.0290	-0.0164
	0.2575	0.6467	0.3486	0.6548	0.2148	0.6889
LSPCID	-0.0150	0.0495	-0.0178	0.0178	-0.0028	-0.0150
	0.0188 **	0 ***	0.0286 **	0.0003 ***	0.7835	0.3919
LCOPPFD	0.0210	0.0146	0.0150	0.0132	0.0097	-0.0720
	0.101	0.5024	0.3603	0.1807	0.6296	0.0403 **
LCRUDFD	0.0046	0.0256	0.0157	0.0113	0.0235	-0.0879
	0.8193	0.4519	0.5406	0.4655	0.4536	0.1101
LSILVFD	0.0416	0.0263	-0.0117	0.0011	0.0121	-0.0184
	0.0078 ***	0.325	0.5606	0.9293	0.6233	0.6682
LGOLDFD	0.0316	0.0218	-0.0079	-0.0081	0.0134	-0.0304
	0.0003 ***	0.1418	0.4801	0.2288	0.3261	0.2045

	const	LVIX	LGPRD
LCORND	0.0175	-0.0289	-0.0011
	0.5317	0 ***	0.1317
LSPCID	0.0235	-0.1226	0.0006
	0.0501 *	0 ***	0.0561 *
LCOPPFD	0.0183	-0.0554	-0.0001
	0.4477	0 ***	0.8878
LCRUDFD	0.0108	-0.0778	-0.0003
	0.7748	0 ***	0.7664

LSILVFD	0.0218	-0.0334	0.0003
	0.4587	0 ***	0.6419
LGOLDFD	0.0331	-0.0004	0.0000
	0.044 **	0.8601	0.9572

Notes: See Appendix I.

Appendix K. Rice VARX-model results.

	LRICED.l1	LSPCID.l1	LCOPPFD.l1	LCRUDFD.l1	LSILVFD.l1	LGOLDFD.l1
LRICED	0.0312	0.0364	-0.0028	-0.0079	-0.0187	0.0696
	0.0332 **	0.0522 *	0.8425	0.3568	0.2877	0.0236 **
LSPCID	0.0029	-0.0432	-0.0007	-0.0002	-0.0100	0.0292
	0.7327	0.0001 ***	0.9304	0.9686	0.3242	0.0991 *
LCOPPFD	0.0021	0.2053	-0.0975	-0.0125	-0.0292	0.0788
	0.9005	0 ***	0 ***	0.204	0.151	0.0265 **
LCRUDFD	-0.0237	0.0831	-0.0280	-0.0337	-0.0169	0.0688
	0.3693	0.0139 **	0.2758	0.0288 **	0.5951	0.215
LSILVFD	0.0197	0.2380	-0.0477	0.0054	-0.0706	0.1165
	0.3398	0 ***	0.0178 **	0.6518	0.0046 ***	0.0073 ***
LGOLDFD	0.0093	0.0544	-0.0286	0.0006	-0.0133	0.0244
	0.4194	0.0002 ***	0.0108 **	0.931	0.34	0.3143
	LRICED.l2	LSPCID.l2	LCOPPFD.l2	LCRUDFD.l2	LSILVFD.l2	LGOLDFD.l2
LRICED	-0.0136	0.0138	0.0035	0.0042	0.0055	-0.0447
	0.3512	0.47	0.8089	0.6237	0.7565	0.1459
LSPCID	-0.0089	0.0466	0.0002	-0.0064	-0.0090	0.0638
	0.2899	0 ***	0.982	0.1955	0.3733	0.0003 ***
LCOPPFD	0.0104	0.0224	-0.0063	0.0039	0.0087	0.0079
	0.5403	0.3101	0.7042	0.6918	0.6696	0.8232
LCRUDFD	0.0137	0.0590	-0.0013	-0.0595	0.1043	-0.0491
	0.6038	0.0865 *	0.9587	0.0001 ***	0.0011 ***	0.3763
LSILVFD	-0.0131	0.0383	-0.0043	-0.0215	0.0174	0.0153
	0.5256	0.1556	0.8311	0.0748 *	0.4857	0.7252
LGOLDFD	-0.0205	0.0249	-0.0012	-0.0078	-0.0073	0.0044
	0.0754 *	0.0971 *	0.9144	0.2435	0.599	0.8571
	LRICED.l3	LSPCID.l3	LCOPPFD.l3	LCRUDFD.l3	LSILVFD.l3	LGOLDFD.l3
LRICED	0.0095	0.0044	-0.0054	0.0153	-0.0044	-0.0178
	0.5142	0.8169	0.7073	0.0738 *	0.8037	0.5617
LSPCID	0.0029	0.0261	-0.0080	0.0269	0.0104	-0.0132
	0.7283	0.0172 **	0.3316	0 ***	0.3025	0.4562
LCOPPFD	0.0011	-0.0107	0.0001	0.0239	-0.0282	0.0133

	0.9474	0.6285	0.9965	0.0154 **	0.1651	0.707
LCRUDFD	-0.0066	-0.0851	-0.0116	0.0041	-0.0163	0.0139
	0.804	0.0133 **	0.6512	0.7899	0.6085	0.8022
LSILVFD	0.0237	-0.0022	-0.0098	0.0055	-0.0083	0.0400
	0.2508	0.934	0.6261	0.6465	0.7396	0.3562
LGOLDFD	0.0076	-0.0196	-0.0103	0.0017	0.0052	0.0137
	0.5077	0.1924	0.3607	0.8016	0.7068	0.5719
	LRICED.l4	LSPCID.l4	LCOPPFD.l4	LCRUDFD.l4	LSILVFD.l4	LGOLDFD.l4
LRICED	-0.0127	-0.0134	0.0186	-0.0077	0.0043	-0.0199
	0.385	0.4834	0.1918	0.3646	0.8052	0.5161
LSPCID	-0.0012	-0.0246	0.0198	0.0030	-0.0086	-0.0112
	0.8854	0.0248 **	0.016 **	0.5396	0.3961	0.5257
LCOPPFD	0.0285	0.0252	0.0030	-0.0031	0.0412	-0.0959
	0.0921 *	0.2533	0.8548	0.75	0.0424 **	0.0068 ***
LCRUDFD	-0.0170	0.0530	0.0554	0.0649	-0.0202	-0.1262
	0.5204	0.1232	0.0312 **	0 ***	0.5235	0.0226 **
LSILVFD	-0.0083	-0.0410	0.0119	0.0150	-0.0199	-0.0362
	0.687	0.128	0.5555	0.2133	0.4234	0.403
LGOLDFD	0.0017	0.0021	0.0029	-0.0037	-0.0106	0.0057
	0.8831	0.8912	0.7971	0.5835	0.4431	0.8142
	LRICED.l5	LSPCID.l5	LCOPPFD.l5	LCRUDFD.l5	LSILVFD.l5	LGOLDFD.l5
LRICED	-0.0119	0.0309	-0.0104	0.0079	-0.0123	0.0350
	0.4141	0.1045	0.4641	0.355	0.4852	0.2528
LSPCID	0.0035	0.0096	-0.0283	-0.0006	0.0263	-0.0023
	0.6769	0.38	0.0006 ***	0.9023	0.0094 ***	0.8981
LCOPPFD	-0.0076	0.0292	-0.0201	-0.0012	-0.0113	0.0566
	0.6534	0.1852	0.2215	0.9004	0.5765	0.1096
LCRUDFD	-0.0139	-0.0461	-0.0449	0.0291	0.0008	-0.0161
	0.5993	0.1802	0.0807 *	0.0594 *	0.9788	0.7709
LSILVFD	-0.0212	0.0099	0.0404	0.0114	-0.0106	0.0000
	0.3049	0.7126	0.045 **	0.3437	0.6687	0.9993
LGOLDFD	-0.0036	0.0071	0.0219	0.0042	-0.0033	-0.0100
	0.7553	0.6343	0.051 *	0.5301	0.8106	0.6794
	LRICED.l6	LSPCID.l6	LCOPPFD.l6	LCRUDFD.l6	LSILVFD.l6	LGOLDFD.l6
LRICED	0.0300	0.0079	-0.0209	-0.0029	0.0123	-0.0349
	0.0402 **	0.6791	0.1429	0.7378	0.484	0.2534
LSPCID	0.0095	-0.0002	-0.0156	-0.0053	0.0096	-0.0135
	0.2613	0.9826	0.0575 *	0.2835	0.3417	0.4431
LCOPPFD	-0.0094	-0.0104	-0.0107	0.0120	-0.0150	0.0343
	0.5788	0.6361	0.5155	0.2259	0.4607	0.3311
LCRUDFD	-0.0024	0.0300	-0.0035	-0.0083	0.0268	-0.0293
	0.9284	0.3833	0.8919	0.5906	0.397	0.5954

LSILVFD	-0.0116	0.0571	-0.0033	-0.0034	-0.0342	0.0459
	0.5728	0.0338 **	0.8694	0.7796	0.1681	0.2878
LGOLDFD	0.0017	-0.0018	-0.0023	-0.0059	-0.0222	0.0056
	0.883	0.9058	0.839	0.3818	0.1079	0.8158

	LRICED.l7	LSPCID.l7	LCOPPFD.l7	LCRUDFD.l7	LSILVFD.l7	LGOLDFD.l7
LRICED	0.0233	0.0125	-0.0049	-0.0119	0.0121	-0.0405
	0.1106	0.5124	0.73	0.1625	0.4918	0.186
LSPCID	0.0043	0.0412	0.0152	0.0007	-0.0166	-0.0056
	0.6098	0.0002 ***	0.0639 *	0.8934	0.0995 *	0.7516
LCOPPFD	-0.0281	0.0494	0.0396	0.0064	0.0042	-0.0229
	0.096 *	0.025 **	0.0163 **	0.5168	0.8372	0.517
LCRUDFD	-0.0188	0.1262	-0.0003	-0.0207	0.0354	-0.0770
	0.4769	0.0002 ***	0.9918	0.1804	0.2639	0.1633
LSILVFD	-0.0279	0.0005	0.0366	0.0078	0.0172	-0.0763
	0.1766	0.984	0.0691 *	0.5161	0.487	0.0772 *
LGOLDFD	-0.0111	-0.0049	0.0232	-0.0050	0.0127	-0.0446
	0.3355	0.7454	0.0388 **	0.4588	0.3576	0.0643 *

	LRICED.l8	LSPCID.l8	LCOPPFD.l8	LCRUDFD.l8	LSILVFD.l8	LGOLDFD.l8
LRICED	-0.0117	0.0126	0.0085	-0.0056	-0.0090	0.0359
	0.4238	0.5099	0.5518	0.5117	0.6087	0.2409
LSPCID	-0.0060	0.0157	-0.0117	-0.0085	-0.0096	-0.0031
	0.4792	0.1517	0.154	0.0857 *	0.3404	0.8591
LCOPPFD	0.0163	-0.0217	0.0399	0.0004	0.0026	-0.0350
	0.3356	0.3246	0.0154 **	0.9641	0.8978	0.3217
LCRUDFD	-0.0155	-0.0331	0.0444	0.0164	-0.0202	0.0216
	0.5562	0.3352	0.0844 *	0.2871	0.5223	0.6952
LSILVFD	0.0437	-0.0487	0.0196	-0.0078	0.0055	-0.0469
	0.0345 **	0.0706 *	0.3305	0.517	0.8257	0.2777
LGOLDFD	0.0345	-0.0502	0.0176	-0.0034	-0.0154	0.0091
	0.0028 ***	0.0008 ***	0.1178	0.618	0.2635	0.7045

	LRICED.l9	LSPCID.l9	LCOPPFD.l9	LCRUDFD.l9	LSILVFD.l9	LGOLDFD.l9
LRICED	0.0029	0.0003	-0.0056	0.0051	-0.0140	0.0546
	0.8453	0.9886	0.6946	0.5475	0.4235	0.0736 *
LSPCID	0.0106	0.0401	-0.0099	0.0155	-0.0150	0.0156
	0.2088	0.0003 ***	0.2256	0.0016 ***	0.1376	0.3739
LCOPPFD	-0.0062	0.0112	-0.0142	0.0202	-0.0154	0.0133
	0.7119	0.6105	0.3877	0.0411 **	0.4467	0.7062
LCRUDFD	0.0070	0.0180	-0.0434	0.0053	0.0659	-0.0751
	0.7921	0.6009	0.0921 *	0.7304	0.0373 **	0.1733
LSILVFD	0.0122	-0.0024	-0.0199	-0.0079	0.0641	-0.0469
	0.5542	0.9291	0.3232	0.5129	0.0096 ***	0.2765
LGOLDFD	0.0088	0.0058	-0.0037	-0.0134	0.0222	-0.0011

	0.447	0.6991	0.7393	0.0465 **	0.108	0.962
	LRICED.l10	LSPCID.l10	LCOPPFD.l10	LCRUDFD.l10	LSILVFD.l10	LGOLDFD.l10
LRICED	-0.0078	0.0118	0.0338	-0.0056	-0.0256	0.0194
	0.5929	0.5363	0.0178 **	0.5134	0.1449	0.5254
LSPCID	-0.0246	0.0036	0.0085	0.0106	-0.0143	0.0154
	0.0034 ***	0.742	0.2993	0.032 **	0.1556	0.3815
LCOPPFD	-0.0172	0.0393	0.0314	0.0082	-0.0232	0.0582
	0.3097	0.0739 *	0.0564 *	0.4064	0.252	0.099 *
LCRUDFD	-0.0282	0.0198	0.0606	-0.0406	0.0300	-0.0734
	0.2858	0.5644	0.0185 **	0.0085 ***	0.3437	0.1832
LSILVFD	-0.0217	-0.0264	0.0088	0.0004	0.0113	-0.0041
	0.2931	0.3265	0.6622	0.9722	0.649	0.9237
LGOLDFD	-0.0060	0.0163	-0.0004	-0.0013	0.0105	-0.0032
	0.6004	0.2781	0.9693	0.8487	0.4463	0.8953
	LRICED.l11	LSPCID.l11	LCOPPFD.l11	LCRUDFD.l11	LSILVFD.l11	LGOLDFD.l11
LRICED	0.0072	0.0286	-0.0127	0.0090	-0.0175	0.0034
	0.6244	0.1329	0.3716	0.2902	0.3188	0.9114
LSPCID	0.0080	-0.0275	0.0219	-0.0083	-0.0006	-0.0152
	0.3426	0.0122 **	0.0075 ***	0.0915 *	0.9564	0.3853
LCOPPFD	0.0047	0.0287	-0.0133	-0.0089	-0.0264	0.0335
	0.7826	0.1923	0.4182	0.3695	0.1927	0.3424
LCRUDFD	0.0181	-0.0079	0.0173	-0.0379	0.0195	-0.0675
	0.4931	0.8191	0.501	0.0141 **	0.5385	0.22
LSILVFD	0.0263	-0.0061	-0.0231	-0.0020	0.0239	-0.0648
	0.2024	0.8216	0.2524	0.8702	0.3343	0.1328
LGOLDFD	0.0099	0.0347	-0.0027	-0.0023	0.0123	-0.0507
	0.3896	0.0207 **	0.8124	0.7308	0.3734	0.035 **
	LRICED.l12	LSPCID.l12	LCOPPFD.l12	LCRUDFD.l12	LSILVFD.l12	LGOLDFD.l12
LRICED	-0.0077	0.0179	0.0105	0.0019	-0.0124	-0.0306
	0.5976	0.3478	0.4616	0.8287	0.4796	0.3163
LSPCID	-0.0183	0.0272	0.0062	0.0038	-0.0088	-0.0200
	0.0301 **	0.0133 **	0.4477	0.4447	0.3812	0.2543
LCOPPFD	0.0009	0.0298	0.0270	0.0115	-0.0041	-0.0120
	0.9589	0.1754	0.1024	0.2438	0.8397	0.7328
LCRUDFD	0.0419	0.0166	0.0406	0.0235	-0.0723	0.0763
	0.1127	0.629	0.115	0.1285	0.0223 **	0.1664
LSILVFD	-0.0352	-0.0264	0.0526	0.0112	0.0327	-0.0640
	0.0884 *	0.3269	0.0091 ***	0.3548	0.1872	0.1376
LGOLDFD	-0.0190	-0.0121	0.0183	0.0006	0.0468	-0.0870
	0.1002	0.422	0.1044	0.9332	0.0007 ***	0.0003 ***
	LRICED.l13	LSPCID.l13	LCOPPFD.l13	LCRUDFD.l13	LSILVFD.l13	LGOLDFD.l13
LRICED	-0.0093	0.0075	-0.0041	0.0095	-0.0183	0.0045

	0.5248	0.6955	0.7726	0.2635	0.2951	0.8839
LSPCID	-0.0011	-0.0150	0.0173	-0.0002	0.0080	-0.0240
	0.8935	0.1719	0.0353 **	0.9701	0.425	0.1724
LCOPPFD	-0.0196	0.0497	0.0169	-0.0001	-0.0441	0.0826
	0.2461	0.0242 **	0.304	0.9894	0.0296 **	0.0194 **
LCRUDFD	0.0024	0.0785	-0.0069	0.0315	-0.0875	0.1726
	0.9271	0.0224 **	0.7899	0.0404 **	0.0057 ***	0.0017 ***
LSILVFD	-0.0265	0.0391	0.0043	0.0078	-0.0739	0.1012
	0.2007	0.1463	0.8318	0.5159	0.0028 ***	0.019 **
LGOLDFD	0.0000	0.0153	0.0012	-0.0045	-0.0303	0.0497
	0.9999	0.3081	0.916	0.5028	0.028 **	0.0391 **
	LRICED.l14	LSPCID.l14	LCOPPFD.l14	LCRUDFD.l14	LSILVFD.l14	LGOLDFD.l14
LRICED	-0.0097	-0.0175	0.0314	-0.0154	-0.0050	0.0067
	0.5083	0.3585	0.0277 **	0.0706 *	0.7743	0.8272
LSPCID	0.0109	0.0011	0.0032	-0.0068	-0.0078	0.0370
	0.1966	0.9171	0.6947	0.1635	0.4386	0.0356 **
LCOPPFD	-0.0026	-0.0269	-0.0057	0.0157	0.0218	-0.0537
	0.8762	0.2219	0.7303	0.1108	0.2818	0.1283
LCRUDFD	-0.0176	-0.0324	0.0116	0.0307	0.0012	-0.0002
	0.5069	0.3455	0.6524	0.0457 **	0.9695	0.9966
LSILVFD	-0.0238	0.1134	-0.0257	-0.0101	0.0068	-0.0311
	0.2507	0 ***	0.2013	0.399	0.7851	0.4719
LGOLDFD	-0.0026	0.0483	-0.0229	0.0056	-0.0184	0.0426
	0.8194	0.0013 ***	0.0414 **	0.4042	0.1836	0.077 *
	LRICED.l15	LSPCID.l15	LCOPPFD.l15	LCRUDFD.l15	LSILVFD.l15	LGOLDFD.l15
LRICED	0.0004	-0.0024	0.0314	-0.0155	-0.0008	0.0023
	0.9791	0.9011	0.0279 **	0.0688 *	0.9657	0.9404
LSPCID	-0.0094	-0.0280	0.0082	0.0073	-0.0053	0.0342
	0.2627	0.0107 **	0.3187	0.1365	0.5978	0.0519 *
LCOPPFD	-0.0191	0.0246	-0.0043	-0.0159	-0.0285	0.1220
	0.259	0.265	0.795	0.1063	0.1598	0.0006 ***
LCRUDFD	-0.0141	-0.0206	0.0751	-0.0144	-0.0262	0.0385
	0.5945	0.549	0.0035 ***	0.3497	0.4071	0.4862
LSILVFD	-0.0375	0.0085	-0.0131	0.0135	-0.0412	0.0847
	0.0701 *	0.7534	0.5169	0.2624	0.0961 *	0.0501 *
LGOLDFD	-0.0190	0.0027	-0.0157	0.0110	-0.0060	0.0297
	0.1001	0.856	0.1625	0.1009	0.6641	0.2182
	LRICED.l16	LSPCID.l16	LCOPPFD.l16	LCRUDFD.l16	LSILVFD.l16	LGOLDFD.l16
LRICED	-0.0037	0.0093	0.0137	-0.0038	-0.0195	0.0045
	0.8002	0.6219	0.3322	0.6549	0.2621	0.8833
LSPCID	0.0095	0.0480	-0.0207	0.0159	-0.0045	-0.0146
	0.2595	0 ***	0.0111 **	0.0011 ***	0.6552	0.405

LCOPPFD	0.0242	0.0132	0.0156	0.0154	0.0103	-0.0712
	0.1521	0.5456	0.3403	0.117	0.6063	0.0429 **
LCRUDFD	0.0052	0.0292	0.0141	0.0112	0.0228	-0.0872
	0.8451	0.3914	0.5817	0.4665	0.4676	0.1125
LSILVFD	0.0394	0.0268	-0.0103	0.0037	0.0158	-0.0171
	0.0567 *	0.3147	0.6062	0.7582	0.5187	0.691
LGOLDFD	0.0181	0.0230	-0.0061	-0.0065	0.0166	-0.0280
	0.1164	0.1211	0.5834	0.3362	0.2261	0.2433

	const	LVIX	LGPRD
LRICED	-0.0066	-0.0126	0.0006
	0.7513	0 ***	0.2519
LSPCID	0.0236	-0.1224	0.0006
	0.0497 **	0 ***	0.0595 *
LCOPPFD	0.0189	-0.0549	0.0000
	0.432	0 ***	0.9999
LCRUDFD	0.0107	-0.0772	-0.0003
	0.7773	0 ***	0.7575
LSILVFD	0.0221	-0.0323	0.0003
	0.4536	0 ***	0.6629
LGOLDFD	0.0337	0.0001	-0.0001
	0.0403 **	0.9487	0.8838

Notes: See Appendix I.

Appendix L. Monthly ARX model with exogenous variables.

ARX model	N=231	Start	Jun-02	End	Aug-21					
	Intercept	AR(1)	AR(2)	VIX	GPR	EPU	CPU	Sigma^2	LL	AIC
Wheat	0.3732	-0.0333		-0.0532	0.0374	-0.0014	0.0041	110.2	-870.87	1755.7
	(0.6688)	(0.0657)*		(0.0331)**	(0.0374)**	(0.0403)**	(0.0104)**			
Corn	0.4743	-0.0029	0.1226	-0.0491	0.036	-0.0696	-0.0017	78.81	-832.19	1680.4
	(0.663)	(0.0665)*	(0.0664)*	(0.0275)**	(0.0309)**	(0.0336)**	(0.0087)***			
Rice	-0.085	-0.0747		-0.0053	-0.0191	-0.0022	0.0031	44.21	-765.4	1544.8
	(0.4074)	(0.0657)*		(0.0211)**	(0.0239)**	(0.0258)**	(0.0067)***			

Notes: Wheat, corn, and rice ARIMA model results. Optimal lags for wheat and rice series are one and corn two, according to AIC.