Energy and Commodity Price Volatility in Sub-Saharan Africa: The Role of Uncertainty.

By

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ABSTRACT

This thesis, focusing on sub-Saharan Africa, investigates the relationship between energy prices, agricultural commodity markets, and policy/events uncertainties. The research is divided into three distinct yet interconnected papers, each employing unique methodologies and data to address specific aspects of this issue. The first paper examines the dynamic relationship between oil prices and food security in sub-Saharan Africa, accounting for the moderating role of global uncertainty, as measured by the World Uncertainty Index. Utilizing a Pooled Mean Group Autoregressive Distributed Lag (PMG-ARDL) model, the study reveals that oil price shocks and heightened global uncertainty negatively impact food security in the region. The effects are found to be homogenous across countries in the region.

The second paper analyses the role of geopolitical risk in the extreme spillovers between energy prices and agricultural commodity prices. Employing a time-varying parameter vector autoregression (TVP-VAR) model and disaggregated geopolitical risk measures, the study finds evidence of significant time-variation and asymmetry in extreme spillovers. Geopolitical risk events significantly influence the intensity and direction of these spillovers, with different risk categories exhibiting varying impacts. In the third paper, the study examines the effect of climate risk on the dynamic spillovers between oil prices and food prices in the sub-Saharan region. Utilizing a GARCH-MIDAS approach for 10 countries, the study reveals that climate risk significantly affects the volatility and interconnectedness of these markets. The findings underscore the importance of accounting for climate risk in assessing the vulnerability of food systems to oil price shocks.

Specifically, the results for paper one show a strong positive significance at 1% level of significance for the five variables including oil prices, WUI, GDP per capita, exchange rate, and the dummies used to control for the structural breaks. The three forms of geopolitical risk are net shock receivers, except for the narrow definition, which is a net shock giver. The narrow definition, likely referring to direct conflicts or wars, shows the highest net connectedness in all countries except Nigeria, where it is second to oil. The lagged impact of climate risk on the volatility of the oil-food connectedness index is captured by θ in paper three. The results show positive and significant values of θ in six countries (Angola, Ghana, Kenya, Senegal, South Africa, and Tanzania), indicating that, on average, an increase in the climate change variable, like higher temperatures, is associated with an increase in the volatility of the connectedness between oil and food prices.

Overall, across all three papers, the findings have important implications for policymakers and stakeholders seeking to enhance food security and economic stability in the face of increasing uncertainties. The findings of this thesis underscore the critical need for policymakers in sub-Saharan Africa to adopt a holistic and multi-dimensional approach to address food security challenges in the face of increasing uncertainties. Policymakers should explicitly acknowledge and account for policy uncertainties in their decision-making processes. This involves developing flexible and adaptive policy frameworks that respond effectively to unforeseen shocks and changing market conditions.

Given the heterogeneous impact of oil price volatility and uncertainty on different developing economies, policymakers should prioritize targeted interventions that protect the most vulnerable populations. Reducing dependence on imported oil and diversifying energy sources can enhance resilience to oil price shocks. Similarly, promoting agricultural diversification and supporting local food production can reduce vulnerability to global food market fluctuations for papers one and two.

Moreover, there is a need to enhance regional cooperation and integration to help mitigate the adverse effects of geopolitical risks and climate change on food security for papers two and three respectively. This may involve sharing information, coordinating policies, and investing in regional infrastructure and early warning systems. Encouraging sustainable agricultural practices and investments in renewable energy can contribute to long-term food security and environmental sustainability. This includes promoting soil conservation, water management, and agroforestry practices. By adopting these policy recommendations, policymakers can create a more resilient and sustainable food system in sub-Saharan Africa, capable of withstanding the challenges posed by oil price volatility, geopolitical risk, and climate change. It highlights the need for tailored policy interventions that address the specific vulnerabilities of different countries and account for the time-varying and asymmetric nature of market interactions.

KEYWORDS: Oil markets, agricultural prices, climate risk, geopolitical risk, volatility, spillover, MIDAS.

DECLARATION

This thesis represents my original work and has been prepared solely to fulfill the Doctor of Philosophy degree requirements at the University of the Witwatersrand, Johannesburg. This work has not been submitted, in whole or in part, for any other degree or examination at this or any other institution.

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DEDICATION

I sincerely dedicate this thesis to my beloved father and mother, who taught me the value of knowledge, my devoted husband, Geoffrey, who taught me the meaning of love, my cherished children, Nqobile and Thembekile, who taught me the joy of life, and my dear brothers and sisters, whose love and support have always been my foundation.

This thesis reflects your enduring presence in my life.

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LIST OF ABBREVIATIONS

ARDL – Autoregressive Distributed Lag

ARIMA – Autoregressive Moving Average

DCC - GARCH – Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity

DY – Diebold Yilmaz

EPU – Economic Policy Uncertainty

GARCH - MIDAS – Generalized Autoregressive Conditional Heteroskedasticity Mixed Data Sampling

GDP – Gross Domestic Product

GRP – Geopolitical Risk

MENA – Middle East and North America

PMG - ARDL – Pool Mean Group Auto Regressive Distributed Lag

QVAR – Quantile Vector Autoregression

SDG – Sustainable Development Goals

SSA – Sub Saharan Africa

T – GARCH Threshold Generalized Autoregressive Conditional Heteroskedasticity

TVP – VAR – Time-Varying Parameter Vector Auto Regression

USA – United States of America

VECM – Vector Error Correction Model

WUI – World Uncertainty Index

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CHAPTER ONE

INTRODUCTION AND BACKGROUND

1.1 Introduction

For centuries, scholars have grappled with the elusive nature of uncertainty, yet the heart of the matter lies in the fundamental distinction between risk and uncertainty. As Keynes (1936) prudently observed, risk is quantifiable, with probabilities that can be calculated and managed. This measurable aspect of uncertainty has been the focus of study from Bernoulli's early work in 1738 to the modern analyses of Archaya et al. (2017) and Giglio et al. (2021). However, true uncertainty, the immeasurable unknown, has often been relegated to the sidelines. This oversight is particularly striking given the profound impact of "Knightian uncertainty" (Knight, 1921). This concept precisely encapsulates events with unknowable probabilities, such as trade wars, geopolitical events, and the looming specter of climate change.

Keynes (1936) recognized the pivotal role of uncertainty in economic behavior, highlighting that investment decisions often rely on intuition and confidence in the face of an unpredictable future. This foundational insight has driven contemporary economics to integrate uncertainty into various facets of research. For instance, modeling techniques now frequently incorporate uncertainty through stochastic processes (De Waal et al., 2015), probability distributions (Binder & Pesaran, 1999), and scenario analysis. In behavioral economics, scholars acknowledge that individuals often rely on heuristics rather than acting as perfectly rational agents, making them susceptible to biases when faced with uncertainty (Plakandaras et al., 2019). In policymaking, economists wrestle with the impact of uncertainty on the effectiveness of interventions, exploring mechanisms to mitigate its adverse effects (Stiglitz, 1974). Thus, uncertainty is not merely a peripheral concern; it is a fundamental force that shapes economic decision-making, market dynamics, and the effectiveness of policy measures. This is precisely why assessing the role of uncertainty is crucial. By understanding how uncertainty affects the interconnectedness of oil and food markets, we can better comprehend the economic implications and develop strategies to enhance resilience and stability in the face of climate risk.

Uncertainty profoundly influences economic decision-making, market outcomes, efficiency, and equity. It compels firms and individuals to navigate critical choices regarding investment, expenditure, employment, and consumption without complete information about the future (Farid et al., 2022). Its pervasive impact extends to prices, supply and demand dynamics, and market equilibrium, potentially precipitating volatility or even market failure (Janda & Krištoufek, 2019). Moreover, uncertainty can stifle investment, misallocate resources, and curtail economic growth. Notably, it can also exacerbate existing socioeconomic disparities, as the economically disadvantaged and marginalized populations are disproportionately susceptible to the adverse consequences of economic shocks with uncertain outcomes (Carter et al., 2017).

Consequently, understanding uncertainty's role in financial markets (Chen & Semmler, 2018), business cycles, international trade, and macroeconomic policy is paramount. Asset pricing and investment strategies intrinsically consider uncertainty surrounding future returns and risks (Kang & Ratti, 2013). Business cycles may stem from uncertainty about future conditions, influencing business decisions. Uncertainty regarding exchange rates, trade policies, and geopolitical risks affects trade flows and international investments (Siami-Namini, 2019). Moreover, policymakers operating amidst uncertainty contend with the potential impact on the effectiveness of their policies.

Different sources of uncertainty include geopolitical events, natural disasters, social unrest (Ahir et al., 2022), economic factors, and climate-related risks (Huynh et al., 2020) that directly affect agricultural production costs and food prices. These events also act as catalysts, amplifying price volatility in the oil and agricultural markets. The volatility originates from the challenges producers and consumers face in anticipating future price fluctuations, resulting in speculative behavior and price swings (Rising et al., 2022). The agricultural sector, heavily reliant on oil-derived fertilizers, pesticides, and fuel for machinery, is particularly vulnerable to uncertainty about future oil prices (Gupta et al., 2021). This uncertainty hinders farmers' ability to make informed production and investment decisions, resulting in suboptimal resource allocation, increased production costs, and higher consumer food prices.

Additionally, uncertainty disrupts supply chains, particularly for agricultural commodities depending on oil as an input or for transportation (Liu & Gao, 2022). Conflicts, sanctions, or political instability in oil-producing regions can directly disrupt oil supply chains (Gabauer & Gupta, 2018). This disruption creates uncertainty in the availability of oil, leading to price spikes and volatility (Roman et al., 2020). Geopolitical events can also disrupt global trade flows, affecting the prices and availability of both oil and agricultural commodities. Trade restrictions, sanctions, or disruptions in shipping routes can create uncertainty in the smooth functioning of international markets, leading to extreme price fluctuations and supply chain bottlenecks (Liu et al., 2019).

Moreover, geopolitical events induce financial market uncertainty, triggering capital flight and heightened risk aversion (Xiao et al., 2023). This fuels the demand for safe-haven assets like gold and the US dollar, indirectly impacting oil and agricultural commodity prices (Arfaoui & Ben Rejeb, 2017). Coupled with unpredictable policy interventions like tariffs, export restrictions, or strategic stockpiling (Kumar, 2017), geopolitical risks amplify market volatility and generate extreme spillovers beyond traditional economic policy uncertainty measures (Zhou et al., 2020).

Climate change exacerbates uncertainty in both oil and food markets through multiple channels. Extreme weather events directly impact agricultural production (Mirón et al., 2023), while disruptions to oil supply chains and the global shift towards renewables introduce volatility in oil prices (Puertas & Marti, 2021). Oil production results in many carbon emissions, leading to climate risk. This has led to policies advocating carbon reduction, which has created uncertainty in financial markets. Investors may reassess the value of fossil fuel assets and shift investments toward renewable energy or other sectors (Zhang et al., 2023). This can lead to volatility in oil prices and financial markets, which can then spill over into agricultural commodity markets through various channels, including changes in investor sentiment, exchange rates, and the cost of capital for agricultural businesses (Giglio et al., 2021).

Lastly, government policies to mitigate climate change, such as carbon taxes or emissions trading schemes, can directly impact the oil market and indirectly affect food prices (Ghadge et al., 2020). The uncertainty surrounding these policies' timing, stringency, and implementation can create additional volatility in both markets as businesses and investors try to anticipate future regulatory changes (Ndako et al., 2021). By considering climate risk, we understand more about the interactions between oil and food prices. This allows for more accurate assessments of potential spillovers, improved risk management strategies, and the development of policies that promote resilience in the energy and food sectors in the face of climate risk.

1.2 Background of Study

Uncertainty plays a multifaceted role in shaping the relationship between oil and food prices (Wen et al., 2021). Firstly, uncertainty stemming from geopolitical events, supply disruptions, or speculative activities within the oil market can create volatility in oil prices (Sharif et al., 2020). This volatility directly translates into uncertainties within the agricultural sector, as oil is a fundamental input for fertilizers, pesticides, transportation, and food processing (Onour, 2021). Consequently, uncertainty-driven spikes in oil prices lead to higher production costs for farmers, often squeezing profit margins and ultimately pushing up food prices for consumers.

Secondly, uncertainty within global financial markets can trigger dynamics and spillover effects between oil and food markets (Wen et al., 2021). For instance, heightened uncertainty can drive investors to safe-haven assets like commodities, including oil and agricultural products. This can artificially inflate prices across both markets. Additionally, with oil often priced in US dollars, uncertain exchange rate fluctuations can create further volatility in agricultural import and export costs (Fasanya et al., 2021). This introduces additional uncertainty in pricing decisions for producers and traders, contributing to food price instability.

Lastly, climate change-related uncertainties pose a major challenge to the oil-food nexus. Increasingly unpredictable weather patterns make agricultural production far less certain regarding yields and crop quality (Birgani et al., 2022). Simultaneously, uncertainties surrounding the future regulatory landscape for carbon emissions and potential shifts in energy policies introduce volatility into the oil market (Zhang et al., 2023). The combined uncertainties create a complex risk environment for agricultural producers and agribusinesses. Uncertainty potentially disincentivizes investment in agriculture and contributes to volatility in food markets, particularly in regions heavily reliant on oil-based inputs and rain-fed agriculture (Giannakas & Yiannaka, 2023).

The relationship between oil, agricultural commodities, and uncertainty holds significant implications for Sub-Saharan Africa (SSA). It is a region characterized by heavy reliance on commodity exports, predominantly oil and agricultural products, and vulnerability to external shocks (Giannakas & Yiannaka, 2023). This interconnectedness has become increasingly evident in recent years, as global events like the COVID-19 pandemic and the Russia-Ukraine conflict have triggered unprecedented volatility in oil and food markets (Sharif et al., 2020). Oil, a critical input for agricultural production and transportation, plays a pivotal role in SSA's food security and economic stability. Fluctuations in oil prices directly impact the cost of agricultural inputs like fertilizers and pesticides and transportation costs, ultimately influencing food prices and overall inflation (Birgani et al., 2022). Moreover, Dorinet et al. (2021) pointed out that the region's dependence on rain-fed agriculture renders it particularly susceptible to climate change-induced uncertainties, such as droughts and floods, which can severely disrupt agricultural production and exacerbate food insecurity.

Additionally, SSA's economies are deeply integrated into global financial markets, making them uniquely vulnerable to external shocks and contagion effects. This vulnerability is amplified by the region's limited economic diversification, high poverty rates, and weak social safety nets (Bjornlund et al., 2022). Uncertainty stemming from global economic downturns, geopolitical events, climate risk, or shifts in investor sentiment can have significant repercussions for the region's oil and agricultural sectors. With a rapidly growing population and persistent food insecurity challenges, SSA is particularly sensitive to disruptions in agricultural production and food supply chains (Dalheimer et al., 2021). The region is disproportionately affected by climate change, experiencing more frequent and severe droughts, floods, and extreme weather events (Kapari et al., 2023). These climatic uncertainties pose significant risks to agricultural productivity and exacerbate food insecurity, making it imperative to examine their impact on the oil-food nexus.

Kapari et al. (2023) also noted that smallholder farmers in Sub-Saharan Africa constitute a significant portion of the agricultural workforce. They mostly practice subsistence farming, which exposes them to extreme weather events like droughts, floods, and heat waves, disrupting agricultural yields (Arora, 2019). They are more susceptible to these climate shocks as they lack the resources to invest in extensive irrigation infrastructure that could buffer against unpredictable rainfall patterns (Fusco, 2022). Farmers face challenges in planning for planting seasons, selecting crop varieties, and managing irrigation needs, resulting in lower average yields as crops struggle in unsuitable conditions. Furthermore, extreme weather events can damage crops, reducing overall quality and potentially leading to spoilage and harvest losses (Puertas & Marti, 2021). The combination of lower yields and diminished quality translates into a smaller pool of available food for consumers, pushing prices upwards. This creates a precarious situation, particularly for vulnerable populations who rely on affordable food staples (Huynh et al., 2020). The economic burden of adaptation is also disproportionately heavy (Carter et al., 2018). The economic burden of adapting to climate change, including investing in new technologies and infrastructure upgrades, will likely fall disproportionately on the region that already struggles to afford food imports when prices rise.

Furthermore, rising food prices due to global market fluctuations and local supply disruptions can further strain national budgets, making it difficult to afford essential food imports when domestic production falls short (Chatziantoniou et al., 2021). These combined challenges can contribute to social and political instability as communities struggle to secure necessities, thereby exacerbating existing food security challenges (Kramer et al., 2022). Moreover, developing nations like those in Sub-Saharan Africa often lack the financial resources to invest in climate-resilient seeds, irrigation systems, and early warning infrastructure. Addressing these equity concerns and ensuring a more equitable distribution of resources for adaptation is crucial for building a more resilient and just global food system.

Moreover, uncertainties surrounding biofuel policies and production play a significant role. Apergis et al. (2017) pointed out that the growing demand for biofuels, promoted as alternatives to fossil fuels, creates increased competition between food and energy crops for land and resources. This fundamental shift in land use patterns can have far-reaching implications (De Nicola et al., 2016). Uncertainties about government subsidies, fluctuating mandates on biofuel use, and unpredictable availability of feedstocks like corn or sugarcane create price volatility that spills over from the energy sector into the food sector. When biofuel mandates increase, demand for staple crops used for biofuel production surges, driving up grain prices (Awad et al., 2008; Paris, 2018). This can lead to higher food prices for consumers, especially those reliant on those staples.

The analysis of oil prices has gained much attention since the dual oil shocks of 1973 and 1979 (Taghizadeh-Hesary et al., 2019). Oil production dropped, and the prices increased, affecting many sectors' productivity. The analysis was pioneered by Hamilton (1983), who found that the rise in oil prices resulted in economic recessions in the US. Unger (1984) did a similar analysis for West Germany and got the same results that recessions in the early 1980s were a result of the 1973 and 1979 oil price shocks. Despite the production disruptions, the demand has continually increased, which has resulted in increased usage and has also led to a rise in carbon emissions. Carbon emissions have led to climate change, which has had a greater impact on agricultural production.

The aforementioned background has led this thesis to focus on three different types of uncertainty: the World Uncertainty Index (WUI), mainly due to its broader coverage of sub-Saharan countries, geopolitical risk (GPR), and climate risk. While existing literature focused on the relationship between oil and food, excluding uncertainty (Nazlioglu & Soytas, 2010; Reboredo, 2012; Abdlaziz et al., 2016; Taghizadeh-Hesary et al., 2019; Roman et al., 2020; Dalheimer et al., 2021; Mohammed, 2022). The papers which focused on oil and uncertainty used Economic Policy Uncertainty (EPU) as the proxy, which is limited to developed economies (You et al., 2017; Hailemariam et al., 2019; Wen et al., 2021; Wang et al., 2022).

1.3 Motivation of the Study

Amidst escalating global volatility, recent tumultuous swings in oil and food markets, fuelled by pandemics, geopolitical conflicts, and climate change-induced events, have exposed the fragility of food systems and intensified the urgency to decipher the relationship between the energy and agriculture sectors (Ringim et al., 2022). This precarious situation is particularly pronounced in SSA, where the dependence on imported food and agricultural inputs amplifies the ripple effects of oil price fluctuations (Ghadge et al., 2020), posing a significant threat to food security and necessitating a deeper exploration of the oil-food nexus within the region's unique context. Moreover, fluctuations in oil prices, driven by geopolitical tensions, supply disruptions, and speculative activities, have profound implications for food security, especially in the SSA region, which is heavily reliant on imported food and agricultural inputs (Wen et al., 2021).

The motivation for this study is further amplified by a critical observation: previous studies have often approached the analysis of oil, food, and uncertainty in a fragmented manner. Numerous studies have explored the relationship between oil and food prices, highlighting the transmission mechanisms of oil price shocks to food markets (Wang et al., 2014; Lucotte, 2016; Tanghizadeh-Hesary et al., 2019; Karakotsios et al., 2021; Roman et al., 2022). Others have focused on the impact of uncertainty on food production and consumption decisions, emphasizing the role of risk aversion and information asymmetry. However, few studies have attempted to integrate these disparate strands of research into a unified framework that captures the interplay of all three variables. The fragmented research landscape, predominantly focusing on individual facets of oil prices, food markets, or uncertainty, has overlooked their simultaneous influence and interconnectedness (Arfaoui et al., 2017). This neglect hinders a comprehensive understanding of developing countries' multifaceted challenges in an increasingly volatile global environment marked by escalating food insecurity and interconnected commodity markets (Elleby et al., 2020).

Also worth noting is that the existing literature has explored the link between oil and food prices, primarily focusing on the direct impact of oil price changes on agricultural production costs (Alpino, 2022; Rani, 2023). However, there remains a significant gap in understanding how uncertainty influences this relationship rather than just price levels. This study aims to fill this gap by examining how different types of uncertainty, including world uncertainty index, geopolitical risk, and climate-related uncertainty, interact with and exacerbate the dynamic spillovers between oil and food markets. Understanding the role of uncertainty is crucial for developing effective policies and risk management strategies to mitigate the negative impacts of price volatility on food security (Ahir et al., 2022). By unravelling the interplay between uncertainty, oil prices, and food markets, this study provides valuable insights for policymakers, agricultural stakeholders, and investors, enabling them to make more informed decisions in an increasingly uncertain world.

1.4 The Research Problem or Gap

The interconnected nature of energy and agricultural commodity markets and the pervasive influence of uncertainty present a critical challenge for developing countries striving to achieve food security and economic stability (Behnassi & El Haiba, 2022). While previous studies have explored the isolated relationships between oil and food prices or food and uncertainty, a comprehensive understanding of the interplay among these three variables remains elusive.

This gap in the literature has hindered the development of effective policies and strategies to mitigate the adverse effects of volatility and uncertainty on food systems in developing countries (Antonakakis & Chatizitoniou, 2014). Existing models often fail to capture the dynamic interactions between energy and agricultural markets, neglecting the role of uncertainty in shaping production, consumption, and investment decisions. This omission is particularly concerning given the increasing frequency and intensity of economic shocks, geopolitical events, and climate-related disruptions that amplify the vulnerability of developing countries to food insecurity (Liu et al., 2019). This study aims to fill this critical gap by developing a comprehensive framework that integrates the analysis of oil, food, and uncertainty. By examining the interactions among these variables, this research provides a more nuanced understanding of the risks and opportunities facing developing countries (Cheng & Cao, 2019). The absence of a unified framework that integrates the analysis of oil prices, food markets, and uncertainty has also limited our ability to assess the effectiveness of different policy interventions.

The fragmentation of studies has significantly limited our understanding by providing only partial views of how oil prices, food prices, and uncertainties interact. For instance, studies that solely examine the relationship between oil prices and food prices, such as ((Raza et al., 2022; Karakotsios et al., 2021; Dalheimer et al., 2021; HadCherifif, et al., 2021; and Taghizadeh-Hesary et al., 2019), may overlook the role of uncertainty, which can independently affect food prices or modify the oil-food price relationship. This is evident in the findings of this study which notes that previous studies have established the link between oil prices and rising food prices but paid less attention to the influence of global economic uncertainties.

This incomplete understanding can lead to misinterpretations or overgeneralizations. For example, a study focusing only on oil prices might suggest that controlling oil prices will stabilize food prices, but if it does not account for uncertainties, it might miss how uncertainties, such as WUI, geopolitical tensions, and climate risk, can independently drive food price volatility. This is particularly relevant in sub-Saharan Africa, where Minot, (2014) has shown that food price volatility has not increased as expected, this might be due to unexamined factors like uncertainties. The lack of a holistic view hinders our ability to anticipate how these variables behave under different scenarios, such as during global financial crises, as discussed in Sun et al. (2023).

Furthermore, the fragmentation of studies has likely hindered policy formulation by leading to policies that are not robust or effective, as they may not account for all relevant factors. Policies based on partial views can fail to address the complex dynamics of oil prices, food prices, and uncertainties, potentially resulting in unintended consequences. For example, a policy aimed at stabilizing food prices by managing oil prices, as suggested in Avalos, (2014 and Dalheimer, (2021), might be ineffective if uncertainties, such as those highlighted in Su et al. (2023), are significant drivers of food price volatility. This paper notes that EPU affects food security by impacting household purchasing power and disrupting supply chains, which fragmented studies might overlook.

Similarly, policies addressing uncertainties, such as those during the 2007-2008 food crisis, might not consider the indirect effects of oil prices, leading to suboptimal outcomes. For instance, export bans or price controls implemented by some countries, as mentioned in Ahir et al. (2022), might have failed to stabilize food prices if they did not account for oil price fluctuations and uncertainties. Moreover, the fragmentation can lead to policies that are not adaptive to changing conditions, such as during economic instability or environmental disasters. For example, Lin & Bai, (2021) discussed how oil price shocks and EPU interact, suggesting that policies ignoring these interactions might fail to mitigate food price volatility effectively. This is particularly critical in developing countries, where Mungai et al. (2022) show that reliance on oil exports can disrupt agricultural imports, exacerbating food insecurity if uncertainties are not considered.

Additionally, the thesis can contribute to policy by providing a framework that captures nonlinear relationships and feedback loops, such as those discussed in Karakotsios et al. (2021), which finds bidirectional linkages between oil and food prices, highlighting the need for policies that account for asymmetries. This is crucial for ensuring food security, especially in regions like sub-Saharan Africa, where Fowowe, (2016) indicates that staple food prices have not become more volatile as expected, possibly due to unexamined factors like uncertainties.

Moreover, most studies examining the relationship between oil prices and food security focused mainly on developed economies (Baek & Koo, 2010; You et al., 2017; Taghizadeh-Hesary et al., 2019; Hailemariam et al., 2019; Aminah, 2022). A comprehensive understanding of how global uncertainty, measured by the World Uncertainty Index, affects this relationship remains elusive. A couple of studies examined the relationship between oil and uncertainty, excluding food (Wen et al., 2021; Lin& Bai, 2021), using the EPU as the measure for uncertainty. The EPU focuses on economic uncertainty without considering political uncertainty and is available for developed economies, neglecting developing ones. This study mainly bridges this gap using the WUI due to its broader scope, global coverage, longer time series, and simplicity (Sharif et al., 2020). WUI captures various uncertainty sources, including economic policy and political, social, and geopolitical events. This makes it a more comprehensive measure of overall global uncertainty.

Also, the WUI covers more countries than the EPU, making it a more suitable measure for cross-country comparisons and analyses of global trends, especially in emerging economies (Plakandaras et al., 2019). It also has a longer historical time series dating back to 1952, while the EPU typically starts in the 1980s. This allows for a more in-depth analysis of long-term trends and historical patterns of uncertainty (Liu & Gao, 2022). Moreover, it is based on a simple and transparent methodology of counting the frequency of uncertainty-related terms in news articles, making it easier to understand and interpret. While the WUI and EPU offer valuable insights into uncertainty, the WUI's broader scope, global coverage, longer time series, and data availability make it a more versatile and comprehensive measure for certain research questions.

Empirically, the first paper uses panel analysis, which allows studies to account for unobserved individual-specific effects that may bias results. This is achieved by including fixed or random effects in the model, which isolate the impact of time-varying factors while controlling for individual characteristics that remain constant over time. This paper employed the model that works consistently with random effects (Taghizadeh-Hesary et al., 2019). It also increases the efficiency and statistical power. By combining cross-sectional and time-series dimensions, panel data increases the number of observations and degrees of freedom, leading to more efficient and precise estimates. This increased statistical power allows for better detection of significant relationships between variables. Therefore, panel data analysis is particularly advantageous when studying the relationship between oil prices, food security, and uncertainty. It allows for the examination of how these variables interact over time and across different countries while controlling for country-specific factors that may influence food security (Aminah, 2022).

Additionally, the interconnected nature of energy and agricultural commodity markets exposes both sectors to significant volatility spillovers, particularly during periods of heightened geopolitical risk (Gkillas et al., 2018). While previous studies have examined the dynamic relationship between these markets, a comprehensive understanding of how extreme spillovers occur and how they are influenced by geopolitical risk remains elusive. This omission is particularly concerning given the increasing frequency and intensity of geopolitical events, which can have profound implications for food security and economic stability.

Existing studies often rely on traditional econometric models that assume constant relationships between variables (Luo et al., 2019; Dalheimer et al., 2021; Kaulu, 2021; Fusco, 2022), failing to capture the time-varying nature of spillovers and the heterogeneous impact of geopolitical risk across different markets and periods. Additionally, these studies often focus on average spillovers, neglecting the extreme events that can disproportionately impact market dynamics. This gap in the literature has hindered the development of effective risk management strategies and policy interventions to mitigate the adverse effects of extreme spillovers on both the energy and agricultural sectors.

This study aims to fill this gap by examining the dynamics of extreme spillovers between energy prices and agricultural commodity markets, with a particular focus on the role of geopolitical risk. Utilizing a time-varying parameter vector autoregression (TVP-VAR) model, this study will investigate how the interconnectedness between these markets evolves and how geopolitical events influence it. Unlike traditional VAR models that assume constant relationships, TVP-VAR allows the coefficients to vary over time (Ye et al., 2022). This is crucial when studying energy and agricultural markets, as their interconnectedness can be influenced by changing economic conditions, policies, and external shocks. Furthermore, the TVP-VAR can quantify and visualize the dynamic spillover effects between energy and agricultural prices, revealing how shocks in one market are transmitted to the other over time (Dada et al., 2022). This can help identify periods of heightened interconnectedness and potential risk contagion.

The escalating climate crisis poses a significant threat to global food and energy systems, particularly in vulnerable regions (Haile, 2017). However, existing research on the dynamic spillovers between oil and food markets often overlooks the long-term impact of climate risk, relying on traditional econometric models that assume constant relationships and focus on short-term price fluctuations (Xie et al., 2022). This neglects the potential for persistent and amplified spillovers due to climate-induced shocks and fails to consider the heterogeneous impact across different regions, hindering a comprehensive understanding of climate risk's influence on these interconnected markets (Bonato et al., 2023).

This research gap has hindered the development of effective risk management and adaptation strategies to mitigate the adverse effects of climate risk on food and energy security. The lack of a comprehensive framework that integrates climate risk into the analysis of oil and food price dynamics has limited our ability to assess the effectiveness of different policy interventions, leaving policymakers with inadequate tools to address this critical challenge. This study aims to fill this gap by examining the dynamic spillovers between oil and food prices in the context of climate risk, focusing on 10 countries in the Sub-Saharan region. By employing a GARCH-MIDAS approach, this study will investigate how climate risk influences these spillovers' magnitude, persistence, and direction.

The GARCH-MIDAS (Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling) approach offers several key advantages for modelling volatility in financial and economic time series. Firstly, it allows for the integration of both high-frequency and low-frequency data into a unified framework. This is particularly useful for studying the impact of macroeconomic variables, often available at lower frequencies, on the volatility of financial assets, typically measured at higher frequencies (Jiang et al., 2019). Secondly, it explicitly separates the long-term volatility component, driven by low-frequency variables, from the short-term volatility component, captured by the GARCH model. This allows for a better understanding of the sources of volatility and their persistence over time. Thirdly, the GARCH-MIDAS is a flexible framework that can accommodate various specifications for both the GARCH and MIDAS components (Ndako et al., 2021). This allows researchers to tailor the model to the specific characteristics of the data and the research question at hand. Lastly, studies have shown that GARCH-MIDAS models often outperform traditional GARCH models in forecasting volatility, particularly at longer horizons. This is due to the incorporation of low-frequency information, which can capture long-term trends and structural changes in volatility.

In the context of studying the relationship between oil prices and food prices under climate risk, the GARCH-MIDAS approach is particularly advantageous. It allows for integrating climate data, often available at lower frequencies, into the analysis of high-frequency price fluctuations. This can reveal how climate-related shocks affect the long-term volatility of oil and food markets, providing crucial information for policymakers and market participants seeking to manage climate-related risks (Tumala et al., 2023).

1.5 Research Questions

The interconnected nature of energy and food markets, coupled with the growing threat of climate change, global uncertainty, and geopolitical instability, has raised critical questions about food security and economic stability in Sub-Saharan African countries. These concerns raised the following fundamental questions pursued in this study research.

i. How does the world uncertainty moderate the dynamic relationship between oil prices and food security in Sub-Saharan African countries?
ii. Do geopolitical risk events influence the extreme spillovers between energy and agricultural commodity prices?
iii. Does climate risk affect the connection between oil prices and food prices?

1.6 Objectives of the Study

This study elucidates the interplay between oil and food production systems in SSA, focusing on the moderating influence of uncertainty and its implications for food security. In answering the research questions, it uses the objectives which include:

i. Examine the dynamic relationship between oil prices, global uncertainty, and food security.
ii. Analyse the role of GPR on the extreme spillovers between energy prices and agricultural commodity prices.
iii. Assess the impact of climate risk on the connection between oil and food prices.

Given the aforementioned objectives, existing studies often fall short of fully capturing the unique context of sub-Saharan Africa due to factors such as political instability, dependence on food imports, and underdeveloped agricultural technology. These factors create a distinct economic environment where traditional models may not adequately reflect the complexities of the region. Incorporating the role of uncertainty, particularly in the context of sub-Saharan Africa, provides a deeper understanding of how these interconnected factors influence market dynamics. Political instability, for instance, can amplify the effects of global uncertainty on food security, while dependence on food imports makes the region more vulnerable to international price fluctuations. Additionally, underdeveloped agricultural technology limits the ability to mitigate adverse impacts effectively.

The motivation for this study is strongly tied to policy relevance. By understanding these dynamics, policymakers can develop more targeted and effective food security policies and energy diversification strategies. The findings can inform efforts to enhance agricultural resilience, reduce dependency on imports, and foster stability in the face of geopolitical and climate risks. Ultimately, this research aims to provide actionable insights that can support sustainable economic development and improve food security in sub-Saharan Africa.

1.7 Significance of the Study

This study is significant due to the recognition that developing nations grapple with challenges in ensuring food security, including endemic poverty, infrastructural deficiencies, and limited access to critical resources. Concurrently, the oil sector assumes a pivotal role as a revenue generator and energy provider for many of these nations (Omisore, 2018), underscoring its significance in their overarching economic trajectories. Moreover, the selected timeframe encompasses key financial and economic events that significantly influenced global oil and agricultural commodity prices. This period cove includes the Asian crisis of 1997-1998, the 2007-2008 global financial crisis, the sharp oil price spike in August 2014 (Liu et al., 2019), the COVID-19 pandemic's economic downturn with Brent crude plummeting below $20 per barrel, the 2020 Saudi Arabia-Russia price war, and the subsequent post-COVID era in 2021 and ongoing Russia – Ukraine and Palestine – Israel war (Xiao et al., 2023).

Delving into the nuances of the oil-food nexus is paramount in achieving Sustainable Development Goals. While there has been some progress in achieving the SDGs in Sub-Saharan Africa (SSA), the region is lagging behind other regions in meeting these goals across various dimensions. According to Adams and Paul (2023), SSA has an SDG index score of 53.6, indicating that the region has achieved only 53.6% of its 2030 SDG targets. This score is significantly lower than other developing regions like Eastern Europe and Central Asia (71.6), Latin America and the Caribbean (69.5), and East and South Asia (65.9). The specific areas in which the region is behind are the ones that are related to our study and are key for human sustenance. These include no poverty, zero hunger, affordable and clean energy, and the last one is climate action. Despite some progress in poverty reduction, SSA still has the highest poverty rate globally, with nearly 40% of the population living below the international poverty line. Undernourishment remains high in SSA, with over 20% of the population facing hunger and food insecurity (Gyimah et al., 2023). The region's heightened vulnerability to climate change, manifested in the increased frequency and severity of extreme weather events, poses significant challenges to sustainable development and necessitates an examination of the oil-food nexus for effective policy formulation toward achieving the SDGs.

1.8 Structure of the Study

Chapter One acts as an exordium for this study and provides the reader with a contextual understanding of the study, its relevance to the field, the research aims, and a succinct articulation of the research problem. Chapter Two investigates the connection between oil and food prices from 2000 to 2020 and considers the role of world uncertainty in twenty-four Sub-Saharan countries. Chapter Three analyses the dynamic effects of geopolitical risks on the linkages between crude oil returns and selected agricultural commodity prices in six sub-Saharan countries. Chapter Four investigates the influence of climate risk on the dynamic spillovers between oil and food prices. Lastly, Chapter Five serves as the concluding section of the study, summarising the key findings and making recommendations for the respective sectors in the region. The recommendations will provide valuable insights for policymakers and market participants seeking to manage the risks associated with the interconnected markets.

CHAPTER TWO

Connection between Oil and Food Security in Sub-Saharan Africa: The Role of Uncertainty.

2.1 Introduction

The agricultural sector globally is facing significant challenges due to escalating uncertainties stemming from economic policies, climate change, demographic shifts, health crises, trade disruptions, geopolitical instability, and social unrest (Behnassi & El Haiba, 2022). This interplay of factors has brought to the forefront two critical issues: ensuring food security for a rapidly growing population and meeting the rising demand for alternative energy sources, particularly oil, a key input in agricultural production. The confluence of these demands, coupled with uncertainty-induced declines in agricultural productivity, exacerbates the pressure on the sector, threatening the attainment of Sustainable Development Goals (SDGs) 1 and 2: No Poverty and Zero Hunger (Gyimah et al., 2023).

Oil plays a significant role in food production, yet its supply is vulnerable to shocks like climate risks, economic uncertainty, political instability, global financial crises, health pandemics, trade conflicts, and foreign exchange volatility, among others (Lin & Bai, 2021; Wen et al., 2021; Hailemariam et al., 2019). These shocks can directly impact production volumes and indirectly increase food prices through higher energy prices, increased costs of agricultural inputs, and higher costs for final product distribution (Dalheimer, 2020; Gohin & Chantret, 2010). This dynamic is especially critical given food's inelastic demand, forcing consumers to bear price hikes.

Uncertainty further complicates commodity markets by delaying key economic decisions like employment, investment, and consumption, while raising financing and production costs (Gulen & Ion, 2016). It can also trigger disinvestment, financial contraction, and shifts in inflation and risk premiums (Hailemariam et al., 2019). These effects ripple through oil and food markets, amplifying price volatility (Kang & Ratti, 2013).

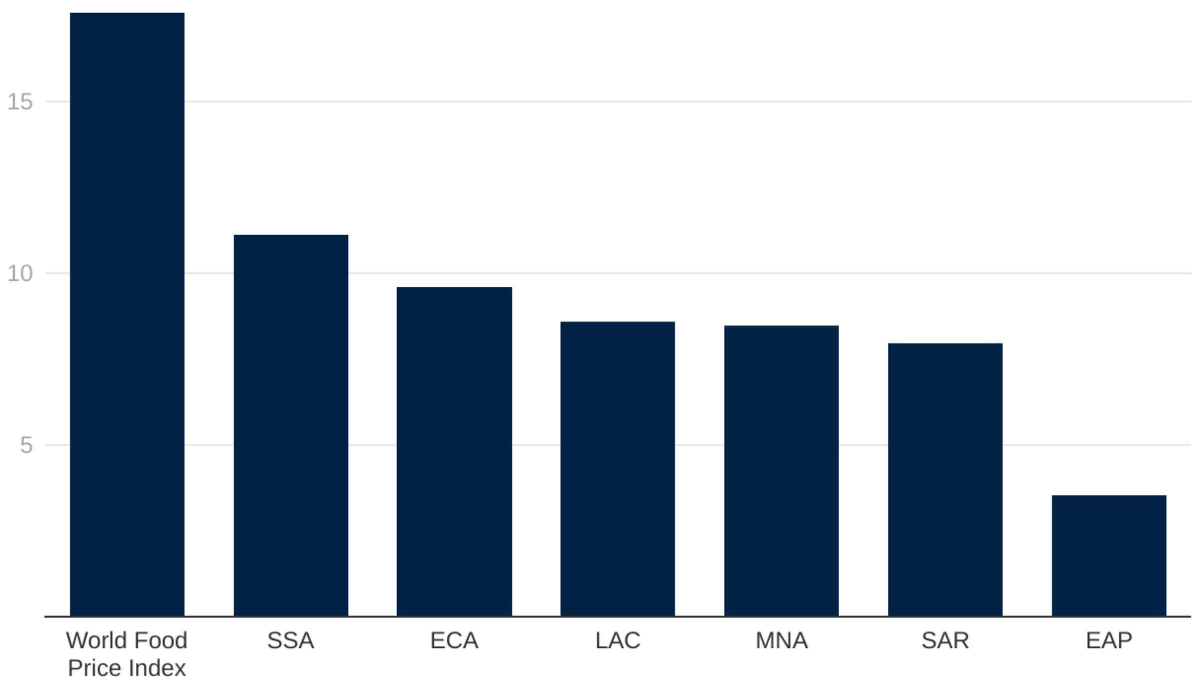
In developing nations, economic volatility shapes policy responses, with governments using monetary and fiscal tools to spur growth (Rehman, 2018). These policy instruments, however, are not exhaustive, and the government's inefficacy in achieving its intended objectives may result in policy changes or reversals, thus engendering policy conflict and uncertainty. These inconsistent policies breed uncertainty, influencing households, firms, and multinationals in their savings, investment, and labor choices. It also heightens risk in forex and oil markets, impacting energy-intensive economies (Kang et al., 2015).

Sub-Saharan Africa (SSA) exemplifies these challenges, hosting 39% of the world's food-insecure households and 22 of 30 food-insecure nations (Sasson, 2012; Bjornlund et al., 2022). Rising oil and food prices since 2010, strain welfare, particularly as uncertainty has surged since 2012, peaking during the 2020 COVID-19 crisis (Karakotsios et al., 2021; Ahir et al., 2022). Market failures and health crises like undernourishment divert funds from food subsidies, worsening food insecurity in the region which has made the least progress in alleviating malnutrition (Omisore, 2018).

SSA's reliance on oil imports where 34 out of 46 countries are net importers ties food prices to global oil shocks (Kapari et al., 2023). Even oil producers like Nigeria export crude and import refined oil at international rates, amplifying vulnerability. This region's high food inflation, as shown in Figure 1.1 below extracted from World Bank (2022) data, underscores the need to study these dynamics.

Figure 1.1: World and regional inflation

Percent, y/y



Notes: Bars denote year-on-year food price inflation (average of January – March 2022). EAP = East and Pacific, ECA = Europe and Central Asia, LAC = Latin America and the Caribbean, MNA = Middle East and

North Africa, SA = South Asia, SSA = Sub-Saharan Africa; EMDEs = Emerging Markets and Developing Economies.
Source: World Bank, 2022

Despite exporting raw commodities, SSA struggles with food insecurity, as multinationals prioritize biofuel and export crops over local needs (Bjornlund et al., 2022). Subsistence farming declines as labor shifts to these ventures, reducing household food access (Dorinet et al., 2021). Unlike in higher-income nations, where expenditure on food constitutes a small portion of household expenses, residents of SSA are susceptible to price jumps, and poor households, spending heavily on food, are hit hardest by price spikes. Consequently, understanding the dynamics of the association between food prices is essential in making relevant food and dietary policies.

Prior studies on oil-food price links have largely focused on advanced economies with fiscal buffers, overlooking sub-Saharan Africa's (SSA) distinct vulnerabilities, such as limited biofuel adoption and heightened exposure to oil shocks as a net importer (Avalos, 2014; De Nicola et al., 2016). This gap is particularly striking given global events like the Russia-Ukraine war and pandemics that further disrupt prices, underscoring the need for a regional perspective (Kaulu, 2021). To address this, this study employs the World Uncertainty Index (WUI), which captures a broad spectrum of economic, political, and global shocks across both developed and developing economies (Ahir et al., 2022). Unlike Economic Policy Uncertainty (EPU), tailored to economic policy in developed nations (Baker et al., 2016), WUI better suits SSA's diverse uncertainty sources, including conflicts and pandemics, offering a more comprehensive lens for analysis.

Furthermore, previous research on the oil-food nexus often relies on VAR, SVAR, or ARDL models, which struggle with limitations such as non-stationary data, structural breaks, and omitted variable bias, particularly in capturing dynamic trends and cross-dependency relevant to developing markets (Chen et al., 2010; Lin & Bai, 2021; Granger & Engle, 1987). To address these shortcomings, this study adopts the Pooled Mean Group Autoregressive Distributed Lag (PMG-ARDL) model, well-suited for non-stationary financial data and capable of handling structural breaks, heterogeneity, and cross-dependence (Westerlund et al., 2013). Unlike earlier approaches, PMG-ARDL enhances policy analysis and uncovers the transmission channels of oil price shocks to food prices under uncertainty. The study also employs Quantile Regression as a robustness check to validate findings across different distribution points, offering deeper and more reliable insights for regions like sub-Saharan Africa (Kapetanios et al., 2011).

Indeed, prior studies present contradictory results on the oil-food price relationship, highlighting the need for such advanced methods. For instance, Taghizadeh-Hesary et al. (2019) and Karakotsios et al. (2021) identified a significant positive link between oil and global food prices, a finding echoed by De Nicola et al. (2016), Sun et al. (2021), Fasanya & Akinbowale (2019), and Cabrera & Schulz (2015), who confirmed a positive association between oil and agricultural prices. Conversely, other research, including Fowowe (2016), Reboredo (2012), and Nazlioglu (2011), found no relationship, supporting the neutrality hypothesis. This mixture of outcomes of positive correlations in some cases and none in others creates uncertainty for policymakers, underscoring the need for further analysis, particularly from a developing market perspective where economic conditions differ starkly from advanced economies.

Building on this foundation, the current study extends prior research on the oil-food price nexus in developing markets, such as Dillon & Barrett (2016) and Dalheimer et al.'s (2021) analyses of oil price shocks on maize in SSA. While those studies focused on single commodities and individual countries, this research adopts a broader, cross-country approach, examining a basket of food prices including those where SSA faces a comparative disadvantage alongside maize, to capture regional dynamics. Crucially, it integrates the World Uncertainty Index (WUI) to assess uncertainty's role amid recent global disruptions, like the Russia-Ukraine conflict (Nhlengetwa et al., 2023) and the COVID-19 pandemic (Khan et al., 2022). By combining PMG-ARDL and Quantile Regression with WUI, and focusing on a wider scope of food prices and regional interactions, this study offers a more comprehensive understanding of the oil-food nexus in SSA, addressing the literature's gaps and inconsistencies to inform targeted policy solutions.

2.2 Literature Review

2.2.1 Theoretical Literature

Oil price fluctuations significantly impact the global economy by influencing various sectors (Raza et al., 2022) through cost-push inflation, transportation costs (Dalheimer et al., 2021), energy expenses, and supply chain disruptions, as oil is a fundamental input. These fluctuations lead to rising production costs for goods and services, which are then passed on to consumers at higher prices. This dynamic particularly affects transportation and energy-dependent sectors, resulting in higher food prices (Ghasemian et al., 2023). , reduced consumer spending, and supply chain disruptions. Sudden spikes in oil prices can cause delays or increased costs in the transportation and delivery of goods, affecting the availability and accessibility of products and leading to shortages and higher prices in the market.

Additionally, oil price volatility impacts exchange rates and trade balances, investor confidence, and market sentiment. For countries that are net importers (Ghasemian et al., 2023), fluctuations can lead to increased import bills, affecting the trade balance and putting pressure on the national currency. This can further influence inflation and economic stability. Sudden spikes or drops in oil prices create uncertainty in financial markets, affecting investment decisions and potentially slowing down economic growth and stability as businesses may delay or reduce investment in response to volatile oil prices. The relatively inelastic nature of oil demand exacerbates these effects (Obadi & Korcek, 2014).

Grounded in Adam Smith's (1776) seminal work on wealth creation through production, the Production Theory posits that factors of production, such as labor and capital as formalized by the Cobb-Douglas function (1928), are fundamental determinants of output levels and profit margins. In the agricultural sector, input and transportation costs, primarily influenced by oil prices, significantly impact production decisions (Raza et al., 2022; Aimer & Lusta, 2021; Baumeister & Killian, 2014). As input prices rise, producers often respond by reducing substitute demand or transferring costs to consumers through a cost-plus pricing strategy. This strategy is prevalent due to its ease of implementation and guaranteed profit margins, particularly for seasonal agricultural products in marginalized rural areas.

Production Theory, based on the neoclassical paradigm of rational choice and market efficiency (Marchionatti, & Gambino, 1977), posits that firms and households, ranging from small-scale entrepreneurs to large corporations, engage in production as a process of converting inputs into outputs to maximize profits (Ozkan et al., 2004). This optimization process entails minimizing costs, maximizing output, and achieving Pareto optimality, all guided by rational decision-making based on available price information. The theory's central tenet is that markets efficiently allocate scarce resources, with producers responding to price signals to determine the optimal combination and quantity of inputs to employ (Pimentel, 1992).

The cost minimization principle, rooted in the works of classical economists such as Adam Smith, David Ricardo, and Karl Marx, elucidates the intricate relationship between production costs, input choices, and output levels. This principle posits that profit-maximizing producers are inherently sensitive to production costs and seek to minimize them. In the face of rising input costs, producers may substitute for cheaper alternatives or pass the burden onto consumers through higher prices. This dynamic is particularly relevant in escalating food prices, exacerbated by the recent surge in oil costs following the Russia-Ukraine conflict (Behnassi & El Haiba, 2022). The cost minimization principle, as empirically confirmed by Berndt & Jorgenson (1978), Chen et al. (2019), and Mohammed (2022), offers valuable insights into the behavior of firms and the functioning of market economies, informing decision-making on production, pricing, and investment strategies.

The output maximization principle involves firms seeking to maximize production to increase profits. This entails increasing sales revenue by producing more goods or services, as long as the marginal cost is lower than the marginal revenue. However, firms face constraints such as limited resources, technological limitations, market competition, and regulations that can limit their ability to increase production. To maximize output, firms must make decisions about the most efficient use of their resources, appropriate production processes, and optimal pricing strategies. This challenge is particularly evident in the agricultural sector, which relies on limited natural resources like land, rain, and oil, and faces regulatory constraints due to the necessity of food.

The Pareto theory, also known as Pareto efficiency or optimality, is a concept in economics named after the Italian economist Vilfredo Pareto. It posits that a situation is considered Pareto efficient when it is impossible to make one person better off without making someone else worse off (Schumpeter, 1949). In this analysis, the theory explains the rationale of the oil sector in expanding or reducing productivity or increasing prices without negatively impacting the productivity of other sectors that rely on oil as a major input, like agriculture and manufacturing.

Pareto efficiency is often used as a benchmark for evaluating economic outcomes or policies. This study is relevant as it provides policy guidance for the oil and food sectors in developing economies (Gollin & Rogerson, 2014). It offers a straightforward approach to identifying areas in business that need adjustment to improve productivity and efficiency without harming other sectors. All four components of the neoclassical theory focus on increasing productivity to improve competitiveness (Kleynhans, 2016). The main conclusions of Pareto theory include ensuring adequate warning and flexibility for affected individuals to create alternative plans, providing clear explanations to impacted parties, implementing a transitional stage for safe changes, and testing the viability of proposed adjustments.

While principles of production theory such as cost minimization, output maximization, and Pareto optimality assume a linear relationship between inputs and outputs, profit theory addresses the non-linearity and asymmetry often observed in sectors like oil and agriculture. This theory focuses on price-based analysis rather than quantity-based, making it more suitable for cross-country comparisons due to the universality of price as a measure. It investigates firm behavior in determining profit levels influenced by market conditions, competition, and other factors, shedding light on profit-maximizing behavior and firms' responses to market changes. In this context, profit is viewed as both a reward for risk-taking and a signal for resource allocation within the economy (Wang & McPhail, 2014).

These theories assume that consumers are price takers without the power to influence input and output prices. Prices and returns to factors of production are determined by supply and demand forces in a perfectly competitive market, which is not realistic. This led to the development of Marshallian theory, which addresses criticisms of the unrealistic assumptions of perfect markets without government intervention, especially in the agricultural and oil sectors (Marshall, 1890). The oil sector, with few producers and buyers, fails to meet the criteria for a competitive market.

The Marshallian economic framework, developed by Alfred Marshall, centers on the behavior of individuals and firms in markets, emphasizing marginal analysis and price elasticity of demand as key tools for understanding economic behavior (Baumeister & Kilian, 2014). A key aspect of this theory is the producer's ability to set prices in imperfect markets with asymmetric information (Batten, 1980), allowing for the selection of cost-minimizing production methods to maximize profits. However, this producer-centric perspective often neglects the influence of other economic agents, such as input owners, which can lead to adverse outcomes like unemployment and poverty due to cost-cutting measures (Narayan & Narayan, 2007). Additionally, the cost-push inflation mechanism inherent in this framework can exacerbate socio-economic disparities by reducing consumer purchasing power through increased prices, particularly for essential goods.

Building upon Hamilton's (1983) foundational concept of energy as a critical driver of production, Tintner et al. (1977) extended the Cobb-Douglas production function to include energy alongside labor and capital. Hudson and Jorgenson (1974) further solidified this by incorporating energy as a distinct production factor. Kümmel et al. (1985) developed differential equations demonstrating the interdependence of capital and energy, highlighting energy's indispensability in production processes, exemplified in the agricultural sector, where machinery relies on fuel.

Conrad and Unger (1984) posited that energy price increases negatively impact energy-intensive industries' productivity and economic growth, evidenced by the West German recessions following the 1973 and 1979 oil price shocks. Van Gool and Bruggink (1985) refined this framework, defining the variable "M" to include all non-energy materials required for production, such as information, coordination controls, and "others." This study adopts this definition, with controls interpreted as policy and monetary controls, proxied by policy uncertainty, inflation, and exchange rate variables, while "others" represent remaining explanatory variables.

These energy theorists, summarized by Kümmel et al. (1985), regard energy as an essential production factor, like labor and capital. They note that industrial development and time will intensify energy demand, as currently experienced globally, with Bloomberg forecasting energy demand to double by 2030. This study aims to provide empirical results and informed policies to address this challenge.

Lucas (1873) integrated mainstream economics into the theory of substitution, explaining the ease of substitutability between commodities. According to Friedman (1986), this depends on the monetary rate of transformation from one production to another. This research relates to the ease of transitioning from fossil fuels to biofuels. Unfortunately, oil, a major production factor, lacks perfect substitutes, and per the law of demand, increased demand results in higher prices. A higher demand for agricultural products to produce biofuels will raise prices since agricultural products depend on finite resources like land and climate, which cannot be easily adjusted to meet increased demand, leading to shortages and higher prices.

Aligned with these theories, this study investigates the relationship between oil prices and food prices. Over the past decade, food prices have surged across the region. With increasing poverty, food accessibility and affordability become critical issues. Agricultural goods are price inelastic, and producers often pass increased production costs onto consumers as higher prices. This results in inequality, as the poor spend a larger portion of their income on food, mainly agricultural produce (Avalos, 2014).

While these theories explain the relationship between oil prices and the agricultural sector, they primarily focus on output rather than price. To understand the price aspect, basic demand and supply theories must be combined with the above theories. For example, consistent with the symmetric concept of shocks and uncertainty, a rise in oil prices affects the production of commodities that use it as an input. According to supply and demand theory, reduced supply of agricultural commodities will push prices up. Therefore, theoretically, increases in oil prices will result in higher food prices. This sets the stage for empirical tests to validate these theories.

2.2.2 Empirical Literature Review

Since 1970, significant research has been on the interlinkages between energy and food prices (Chapman, 1974). This rise in research interests is buttressed by a Bloomberg forecast showing that the energy demand will double by 2030. However, Alessio (1981) showed that the shortage of this important commodity is inevitable due to the industrial advancement of societies. If the prediction is true, it will likely have far-reaching economic implications. Since oil is an important input in production, it determines the price of commodities, levels of output, employment, and economic growth. Several studies, both in developing and developed countries, analyzed the relationship between oil prices and food prices (Nazliogu & Soytas, 2011; Reboredo, 2012; Dillon & Barrett, 2015; Fowowe, 2016; Zmami & Ben-Salha, 2019).

Table 2.1: Studies on oil, food price, and uncertainty

Author	Period	Methodology	Countries	Findings
Zhang et al. 2010	1989 - 2008	VECM	USA	No relationship
Baek & Koo, 2010	1991 - 2008	Cointegration	USA	Relationship
Chen et al. 2010	1983 - 2012	ARDL	USA	No relationship
Nazlioglu & Soytas, 2010	1994 - 2010	VAR	Turkey	No relationship
Nazlioglu, 2011	1994 - 2010	VAR	World	Relationship
Reboredo, 2012	1998 - 2011	ARIMA & TGARCH	World	No relationship
Baumeister & Killian, 2014	2006 - 2013	VAR	USA	No relationship
Obadi & Korcek, 2014	1975 - 2013	VECM	World	Relationship
Dillon & Barrett, 2015	2000 - 2012	VECM	Tanzania, Uganda	Relationship

			Ethiopia, Kenya	
Abdlaziz, 2016	1990 - 2013	VECM	World	Relationship
Fowowe, 2016	2003 - 2014	Cointegration & Causality test	South Africa	No relationship
Taghizadeh-Hesary et al. 2019	2000 - 2016	Panel VAR	Asian countries	Relationship
Roman et al. 2020	1990 - 2000	VECM	World	Relationship
Karakotsios et al. 2021	2000 - 2015	Asymmetric ARDL	World	Relationship
Dalheimer et al. 2021	2006 - 2019	Structural VAR	Sub-Sahara Africa	Relationship
Hadj Cherif et al. 2021	2000 - 2020	ARDL	MENA	Relationship
Hanif, 2021	1990 - 2018	Bivariate copulas	World	Relationship
Kaulu, 2021	1982 - 2021	VAR & VECM	World	Relationship
Hassan, 2022	2000 - 2020	Panel VAR	Asian countries	Relationship
Mohammed, 2022	2001 - 2020	Cointegration	Iraq	Relationship
Raza et al. 2022	1993 - 2020	Wavelet & DY	World	Relationship
You et al. 2017	1995 - 2016	Quantile regression	China	Relationship
Hailemariam et al. 2019	1997 - 2018	Nonparametric Panel regression	G7 Countries	Relationship
Wen et al. 2021	1998 – 2020	ARDL	China	Relationship
Aimer & Lusta, 2021	1997 - 2020	ARDL	USA	Relationship
Lin & Bai, 2021	1997 - 2019	Bayesian VAR	World	Relationship
Ringim et al. 2022	1994 – 2019	DCC-GARCH	Russia	Relationship
Wang et al. 2022	2010 - 2022	Quantile ARDL	China	Relationship

Notes: ARDL is the autoregressive distributed lag; VAR is the Vector Autoregressive model; Vector Error Correction Model (VECM); Autoregressive Moving Average (ARIMA); Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH); Middle East and North America (MENA).

Papers on oil, economic policy uncertainty, and other variables include You et al., 2017; Hailemariam et al., 2019; Wen et al., 2021; Aimer & Lusta, 2021; Lin & Bai, 2021; Ringim et al., 2022 and Wang et al., 2023.

Source: Compiled by the author

The earliest studies that tested the role of energy on economic growth include (Hudson & Jorgenson, 1974; Berndt & Jorgenson, 1978; Conrad & Unger, 1984). Hudson & Jorgenson (1974) did a study on the impact of energy on different economic sectors in the USA, including agriculture, transportation, mining, manufacturing, and construction. They used the Leontif input-output theory, which combines the input and output theory. They did the interindustry modeling of the assessment of the complete production chain, starting from inputs going through the intermediate levels until the final goods and services for consumption. The inputs they considered were energy, labor, capital, and materials. The energy inputs comprise all types of energy, which include crude petroleum, refined petroleum, coal, electricity, gas from gas utilities, and natural gas. They found that the usage of petroleum slowly increased as the sectors found ways to reduce the demand for petroleum. They also found that the demand for gas was expected to decline due to a loss of relative importance compared to other fuels. This is directly the opposite of what the global economy is experiencing in the 21st century, which has seen a huge growing demand for petroleum and gas usage (Isiksal et al., 2022).

Berndt & Jorgenson (1978) went on to assess the relationship between energy and economic growth as a whole instead of focusing on specific sectors. They found that increases in petroleum prices negatively affect economic growth. The economic growth reduction has ripple effects on the real disposable income, the trade-off between investment and consumption, and reduced fiscal space due to a shrinking tax base due to tax cuts or higher expenditures. This is in line with the input theory, which postulates that a rise in input prices will negatively affect the output of sectors, resulting in poor economic growth, thereby affecting a lot of macroeconomic variables like inflation, employment, taxes, and income levels, among others. There is a need to assess if energy prices affect food inflation in the African region.

A similar study by Conrad & Unger (1984) focused on West Germany and examined the same relationship (Jorgenson, 1978). They also found similar results regarding the negative impact of energy on economic growth. They explained that the recessions experienced in the early 1980s resulted from the 1973 and 1979 oil price shocks. They went on to show that the increases in the price of energy directly reduce the usage of other factors of production, such as capital, which intensively uses energy. This will have a multiplier effect on the productivity of the sectors. This also applies to the agricultural sector, as most of the capital needs energy for functionality. It, therefore, implies that shocks in energy prices will affect the usage of capital, which will deter productivity, especially if the shock is a rise in energy prices.

We move on to recent studies on the relationship between oil and food prices. These studies are primarily categorized according to their research areas: those focused on oil and food prices and those focused on oil, economic policy uncertainty, and other variables. The first primary category is further divided according to their findings: a significant relationship that can be either positive or negative and those that find no relationship. The studies which find a significant oil-food relationship include (Raza et al., 2022; Aminah, 2022; Mohammed, 2022; Karakotsios et al., 2021; Dalheimer et al., 2021; HadCherifif, et al., 2021; Olayungbo, 2021 and Taghizadeh-Hesary et al., 2019). Specifically, Raza et al. (2022) employed a wavelet approach using world prices and found a positive bidirectional correlation. Similarly, Hassan, (2022) did a study on five emerging Northeast Asian countries and found that food prices respond positively to oil shocks. A study on the impact of oil prices on food prices in Iran using a cointegration test from 2001 to 2022 by Mohammed (2022) found a monodirectional positive relationship between food prices and oil prices. Except for Aminah (2022), these studies focus on individual countries. However, some find it bidirectional, and some monodirectional. This might be because they focused on different countries at different periods and stages of development.

Karakotsios et al. (2021) also analyzed the oil's linear and asymmetric impact on global food prices from 2000 to 2015. The linear model shows a long-run bidirectional relationship between oil and food prices. Using the asymmetric model, they also find a unidirectional relationship between oil and food prices. The latter finding supports the production theory when oil is used as a major input in producing food. A similar finding has been reported by Hadj Cherif et al. (2021) for the Middle East and North Africa (MENA). They examined the connection between oil and food prices from 2000 to 2020 using the linear and nonlinear ARDL and found a significant positive long-run impact of oil on food prices, which is higher among oil exporters than oil importers. Another analysis was done by Dalheimer et al. (2021) analyzing eight SSA countries from 2006 to 2019 using the Structural VAR method. They showed that African corn markets are responsive to oil prices. Olayungbo, 2021 studied food-importing and oil-exporting countries from 2011 to 2015 using panel ARDL. He found a significant positive long-run and negative short-run relationship. Surprisingly, in the same paper, Karakotsios et al. (2021) reported both unidirectional and bidirectional relationships while examining the same country for the same period. This might be attributed to the use of two different models. Therefore, models are key as they lead to different results, and due diligence must be done to develop the right model for the analysis. It is crucial to do all the necessary tests, as Westerlund (2006) mentioned, to develop the most suitable model to produce consistent results.

Hanif et al. (2021) assessed the spillovers between oil and food prices using world prices from 1990 to 2018. They employed the Bivariate Copulas model and found the asymmetric spillovers between the two commodities. Kaulu (2021) employed a VAR and VECM analysis from 1982 to 2021 using world prices to assess the effects of oil on copper and maize prices. A long-run connection was found between crude oil and copper prices and maize prices using the VAR model. However, no relationship was found between oil, copper, and maize using the VECM, supporting the neutrality hypothesis. A VECM model was also employed in evaluating the relationship between crude oil prices and 5 food price indices by Roman et al. (2020) from 1990 to 2020. They found a long-run relationship between crude oil and the beef index. A short-run relationship between oil and the cereals price index was also found. Taghizadeh-Hesary et al. (2019) used a panel VAR model to analyze the association between oil-food prices. They found a positive response of food prices to oil prices. Additionally, Baek & Koo (2010) explored the determinants of food inflation in the USA using a cointegration test for the period 1991 to 2008. They discovered that energy prices influence food prices. They went on to show that the developments towards biofuel extracted from crops further strengthen the link between oil and food prices.

A second group of studies under the first primary group based on findings report no evidence of a relationship between oil and food prices. This means that they support the neutrality hypothesis. Amongst this group includes (Fowowe, 2016; Reboredo, 2012 and Nazlioglu & Soytas, 2010). Fowowe (2016) examined the relationship between oil and food prices in South Africa using non-linear causality and cointegration tests covering 2003-2014. They found no proof of a long-run relationship between the prices of oil and food prices. Similar results were reported by Baumeister & Killian (2014) for the USA. Reboredo (2012), using world prices, also finds no relationship. The neutrality hypothesis was also supported by Zhang et al. (2010) for the USA as well as Nazlioglu & Soytas (2010) for Turkey. These results are the direct opposite of the first group discussed earlier, which found a relationship that was either positive or negative and bidirectional or unidirectional. However, the comparison of the results is arduous mainly because they focus on different countries at different periods. Mostly, there is insufficient data for the different papers to carry out an exhaustive comparison.

The second primary group examines the relationship between oil, food, and uncertainty. A paper by Wang et al. (2023) assessed the relationship between oil prices, EPU, and green bond index in China using quantile ARDL for the period 2010 to 2022. They find a long-term relationship. Additionally, Ringim et al. (2022) did a study on EPU and energy prices in Russia using DCC GARCH models from 1994 to 2019. A stronger correlation between EPU and gas than EPU and oil was found. A paper by Yuan et al. (2022) explores the connection between EPU, oil, and stock markets in the BRIC nations. The multivariate quantile VAR model was used to analyze the viable uneven linkage across the whole distribution rather than scarcely on the conditional mean. The empirical effects show that, whilst the Brent oil marketplace is wealthy, EPU in China and India hurts oil returns, while EPU in Russia and Brazil has a positive impact. This paper finds conflicting results in different countries, possibly because they used oil returns instead of prices. The use of oil prices is preferred over the use of oil returns because prices provide a more direct and instant measure of the oil value. Prices can also be easily compared across distinctive times and locations, whereas returns are affected by elements like investment and taxes, which differ across nations. Additionally, oil prices are widely used in economic evaluation and forecasting and are frequently used as a benchmark for different energy prices.

Additionally, under the same category, Aimer & Lusta (2021) analyzed the asymmetric impact of oil prices on EPU for the USA using the ARDL model from 1997 to 2020. A long-run relationship was found. The assessment of the nonlinear impact of EPU on food prices in China from 1998 to 2020 was done by Wen et al. (2021). They showed that an increase in EPU leads to a significant increase in food prices in the short- and long run. A study examining the relationship between oil and EPU was carried out by Lin & Bai (2021). They find that oil shocks have larger fluctuation on EPU and vice versa. Hailemariam et al. (2019) analyzed the relationship between oil and EPU in the G7 countries from 1997 to 2017. They found that the effect of oil prices on EPU changes over time. All the studies that included uncertainty found a significant relationship, showing that it plays an important role that should not be ignored. Despite playing a key role, there is limited empirical evidence on the relationship between EPU, oil, and food prices. Nothing is known about the role of uncertainty in developing economies, mainly because of scant data on EPU, which focuses mostly on developed economies (Baker, 2016).

From the empirical analysis, there are studies which focused on SSA countries. They include Dillon & Barrett (2016), which examined the pass-through of global oil prices to local maize prices in Kenya. Using a Vector Error Correction Model (VECM), they found that oil price increases significantly affect maize prices, primarily through transportation costs. Their focus on maize reflects its importance as a staple, but it limits the scope to a single commodity. Fowowe (2016) analyzed the relationship in South Africa using cointegration and causality tests. It found no long-run relationship between crude oil prices and agricultural commodity prices, including maize, wheat, and soybean. This finding contrasts with others, suggesting regional variations and highlighting the complexity of the oil-food price nexus in SSA.

Fasanya & Akinbowale (2019) investigated volatility spillovers between crude oil and food prices in Nigeria using the Diebold Yilmaz. Covering monthly data from January 1997 to December 2016, they found significant volatility transmission from oil prices to food prices, with positive spillovers indicating that oil price fluctuations increase food price volatility. Unlike maize-focused studies, this work used a food price index, offering a broader perspective. Dalheimer et al. (2021) used Structural Vector Autoregressive (SVAR) models to investigate oil market shocks on local corn prices across eight SSA countries. They found that disruptions in global oil supply can lead to increased corn prices, unlike oil-specific demand shocks, which have less impact. Like the others, this study focused on corn, limiting its applicability to broader food price dynamics.

Gummi et al. (2021) examined the impact of oil prices on food prices in Nigeria using asymmetric and partial structural change models. Using data from January 2000 to September 2019, they found that positive changes in crude oil prices reduce food prices in the long run, while negative changes co-move with food prices. In the short run, both positive and negative changes in oil prices positively affect food prices, suggesting oil price dynamics influence food price stability through supply channels. Okou et al. (2022) analyzed domestic and external drivers of local staple food prices in SSA using data from 15 countries. They found that external factors, particularly global food prices influenced by oil, drive food price inflation, with a near-complete pass-through for highly imported staples. Domestically, greater local production and lower consumption shares can mitigate price volatility. This study broadens the scope beyond maize, offering insights into multiple staples.

Akinlo (2024) examined the asymmetric impact of oil prices on the real sector in SSA oil-importing countries. Using a nonlinear autoregressive distributed lag model on panel data from 20 oil-importing nations between 1987 and 2021, they found that oil price changes have asymmetric effects on different sectors, with implications for food production and prices through the real sector.

Each study employed different econometric methods, reflecting the diversity in analytical approaches. Dillon & Barrett (2016) used VECM to capture long-run and short-run dynamics, suitable for time series data with cointegration. Fowowe (2016) applied cointegration and causality tests, effective for examining long-run relationships and directional impacts. Fasanya & Akinbowale (2019) used DY to capture volatility spillovers, offering a broader food price perspective. Dalheimer et al. (2021) used SVAR, building on Kilian's (2009) oil market model, to identify specific oil shock types. Okou et al. (2022) used panel data analysis to assess staple food prices, Gummi et al. (2021) used asymmetric and partial structural change models, and Akinlo (2024) used cross-sectional dependence ARDL. These methods highlight the evolving sophistication in capturing the oil-food price nexus.

The reliance on maize prices as a proxy for food prices presents several limitations. Firstly, SSA's food consumption varies widely; while maize is a staple in East and Southern Africa, West Africa relies more on rice and cassava. Secondly, different food items have varying dependencies on oil prices. For instance, maize production may be heavily reliant on oil for fertilizers and machinery, while cassava, often grown with less mechanization, might be less affected. Transportation costs, a significant channel for oil price pass-through, also differ; perishable items like vegetables may face higher impacts due to refrigeration needs compared to grains.

Moreover, these studies largely overlook the role of uncertainty, which significantly influences the oil-food price relationship. Factors such as economic policy shifts, geopolitical conflicts, climate variability, and global health crises like the COVID-19 pandemic introduce volatility that can amplify or dampen oil price effects on food markets, yet this dimension remains underexplored in the existing SSA-focused research, limiting the understanding of how unpredictable conditions shape price dynamics across diverse food items.

The first primary category is a first step towards understanding the relationship between oil and food prices. However, they ignored the role of uncertainty, which is on the rise globally due to pandemic outbreaks, trade conflicts, and political unrest, among other things. No one knows when these incidents will end, which further increases the uncertainty, thereby calling forth the assessment of its impact on the oil-food relationship. The studies often provide conflicting evidence even when similar datasets are applied. Some find either positive, negative, or no effect of changes in oil prices on food prices. This is unfortunate as such information has important implications for the energy-food policy nexus, poverty, and trade. This might be attributed to their failure to pay attention to uncertainty, which affects financial relationships, according to Antonakakis et al., (2014).

The second primary category includes uncertainty with oil or food, without combining the three variables in one assessment. This relationship is crucial with the growing uncertainty and rising oil and food prices. The studies employ parametric models with restrictive forms, and this is likely to give biased findings if knowledge of prior functional forms is opaque (Breitung & Pesaran, 2008). They fail to account for structural breaks and cross-sectional dependence, which implies that these results are either biased or inconsistent (Taghizadeh-Hesary et al., 2019; Karakotsios et al., 2021). Our paper aims to bridge this lacuna in the literature by using second-generation tests for panel data. These will give us results that are crucial in choosing the suitable model that captures the structural breaks and the cross-section dependency.

A significant oversight in the extant literature is the disregard for structural breaks, with few studies acknowledging the limitations of first-generation tests in detecting multiple breaks (Karakotsios et al., 2021). This neglect is particularly concerning given the inevitability of economic structural shifts due to business cycles and policy changes. The omission of such breaks can lead to inconsistent and ambiguous results, as evidenced by the mixed findings in prior research. Furthermore, the absence of tests for cross-dependence and endogeneity in panel analyses raises concerns about model misspecification and biased estimates (Westerlund & Edgerton, 1996), highlighting the need for methodological rigor in future investigations.

2.3 Theoretical Framework

In understanding the interlinkages between oil and food prices, we adopt a production theory approach by Hudson and Jorgenson (1974), who considered energy as an important factor of production just like capital and came up with an output function: Y = f (L, K, E, M)**.** This theory is made up of four components: labor, capital, energy, and material. It emphasizes the importance of energy, just like labor and capital, in producing goods and services. Van Gool and Bruggink (1985) supported the production function of Hudson and Jorgenson and went on to describe M as all the other non-energy materials required for production, which include information, coordination controls, and others. This is the definition this paper is going to follow where the controls relate to policy controls, which result in policy uncertainty, which is one of our important variables. The controls also encompass monetary controls, proxied by inflation and exchange rate, while others represent all the other explanatory variables in the paper.

By linking these inputs, we obtain a production function (Equation 1). This equation represents the supply side with agricultural products as output (Y_A):

$$Y_A = F(L, K, E, M) \tag{1}$$

Where L is the labor share employed in the agricultural sector, K is capital necessary in producing a given good, which can be thought of as land, E is the energy in this case, it is proxied by the oil, and M is all the other non-energy inputs, which include economic policy uncertainty, inflation, exchange rate, economic index, and oil production in this paper. These inputs are paid their marginal product: *i.e.*, capital is paid rent/interest rate (r), labor is paid wages (w), while energy is paid its actual price (P_E). By multiplying unit prices paid for inputs by the quantities used, we get the total cost of production. Therefore, a rise in input prices is likely to cause an increase in the price of food. This is because food is a necessity and, therefore, has inelastic demand.

The profit function of an economic agent can be obtained as total revenue less total cost. Total revenue is a product of the price (P) and supply of an agricultural product. If we assume imperfect market competition, the first-order condition for a profit maximization agent can be summarized below.

$$P = \frac{1}{d_1}Y + \frac{\partial L}{\partial Y}w + \frac{\partial K}{\partial Y}r + \frac{\partial E}{\partial Y}P_E + \frac{\partial M}{\partial Y} \tag{2}$$

We formulate the demand side equation as in equation 3 below:

$$Y_D = \beta_0 - \beta_1 P + \beta_2 X \tag{3}$$

Where; Y_D captures the demand for a good, P is the price of that good, while X represents other factors that are likely to influence a household's demand for food besides its price.

If we assume that the market is in equilibrium, we obtain the model shown in Equation 3. The model we estimate can mathematically be written as below (equation 4).

$$P = \frac{\beta_0}{\beta_1} - \frac{1}{\beta_1} Y_D + \frac{\beta_2}{\beta_1} X + \varepsilon_{it} \quad (4)$$

From equation 4, P represents the food prices, Y_D is the demand for food, π_1 represents the responsiveness of prices to changes in production, and X represents all the variables that are likely to impact the prices of food. In equation 4, $\pi_0 = \frac{\beta_0}{\beta_1}$; $\pi_1 = \frac{1}{\beta_1}$ while $\pi_2 = \frac{\beta_2}{\beta_1}$. The impact multiplier matrix (π_1) has a recursive structure such that the reduced form errors (ε_{it}) can be decomposed as $\varepsilon_{it} = \pi_1 \varepsilon_{it}$.

$$P = \pi_0 - \pi_1 Y_D + \pi_2 X + \pi \varepsilon_{it} \quad (5)$$

From the law of demand, the major determinant of the demand for the good is its price, which is represented by P in equation 5. Equation 5 explains the law of demand, which states that there is an inverse relationship between the price of a good and the quantity demanded. X represents all the other variables that affect food production, which is an agricultural commodity. These include the inputs required like energy which will be represented by crude oil, the supply of oil in the market being determined by production, labor which is proxied by employment, the level of uncertainty, the land required for farming, the income levels which enables the purchasing of the inputs, exchange since most countries import oil and the economic index which represents the level of economic activity. Using these variables, we can estimate the impact of oil price shocks on food prices using the following reduced-form panel model:

$$\begin{aligned} Food\ price_{it} &= \beta_0 + \beta_1 Oil\ price_t + \beta_2 Exchange\ rate_{it} + \beta_3 Land_{it} + \\ &\beta_4 Employment_{it} + \beta_5 GDP\_C_{it} + \beta_6 World\ uncertainty_{it} + \varepsilon_{it} \quad (6) \end{aligned}$$

Where; $Food\ price_{it}$ represents food prices for country *i* at time *t* and $Oil\ price_t$ is the global price of oil at time t. $Exchange\ rate_{it}$ is the real exchange rate. Moreover, $Land_{it}$ and $Employment_{it}$ represents the share of the total land area dedicated to agricultural production and the share of employment in the agricultural sector. Finally, while GDP_{it} and

$World\_uncertainty_{it}$ are the Gross Domestic Product (GDP) per capita of each country and world uncertainty is the world uncertainty index in each of the countries used in this study.

It is important to note that panel analysis is being adopted mainly due to its ability to gain statistical potency by pooling the information across elements, thereby enhancing the bad precision of univariate assessments. This has mainly been achieved by applying what is probably known as a 'first generation of panel cointegration tests,' which depend on simplifying assumptions. This is complex in that the violations of those assumptions can significantly result in distorted estimates. It is, therefore, imperative to run the necessary tests like unit root test, cross dependency, and panel cointegration.

2.3.1 Empirical Strategy

Since the introductory work of Perron (2006), it is well known that it is vital to permit structural breaks when testing time series for unit roots. The failure to recognize the capability presence of structural breaks can also cause misleading inferences concerning the integration order. For example, data with structural breaks can be considered non-stationary when stationary, and it will be misleading when deciding what model to use, resulting in wrong inferences and estimates. Moreover, Breitung & Pesaran (2008) postulated that it is improper to presume that there is no cross-dependence across panel members when doing panel analysis. Indeed, the belief in independence is commonly not legitimate, particularly within the analysis of macroeconomic or monetary data that have sturdy inter-economic system linkages (Urbain & Westerlund, 2006).

Consequently, this paper used contemporarily developed panel strategies that harbour both structural breaks and cross-sectional dependence concurrently instead of neglecting them or maybe attending to one issue at a point in time. Since those econometric techniques have been rarely used within the empirical literature, this paper is going to add to the literature by applying them and presenting the results. Firstly, the cross-dependence test advanced by Pesaran (2004) is done, followed by the test for panel unit root initiated by Bai & Carrion-i-Silvestre (2009). It is suitable since it performs better in the presence of structural breaks and cross-dependence. Furthermore, the panel cointegration test is carried out with the aid of Westerlund & Edgerton (2007), which considers structural breaks and dependence across nations. After the tests, the Common Correlated Effects for assessing the long-run relationship postulated by Pesaran

(2006) are discussed and applied. Ultimately, this paper also discussed and used the Common Correlated Effects Mean Group and Common Correlated Effects Pooled.

This paper is going to follow Westerlund & Edgerton's (2007) model in testing for panel cointegration with the following model:

$$y_{it} = \alpha_i + \eta_i t + \delta_i D_{it} + x'_{it}\beta_i + (D_{it}x_{it})'\gamma_i + z_{it}, \tag{7}$$

$$x_{it} = x_{it-1} + w_{it}, \tag{8}$$

Where i = 1…, N represents the panel members, t = 1…, and T is the time period. D_{it} is a scalar break dummy with D_{it} = 1 if $t > T_i$ and zero otherwise. α_i and β_i are intercept and slope coefficients before the break while δ_i and γ_i are changes in these parameters after the break, w_{it} is an error term. z_{it} is the disturbance term produced through the subsequent model that permits cross-sectional dependence via unobserved familiar factors,

$$z_{it} = \lambda'_i F_t + v_{it} \tag{9}$$

$$F_{jt} = \rho_j F_{jt-1} + u_{jt} \tag{10}$$

$$\phi_i(L)\Delta v_{it} = \phi_i v_{it-1} + e_{it} \tag{11}$$

Where $\phi_i(L)$ is a scalar polynomial in the lag operator L, F_t is a matrix of unobservable common elements with a dimension of r. F_{jt} with j = 1, ..., r, and λ_i is the corresponding vector of factor loading parameters. The error term u_t does not depend on e_{it} and w_{it} for all i and t, and e_{it} has zero mean and independent across each i and t. Under the belief that $\rho_j < 1$ for all j, it is believed that F_t is stationary based on the integration order of the composite regression error z_{it} only depends on the integration degree of the idiosyncratic disturbance term v_{it}.

If the results show cross-dependency across the units, it will imply that using the panel VAR might result in inconsistent results. Therefore, the Pooled Mean Group Autoregressive Distributed Lag proposed by Pesaran (2006) must be adopted, as it performs better with structural breaks and cross-dependence.

Pesaran (2006) proposed Pooled Mean Group (PMG) estimators to estimate heterogeneous panel facts models with a multifactor error structure. The primary concept is to filter the cross-unit regressors using cross-section averages of the outcome variable and the observed regressors. Thus, cross-sectional dependence can be annihilated because the cross-section averages can approximate the unobserved common elements. Therefore, estimating the number of stationary factors will not be necessary. The CCE system may be computed by running panel regressions where the located regressors are augmented with cross-sectional averages of the outcome variable and the cross-unit specific regressors. Pesaran (2006) advanced two CCE estimators, the pooled and mean group CCE estimator, to take into account different associated estimation and inference issues. Kapetanios et al. (2011) expanded the work of Pesaran (2006) to the case in which the unobserved common elements are nonstationary. They show that the pooled mean estimators are consistent even in the presence of unit roots in the unobserved common elements and are sturdy to structural breaks in the mean of these unobserved factors.

The heterogeneous panel model can be specified as:

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + e_{it} \tag{12}$$

Where t is period from t = 1…, T and i are the panel members from i = 1…, N. d_t is an n x 1 matrix of observed common effects like intercepts and seasonal dummies which are deterministic components. They also include the non-stationary observed effects like the price of oil. x_{it} is a vector of k x 1 representing the observed cross-unit-specific regressors. e_{it} is the error term which is specified by the following multifactor structure;

$$e_{it} = \gamma_i' f_t + \varepsilon_{it} \tag{13}$$

where f_t represents a vector of m x 1 which are unobserved common factors, and the cross-unit specific disturbance term is ε_{it} assumed to be independently distributed of (d_t, x_{it}). Since f_t might be correlated with (d_t, x_{it}), the following general model can be specified,

$$x_{it} = A_i' d_t + \Gamma_i' f_t + v_{it} \tag{14}$$

Where A_i and Γ_i are fixed components matrices of n x k and m x k respectively. v_{it} represents specific components of x_{it}. It's assumed to be independently distributed of the common effects.

Combining equations 12,13 and 14 gives,

$$\underset{((k+1)\times 1)}{z_{it}} = \begin{pmatrix} y_{it} \\ x_{it} \end{pmatrix} = \underset{((k+1)\times n)}{B_i'} \underset{(n\times 1)}{d_t} + \underset{((k+1)\times m)}{C_i'} \underset{(m\times 1)}{f_t} + \underset{((k+1)\times 1)}{u_{it}} \quad (15)$$

Where

$$u_{it} = \begin{pmatrix} \varepsilon_{it} + \beta_t' v_{it} \\ v_{it} \end{pmatrix} = \begin{pmatrix} 1 & \beta_i' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \varepsilon_{it} \\ v_{it} \end{pmatrix}, B_i = (\alpha_i \quad A_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}, C_i = (\gamma_i \quad \Gamma_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix} \quad (16)$$

I_k is the identity matrix of order k. Matrix of the unobserved factor loadings determining the rank of $\widehat{b}$.

It follows that the Pooled Mean Group (PMG) is generated by averaging the individual pooled estimators, $\widehat{b_\iota}$ of β_i which is given by;

$$\hat{b}_{PMG} = \frac{1}{N} \sum_{i=1}^{N} \widehat{b_\iota} \quad (17)$$

$$\hat{b}_i = (X_i' \bar{M} X_i)^{-1} X_i' \bar{M} y_i \quad (18)$$

With $X_i = (x_{i1}, \ldots, x_{iT})', y_i = (y_{i1}, \ldots, y_{iT})$, and $\bar{M} = I_T - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}'$ where $\bar{H} = (D, \bar{Z})$. D and $\bar{Z}$ represent the observation matrices on d_t and $\bar{z}_t$ with order (T $\times\, n$) and (T $\times\, (k+1)$ respectively. The Pooled Mean Group (PMG) is also estimated using the following equation,

$$\hat{b}_{PMG} = (\sum_{i=1}^{N} X_i' \bar{M} X_i)^{-1} \sum_{i=1}^{N} X_i' \bar{M} y_i \quad (19)$$

2.3.2 Panel Causality

This paper employs the dynamic pooled mean group (PMG) postulated by Pesaran et al. (1999) to estimate the causal relationship. The model permits the exploration of long-run homogeneity without assuming that the short-run dynamics are the same across the countries. This differs from the instrumental variable estimators, which pool the individual units together plausibly assuming that the short-run dynamics are the same, permitting only the intercepts to vary across nations. Additionally, the mean group estimator that takes the coefficient mean of the national-precise regressions is a regular but not exact estimator when both N and T are small. In evaluation, the PMG estimator is predicated by pooling and averaging coefficients (Isiksal et al., 2022). The ideal lag period is selected by way of the Schwarz Information Criterion.

The dynamic panel specification is as follows,

$$\Delta Food\ price_{it} = \alpha_i^{fp} + \sum_{k=1}^{h} \theta_{1i,k}^{fp}\ \Delta Food\ price_{i,t-k} + \sum_{k=0}^{h} \theta_{2i,k}^{fp} \Delta Oil\ price_{i,t-k} + \sum_{k=0}^{h} \theta_{3i,k}^{fp} \Delta World\ uncertainty_{i,t-k} + \sum_{k=o}^{h} \theta_{4i,k}^{fp} X_{i,t-k} + \lambda_i^{fp} \varepsilon_{i,t-1}^{fp} + u_{it}^{fp} \quad (20)$$

$$\Delta Oil\ price_{it} = \alpha_i^{op} + \sum_{k=1}^{h} \theta_{1i,k}^{op} \Delta Oil\ price_{i,t-k} + \sum_{k=0}^{h} \theta_{2i,k}^{op}\ \Delta Food\ price_{i,t-k} + \sum_{k=0}^{h} \theta_{3i,k}^{op} \Delta World\ uncertainty_{i,t-k} + \sum_{k=o}^{h} \theta_{4i,k}^{op} X_{i,t-k} + \lambda_i^{op} \varepsilon_{i,t-1}^{op} + u_{it}^{op} \quad (21)$$

Where i = 1…, N represents countries, t = 1…, T is the period. $Food\ price_{it}$ is the food price, $Oil\ price_{it}$ is the oil price, $World\ uncertainty_{it}$ is the World Uncertainty Index and X_{it} represents all the other control variables in our paper, which include the real exchange rate, share of total land area dedicated to agricultural production, the share of employment in the agricultural sector, and Gross Domestic Product per capita. Δ represents the first difference, α_i denotes the fixed effects, k represents the lag length, $\varepsilon_{i,t-1}$is the error term that is lagged for one period and u_{it} represents the error term that is serially uncorrelated with zero mean. $\theta_{1i,k}^{j}$ is short-run dynamics while the speed of adjustment is denoted by λ_i.

2.4 Data Sources

The study analyses annual data for 24 countries in the Sub-Sahara Africa region from 2000 to 2020.[1] This dataset is panel in nature. Therefore, we can obtain accurate inferences because of

[1] These include Nigeria, Mauritius, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Democratic Republic of Congo, Ethiopia, Gambia, Ghana, Guinea, Kenya, Madagascar, Malawi, Mali Mozambique, Niger, Rwanda, Senegal, South Africa, Togo, Tanzania, Zambia.

more degrees of freedom and sample variability. Moreover, panel datasets are helpful in portraying the dynamics at given periods in time.

We collected our dataset from several sources: World Development Indicators (WDI), World Bank Commodity Price, Policy uncertainty, and the Food and Agriculture Organisation of the United Nations (FAO) Statistics. These variables include international oil price (Brent crude oil), food prices (which we proxy by food consumer price indices), inflation rate, real exchange rate, GDP per capita, share of agricultural land, employment share in the agricultural sector, and change in oil production. Finally, we included an index of the global real economic activity in the industrial commodity markets, and economic policy uncertainty (see Table 2.2). Our choice of countries is purely based on the availability of data.

Table 2.2: Variable description and data sources

Variable	Description	Source
Food CPI	Consumer prices, Food indices (2015=100)	http://fenix.fao.org/faostat/internal/en/#data/CP
Oil Price	Annual crude oil, average spot price of Brent, Dubai, and West Texas Intermediate, equally weighted	https://www.worldbank.org/en/research/commodity-markets
WUI	World Uncertainty index for specific countries	https://worlduncertaintyindex.com
GDP_C	Gross Domestic Product (GDP) per capita (constant 2015 US$)	https://databank.worldbank.org/source/world-development-indicators
Exchange rate	Official exchange rate (Local Currency Unit	https://databank.worldbank.org/source/world-development-indicators

	(LCU) per US$, period average)	
Employment	Share of employment in agriculture, forestry and fishing in total employment-ILO Modelled estimates	http://fenix.fao.org/faostat/internal/en/#data/OEA
Land	% share of total land area dedicated to agricultural production	http://fenix.fao.org/faostat/internal/en/#data/RL

2.5 Results Presentation and Analysis

2.5.1 Descriptive Statistics

Table 2.3 below shows the descriptive statistics of the variables used in this paper. The standard deviation shows that the Gross Domestic Product (GDP) per capita has high fluctuations. This can partly be attributed to the inclusion of Nigeria and South Africa, the largest economies in Africa (Balcilar et al., 2019). The share of employment in the agricultural sector was high (approximately 52%) in general. In some economies, the agricultural sector contributed about 92% of the total employment. For countries that have a strong manufacturing sector (in this case, South Africa), agricultural employment share is approximately 5% of the total. The share of the total land area allocated to agriculture was also high. For instance, most countries allocated about 50% of their total land mass to agricultural production.

Table 2.3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Food CPI	504	4.232	0.548	2.242	5.338
Oil Price	504	4.101	0.375	3.462	4.621
WUI	504	0.230	0.207	0	1.343
Exchange rate	504	5.016	2.157	-0.607	9.166
GDP_C	504	6.824	1.014	4.718	9.324
Land	504	3.805	0.457	2.422	4.415
Employment	504	3.783	0.705	1.526	4.522

Source: Author’s compilation

The standard deviation of 0.375 is a measure of the spread or variability of the dataset. It describes the deviation or variation of the values from the mean. In this case, the standard deviation of 0.375 units indicates that 68% of the oil prices fall within one standard deviation of the mean, between 3.725 (4.10 - 0.375) and 4.475 (4.10 + 0.375).

2.5.2 Statistical Tests Results

Table 2.4 provides a Bonferroni pairwise correlation matrix (Olejnik, 1997). We find a positive association between crude oil prices and food prices. These effects are statistically significant at conventional levels (P<0.01). Interestingly, we find a negative relationship between food prices, land, and employment. The strength of the negative relationship is in favour of employment.

Table 2.4: Bonferroni pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Oil price	1.000						
(2) WUI	0.1301*	1.0000					
	(0.0034)						
(3) Exchange rate	0.0202	-0.1026*	1.0000				
	(0.6507)	(0.0213)					
(4) GDP_C	0.2580*	0.4159*	-0.3574	1.0000			
	(0.0000)	(0.0000)	(0.0000)				
(5) Land	0.0816*	-0.0277*	0.0868*	-0.150*	1.0000		
	(0.0671)	(0.5352)	(0.0514)	(0.007)			
(6) Employment	-0.0496*	-0.3930*	0.4098*	0.8359*	0.1739*	1.0000	
	(0.2667)	(0.000)	(0.000)	(0.0000)	(0.0001)		
(7) Food price	0.3759*	0.3007*	0.1417*	0.4040*	-0.019*	0.2178*	1.0000
	(0.0000)	(0.0000)	(0.0014)	(0.0000)	(0.0000)	(0.0000)	

Notes: ***p<0.01, ** p<0.05, * p<0.1
Source: Author's compilation

We also observe that a rise in world uncertainty in each period is positively related to food prices. Finally, we find that changes in that share of land allocated to agricultural production have the least positive effect on food prices. This result can partly be explained by the fact that most countries in SSA use traditional farming methods, and yield levels are low. This means they must rely more on imports to meet the local demand. Another possible explanation is the exposure to the changing weather patterns. Most African countries rely on rain-fed agriculture to produce their food. This means that any variation in weather patterns is likely to be associated with lower yields. This negatively impacts household welfare.

Table 2.5: Sequential test for multiple breaks at unknown breakpoints

	Test Statistic	1% critical Value	5% critical Value	10% critical Value
F (1|0)	11.76	4.08	3.35	2.99
F (2|1)	2.08	4.32	3.69	3.34
F (3|2)	1.34	4.51	3.84	3.53
F (4|3)	5.39	4.59	3.96	3.68

The Bai and Perron (2007) structural break tests, as presented in Table 2.5, reveal a maximum of four and a minimum of one structural break in the sample data. This finding underscores the necessity of selecting a methodological approach robust to structural breaks. Traditional linear and nonlinear models, such as VECM, VAR, and ARDL, as well as conventional panel models like Fixed Effects and Random Effects, exhibit limitations in the presence of such breaks. Conversely, the PMG-ARDL model selected for this study demonstrates superior performance in accommodating structural breaks, ensuring the robustness and validity of the analysis.

Table 2.6: Cross-section dependence

Variable	Alpha	Std. Error	[95% Conf. Interval]	
Food CPI	1.0077	0.0818	0.8474	1.1679
Oil price	1.0077	0.267	0.9548	1.0606
WUI	0.9718	0.0519	0.8699	1.0707
GDP_C	1.0076	0.0327	0.9436	1.0717

Exchange rate	0.8924	1.097	-1.2578	3.0426
Employment	0.9565	0.0489	0.8607	1.0523
Land	0.9998	0.3142	0.9382	1.0613

Source: Compiled by the author

The alpha value lies between 0.5 and 1, showing strong cross-sectional dependence across the panel members. This, therefore, implies that the traditional models of panel analysis are inconsistent since they rely on the assumption of independent and identically distributed errors between units. However, when there is dependence across units, this assumption is violated and can result in inconsistent estimations and incorrect inferences (Pesaran, 2004). To address this issue, it is necessary to adopt models for estimating panels with cross-sectional dependence, like the Pooled Mean Group model, as it can use the cross-sectional and temporal variation in the data to improve the estimation efficiency (Pesaran, 2006).

Table 2.7: Panel unit root tests with cross-sectional dependence

	Bai and Ng - PANIC		Pesaran-CIPS	
Variable	Pooled statistic value	p-value	t-statistic	p-value
Food CPI	5.2636	0.0000	-2.1419	<0.10
Oil price	12.4457	0.0000	0.0000	>0.10
WUI	5.1262	0.0000	-2.6252	<0.01
GDP_C	2.3079	0.0210	-2.3162	<0.05
Exchange rate	2.4669	0.0136	-2.8336	<0.01
Employment	7.1654	0.0000	-2.3843	<0.01
Land	2.9918	0.0028	-2.1221	<0.10

Source: Author’s compilation

Given the cross-sectional dependence inherent in the variables, a second-generation unit root test is employed. Specifically, the Pesaran CIPS test is utilized to account for both cross-sectional dependence and heterogeneity (Im, Pesaran & Shin, 2003). Additionally, the Bai and Ng Panel Analysis of Non-stationarity in Idiosyncratic and Common Components (PANIC) test, chosen for its ability to analyze and disentangle different types of non-stationarity in panel data, is applied to further assess non-stationarity (Pesaran, 2007). As shown in Table 2.7, the unit root tests confirm the stationarity of the variables, necessitating a Hausman test to determine the appropriate model. The Hausman test results, presented in Table 2.8, will guide the selection of the most consistent model for subsequent analysis.

Table 2.8: Hausman test

Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random		614.3170	6.0000	0.0000
Cross-section random effects test comparisons:				
Variable	Fixed	Random	Var (Diff.)	Prob.
Oil price	13.4550	-1.5043	1.8846	0.0000
WUI	10.4365	40.3211	4.4758	0.0000
GDP_C	47.7259	33.5092	8.2306	0.0000
Exchange rate	35.9442	8.0858	5.6739	0.0000
Employment	-19.7945	19.1364	37.7357	0.0000
Land	-7.5215	7.6729	12.003	0.0000

Source: Compiled by the author

The p-value is less than 5% significance level; therefore, the fixed effect variable is more appropriate. This shows that the hypothesis that certain restrictions on the long-term predictor make it homogeneous is valid. This implies that the PMG method is more resilient than the Mean Group (MG) technique. The study used the PMG-ARDL model, a panel data regression model that allows for homogeneity in the long-run coefficients across different units in a panel. It is particularly useful when the units in the panel are interdependent, have structural breaks, and the data set is relatively small (Dobnik, 2012).

2.5.3 Regression Results

Table 2.9: Regression results without structural breaks

Variable	Coefficient	Std. Error	t-Statistic	Prob.

	Long-run (Pooled) Coefficients			
Oil price	5.0240**	2.0271	2.4784	0.0135
WUI	6.6533***	2.4887	2.6734	0.0078
GDP_C	27.0321***	6.9014	3.9169	0.0001
Exchange rate	17.6747**	7.7758	2.2730	0.0235
Employment	-15.0402	11.5670	-1.3003	0.1941
Land	-7.5468**	3.4538	-2.1851	0.0294
	Short-run (Mean-Group) Coefficients			
COINTEQ	-0.2148	0.0631	-3.4012	0.0007
Oil price	-1.7405**	1.0838	-1.6059	0.1090
WUI	0.5146	1.5801	0.3257	0.7448
GDP_C	3.5400	6.4086	0.5524	0.5809
Exchange rate	15.3137**	7.7547	1.9748	0.0489
Employment	147.0608	111.8703	1.3146	0.1893
Land	21815.00	21671.420	1.0066	0.3146
C	-87.80779*	51.7467	-1.6969	0.0904
Trend	0.7465***	0.2220	3.3630	0.0008

Notes: ***p<0.01, ** p<0.05, * p<0.1
Source: Compiled by the author

The crude oil is significant at a 1% level, showing a positive relationship with food prices in the long run. This means that oil prices positively affect food prices in the long run as the changes in oil prices will be enacted in food prices in the long run and not in the short run similar to (Karakotsios et al., 2021). This means that the impact of changes in oil prices on food prices may not be immediate. For example, it may take time for changes in oil prices to affect the cost of transporting food from farms to markets, affecting food prices. This time lag can result in a weaker relationship between oil prices and food prices in the short run. Additionally, food prices are subject to seasonal variations, which can mask the relationship between oil prices and food prices in the short run. For example, food prices may fall during the harvest season even if oil prices rise, as increased supply can offset any impact from higher transportation costs.

The findings of this study suggest that crude oil holds significant importance at the 1% level, indicating a positive and long-run relationship with food prices (Hadj Cherif, 2021). Specifically, the results reveal that fluctuations in oil prices positively affect food prices in the long run, as changes in the former are reflected in the latter over an extended period rather than immediately. It is noted that the effect of oil price changes on food prices is subject to a time lag, whereby alterations in transportation costs resulting from shifts in oil prices may not immediately impact the price of food. This may lead to a weaker relationship between oil prices and food prices in the short run, with the magnitude of the effect becoming more pronounced in the long run. Furthermore, seasonal variations in food prices may obscure the link between oil prices and food prices in the short run. During harvest periods, for instance, food supply increases may counteract any upward pressure on prices from rising transportation costs. Thus, while the positive relationship between oil and food prices holds over the long term, short-term fluctuations and seasonal patterns may dampen its effects. The results are similar to (Dillon & Barret, 2015; Tanghizadeh-Hesary et al., 2019; Hadj Cherif, 2021; Aminah, 2022).

There is also a significant positive relationship at 1% between world uncertainty and food prices in the long run, showing that uncertainty plays a crucial role in food prices. This is mainly because SSA countries are largely agricultural economies, and the impact of uncertainty on food prices may be muted in the short run if there is a surplus of locally produced food. This is because local production may insulate SSA from uncertainty in the short run. This can also be attributed to price controls on basic food items in some of the SSA countries, limiting uncertainty impact on food prices in the short run (Wen et al., 2021).

The other control variables included in this analysis also positively impact food prices, except for land and employment. The GDP per capita positively affects food prices as it is a proxy that determines the demand for food. Remember, food is a basic good, and the price elasticity is inelastic since it is a basic normal good. As income levels increase, the demand for food will also increase, hence the significant positive relationship. Land negatively affects food prices since it is a critical natural resource for the production of food. Therefore, the price of land can significantly impact the cost of producing food. When the price of land increases, it becomes more expensive for farmers to acquire and use land for agricultural production. This can lead to a decrease in the supply of food, which can drive up food prices. Higher land prices can also lead to higher input costs for farmers, such as rent, property taxes, and interest on loans used to purchase or lease land. These costs can then be passed on to consumers in the form of higher food prices.

The exchange rate positively affects food prices in the short and long run, mainly because SSA is a major import of inputs used in food production, such as oil and fertilizer. It also imports some major food commodities where the exchange rate plays a pivotal role. For example, if the exchange rate of a country's currency increases relative to other currencies, the cost of importing food products may become more expensive. This can lead to higher food prices in the short run as the cost of production and transportation increase. In the long run, exchange rates can also impact food prices by affecting the overall competitiveness of a country's agricultural sector (Siam-Namini, 2019).

It is widely acknowledged that financial data, especially oil prices, are susceptible to structural shocks (Fasanya et al. 2019), due to the complex and interconnected nature of the oil market, which includes factors such as geopolitical instability, supply disruptions, changes in demand, OPEC policies, and speculation. Ignoring these structural breaks in regression analysis could lead to biased estimates, particularly if the breaks are significant. Therefore, we initially identified any potential breaks in the relationship between oil and food prices and controlled for them, focusing on the periods that were similar across countries: 2005, 2008, and 2012.

To account for these structural breaks, we incorporated dummy variables representing significant periods of change, such as the Asian demand increases and the global financial crisis during the years 2005, 2008, and 2012. By assigning a value of 1 during these periods and 0 otherwise, we were able to control for structural shocks that would otherwise bias our estimates. This inclusion of dummy variables significantly enhanced the explanatory power of our model, as evidenced by the newfound significance of previously insignificant variables. Our approach underscores the importance of recognizing and adjusting for structural breaks in financial data to achieve more accurate and reliable results as shown in Table 2.10.

Table 2.10: Regression results with structural breaks

Variable	Coefficient	Std. Error	t-Statistic	Prob.
	Long-run Pooled Coefficients			
Oil price	0.1664***	0.0165	10,0704	0,0000
WUI	0.1798***	0.0628	2,8644	0,0044
GDP_C	0.0740**	0.0371	-1,9934	0,0468
Exchange rate	0.3189***	0.0314	10,1453	0,0000
Employment	0.0520	0.0489	1,0636	0,2881

Land	-0.0094	0.0163	-0,5752	0,5654
Dummy 1	0.1254***	0.0156	8,0243	0,0000
Dummy 2	-0.0977***	0.0174	-5,6050	0,0000
Dummy 3	-0.0618***	0,0140	-4,3961	0,0000
Short-run Mean-Group Coefficients				
COINTEQ	-0.4551	0.0929	-4.9014	0.0000
Oil price	-0.0340***	0.0125	-2.7106	0.0070
WUI	0.0886**	0.0457	-1.9387	0.0501
GDP_C	-0.1811**	0.0857	-2.1124	0.0352
Dummy1	0.0502***	0.0140	3.5814	0.0004
Dummy2	0.0452***	0.0110	4.1083	0.0000
Dummy3	0.0199*	0.0108	1.8325	0.0675
C	0.8270***	0.1106	7.4750	0.0000
@TREND	0.0313***	0.0049	6.3933	0.0000

Notes: ***p<0.01, ** p<0.05, * p<0.1

Source: Author's compilation

Oil is a crucial input in the production and distribution of food, including farming, transportation, and processing. Therefore, any significant increase in oil prices can increase the cost of producing and distributing food products, ultimately leading to higher food prices. For example, farming relies heavily on fuel for operating machinery and equipment, as well as for irrigation and transportation. As oil prices rise, the cost of fuel increases, which raises the cost of producing and harvesting crops. Similarly, food processing and packaging require significant energy from oil or natural gas. Higher oil prices will increase the cost of energy, which, in turn, increases the cost of processing and packaging food. Transportation is another key area where oil prices can affect food prices. Most food products are transported over long distances, often across borders and oceans, and rely on trucks, ships, and airplanes, which consume large amounts of fuel. As the price of oil increases, the cost of transportation increases, which leads to higher food prices (Roman et al., 2020; Olayungbo, 2021).

Uncertainty can significantly affect food prices in the short run because it can cause disruptions to the supply chain, which can lead to temporary shortages and price spikes. Several sources of uncertainty can affect the food market, including weather, geopolitical events, and changes in trade policies. For example, extreme weather events, such as floods or droughts, can damage crops and disrupt the supply of certain food products. This can lead to temporary shortages and price increases until the supply chain is restored. Similarly, geopolitical events such as wars, conflicts, and trade disputes can lead to disruptions in the flow of food products across borders, leading to temporary shortages and price spikes. The GDP per capita also significantly affects food prices in the short run because it reflects the purchasing power of consumers. When GDP per capita increases, consumers have more disposable income to spend on food, which can increase demand and drive-up prices and vice versa. Moreover, GDP per capita can also affect food prices indirectly by impacting the production and distribution of food. With high GDP per capita, countries tend to have more developed infrastructure, such as better transportation networks, advanced storage facilities, and efficient supply chains. This can help reduce the costs of producing and distributing food, which can translate into lower food prices for consumers.

Table 2.11: Regression results for asymmetric oil prices

Variable	Coefficient	Std. Error	t-Statistic	Prob.
	Long-run (Pooled) Coefficients			
WUI	176.5159***	27.2770	6.4712	0.0000
Oil Price+	3.5952***	0.8904	4.0379	0.0001
Oil Price-	-7.7078	5.1824	-1.4873	0.1376
GDP_C	0.0095***	0.0015	6.2945	0.0000
Employment	-0.6172***	0.1810	-3.4096	0.0007
Ex rate	-0.0090**	0.0038	-2.3423	0.0196
C	39.9689***	11.3525	3.5207	0.0005
	Short-run (Mean-Group) Coefficients			
COINTEQ	0.0323	0.0189	1.7115	0.0876
WUI	14.6637***	4.6820	3.1319	0.0018
Oil Price+	0.3748	0.2750	1.3627	0.1736
Oil Price-	0.0325	0.2459	0.1322	0.8949
D(GDP_C)	0.0393**	0.0156	2.5256	0.0119
Employment	0.4569	0.3852	1.1863	0.2361
Ex rate	0.6370	0.4435	1.4365	0.1515

Notes: ***p<0.01, ** p<0.05, * p<0.1
Source: Author's compilation

In assessing the role of uncertainty in the oil-food nexus, it is important to assess the asymmetric shocks. The results are presented in Table 2.11, with the positive oil shocks significantly affecting food prices at a 1% level of significance, while the negative shocks are significant at 10%. Increases in oil prices result in increases in food prices in the long run, mainly due to adjustment lags and price transmission mechanisms. In the short run, agricultural markets may not be able to adjust to changes in oil prices immediately. This could be due to existing contracts, production cycles, and inventory levels. These adjustment lags can delay the transmission of oil price shocks to food prices. Moreover, oil price shocks are transmitted to food prices through various channels, including energy costs for agricultural production, transportation costs, and oil-derived inputs like fertilizers and pesticides. These transmission mechanisms may take time to fully manifest in the short run.

Table 2.12: Regression results with the interactive term using Quantile Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Oil price	0.5014***	0.0916	5.4712	0.0000
WUI	19.3717***	3.8944	4.9743	0.0000
Oil*Uncertainty	-4.2368***	0.9074	-4.6694	0.0000
GDP_C	0.2198***	0.0428	5.1388	0.0000
Exchange rate	0.0848***	0.0109	7.7766	0.0000
Employment	0.0929*	0.0492	1.8896	0.0594
Land	-0.0119	0.0393	-0.3039	0.7614
C	-0.1135	0.5028	-0.2258	0.8215

Notes: ***p<0.01, ** p<0.05, * p<0.1
Source: Author's compilation

To answer the main research question completely, there is a need to include the interactive terms of oil price and uncertainty using a different model for robustness. The Quantile regression is consistent mainly due to its ability to account for individual heterogeneity by estimating individual-specific fixed effects (Hau et al., 2020). This allows for a more accurate estimation of the relationship between variables over time. It also allows for modeling non-linear relationships between variables, which can be particularly useful when dealing with panel data where the relationship between variables may change over time. Additionally, the estimation procedure minimizes the sum of absolute deviations rather than squared deviations. This makes quantile regression particularly useful when dealing with panel data where outliers are common.

As shown in Table 2.12, the interactive term is significant at the 1% level, which is the highest level of significance. However, it is showing a negative relationship with food prices. This can be attributed to the fact that the double impact of oil prices and uncertainty will result in higher prices, which will reduce the demand for other food products as people look for relatively cheaper alternatives. Once the demand reduces, the price will also decrease. The higher increase in price will force the producers and distributors to look for other efficient alternative ways, which can help reduce the cost, thereby lowering the prices. It can also be due to government controls, including subsidies and price controls.

2.6 Conclusion and Policy Implications

This study examined the impact of uncertainty on the oil-food price nexus in 24 developing countries from 2000 to 2020, utilizing the novel World Uncertainty Index. From the panel countries under study, only Nigeria and Congo are net exporters, and the other 22 countries are net importers, showing the reliance on oil as the major source of energy in the production, packaging, and distribution of food. Recognizing the multifaceted nature of this relationship, the study accounted for structural breaks and cross-sectional dependence, confirming the significance of oil prices, uncertainty, and GDP per capita on food prices in both the short and long run (Gummi et al., 2021; Oku et al., 2022). This analysis highlights the importance of uncertainty considerations, particularly for developing countries heavily reliant on oil imports amidst recent global events amplifying uncertainty levels.

The significant positive relationship, both in the short run and long run, emphasizes the importance of decreasing reliance on oil, particularly for a region facing significant challenges in achieving food security with around 20% of the population which is undernourished(Kapari et al., 2023). It is vital to explore alternative energy sources, particularly renewable ones, promote organic farming, and invest in research and development of alternative food production technologies to reduce reliance on oil. Failure to do so could result in unstable food prices that are susceptible to external shocks. There is also a need to reduce reliance on imports for food products, especially for countries like Nigeria, South Africa, Kenya, Ghana, Cameroon, and Tanzania, which are net importers and encourage domestic production to meet domestic demand. They should also promote regional trade agreements, which will reduce transport costs, thereby reducing food prices.

All the necessary stakeholders should work together to enact and implement policies that help achieve food security. One of the key policies is investing in agriculture, which is the source of food. This includes investing in research to come up with efficient non-energy technologies, offering subsidies to increase domestic production, and also building more food reserves for the storage of food to cushion against shocks. In doing so, they should pay much attention to uncertainty as it is crucial and significantly affects the relationship between oil and food. The paper has shown that uncertainty exacerbates the volatility of both prices, leading to significant economic, social, and political consequences.

CHAPTER THREE

Disentangled Geopolitical Risk and the Dynamics of Extreme Spillovers between Energy Prices and Agricultural Commodity Markets.

3.1 Introduction

The international prices of agricultural commodities have experienced a significant upward trend since 2003, reaching a peak around 2008, marking the most substantial increase since the 1970s (FAO, 2020; World Bank, 2022). World Bank estimates reveal an 80% surge in commodity prices between 2006 and 2007, paralleling a similar pattern of price escalation in the energy sector. This trend continued in 2022, with projected increases of 50% for energy prices and 20% for agricultural commodities.

The escalation in commodity prices can be attributed to several interconnected factors. Firstly, the substitution effect in demand, where consumers shift towards alternative goods in response to rising prices, may partially mitigate the initial price pressures (Albulesu et al., 2020). Secondly, the surge in prices for key commodities like oil has cascading effects on manufacturing costs across various sectors. For instance, escalating oil prices increase agricultural input costs, such as fertilizers and fuel, while also driving up metal extraction and refinery costs, impacting renewable energy technologies (Raza et al., 2022). Thirdly, governmental responses to soaring fuel prices, often involving subsidy and tax reductions while offering short-term relief, may fail to address the underlying issue of growing energy demand and may disproportionately benefit less vulnerable entities.

The international growth in inflation also increases the manufacturing costs of commodities, such as transportation and storage costs, wages, and borrowing costs. This will result in reduced purchasing power and increases in inequality and poverty. It also threatens food insecurity, which is already a challenge in developing nations (Dalheimer et al., 2020). Fourthly, geopolitical risks are increasing, and they affect the prices of different commodities. Potential uncertainties and threats arise from political, social, and economic factors in different regions that disrupt supply chains, change market dynamics, and increase costs. It encompasses a wide range of events and situations that can significantly impact the stability and security of nations and the global community. Geopolitical risks may arise from political instability, armed conflicts, trade disputes, terrorism, changes in government policies, diplomatic tensions, and international relations (Caldara & Iacoviello, 2022). These risks can have far-reaching implications for society, including economic activities, financial markets, investments, trade, and international relations. They can also influence investor sentiment and cause fluctuations in financial markets. As a result, understanding and managing geopolitical risks is crucial for governments, businesses, investors, and policymakers to make informed decisions and mitigate potential adverse impacts. On the other hand, geopolitical tensions, conflicts, or policy changes also affect the agricultural sector by causing disruptions in production and supply chains, limiting the availability of inputs and commodities in the market (Tiwari et al., 2021). This will lead to increased price volatility as demand and supply imbalances emerge. Furthermore, trade disruptions resulting from geopolitical risk directly affect agricultural commodity price volatility by disturbing production and trade routes on the exporting side. Importing countries that depend heavily on agricultural imports may encounter price volatilities and supply uncertainties if geopolitical events impact their trading partners.

A pertinent example of this phenomenon is the ongoing conflict between Russia and Ukraine, which has ramifications for the trading partners globally, including the Sub-Saharan Africa (SSA) region. Russia and Ukraine collectively played a significant role in supplying wheat to SSA, with Russia accounting for a larger share (17-32%) compared to Ukraine (4-12%). While Ukraine held a more substantial share in maize exports to SSA (16%), Russia's contribution was less than 5%. However, the ongoing conflict and subsequent disruptions to Ukrainian exports have heightened concerns about the region’s potential food shortages and price spikes (Nhlengethwa et al., 2023).

In SSA, a significant proportion of about 60% relies on agriculture for livelihood and sustenance; the escalating food prices have intensified food insecurity and malnutrition, particularly among vulnerable populations. The region's heavy reliance on imported food and agricultural inputs, coupled with its limited capacity to absorb price shocks, has rendered it particularly susceptible to these global market fluctuations. The rising cost of essential staples like wheat, maize, and rice has strained household budgets, reduced purchasing power, and exacerbated socio-economic inequalities (Dalheimer et al., 2021). This situation has been further aggravated by the disruption of global supply chains due to the pandemic and geopolitical conflicts, hindering access to affordable food in the region.

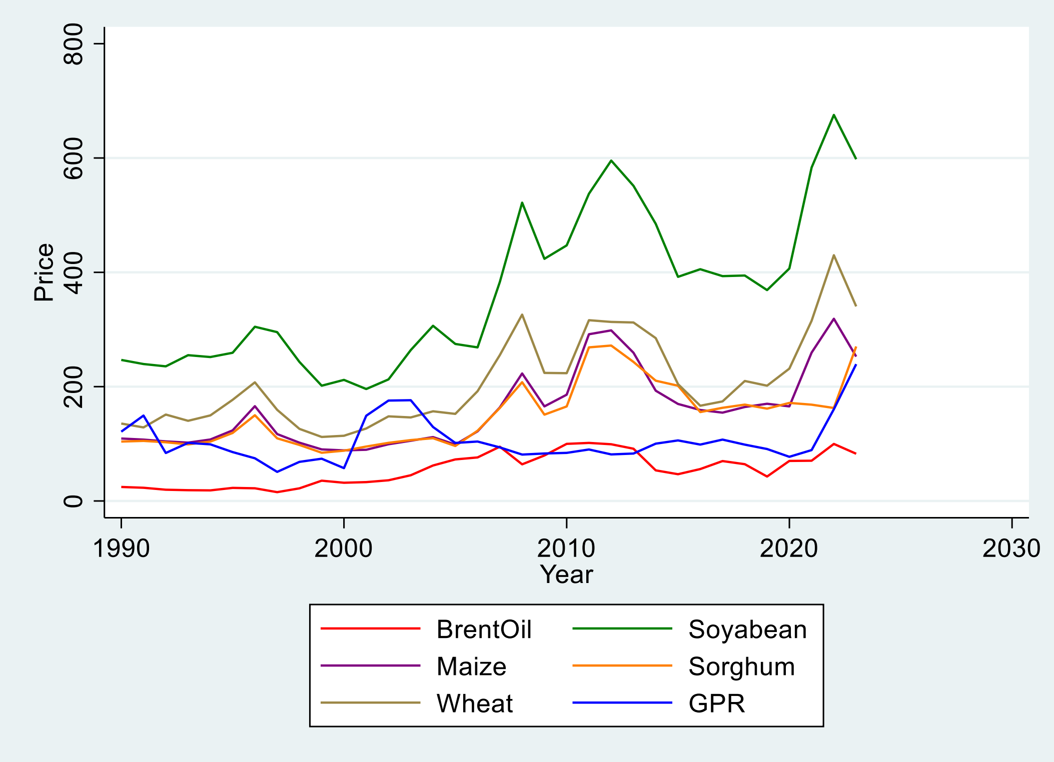
Uncertainty regarding political stability, property rights, and trade policies can significantly deter investment in agricultural infrastructure, technology, and production capacity. This reduction in investment negatively affects productivity, supply levels, and the overall dynamics of the market, potentially leading to increased price volatility. Geopolitical risks further influence market sentiments, fostering speculation within agricultural commodity markets and amplifying price fluctuations. For example, the emergence of the COVID-19 pandemic escalated geopolitical risks through supply chain disruptions and heightened protectionism (Sharif et al., 2020). These circumstances prompted countries to impose trade barriers and tariffs, intensifying geopolitical tensions and impacting global trade and economic interconnectedness. The heightened uncertainties and potential conflicts in international relations underscore the relationship between oil prices, agricultural prices, and geopolitical dynamics.

In light of these developments, our research investigates whether geopolitical risk events influence the extreme spillovers between energy and agricultural commodity prices. This inquiry is crucial because geopolitical events—such as conflicts, sanctions, and political instability—can create significant disruptions in global markets (Ahir et al., 2022). Oil prices are susceptible to geopolitical risks due to the strategic importance of oil-producing regions and the potential for supply interruptions. Similarly, agricultural commodity prices are affected by geopolitical events that impact trade routes, input costs (including fuel for transportation and machinery), and overall market confidence. Understanding this interplay is essential for effectively navigating and mitigating the associated risks.

3.1.2 Trends in Commodity Price Volatility

Crude oil prices have witnessed more frequent volatility between 1990 -2020 than in any other period (see Figure 3.1). For instance, around 2015, oil prices fell due to the OPEC agreement to maintain output, combined with the inverse expectations in the worldwide monetary markets. 2018, the oil demand was substantially stricken by exchange frictions and the Covid-19 pandemic. This was followed by a sharp rise in prices partly due to the relaxation of pandemic restrictions. These frequent volatilities are occasioned by unexpected demand for oil in emerging markets, removal of speculative funds, and the falling demand for crude oil in advanced economies.

Figure 3.1: Oil prices and selected agricultural commodities.



Source: World Bank, 2023

The volatilities impact the international market and developing economies like Sub-Saharan Africa (SSA), where crude oil plays a major role. The SSA region witnessed a higher rise in food inflation compared to other regions around the world, at around 11 % compared to Europe's 9% (World Bank, 2022). In developing economies like SSA, agriculture not only employs about 52% of the population but is also a source of food, with smallholder farmers playing a key role since the region is dominated by subsistence farming. Therefore, a rise in oil prices is a great concern.

The impact of rising commodity prices is particularly pronounced in developing nations like SSA. Such price rises are associated with high poverty levels in these economies. Evidence suggests that approximately 30% of the impoverished population around the world reside in the SSA region. According to the World Bank (2023), Nigeria, the Democratic Republic of Congo, and Ethiopia experience high levels of extreme poverty. The disparities reflect the uneven progress observed globally that it is only SSA where poverty is still very high. It is essential to move beyond the sole focus on reducing the global poverty rate below 3% and strive for inclusive economic development that benefits all countries and all people, which is why the paper is focusing on country-specific analysis.

There are three possible explanations for high levels of poverty. First are limitations in the fiscal capacity to support affected sectors through subsidies or tax holidays. In countries with large fiscal bases, their budgets are strained by health uncertainties like the Covid-19 pandemic. According to Tiwari et al. (2022), the COVID-19 pandemic exacerbated the challenges faced by developing nations in meeting the Sustainable Development Goal of allocating at least 15% of their budgets to the health sector. Another possible explanation for the higher level of poverty is the high level of debt burden in the SSA region. Specifically, the debt burden in the region almost doubled between 2011 and 2020: 23.4 and 43.7% in 2011 and 2020, respectively. This implies that much of its taxes are used to repay the loans at the expense of improving the welfare of citizens. Finally, the region is known for its volatile commodity prices compared to other regions around the world.

Several empirical studies have been undertaken to offer explanations for the causes of these rises in agricultural commodity prices (Chiu, 2015; Fowowe, 2016; Ji et al., 2018 & Hau et al., 2020). This is attributed to the fact that they directly impact productivity and accelerate inequality in emerging markets. One relevant explanation that has received less attention, especially in developing countries, is the role of crude oil and geopolitical risk. Crude oil influences agricultural production and, hence, prices through several channels. Specifically, higher energy costs suggest a higher cost of production. This increases the cost of energy-intensive agricultural inputs like fertilizers and chemicals. The effect of energy prices on agricultural markets also happens through the cost of preparing and moving the products. For example, the distribution of spatially scattered farm products to consumers who are more amassed in urban zones includes some transport costs that are altogether affected by energy prices (Cabreras & Schulz, 2016). Additionally, geopolitical risk affects oil prices directly since it affects investment decisions, considering oil's status as an investment portfolio (Zhang et al., 2023). It also affects agricultural prices through production and supply disturbances.

Extant literature on the interrelationship between oil prices and commodity prices is wide and growing rapidly. It can be grouped according to the variables under study. The first group is those studies focusing on the interlinkages between crude oil prices and agricultural commodities (Gardebroek & Hernandez, 2013; Nazlioglu, 2013; Wang & McPhail, 2014; Cabrera & Schulz, 2016; Fowowe, 2016; Luo & Ji, 2018; Shahzad, 2018, Dahl et al., 2020; Hau et al., 2020 and Dalheimer et al., 2021). These studies apply Structural VAR, Diebold-Yilmaz framework, and GARCH models and find a positive association between these commodities. These models, however, treat parameters as fixed over the entire sample period. Our study complements these previous studies' findings using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, which can accommodate shifts in the coefficients and covariances over time. Furthermore, the model can handle structural breaks common in time series datasets (Plakandaras et al., 2019; Wen et al., 2021).

The second group of studies focuses on the interlinkages between oil, geopolitical risk (GPR), and stock returns (Noguea-Santaella, 2016; Antonakakis et al., 2017; Liu et al., 2019; Alqahtani et al., 2020; Huang et al., 2021; Kumar et al., 2021; Monge et al., 2023; Ren et al., 2023 and Zhang et al. 2023). They find that exposure to GPR and oil price shocks negatively impact stock market returns. We, however, focus on developing economies and analyze the role GPR plays in the spillovers between oil and agricultural commodities. This is important because agriculture contributes a larger share of GDP in these economies, and its productivity is susceptible to shocks that result in higher prices that threaten food security. We show that exposure to GPR positively impacts agricultural prices, and these effects are higher for rice than maize. Our findings mirror those of Dalheimer et al. (2021) and Dahl et al. (2020) combined in Sub-Saharan Africa and the world, respectively. Dahl et al. (2020) found a positive correlation between GPR and oil prices. The paper has an advantage here. First, it focuses on agriculture-based economies, which also happen to be importers of crude oil, except for Nigeria. Secondly, it incorporates GPR as an additional control in our regression analysis (Antonakakis et al., 2017; Sharif et al., 2020; Kumar et al., 2021). This is vital since GPR has the potential to disrupt local production, international markets, and global trade flows, resulting in permanent shocks.

Understanding how these risks impact crude oil and agricultural commodity prices helps assess broader economic consequences. It also helps in understanding the energy-food nexus in the agricultural sector. It is also important to note that geopolitical risks are dynamic and can evolve (Zhang et al., 2023). Understanding their simultaneous effects on oil and agricultural commodities helps in long-term planning and preparedness for various scenarios. Firstly, recognizing the interconnected nature of the crude oil market, we examine the relationship between crude oil prices on selected agricultural commodities considering geopolitical risk (GPR). Previous studies (see Alqahtani et al., 2020; Hoque & Zaidi, 2020; Sharif et al., 2020; Zhou et al., 2020; Ndako et al., 2021; Salisu et al., 2022 & Zhang et al., 2023) have only assessed the interlinkages between crude oil, geopolitical risk, and stock market returns ignoring how they impact agricultural commodity prices. This allows us to capture the country's dependencies and the spillover effects of oil and GPR on the agricultural market.

Secondly, the paper goes beyond the general analysis. It delves into the impact of oil and GPR on agricultural commodity volatility across different countries, specifically the exporting and importing in developing nations, for comparison purposes. Previous studies were mostly focused on developed and emerging economies (Apergis et al., 2018; Alqahtani et al., 2020; Zhou et al., 2020 & Salisu et al., 2022). Thirdly, due to some possible econometrical challenges of non-stationarity and structural breaks, this paper is going to use the time-varying parameter vector autoregression (TVP-VAR) model, which is a powerful tool for capturing parameter instability within the data-generating process. In economic and financial time series, the relationships between variables often change over time due to policy adjustments, economic shocks, or structural shifts. The model can effectively adapt to these changes and provide more accurate forecasts and inferences by allowing the parameters to vary over time. Compared to traditional fixed parameter VAR models, the TVP-VAR model exhibits improved volatility accuracy. This superiority arises from its ability to adapt to evolving relationships between variables. By permitting time-varying parameters, the model can capture dynamic changes and structural shifts that fixed parameter models fail to capture (Zhou et al., 2020).

3.2 Literature Review

3.2.1 Theoretical Literature

The agricultural sector is one of the key sectors in developing countries. It employs about 52 % in the sub-Saharan Africa (SSA) region as of 2019 (Bjornlund et al., 2022). However, the sector's productivity depends wholly on the type of inputs (consumable or non-consumable) used. According to Input – Output Theory by Leontief (1986), consumable inputs are used in everyday production, including seeds, fertilizer, and oil. It deals with the interdependence of different sectors in an economy and the flow of goods, services, and resources among the sectors. It is based on the idea that the production of one industry depends on the output of others and that changes in one sector have a ripple effect throughout the economy. The theory is used to analyze the impact of changes in production, technology, trade, and other factors on the economy. The main tool of input-output analysis is a matrix that shows the flow of goods and services between industries and households. It forms the basis for analyzing the spillover effects between oil and the agricultural sector. This theory criticizes the traditional supply theory assumption that inputs are fixed. However, we know that the amount of inputs used in production changes due to shocks impacting supply and demand, and this is common when either monopolists or oligopolists supply inputs. He believed that shocks affecting production would also impact the demand for inputs like oil. It is important to note that oil is scarce and has no closer substitutes. Hence, the oil market is oligopolistic in structure. Gosh pointed out that the allocation function determines the quantities taken by different sectors in such markets. In such a situation, production capabilities play a minor role.

However, for the input-output theory to hold, the supply theory of Marshall (1890) and the demand theory are necessary. The modern version of supply theory deals with the behaviour of firms and the relationship between the number of goods and services they produce (supply) and the price at which they sell these goods and services. The basic idea behind supply theory is that as the price of a good increases, firms are incentivized to produce and sell more of that good. The theory also considers how factors such as production costs, technology, and market competition impact the supply of goods and services. Supply theory provides a framework for understanding how firms make production and pricing decisions and how these decisions affect the market and economy.

The supply theory is linked to the supply disruption theory, which incorporates geopolitical risk as one of its key variables. The theory states that geopolitical events that disrupt oil supply, such as wars, embargoes, or sabotage, can lead to higher oil prices. This is because they lead to a decrease in supply, which can lead to increased demand as buyers compete for limited supply. Examples of supply disruptions that have led to higher oil prices include the Iran-Iraq War (1980-1988), the Gulf War (1990-1991), the Venezuelan oil strike (2002-2003), the Syrian civil war (2011), the Libyan civil war (2011), ongoing Russia-Ukraine war. The Yom Kippur War (1973) led to a 50-60% hike in oil prices (Liadze et al., 2023). Thus, the supply disruption theory is a valid theory that can help to explain the relationship between geopolitical risk and oil prices.

The Resource Curse Theory analyzed by Sachs & Warner, (2001) suggests that countries rich in oil resources might prioritize the oil sector at the expense of agriculture. This prioritization can lead to underinvestment in agricultural infrastructure, technology, and research, hindering the sector's development and productivity. Consequently, these countries may become increasingly reliant on food imports to meet domestic demand. This dependence on food imports creates a vulnerability to geopolitical risks (Michaels, 2011). For instance, political instability or conflicts in oil-producing regions can disrupt oil production and exports, leading to price spikes. These higher oil prices can, in turn, increase the cost of imported food, making it less affordable for consumers and exacerbating food insecurity. Furthermore, the focus on oil extraction may divert resources and attention away from developing a robust domestic agricultural sector, leaving the country ill-equipped to respond to food shortages or price shocks (Peersman et al., 2021). This can lead to a vicious cycle, where reliance on imported food reinforces the neglect of agriculture, further increasing vulnerability to geopolitical risks and ultimately jeopardizing food security.

Geopolitical instability, encompassing conflict, unrest, and policy unpredictability, profoundly disrupts food systems, particularly in vulnerable regions (Keohane, 2020). This disruption manifests through agricultural production losses due to infrastructure damage, farmer displacement, and resource scarcity. Moreover, instability can trigger supply chain disruptions, leading to food shortages and price hikes, especially in import-dependent countries. The resulting uncertainty further deters agricultural investment, hindering long-term productivity and resilience. The Russia-Ukraine conflict exemplifies this phenomenon, with its disruption of global grain exports causing widespread food insecurity, underscoring the interconnectedness of global food systems and their vulnerability to geopolitical shocks.

These theories work hand in hand with demand theory. The idea behind demand theory is that as the price of a good decreases, consumers are incentivized to purchase and consume more of that good. The theory also considers how factors such as income, tastes, expectations, and availability of substitutes impact demand for goods and services. Demand theory provides a framework for understanding how consumers make purchasing decisions and how these decisions affect the market and the whole economy. The demand theory holds that when there is no scarcity, suppliers are willing to supply more goods at the prevailing prices in the market.

However, the oil market is an exception since suppliers are price-sensitive and able to limit the supply, creating shortages. Under these conditions, Gosh came up with a simple function expressed as: $x_{ij} = \alpha_{ij} X_j$. The interconnectedness of the energy and agricultural sectors is evident in the production function, where x_{ij} represents the output of crude oil sold to the agricultural sector and X_j represents the agricultural output. Given that energy, such as oil, is a crucial input in food production (Balcilar, Ozdemir & Arslanturk, 2010), rising energy prices can constrain agricultural output and elevate processing, packaging, and distribution costs

(Baumeister & Kilian, 2014). However, Trujillo-Barrera, Mallory & García (2011) suggest that the utilization of crops for biofuel production may mitigate this interdependence.

This production function framework underscores the sensitivity of producers to input prices, particularly in the agricultural sector where input and transportation costs constitute a significant portion of production expenses. Due to the seasonality of agricultural production in developing nations, producers, especially smallholder farmers, bear the brunt of these costs, which can erode their revenue and hinder their ability to purchase essential inputs. Ultimately, fluctuations in energy prices impact intermediate and final goods, affecting overall agricultural output.

For instance, energy is a vital input in the production of food (Balcilar, Ozdemir & Arslanturk, 2010). The potential price weights from increasing prices of energy constrain food production and may raise processing costs of food, packing, and dissemination (Baumeister & Kilian, 2014). According to Trujillo-Barrera, Mallory & García, (2011), the utilization of crops for biofuel production may reduce the interlinkages between agricultural and energy markets. This function implies that producers are keen on the price of these factors of production and will try to minimize the cost of production. Inputs and transport constitute higher production costs (Li et al., 2022). Since agricultural commodities are seasonal, especially in developing nations, the producers bear these costs, which eats into their revenue. For smallholder farmers, higher prices impact their ability to purchase essential inputs. Either way, this will affect the output of intermediate and final goods and the agricultural sector.

3.2.2 Empirical Literature

Several studies have assessed the relationship between oil and agricultural commodity prices (see Nazlioglu, 2013; Wang & McPhail, 2014; Zhang & Qu, 2015; Fowowe, 2016; Luo & Ji, 2018; Fasanya & Ankinbowale, 2019; Dahl et al., 2020 and Dalheimer et al., 2021). The findings from these studies are often mixed: either positive, negative or no relationship. One possible explanation for the mixture of findings is the failure to consider the role of geopolitical risks. This has motivated active research on how GPRs impact crude oil prices, metal prices, and stock market returns. For instance, some papers have analyzed the impact of geopolitical risk on oil prices (Nogue-Santaella,2016; Liu et al., 2019; Plakandaras, 2019; Qui et al., 2020; Huang et al., 2021; Salisu et al., 2021; Ren et al., 2023; Zhang et al., 2023a; Zhang et al., 2023b; Xiao et al., 2023) while other have assessed the interlinkages between geopolitical risk and stock returns (Arpegis, 2017; Ndako et al., 2021; Salisu et al., 2022; Zhang et al., 2023c). There is also a stance of study that has combined geopolitical risk, oil prices, and stock market returns

(Antonakakis et al. 2020; Charfeddine & AI Refail, 2019; Alqahtani et al., 20202; Hoque & Zaidi, 2020 and Kumar et al., 2021). The other category of studies has focused on the interlinkages between geopolitical risk and metal price returns and volatility (Baur & Smales, 2020; Zhou, 2020; (Li et al., 2021a; Li et al., 2021b). The findings from these studies are clear: GPRs impact crude oil prices, stock market returns, and metal prices see table below.

Table 3.1: A Summary of Empirics

S/N	Year	Author	Title	Region	Scope/Data	Methodology	Findings
		Part a:	**Oil and agriculture**				
1	2013	Gardebroek and Hernandez	Do energy prices stimulate food price transmission between volatility? Examining volatility transmission between US oil, ethanol, and corn markets	USA	Weekly data from September 1997 to October 2011	Multivariate GARCH	No evidence of volatility in energy markets stimulating price volatility in the US corn markets
2	2011	Nazlioglu et al.	World oil and agricultural commodity prices from non-linear causality	Global market	Weekly data from January 1994 to August 2010	Causality test	Persistent unidirectional nonlinear causality running from the oil prices to the corn and soybean prices
3	2014	Baumeister and Killian	Do oil prices increase and cause higher food prices?	USA	Monthly data from May 2006 to May 2013	Cointegration test	There is no evidence that increases in oil prices drive the food production costs
4	2014	Wang and McPhail	Oil prices shock and agricultural commodity prices	USA	Monthly data from 1980M1 to 2010M12	Structural VAR	Oil shocks have an impact on agricultural commodities before the financial crisis and a greater impact after
5	2015	Zhang and Qu	The effects of global oil price shocks on China's agricultural commodities	China	Daily data from September 2004 to April 2014	ARMA GARCH	Asymmetric oil shocks on agricultural commodities except for natural rubber

6	2016	Cabrera and Schulz	Volatility linkages between energy and agricultural commodity prices	Germany	Weekly data from May 2003 to July 2012	DCC GARCH	Persistent market shocks have positive correlation and in the long-run prices comove towards equilibrium
7	2016	Fowowe	Do oil prices drive agricultural commodity prices? Evidence from South Africa	South Africa	Weekly data from January 2003 to January 2014	Cointegration and causal test	Agricultural prices are neutral to oil prices in both the short and long run. There is need to focus on local measures to control agricultural prices
8	2018	Ji et al.	Risk spillover between energy and dependence-switching coVAR -copula model	World	Daily data from January 2000 to December 2015	Time-varying copula CoVAR-copula	The influence of natural gas on agricultural return risks is slightly smaller than the influence of the oil market
9	2018	Luo & Ji.	High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity	USA & China	Daily data from January 2008 to December 2015	Vector HAR & DY	The sensitivity of China's agricultural markets to oil price volatility is greater than their influence on international oil prices. Panic in the oil market can increase its volatility and spillover effects

10	2018	Shahzad	Asymmetric risk spillovers between oil and agricultural commodities spillovers between oil and agricultural commodities	World	Daily data from January 2000 to June 2017	Bivariate Copula & ARMA GARCH	Asymmetric spillovers from oil to agriculture that increase during financial crises
11	2019	Fasanya and Akinbowale	Modelling the return volatility spillovers of crude oil and food prices in Nigeria	Nigeria	Monthly data from January 1997 to June 2017	DY (2012)	The spillover indexes show that there is an interrelationship between crude oil and food prices
12	2019	Hailemariam et al.	Oil prices and economic policy uncertainty: Evidence from nonparametric panel data model	G7 countries	Monthly data from January 2001 to June 2018	Nonparametric Panel CCEMG	An increase in aggregate demand result in economic booms such that an increase in oil prices have the effect of mitigating economic policy uncertainty contributing to economic growth
13	2020	Dahl et al.	Dynamics of volatility spillover in commodity markets. Linking crude oil to agriculture	World	Daily data from July 1985 to June 2016	DY (2012) & EGARCH	Bidirectional spillovers among the futures markets of crude oil and agricultural commodities increased during the financial crisis

14	2020	Hau et al.	Heterogenous dependence between crude oil price volatility and China's agriculture. Evidence from Quantile regression	China	Weekly data from January 1990 to December 2019	Quantile Regression	Heterogenous dependence between crude oil volatility and agriculture futures across quantiles
15	2021	Dalheimer et al.	The threat of oil market turmoils to food price stability in Sub-Saharan	Sub-Sahara Africa	Monthly data from January 2006 to June 2019	Structural VAR	African maize markets exhibit comparatively lower susceptibility to the effects of oil demand than US markets
16	2022	Asadi et al.	Volatility spillovers amid crude oil markets in the US and China based on time-frequency domain connectedness	US & China	Daily data from 2008M8 - 2020M12	Quantile VAR	The relationship among energy, stock, and currency markets is not high. Shanghai stock and coal cannot be used for portfolio diversification
		Part b:	**Geopolitical risk and**	**other variables**			
17	2016	Noguea-Santaella	Geopolitics and the oil price	Global market	Monthly data from 1859M9 - 2013M3	ARMA GARCH	Geopolitical events were influential before 2000 and not effective after
19	2017	Antonakakis et al.	Geopolitical risks and the oil-	Global market	Monthly data from	BEKK-GARCH	Geopolitical risks exert an adverse influence

			stock nexus over 1899 - 2016		1899M1 - 2016M12		on the volatility of oil returns
20	2017	Arpegis et al.	Does geopolitical risks predict stock companies? Evidence from a non-parametric approach	Global defense firms	Monthly data from January1985 to December 2016	Nonparametric causality test	Geopolitical risks predict volatility therefore there is need to protect or adjust risks when making investments of certain companies during stressful times of geopolitical risks
21	2018	Gkillas et al.	Volatility jumps. The role of geopolitical risks	US	Monthly data from January 1899 to December 2017	Causality in Quantile	Geopolitical risks predict volatility jumps in the Dow Jones Industrial Average. Higher geopolitical risks increase volatility jumps than lower values
22	2019	Aysan et al.	Effects of Geopolitical on Bitcoin returns and volatility	Global market	Daily data from July 2010 to May 2018	Bayesian Structural VAR & Quantile Regression	Geopolitical risks have a predictive power on both the returns and volatility of Bitcoin
23	2019	Charfeddine and AI Refail	Political tensions, stock market dependence, and volatility spillover. Evidence from the recent intra-GCC countries	GCC	Monthly data from January 2011 to September 2018	Multivariate GARCH	The recent GCC crisis of June 2017 significantly affected the level of stock market dependence and volatility spillovers between Qatar and the other

							GCC countries except for Bahrain
24	2019	Liu et al.	Geopolitical risks and oil volatility: A new insight	Global market	Daily data from January 1886 to May 2017	GARCH-MIDAS	Geopolitical risks and geopolitical risks lead to oil market fluctuations and they both lead to higher economic returns
25	2019	Plakandaras et al.	Point and density forecasts of oil returns: The role of geopolitical risks	Global market	Monthly data from January 1985 to June 2017	TVP-VAR	Geopolitical risk emanating from war is more accurate in point-forecasting of oil returns in the shortrun while composite GPRs from emerging markets point-forecast oil returns in the medium run
26	2020	Alqahtani et al.	Predictability of GCC's role in geopolitical risks and crude oil returns	GCC	Monthly data from February 2007 to December 2018	Feasible Generalised Least Square (FGLS)	Crude oil prices are a better predictor of stock returns
27	2020	Baur and Smales	Hedging geopolitical risks with precious metals	Global market	Daily data from January 1885 to October 2018	Univariate Regression & E-GARCH	Geopolitical risk has a significant impact on the conditional variance in gold and not on the other precious metals

28	2020	Hoque and Zaidi	Global and country-specific geopolitical risk and uncertainty and stock return of fragile emerging markets	Brazil, India, Turkey, Indonesia, and South Africa	Monthly data from January to June 2017	Markov-switching	The geopolitical risk has negative effects in all countries across different volatility regimes except for India and Indonesia
29	2020	Qui et al.	Asymmetric effects of geopolitical risks on different market conditions energy returns and volatility under different market conditions	Global market	Monthly data from June1990 to October 2018	Quantile Regression	Geopolitical risk has significant negative effects on crude oil but no effect on gas returns
30	2020	Sharif et al.	Covid-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy. Fresh evidence from the wavelet-based approach	US	Daily data from January 2020 to October 2020	Wavelet based approach	The markets react more to oil shocks than Covid-19. The Covid-19 has an immediate and profound effect on economic policy uncertainty

31	2020	Zhou et al.	The effects of geopolitical risks on the stock dynamics of China's stock rare metals: A TVP-VAR analysis	China	Monthly data from February 2000 to December 2018	TVP-VAR	Act-based geopolitical risks affect the stock returns negatively while broad geopolitical risks have stronger positive effects on stock volatility
32	2021	Huang et al.	Nonlinear dynamic correlation between geopolitical risk and oil prices, A study based on high frequency data	Global	Monthly data from September 2000 to June 2018	DCC-MVGARCH	Geopolitical risk mainly affects oil volatility rather than returns. There is a bidirectional relationship between GPR and oil volatility
33	2021	Kumar et al.	Do geopolitical risks improve the directional predictability from oil to stock returns of exporting and oil-importing countries?	Emerging markets	Daily data from January 2001 to April 2019	Quantile dependence approach	Response of oil exporting equity markets to oil shocks significantly higher and more persistent than oil-importing
34	2021	Li et al.	Dynamic spillovers of geopolitical risks and gold prices: New evidence from	Emerging markets	Monthly data from February 1985 to June 2019	Diebold Yilmaz (2012)	Geopolitical risk and gold returns have significant spillovers. GPR in Indonesia, Venezuela, Russia, China and Turkey have

			18 emerging markets				greatest impact on gold prices
35	2021	Li et al.	Analysing the time-frequency connectedness among oil, gold prices and BRICS geopolitical risk	BRICS - Brazil, India, Russia, China, and South Africa	Monthly data from January 2002 to December 2019	Diebold Yilmaz (2012)	Spillovers are stronger in the short run than in the long run. China's GPRs have the greatest impact on gold, oil, and other countries' GPRs
36	2021	Ndako et al.	Geopolitical risk and return volatility of Indonesia and Malaysia. A GARCH-MIDAS approach	Indonesia Malaysia	Daily data from November 2008 to August 2020	GARCH-MIDAS	Country specific geopolitical risk predicts volatility in Malaysia and not in Indonesia It might be due to government suppression of capital flight in Indonesia
37	2021	Salisu	Geopolitical risk and forecastability of tail risk in the oil market: Evidence from a century of monthly data	Global market	Monthly data from January 1916 to June 2020	Univariate regression & E-GARCH	Geopolitical risks associated with threat are significant predictors of tail risk in the oil market
38	2022	Salisu et al.	Geopolitical risk and stock market volatility in emerging markets: A GARCH-	Emerging economies	Daily data from January 1997 to May 2020	GARCH-MIDAS	Stock market in emerging markets responds more positively to geopolitical risks

			MIDAS approach				
39	2023	Monge et al.	The impact of geopolitical risk on the behavior of oil prices and freight rates	Global	Monthly data from January 1985 to May 2021	Fractional Cointegration VAR	GPR significantly and permanently affects oil prices and freight rates requiring strong measures for series to revert to the original form
40	2023	Ren et al.	The asymmetric effect of GPR on China's crude oil prices. New evidence from a QARDL approach	China	Monthly data from March 2018 to September 2022	Quantile ARDL	The presence of a sustained equilibrium connection between China's crude oil and GPR, even when accounting for global oil prices, investment, and crude oil inventory
41	2023	Wang et al.	Green financing, financial uncertainty geopolitical risk, and oil price volatility	Global market	Yearly data from 1985 to 2020	Quantile ARDL	Financial stress and GPR exert a detrimental influence on green investment while oil price volatility and investment in clean energy yield a positive impact on green investment

42	2023	Xiao et al.	Impact of geopolitical risks on investor attention and speculation in the oil market: Evidence from non-linear and time-varying analysis	Global market	Monthly data from January 2004 to December 2020	Quantile ARDL	Geopolitical actions and threats exhibit a positively changing impact on investor attention over time
43	2023	Zhang et al.	Asymmetric spillover of geopolitical risk and oil volatility. A global perspective	North and South America, North and East Europe South and West Europe, Middle East and Africa, Asia and Oceania	Monthly data from January 1986 to December 2021	Diebold Yilmaz (2012)	Increasing spillover effects arising from GPRs across all regions are particularly evident during significant events such as the two Gulf wars and the Arab Spring
44	2023	Zhang et al.	Not all geopolitical shocks are alike: Identifying price dynamics in the crude oil market under shocks	Global market	Monthly data from January 1986 to December 2021	TVP-SVAR	Future oil prices react distinctively to geopolitical shocks stemming from war, terror, nuclear, and troops

45	2023	Zhang et al.	Geopolitical risk and stock market volatility: A global perspective	Asia, Europe, America, Africa, Australia, and the Middle East	Daily data from March 2017 to March 2022	Bias-Corrected Least Square Dummy Variable	Geopolitical risks positively affect stock market volatility. It has a greater impact on stock market volatility for emerging economies, crude oil exporting countries, and countries at peace

However, these studies apply different models in their analysis. For instance, some papers use causality and cointegration tests (Nazlioglu et al., 2011; Baumeister & Killian, 2014 and Fowowe, 2016), while others apply the SVAR model (Wang & McPhail, 2014 and Dalheimer, 2021). These models suffer from small sample bias, multicollinearity problems, and failure to account for endogeneity problems. In addition, they assume linearity in variables, which usually does not hold in financial and economic datasets.

Other studies have applied the GARCH model and its extensions like the ARMA-GARCH model (Zhang & Qu, 2015; Noguea-Santaella, 2016 ; Shazad, 2018); BEKK-GARCH model (Antonakakis et al., 2017); DCC-GARCH (Cabrera & Schulz, 2016; Huang et al., 2021); E-GARCH model (Baur & Smales, 2020; Dahl et al., 2020; Salisu et al., 2021); GARCH-MIDAS (Liu et al., 2019; Ndako et al., 2021; Salisu et al., 2021) and Multivariate GARCH models (Gardebroek & Hernandez, 2013; Charfeddine & AI Refail, 2019). Other groups of studies have used the Diebold-Yilmaz (DY) model (Fasanya & Akinbowale, 2019; Dahl et al., 2020; Li et al., 2021a; Li et al., 2021b; Zhang et al., 2023). However, these models suffer from several weaknesses. First, they assume the existence of a linear relationship between GPR and crude oil prices or oil and agriculture. Secondly, GARCH and DY models fail to capture the dynamic evolution of spillover effects over different periods. Third, these models suffer from a model selection problem, which biases the results. Finally, the DY depends on the frequency of data, which means it performs differently depending on whether the dataset is daily, weekly, or monthly. This limits its applicability.

Given the above weakness of these earlier models, recent studies either use causality in quantile regression (Gkillas et al., 2018), quantile regression (Aysan, 2019; Hau et al., 2020; Qui et al., 2020; Kumar et al., 2021) or quantile ARDL (Ren et al., 2023; Wang et al., 2023 and Xiao, 2023). Nevertheless, quantile regressions and ARDL require larger datasets to ensure meaningful results across different quantiles. In addition, it is hard to determine the appropriate number of lags and quantiles for the model. Finally, when using multiple quantiles, there is a risk of overfitting the model to noise, especially if the dataset is not sufficiently large.

In this paper, we circumvent these challenges using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model. TVP-VAR allows time-varying parameters to capture changing relationships in the data over different periods. This flexibility is particularly useful when economic conditions or relationships evolve. The model adapts to changes in data patterns, making it well-suited for capturing structural breaks, regime shifts, and varying volatility in economic and financial series (Fasanya & Oyewele, 2023). It can provide more accurate and realistic modelling of time-varying relationships compared to traditional fixed-parameter VAR models. The model allows for analyzing the impact of policy changes or external shocks while accounting for changing relationships over time, enhancing the understanding of policy effects. It can also capture nonlinear relationships between variables, which linear models like standard VAR might miss.

A key advantage of the TVP-VAR model lies in its flexibility in modeling complex time series data. It can accommodate non-linear dynamics and effectively capture time-varying patterns within the data. This flexibility makes it well-suited for analyzing economic and financial time series that display non-stationary and non-linear behavior. Additionally, the model provides a framework for conducting inference on structural breaks or regime shifts. It allows for identifying and estimating the timing and magnitude of such breaks within the data (Zhang et al., 2023b). This capability is valuable for understanding changes in the relationships between variables and their economic interpretation. The TVP-VAR model offers notable advantages in capturing parameter instability, improving forecasting accuracy, accommodating complex time series data, and facilitating inference on structural breaks. These features make it a valuable tool for analyzing economic and financial time series.

3.3 Data Sources

We use monthly data containing GPR indices, crude oil spot prices, and selected agricultural commodity prices for selected countries in Sub-Saharan Africa. Our sample datasets cover January 2000 to November 2023 but with different start and end dates depending on data availability. See Table 3.2 for details.

Table 3.2: Selected crops per country.

Country	Crops covered	Source market of prices
Cameroon	Maize and Rice	Yaoundé retail prices
Ethiopia	Maize, Wheat, and Sorghum	Addis-Ababa wholesale prices
Ghana	Maize, Rice, and Sorghum	Accra wholesale prices
Nigeria	Maize and Sorghum	Lagos wholesale prices
South Africa	Maize, Rice, and Wheat	Randfontein wholesale prices
Tanzania	Maize and Rice	National average (wholesale prices)

Source: Author's compilation

3.4 Variable Description

3.4.1 Crude Oil Prices

This paper uses Brent crude oil spot prices expressed in the United States of America dollar per barrel. Brent crude serves as the primary benchmark for pricing African crude oil exports (Cheng & Cao, 2019). This makes it a more accurate indicator for understanding the transmission of oil price shocks to domestic markets in the region. It is highly sensitive to global economic and geopolitical events that can significantly impact SSA economies. This makes it a more appropriate proxy for capturing the effects of global factors on the region's economic performance. Numerous studies focusing on the impact of oil prices on African economies have used Brent crude as the preferred benchmark (Ederington et al., 2021; Jena et al., 2022; Wei et al., 2022). This ensures consistency with existing literature and allows for meaningful comparisons and validation of findings. It provides a more accurate and comprehensive representation of the global oil market dynamics that significantly influence the region's economies. These crude oil spot prices are freely downloadable from https://fred.stlouisfed.org/series/WTISPLC.

3.4.2 Agricultural Commodities

We use the Food and Agricultural Organization of the United Nations food price monitoring and analysis dataset for selected agricultural commodities in the selected African countries. We source these price datasets from https://fpma.fao.org/giews/fpmat4/#/dashboard/tool/domestic. Specifically, we obtained wholesale and retail prices of maize, wheat, sorghum, and rice in each of the countries. We initially wanted to analyze the same crops across countries, but the availability of data limited us. Agricultural prices directly impact consumers' costs. Affordable food prices are essential for food security, especially for low-income populations (Dalheimer, 2021). Fluctuations in agricultural prices can affect the affordability and availability of essential food items. This dataset has missing values. First, we filled these missing values by averaging the last five years of monthly datasets. This affected five data points in Nigeria, three in Tanzania, 22 in Ethiopia, and 19 data points in Ghana. For countries with missing data at the start of the period, like Nigeria, we proxy maize and sorghum prices with Kano retail prices. Specifically, for Nigeria commodity prices data starting 2006 month one to 2012 months 4 and 5, we applied Kano retail prices from maize and white sorghum, respectively.

3.4.3 Geopolitical Risk (GPR) Indices

This study uses Caldara and Iacoviello's (2018) GPR indices.[2] We used four different indicators of uncertainty constructed by Caldara and Iacoviello, namely: geopolitical threats (GPR_T), geopolitical acts (GPR_A), geopolitical tension in broad ranges (GPR_B), geopolitical tension in narrow ranges (GPR_N). GPR is a political and economic instability risk caused by conflict or tensions between states. This includes wars, terrorism, border disputes, trade wars, and other events that disrupt the normal and peaceful course of international relations. We follow earlier literature (see Antonakakis et al. 2017; Gkillas et al. 2018; Zhou et al. 2020 & Zhang et al. 2023b) and use monthly values of GPR across the six African countries.[2] These countries were selected based on their participation in agriculture exports and data availability.

These indices of geopolitical risk have been used in economic analysis and are shown to be a good indicator of uncertainty (Balcilar et al., 2018). The indices provide a quantitative measure of risk and are constructed based on a tally of newspaper articles covering geopolitical tensions. The Caldara and Iacoviello GPR index reflects automated text-search results of the electronic archives of 10 newspapers: Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post. Caldara and Iacoviello calculate the index by counting the number of articles related to adverse geopolitical events in each newspaper each month (as a share of the total number of news articles).

The search is organized into eight categories: War threats (Category 1), Peace threats (Category 2), Military build-ups (Category 3), Nuclear threats (Category 4), Terror threats (Category 5), Beginning of war (Category 6), Escalation of war (Category 7), Terror acts (Category 8). Caldara and Iacoviello also construct two sub-indexes based on the search groups above. The

[2] These countries include Cameroon, Ethiopia, Ghana, Nigeria, South Africa, and Tanzania.

Geopolitical Threats (GPRT) include words belonging to categories 1 to 5 above. The Geopolitical Acts (GPRA) index includes words belonging to categories 6 to 8.

The computation of this measure hinges on the aggregation of news articles centered on geopolitical risk from a selection of 10 prominent international newspapers. Subsequently, the data is normalized to an average value of 100. Notably, the newspapers within the GPR index predominantly hail from the United States, United Kingdom, and Canada. To check if the risk is not biased towards the US since 6 newspapers are from the US, they tested for correlation between US-based and non-US-based newspapers and found that they were highly correlated with a correlation of 0.88. This shows that most geopolitical events are important and have such a wide-ranging impact that they are covered similarly by newspapers in both the US and other countries around the world.

3.5 Methodology

The Diebold and Yilmaz (2009, 2012) connectedness approach is widely used for analyzing spillovers in predetermined networks. However, despite its popularity, this method relies on a rolling window Vector Autoregressive Regression (VAR) model, which has notable weaknesses: sensitivity to outliers, arbitrary selection of rolling window size, inability to handle low-frequency datasets and loss of observations due to windowing. To address these limitations, we employ the more recent Time-Varying Parameter VAR (TVP-VAR) model developed by Koop and Korobilis (2014), which extends the Diebold-Yilmaz framework. The TVP-VAR model allows variances to fluctuate over time through stochastic volatility estimated via a Kalman filter with forgetting factors. This dynamic approach overcomes the inherent challenges of the Diebold-Yilmaz method, offering a more robust and flexible framework for analyzing spillovers in financial markets.

Building on the adoption of the TVP-VAR model, we now formalize our methodological framework through the presentation of the underlying equations. This model accommodates time-varying parameters and stochastic volatility, enabling us to capture dynamic relationships and spillover effects between energy and agricultural commodity prices over time. By specifying the precise mathematical structure, we illustrate how the model adjusts to changes in the data, allowing for a more nuanced analysis of connectedness that accounts for potential shifts due to geopolitical risk events. The following equations lay the foundation for our empirical approach, detailing the mechanisms through which we estimate the time-varying coefficients and covariance matrices essential for assessing extreme spillovers in the market.

$$Y_t = \beta_t Y_{t-1} + \epsilon_t, \qquad \epsilon_t | F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu_t, \qquad \nu_t | F_{t-1} \sim N(0, R_t) \tag{2}$$

In equations 1 and 2, Y_t, and Y_{t-1} are $N \times 1$ and $Np \times 1$ conditional volatility and lagged conditional vectors, respectively. In addition, β_t, and ϵ_t are $N \times P$, and $N \times 1$ time varying coefficient matrix and error disturbance vector, respectively while F_{t-1} contain information until $t-1$ Finally, ϵ_t is a $N \times 1$ dimensional error disturbance vector with a variance-covariance matrix I distributed(S_t) while ν_t is a dimensional error matrix with $Np \times Np$ variance-covariance matrix.

Since the TVP-VAR model is an extension of the Diebold and Yilmaz connectedness approach, it necessitates the calculation of generalized impulse response functions (GIRF) and generalized forecast error variance decomposition (GFEVD). Using time-varying variance-covariance matrices S_t and R_t , we estimate the generalized Diebold-Yilmaz connectedness measures based on GIRF and GFEVD. This methodology follows the work of Antonakakis and Gabauer (2017), Koop et al. (1996), and Pesaran and Shin (1998). By incorporating GIRF and GFEVD, we align the dynamic features of the TVP-VAR model with the connectedness framework, allowing us to capture the evolving spillover effects more accurately.

As a first step in calculating GIRF and GFEVD, we transformed VAR to its moving average representation following the Wold theorem. See Equations 3-6 below.

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \tag{3}$$

$$Y_t = A_t \epsilon_t \tag{4}$$

$$A_{0,t} = I \tag{5}$$

$$A_{i,t} = \beta_{1,t} A_{i-1,t} + \cdots + \beta_{p,t} A_{i-p,t} \tag{6}$$

In equation 6, $\beta_{i,t}$ and $A_{i,t}$ are $N \times N$ dimensional matrices and are therefore summarized as: $A_t = [A_{1,t}, A_{2.,t}, \ldots, A_{p,t}]'$ and $\beta_t = [\beta_{1,t}, \beta_{2.,t}, \ldots, \beta_{p,t}]'$

3.5.1 Generalized Impulse Response Function

Continuing from our integration of the Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance Decomposition (GFEVD) within the TVP-VAR framework, we address the challenge posed by the absence of a structural model in our analysis. Without a predefined structural model, we calculate the difference between the J^{th}-step ahead forecasts when a specific variable, say i is subjected to a one-time shock and when it remains unshocked. This difference effectively captures the impact attributed solely to the shock in variable i. In essence, the (GIRF) (ψ_(j.t)^g (J)) quantifies the response of the variables to a shock. This approach allows us to measure how shocks propagate through the system over time, even in the absence of structural identification. The mathematical formulation of this response is provided in equations 7 to 9 below.

$$GIR_t(J, \delta j_{,t}, F_{t-1}) = E\left(Y_{t+J} \middle| \epsilon_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(Y_{t+J} \middle| F_{t-1}\right) \tag{7}$$

$$\psi^{g}_{j.t}(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{iit}}} \frac{\delta_{j,t}}{\sqrt{S_{iit}}} \;; \qquad \delta_{j,t} = \sqrt{S_{jj,t}} \tag{8}$$

$$\psi^{g}_{j.t}(J) = A_{J,t} S_t \epsilon_{j,t} S_{jj,t}^{-0.5} \tag{9}$$

In the equations 7-9, J, $\delta_{j,t}$, and $F_{t-1}$are forecast horizon, and selection vector with J^{th} position and zero otherwise.

3.5.2 Generalized Forecast Error Variance Decomposition

We then calculate generalized forecast error variance decomposition (GFEVD) $(\tilde{\phi}^{g}_{ij,t}(J))$ which is the variance share a variable has on others. The variance share is normalized so that each row adds up to one – implying that the sum of all variables should explain 100% of the variable i's forecast error variance. The GFEVD is calculated using equation 10.

$$\sum_{j=1}^{N} \tilde{\phi}^{N}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \psi^{2,g}_{ij,t}}. \tag{10}$$

Based on equation 10, $\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{N}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^{N}(J) = N$. Moreover, in equation 10, $\sum_{t=1}^{J-1} \psi_{ij,t}^{2,g}$ and $\sum_{j=1}^{N} \sum_{t=1}^{J-1} \psi_{ij,t}^{2,g}$ are the cumulative effect of a shock to variable i and cumulative effect of all shocks, respectively.

Based on GFEVD, the total connectedness index can be estimated as below.

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{g}(J)} * 100 \ ; \ = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{N} * 100 \qquad (11)$$

This index shows how a shock to one variable spread to other variables. the total connectedness approach can be sub-divided into three parts. First is the total directional connectedness to others which analyses a case where variable i transmits a shock to all other variables, say j. The equation is below.

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^{g}(J)} * 100 \qquad (12)$$

A second part of the total connectedness approach is the total directional connectedness from others- i.e., the directional connectedness to a variable, say i receives from other variables j.

$$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ji,t}^{g}(J)}{\sum_{i=1}^{N} \tilde{\phi}_{ji,t}^{g}(J)} * 100 \qquad (13)$$

Finally, we obtain net total directional connectedness (equation 14) by subtracting equation 12 from 13. Equation 14 shows how much influence variable i has on a network. A positive value implies that the variable i has a stronger influence on the network than it is being influenced by it. A negative value, on the other hand, implies that the variable i is being driven by the network.

$$C_{i,t}^g = C_{i\rightarrow j,t}^g(J) - C_{i\leftarrow j,t}^g(J) \qquad (14)$$

To test the existence of the bidirectional relationship, we computed a net pairwise directional connectedness (NPDC) (see Equation 15).

$$NPDC_{ij,t}(J) = \tilde{\phi}_{ji,t}^{g}(J) - \tilde{\phi}_{ij,t}^{g}(J) \qquad (15)$$

From equation 15, a negative value of NPDC indicates that variable i is dominated by variable j and vice versa showing variable i is a net shock receiver (Dahl et al., 2023).

To further ensure the robustness of our results, we now move to validate our findings using the Quantile Vector Autoregression (QVAR) model (Ando et. al., 2018). The QVAR approach allows us to examine the relationships between variables across different points in their conditional distribution, capturing potential asymmetries and tail dependencies that the TVP-VAR model might not fully address. By applying the QVAR model, we can test whether the spillover effects observed are consistent across various quantiles, thereby reinforcing the reliability of our analysis. This step enhances our understanding of the dynamics between energy and agricultural commodity prices, providing a more comprehensive assessment of their interconnectedness in the presence of geopolitical risk events.

3.5.3 Quantiles Vector Autoregressive (QVAR) Model

A QVAR model allows for the estimation of dependency between y_t and x_t at every quantile conditional on the distribution of y_t given x_t (Koenker & Bassett, 1978; Koenker & Ng, 2005).

Formally, the QVAR model can be written as:

$$\mathrm{Q}_{\tau}(y_t|x_t) = x_t\beta(\tau) \qquad (16)$$

where Q_τ is the τth conditional quantile function of y_t. Moreover, τ is the quantile which varies between 0 and 1, x_t is a vector of explanatory variables. Finally, $\beta(\tau)$ defines the dependence association between x_t and the τth conditional quantile function of y_t.

The QVAR process of order p can be estimated as below;

$$y_t = c(\tau) + \sum_{j=1}^{p} B_j(\tau)\, y_{t-j} + \varepsilon_t(\tau) \qquad (17)$$

In equation 17 above, y_{t-j} and y_t are $k \times 1$endogenous variable vectors; is the lag length while $c(\tau)$ is a conditional vector with $k \times 1$ as its dimension. In addition, B_j is a a $k \times k$ dimension QVAR coefficient matrix, and $\varepsilon_t(\tau)$ is a $k \times 1$ dimension error vector with a $k \times k$ dimensional variance-covariance matrix, $\sum(\tau)$. Finally, we can transform QVAR into Quantile Vector Moving Averages (QVMA(∞) following (Equation 18).

$$y_t = c(\tau) + \sum_{j=1}^{p} B_j(\tau)\, y_{t-j} + \varepsilon_t(\tau) = c(\tau) + \sum_{i=1}^{\infty} B_i(\tau)\, y_{t-i} \qquad (18)$$

Therefore, we can estimate $\hat{B}(\tau)$ and $\hat{c}(\tau)$ if the error term conforms to population quantile restriction as shown below.

$$Q_\tau\left(y_t \middle| y_{t-1}, \dots y_{t-p}\right) = c(\tau) + \sum_{j=1}^{p} B_j(\tau)\, y_{t-j} \tag{19}$$

Thereafter, we calculate the J-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) ($\tilde{\phi}_{ij}^{g}(H)$) (Koop et al., 1996; Pesaran and Shin, 1998). See equation 20 and 21;

$$\phi_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(\varepsilon_i' \psi_h(\tau)\, \Sigma(\tau) \varepsilon_j\right)^2}{\sum_{h=0}^{H-1} \left(\varepsilon_i' \psi_h(\tau)\, \Sigma(\tau) \psi_h(\tau)' \varepsilon_i\right)} \tag{20}$$

$$\tilde{\phi}_{ij}^{g}(H) = \frac{\phi_{ij}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij}^{g}(H)} \tag{21}$$

Based on equation 20, $\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{k} \tilde{\phi}_{ij}^{k}(H) = k$. Moreover, ε_i is a zero vector with ones in its ith position. We then normalize each entry of the variance decomposition matrix using equation 21 above. Based on GFEVD, we obtain the total spillover index at quantile τ as below. This index shows how a shock to one variable spreads to other variables, as below.

$$C_i^{g}(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} \tilde{\phi}_{ji}^{g}(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\phi}_{ji}^{g}(\tau)} * 100 \tag{22}$$

A total connectedness index can be sub-divided into three parts. First is the total directional spillover index to others (Equation 23). This index analyses a situation where variable i transmits a shock to all other variables, say j. The equation is below;

$$C_{i \to j}^{g}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}_{ji}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\phi}_{ji}^{g}(\tau)} * 100 \tag{23}$$

The second part is the total directional spillover index of a variable, say i receives from other variables, say j (Equation 24).

$$C_{i \leftarrow j}^{g}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}_{ji}^{g}(\tau)}{\sum_{i=1}^{N} \tilde{\phi}_{ji}^{g}(\tau)} * 100 \tag{24}$$

stronger influence on the network than it is being influenced by it. A negative value, on the other hand, implies that the variable i is being driven by the network.

$$C_i^g = C_{i \to j}^g(\tau) - C_{i \leftarrow j}^g(\tau) \quad (25)$$

We selected our lags based on Schwartz information criterion which suggests 3 lags while keeping the maximum lags at 30 and the forecast horizon at 10.

3.6 Results Presentation and Analysis

3.6.1 Data Description

To conduct our analysis, we utilize Brent crude oil spot prices expressed in U.S. dollars per barrel, as Brent crude serves as the primary benchmark for African crude oil exports and accurately reflects global market dynamics impacting Sub-Saharan African economies. We source wholesale and retail prices of key agricultural commodities—maize, wheat, sorghum, and rice—from the Food and Agricultural Organization's food price monitoring and analysis dataset, acknowledging limitations in data availability across different crops and countries. Additionally, we incorporate Caldara and Iacoviello's (2018) Geopolitical Risk (GPR) indices—specifically geopolitical threats (GPRT), geopolitical acts (GPRA), geopolitical tensions in broad ranges (GPRB), and narrow ranges (GPRN)—to capture political and economic instability risks. The six African countries selected for this study are based on their participation in agricultural exports and data availability, enabling us to comprehensively explore the interplay between oil prices, agricultural commodity prices, and geopolitical dynamics in the region.

Table 3.3: Summary Statistics

Panel A: Oil										
Series	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Obs.
CMR	0.221	1.496	54.744	-59.26	10.992	-0.951	10.981	622.680	0.000	221
ETH	0.386	1.752	54.744	-59.26	10.428	-0.954	10.895	778.041	1.124	283
GHA	0.103	1.490	54.744	-59.26	11.158	-0.942	10.853	573.539	2.872	211
NGA	0.230	1.502	54.744	-59.26	10.973	-0.951	10.949	626.268	1.018	225
ZAF	0.386	1.752	54.744	-59.26	10.428	-0.954	10.895	778.041	1.124	283
TZA	0.103	1.490	54.744	-59.26	11.158	-0.942	10.853	573.539	2.872	211

Panel B: Geopolitical risk (Broad)										
CMR	4.725	4.697	5.638	4.399	0.266	1.270	6.644	182.525	0.000	221
ETH	4.712	4.691	5.638	4.163	0.205	0.812	6.148	147.974	7.378	283
GHA	4.736	4.712	5.638	4.399	0.163	1.347	7.000	204.468	3.983	211
NGA	4.724	4.700	5.638	4.399	0.165	1.281	6.682	188.624	1.082	225
ZAF	4.712	4.691	5.638	4.163	0.205	0.812	6.148	147.974	7.378	283
TZA	4.736	4.712	5.638	4.399	0.163	1.347	7.000	204.468	3.983	211
Panel B: Maize										
CMR	0.684	1.465	31.425	-29.09	7.393	-0.214	6.183	95.452	0.000	221
ETH	0.475	0.256	44.110	-52.25	9.756	-0.486	7.770	279.446	2.085	281
GHA	0.220	-0.052	34.101	-35.93	10.557	-0.233	5.071	39.620	2.493	211
NGA	0.135	0.180	38.289	-39.52	10.419	0.359	5.859	81.475	2.032	225
ZAF	0.136	0.904	26.120	-29.35	8.516	-0.403	4.737	43.230	4.010	283
TZA	0.174	0.597	30.302	-24.20	8.032	-0.089	3.778	5.595	0.061	211
Panel C: Rice										
CMR	0.428	0.000	15.907	-21.36	3.973	-0.267	8.448	277.165	0.000	221
GHA	0.434	-0.543	105.182	-45.54	11.989	4.028	35.390	9793.559	0.000	211
ZAF	0.425	0.141	17.835	-28.81	5.378	-0.335	6.811	176.577	4.538	283
TZA	0.311	0.781	23.011	-18.25	6.195	-0.060	3.834	6.242	0.044	211
Panel D: Wheat										
ETH	0.507	-0.041	33.810	-21.57	6.259	0.410	6.765	175.067	9.653	283
ZAF	0.124	0.000	29.783	-26.36	6.114	0.469	8.071	313.620	7.874	283
Panel E: Sorghum										
ETH	0.402	0.159	29.096	-28.58	7.701	0.069	5.693	85.713	2.442	283
GHA	-0.131	-0.319	31.361	-22.50	7.042	0.823	8.138	255.872	2.742	211
NGA	0.210	0.000	47.972	-40.56	11.896	0.178	6.396	109.320	1.826	225

Table 3.3 shows the data summary for the six countries with different crops and specific prices. We start by considering the crop prices across the board, with the highest and lowest values being on Ghana's rice and Ethiopia's maize, respectively. Additionally, we assess the volatility of the data being measured by standard deviation. The prices show strong volatilities across the variables, with rice, sorghum, and crude oil showing higher volatilities of 11.989, 11.895, and 11.158, respectively. These high volatilities in both the agricultural sector and oil support

the theoretical literature that shocks in oil prices will be transmitted into the agricultural sector in the form of higher prices since oil is a major input. This is not surprising since high volatility is expected of financial data (Data et al., 2023). Surprisingly, the Jarque-Bera test of normality accepts the null hypothesis of normal distribution except for Cameroon variables and the GPRA for Ghana, Nigeria, and Tanzania. This is further supported by both the positive and negative skewness across the variables and higher values for kurtosis than the expected value of 3.

Table 3.4: Unit root test

Philip Peron									
CAMEROON									
Series	Oil	GPRA	GPRB	GPRN	GPRT	Maize	Rice	Sorghum	Wheat
t-Stat.	-10,61 ***	-6,192 ***	-6,762 ***	-7,133 ***	-7,932 ***	-15,29 ***	-13,78 ***	==	==
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	==
TANZANIA									
t-Stat.	-10,23 ***	-5,896 ***	-6,308 ***	-7,04 ***	-7,573 ***	-8,709 ***	-11,269 ***	==	==
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	==
GHANA									
t-Stat.	-10,23 ***	-5,896 ***	-6,308 ***	-7,04 ***	-7,573 ***	-12,941 ***	-18,526 ***	-14,557 ***	==
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==
NIGERIA									
t-Stat.	-10,78 ***	-6,497 ***	-6,66 ***	-7,17 ***	-7,93 ***	-15,337 ***	==	-13,432 ***	==
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)	==
ETHIOPIA									
t-Stat.	-12,47 ***	-5,468 ***	-6,572 ***	-5,606 ***	-6,841 ***	-12,652 ***	==	-13,844 ***	-12,636 ***
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)	I(0)
SOUTH AFRICA									
t-Stat.	-12,47	-5,468	-6,572	-5,606	-6,841	-11,902	-15,875	==	-11,769

	***	***	***	***	***	***	***		***
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)
Augmented Dickey-Fuller									
CAMEROON									
t-Stat.	-9,992	-3,195	-6,808	-4,02	-6,012	-11,754	-13,79	==	==
	***	***	***	***	***	***	***		
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	==
TANZANIA									
t-Stat.	-9,63	-5,599	-6,366	-4,049	-5,823	-8,66	-4,18	==	==
	***	***	***	***	***	***	***		
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	==
GHANA									
t-Stat.	-9,651	-3,086	-4,24	-3,432	-4,627	-3,381	-8,851	-14,525	==
	***	***	***	***	***	***	***	***	
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==
NIGERIA									
t-Stat.	-9,966	-3,324	-6,66	-4,088	-6,02	-15,337	==	-7,569	==
	***	***	***	***	***	***		***	
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)	==
ETHIOPIA									
t-Stat.	-11,45	-5,729	-6,551	-5,606	-5,806	-6,137	==	-4,632	-12,605
	***	***	***	***	***	***		***	***
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)	I(0)
SOUTH AFRICA									
t-Stat.	-11,45	-5,729	-6,551	-5,606	-5,806	-12,111	-12,5	==	-5,187
	***	***	***	***	***	***	***		***
Sig. Level	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	==	I(0)

Source: Compiled by the author

Furthermore, time series large data sets are susceptible to non-stationarity. This is the major reason why we employed the return series. Therefore, there is a need to test if the returns are stationary using at least two-unit root tests. The paper employed the Philips Peron (PP) and the Augmented Dickey-Fuller (ADF) with the results presented in Table 3.4 above. All the series are stationary at a 1% significance level except for geopolitical risk from acts, which is stationary at a 10 % significance level. This shows that whenever one is dealing with financial time series data, it is important to calculate the returns instead of using the level values (Fasanya et al., 2021).

3.6.1 Spillover Results

The dynamic extreme spillovers are analyzed using the TVP-VAR approach following Antonakakis & Gauber, 2017. The results for the average connectedness measure are specifically presented in Table 3.5 according to the countries and variables under study. The results provide evidence of significant connectedness between oil, geopolitical risk, and agricultural commodities across the countries. The highest TCI value is 57.6 for Ethiopia, indicating that, on average, 57.6% of the error variance in agricultural commodities can be credited to varying oil and geopolitical risk shocks. The lowest TCI value is for Ghana, with about 35% variations in agricultural commodities attributed to oil and geopolitical risk shocks. This means that more than a third of the variations are from oil and geopolitical risk, a significant fraction of an economy undergoing structural service adjustments (Ferreira, 2022).

Table 3.5: Dynamic connectedness results for the variables across countries

CAMEROON								
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	FROM
Oil	91.17	0.73	0.29	0.21	0.40	3.90	3.30	8.83
GPRT	0.53	46.98	6.81	20.13	24.38	0.63	0.53	53.02
GPRA	0.69	6.65	55.59	12.59	23.09	0.57	0.83	44.41
GPRB	0.74	15.43	15.53	56.03	10.61	1.01	0.65	43.97
GPRN	0.35	20.84	19.84	11.36	46.63	0.49	0.49	53.37
Maize	3.95	0.69	0.31	0.47	0.34	91.0	3.24	9.0
Rice	8.44	0.32	1.15	0.89	0.48	3.53	85.19	14.81
TO Others	14.7	44.66	43.94	45.64	59.3	10.14	9.05	227.42
Net connectedness	5.86	-8.36	-0.48	1.67	5.93	1.14	-5.77	**TCI=37.9**

TANZANIA								
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	FROM

Oil	95.36	0.56	1.63	0.29	1.16	0.59	0.41	4.64
GPRT	0.43	45.23	6.14	16.22	28.46	2.09	1.41	54.77
GPRA	1.13	5.20	59.81	11.79	16.77	0.87	4.42	40.19
GPRB	1.82	15.77	13.78	53.67	12.0	1.68	1.28	46.33
GPRN	0.76	22.35	14.82	9.92	49.31	1.03	1.81	50.69
Maize	0.23	0.66	1.17	1.25	0.35	74.20	22.14	25.80
Rice	0.30	0.68	1.09	0.70	1.33	26.98	68.91	31.09
TO Others	4.68	45.21	38.64	40.18	60.07	33.25	31.47	253.50
Net connectedness	0.03	-9.55	-1.55	-6.15	9.38	7.45	0.39	**TCI=42.3**

GHANA

Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	Sorghum	FROM
Oil	93.82	0.78	1.72	0.48	1.22	0.34	1.25	0.40	6.18
GPRT	0.64	48.49	5.81	13.35	29.90	0.66	0.52	0.63	51.51
GPRA	0.89	5.44	61.71	11.21	17.89	1.31	0.29	1.27	38.29
GPRB	2.50	11.87	14.74	57.57	9.97	1.41	0.95	0.99	42.43
GPRN	0.65	23.40	16.09	9.34	48.30	1.03	0.16	1.02	51.70
Maize	1.69	0.81	3.23	0.18	2.75	76.41	2.39	12.55	23.59
Rice	0.47	0.40	1.67	1.13	1.60	2.10	90.66	1.99	9.34
Sorghum	2.01	1.05	5.40	0.82	2.31	8.62	2.16	77.63	22.37
TO Others	8.85	43.76	48.65	36.50	65.64	15.45	7.74	18.84	245.43
Net connectedness	2.66	-7.76	10.36	-5.93	13.94	-8.14	-1.61	-3.53	**TCI=35.06**

NIGERIA

Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Sorghum	FROM
Oil	94.22	0.81	0.56	0.28	0.94	1.66	1.54	5.78
GPRT	0.98	47.06	6.93	18.84	24.99	0.78	0.42	52.94
GPRA	1.54	6.77	52.99	13.81	22.16	1.38	1.35	47.01
GPRB	1.13	14.99	14.39	54.22	11.19	0.97	3.09	45.78
GPRN	0.77	18.65	20.78	11.27	46.20	1.52	0.81	53.80
Maize	5.75	3.40	0.84	2.79	1.42	65.57	20.24	34.43
Sorghum	8.36	2.48	1.43	3.47	0.98	20.32	62.97	37.03
TO Others	18.53	47.10	44.93	50.45	61.68	26.62	27.45	276.77

Net connectedness	12.75	-5.84	-2.08	4.67	7.88	-7.81	-9.58	**TCI=46.1**	
SOUTH AFRICA									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Wheat	Rice	FROM
Oil	83.59	2.47	1.53	2.44	1.46	1.12	2.27	5.11	16.41
GPRT	1.20	36.08	13.76	19.64	27.73	0.61	0.70	0.29	63.92
GPRA	0.55	13.14	37.54	19.36	28.09	0.58	0.35	0.39	62.46
GPRB	0.76	20.51	18.15	34.97	23.94	1.12	0.33	0.22	65.03
GPRN	0.41	19.54	24.24	19.38	35.56	0.28	0.38	0.22	64.44
Maize	2.52	1.84	1.07	1.17	0.42	85.75	5.39	1.84	14.25
Wheat	1.98	2.33	0.60	0.87	1.03	2.77	86.74	3.69	13.26
Rice	7.30	1.87	0.80	0.55	0.48	1.89	4.11	82.99	17.01
TO Others	17.14	61.70	60.15	63.39	83.16	8.38	13.54	11.75	319.21
Net connectedness	0.73	-2.22	-2.31	-1.63	18.71	-5.87	0.28	-5.25	**TCI=45.3**
ETHIOPIA									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Sorghum	Wheat	FROM
Oil	70.58	2.04	7.10	3.98	6.67	0.82	2.61	0.28	29.42
GPRT	0.67	39.27	6.84	11.52	22.79	1.05	0.70	1.10	60.73
GPRA	0.32	12.03	30.72	9.79	24.93	2.12	0.41	1.27	69.28
GPRB	0.58	20.13	13.76	29.95	16.29	1.35	0.72	3.67	70.05
GPRN	0.71	22.85	15.03	9.52	33.30	2.27	0.66	0.76	66.70
Maize	3.22	0.86	2.31	0.91	2.35	74.50	12.32	2.40	25.50
Sorghum	2.27	1.41	1.71	1.32	2.03	28.88	55.58	4.87	44.42
Wheat	0.82	2.61	0.28	2.04	7.10	6.60	0.93	79.54	20.46
TO Others	10.25	81.91	68.14	49.23	99.36	44.44	18.83	15.26	460.85
Net connectedness	-19.17	21.18	-1.14	-20.83	32.66	18.94	-25.59	-5.20	**TCI=57.6**

Source: Compiled by the author

Table 3.5 above also examines net directional spillovers, differentiating between the total contributions an asset receives FROM others and the total contributions it imparts TO others. Positive values indicate that the respective series acts as a net shock giver, transmitting more than it receives, while negative values suggest it functions as a net shock receiver, receiving more than it transmits. The outcomes of our investigation reveal varying levels of spillover effects across the markets, with all series significantly engaged in both giving and receiving shocks.

Analyzing the results of dynamic connectedness in terms of oil, we find that it is a net shock giver in all the countries except for Ethiopia (-19.17). These findings align with expectations and complement the theoretical literature that oil is a major input in the production of agricultural goods, and any shocks it experiences will be transmitted to other commodities. It also complements the empirical literature according to findings by (Naziliougu et al., 2013, Dahl et al., 2020 & Hau et al., 2020). Countries must reduce reliance on oil by decentralizing the agricultural markets to cut transport costs. Surprisingly, the three forms of geopolitical risk are net shock receivers, except for the narrow definition. This is because geopolitical risks often arise from complex interactions between different countries, organizations, and individuals, and these interactions can be difficult to predict and control. For example, there will be trade restrictions, which will lead to geopolitical risks from threats. This will then disrupt the supply chain in the different sectors which will result in higher prices.

Surprisingly, the three forms of geopolitical risk are net shock receivers, except for the narrow definition, which is a net shock giver. The narrow definition, likely referring to direct conflicts or wars, shows the highest net connectedness in all countries except Nigeria, where it is second to oil. This is because Nigeria, an oil-producing country, has oil as the highest shock giver. Narrow geopolitical risks, such as wars, can lead to stockpiling of oil and food, and increasing prices, as seen in examples like the US-China trade war (affecting agricultural tariffs) and the Russia-Ukraine war (disrupting oil and wheat flows). The Israel-Palestine conflict since October 2021 also affected regional trade (Tiwari, 2021). Geopolitical risks, especially narrow definitions, increase oil price volatility, raising production costs for SSA farmers, particularly in oil-importing countries. This leads to higher agricultural prices, with spillovers from oil to agricultural markets amplified during crises. The net shock receiver status of broader geopolitical risks suggests complex, unpredictable interactions, potentially disrupting supply chains and leading to higher prices through trade restrictions (Su et al., 2019).

The paper also analyzed the connection between crops in different countries. The results show evidence that the crops are net shock receivers except for maize, which reveals a moderate level of spillover effects across countries. Maize in Cameroon (1.14), Ethiopia (18.94), and Tanzania (7.45) is a net shock giver, while it is a net shock receiver in Ghana (-8.14), Nigeria

(-7.81) and South Africa (-5.87). This is mainly because maize is a staple food in the Sub-Saharan region, and its production is susceptible to geopolitical risk, oil shocks, and climate change, resulting in droughts and floods. These shocks affect its production, which also affects the production of other crops, as evidenced by the bidirectional relationship between the agricultural commodities in different countries. These are maize and rice in Ethiopia and Cameroon, maize and sorghum in Nigeria and Ghana, and wheat and rice in South Africa. This is so interesting since the crops are affected by the same factors as geopolitical risk, oil shocks, and environmental factors. This is similar to the disaggregated indexes of geopolitical risk since their sources are the same. There is also evidence for a bidirectional relationship between the oil and the agricultural sectors in Cameroon and South Africa, specifically maize, rice, and oil.

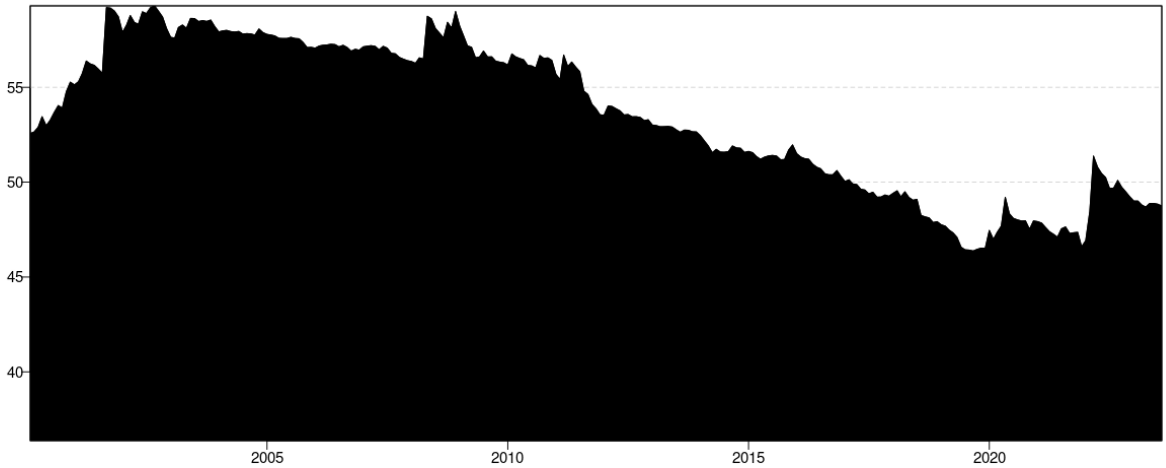
Overall, the average connectedness results show that the countries are relatively connected, and Ethiopia is well connected with (TCI) of 37.9. This means there is a significant spillover between the oil, geopolitical risk, and agricultural sectors, and shocks in one sector can quickly propagate to others. The narrow geopolitical risk sector is the most connected sector across the board, with a net connectedness as high as 32.66 in Ethiopia and a minimum of 5.93 in Cameroon. It is followed by the oil sector, which has a maximum connectedness of 12.75 in Nigeria. This means that the oil sector positively impacts the overall economy. The maize is also relatively well-connected, with a maximum net connectedness of 18.94 in Ethiopia and -8.14 in Ghana. This is mainly because maize is a staple food in these countries.

The connectedness presented in the average connectedness table can be graphically presented. As observed from the diagrams, the connectedness varies over time and the major spikes are similar across the countries. The major ones are around 2006 and 2022, when there was the global financial crisis, which resulted in oil price shocks, and the Russia – Ukraine war, which is a geopolitical risk that also affected oil prices and agricultural prices among other commodities (Abay et al., 2023).

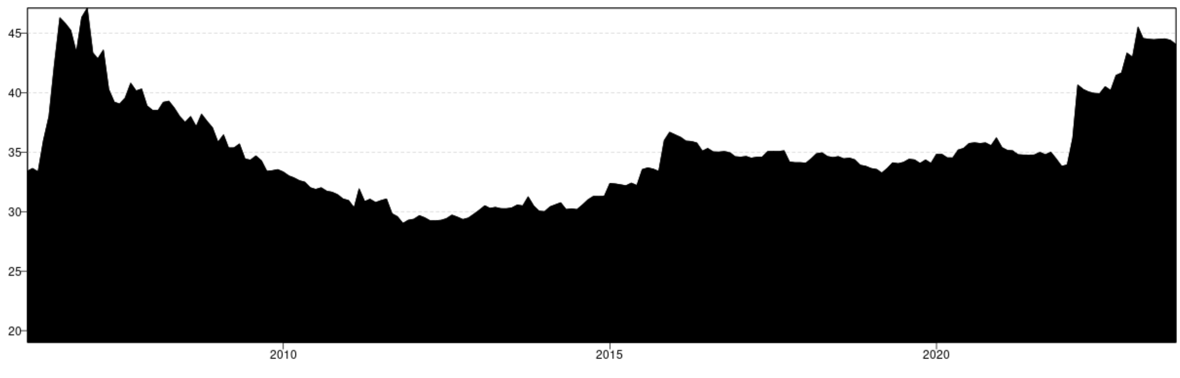
Figure 3.2: Dynamic total connectedness for different countries

Cameroon

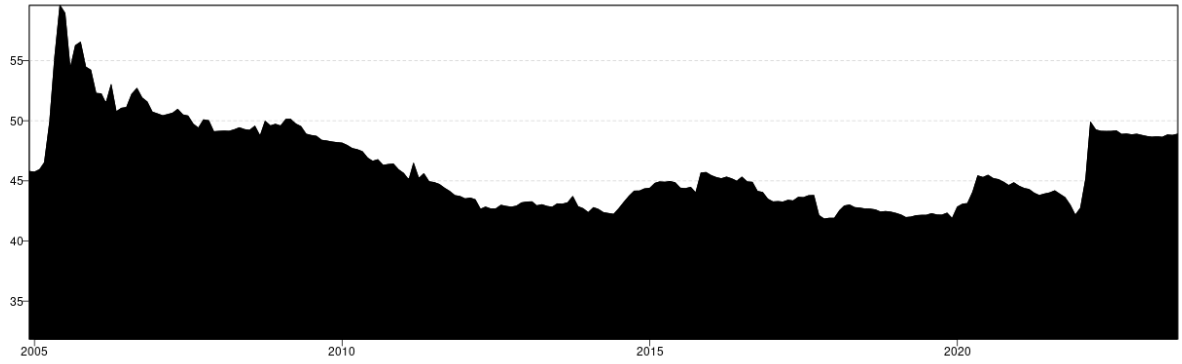
Ethiopia



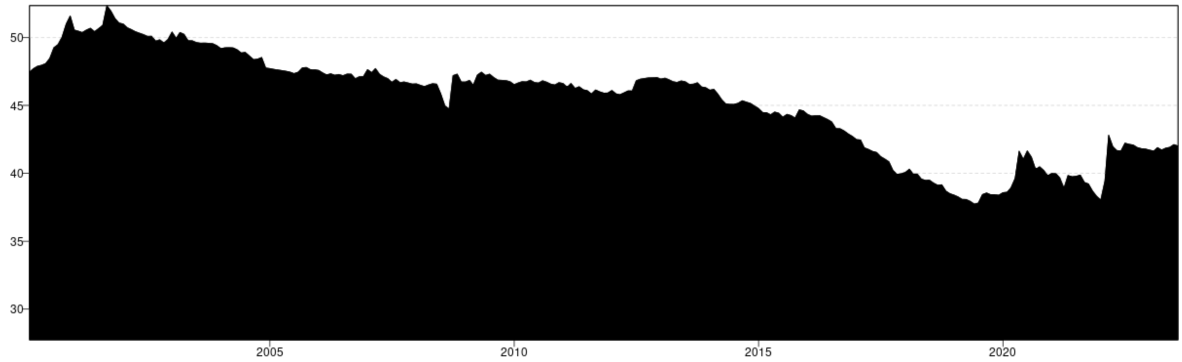
Ghana



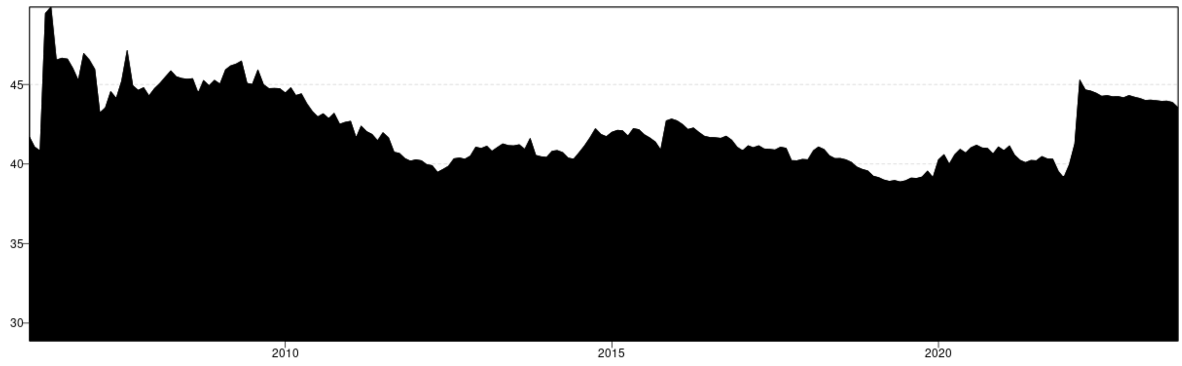
Nigeria



South Africa



Tanzania



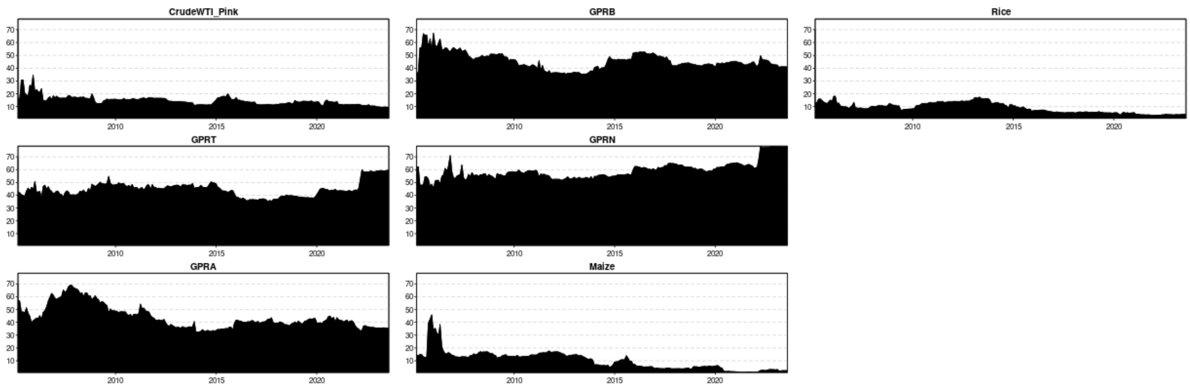
The varying connectedness supports the evidence that these markets are characterized by significant volatilities (Luo & Ji, 2018). The graphs show that oil shocks persistently impact cereal crop shocks. This means that when the price of oil increases, the price of cereal crops increases. This is because oil is used in producing and transporting cereal crops (Fasanya & Akinbowale, 2019). This is similar to the average connectedness table results, which show that oil is a net shock giver. It also shows that oil shocks persistently impact geopolitical risk since GPR is a net shock receiver. This means that when the price of oil increases, it leads to an increase in geopolitical risk. This is because oil is a key strategic resource, and changes in its price can lead to instability and conflict.

Additionally, as mentioned earlier net connectedness is found by subtracting the total connectedness FROM others from TO others, we can graphically present the FROM and TO other figures. They are presented together so that we can visualize the net spillovers amongst the series.

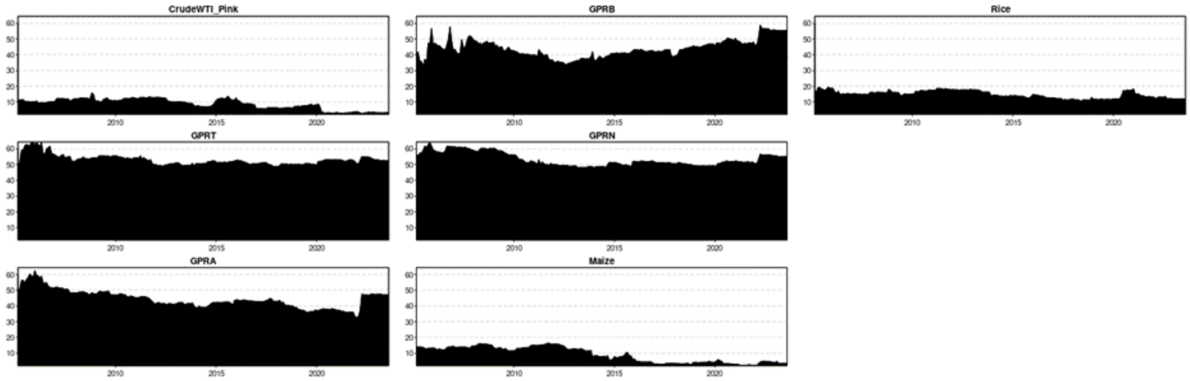
Figure 3.3: Net connectedness

Cameroon

TO Others

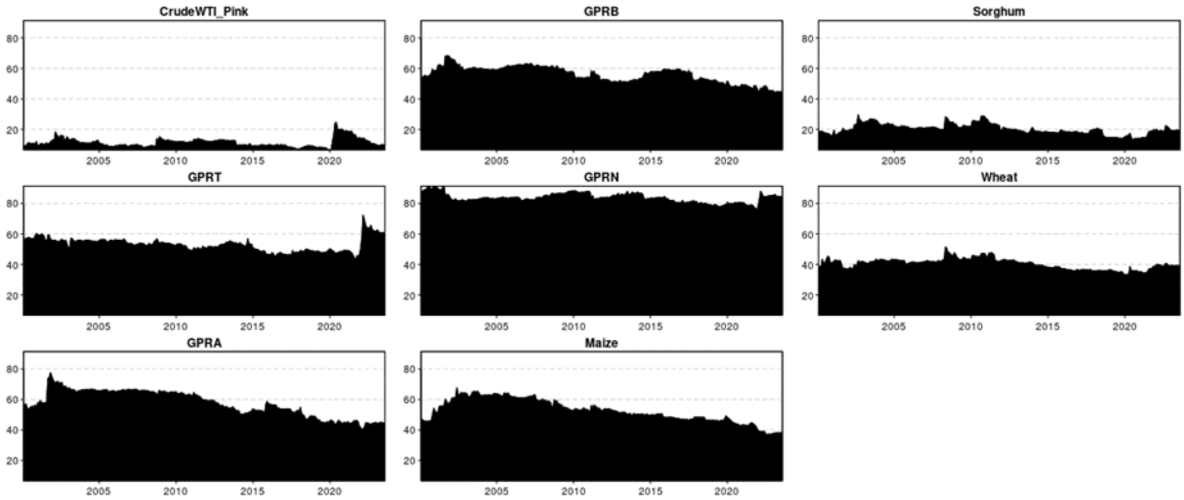


FROM Others

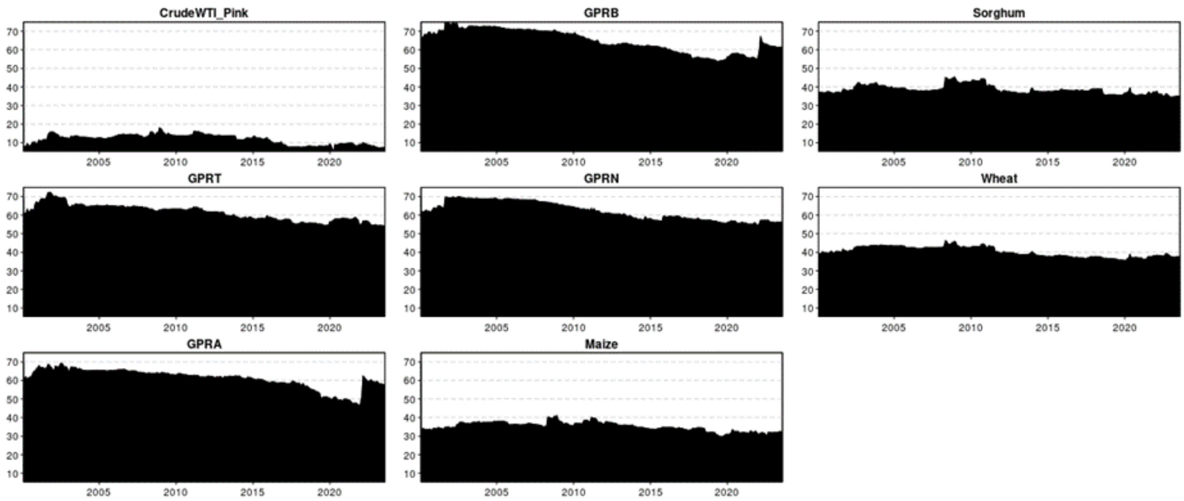


Ethiopia

TO Others

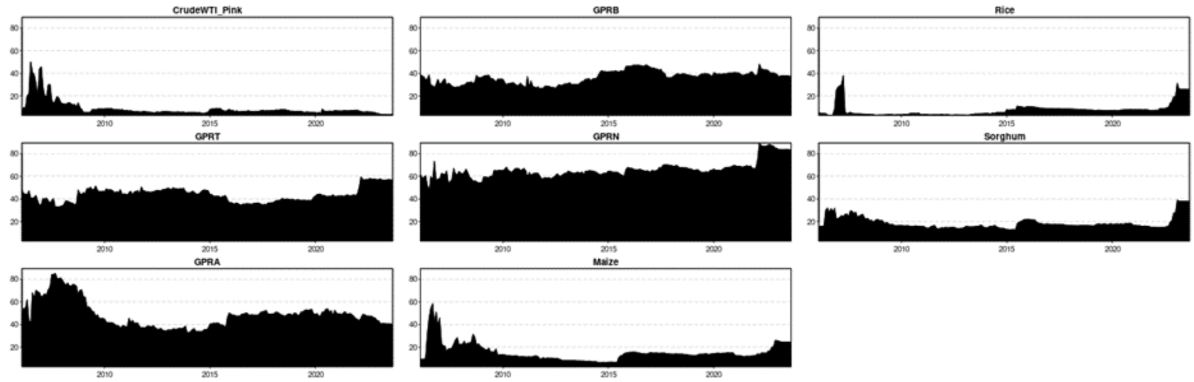


FROM Others

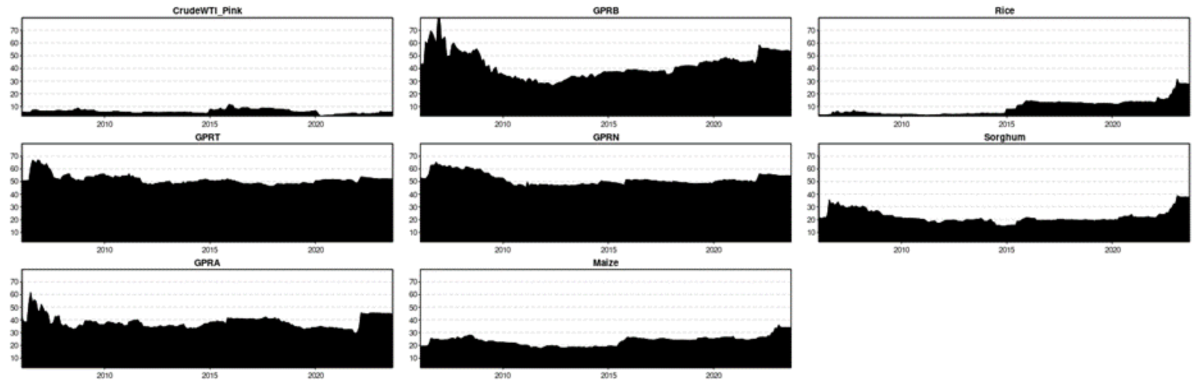


Ghana

TO Others

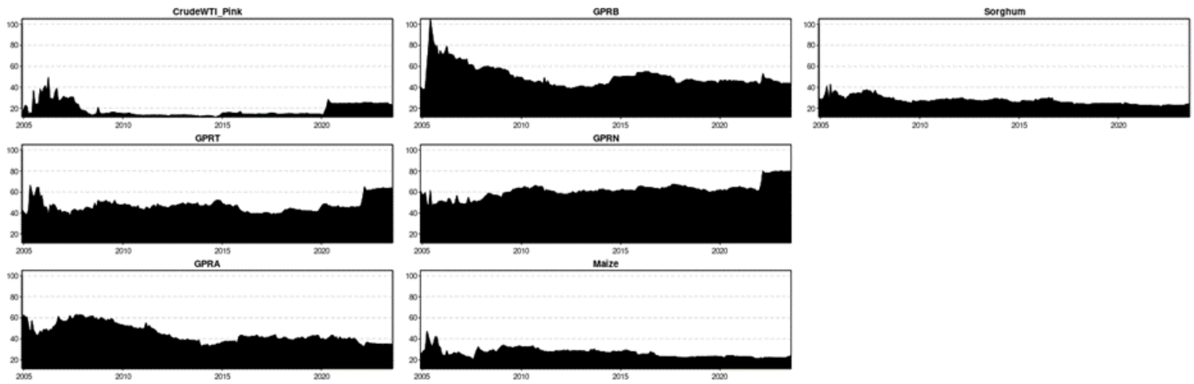


FROM Others

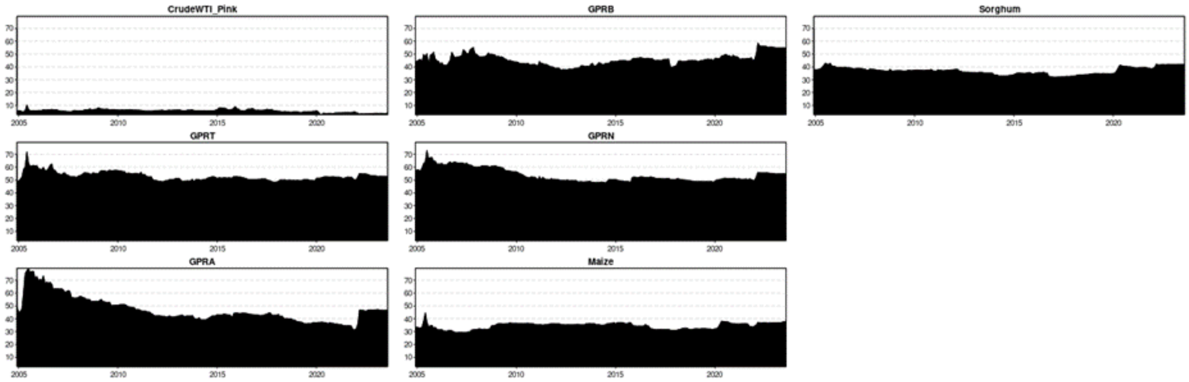


Nigeria

TO Others

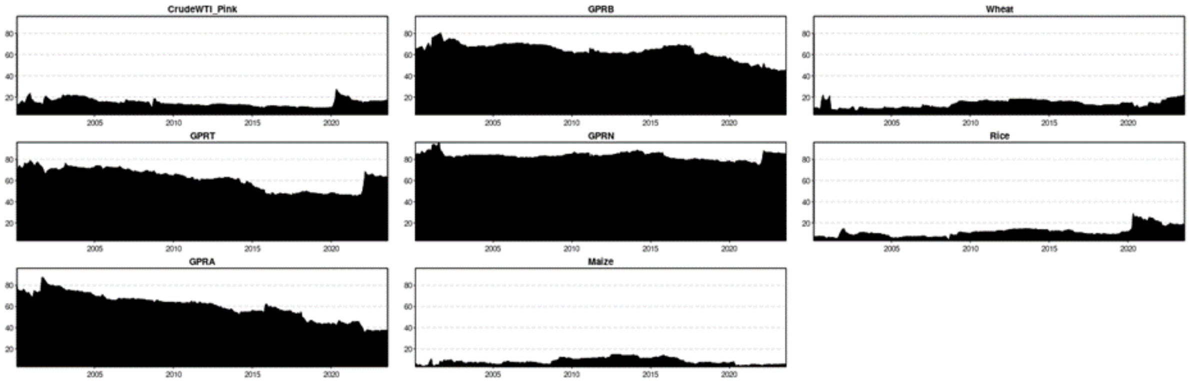


FROM Others

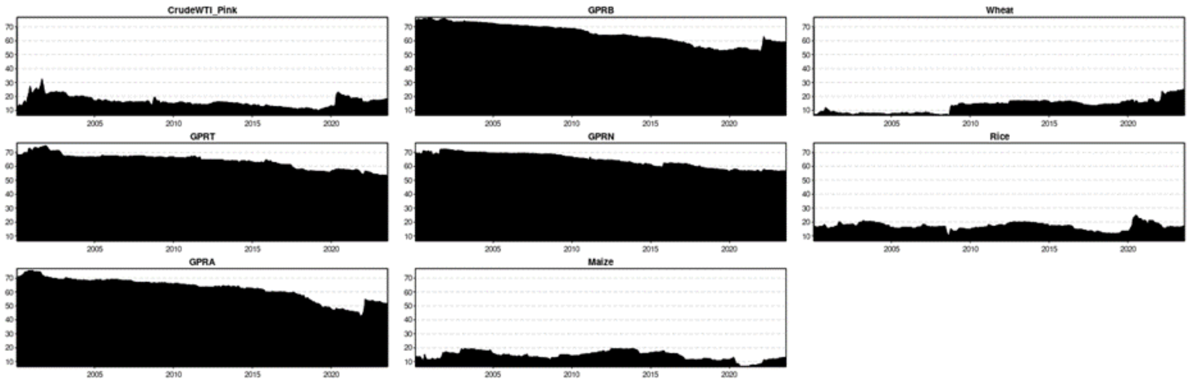


South Africa

TO Others

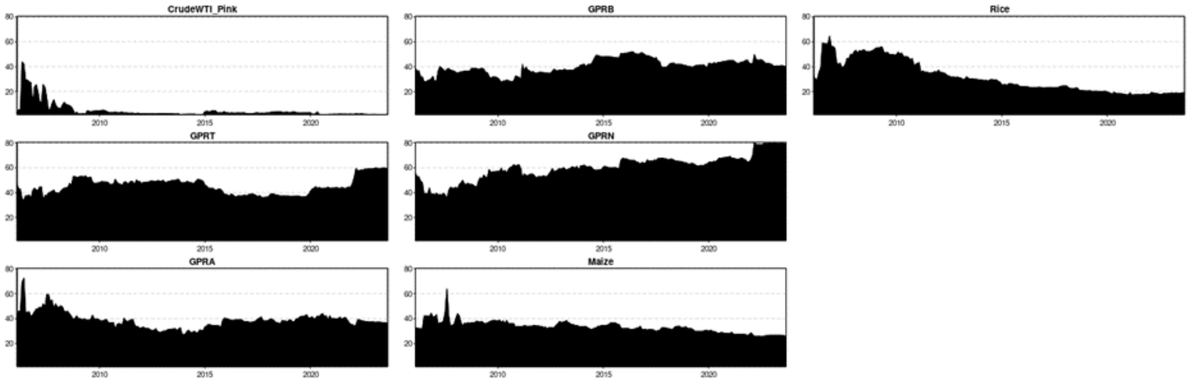


FROM Others

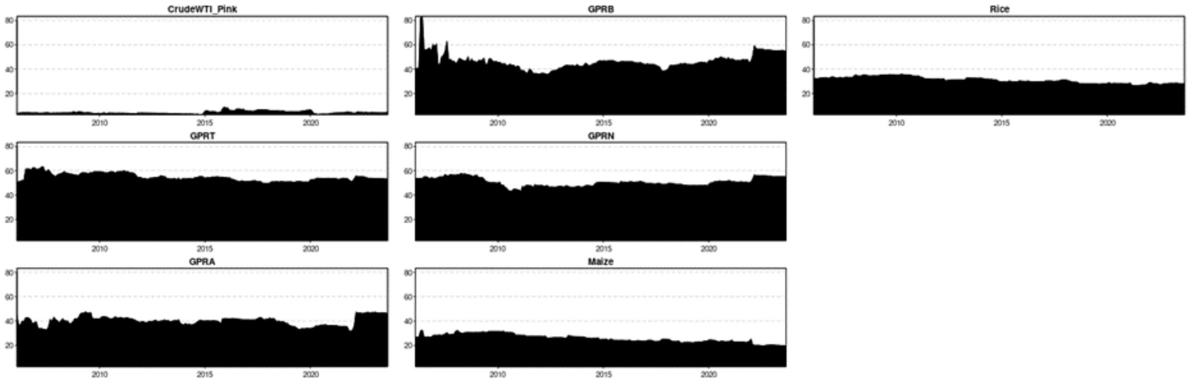


Tanzania

TO Others



FROM Others

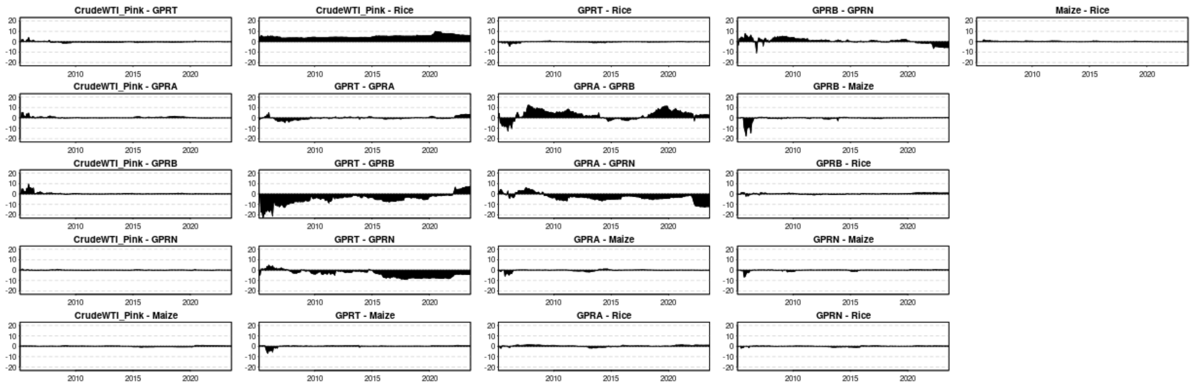


The three forms of geopolitical risk (GPRT, GPRA, and GPRB) are net receivers from oil and agricultural commodities. This means that shocks in the oil sector are transmitted to geopolitical risk because oil is a finite good, and any shocks will result in conflict and social unrest, which are forms of geopolitical risk. For example, the Gulf War in 1990, the Libyan civil war in 2011, the ongoing Iraq-USA fallout, and the Russia-Ukraine war. These results are different from (Monge et al. 2023 and Zhang et al. 2023), who tested the impact of geopolitical risk on oil. They find a unidirectional relationship, yet this paper finds a bidirectional relationship. The crop shocks also have a persistent impact on geopolitical risk. This means that when the price of crops increases, it leads to an increase in geopolitical risk. This is because cereal crops are a staple food, and changes in their price can lead to food shortages and social unrest.

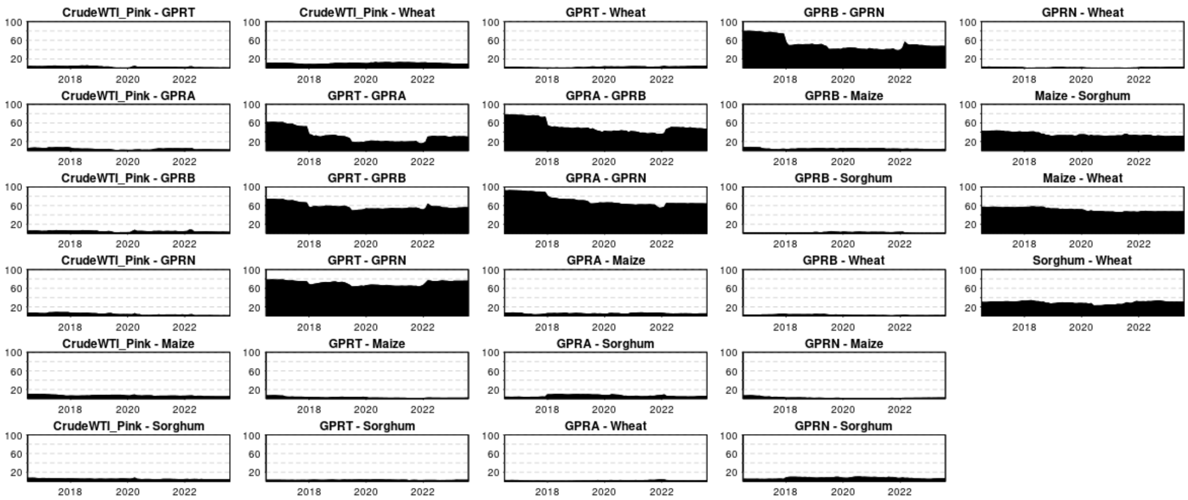
The results can also be presented using the pairwise connectedness as below for the different series across different countries. Pairwise connectedness, also known as directional or asymmetric connectedness, is a measure of the causal flow of volatility between two variables. It quantifies how much one variable's volatility affects another variable's volatility. In other words, it assesses whether shocks in one variable propagate to the other variable.

Figure 3.4: Pairwise connectedness

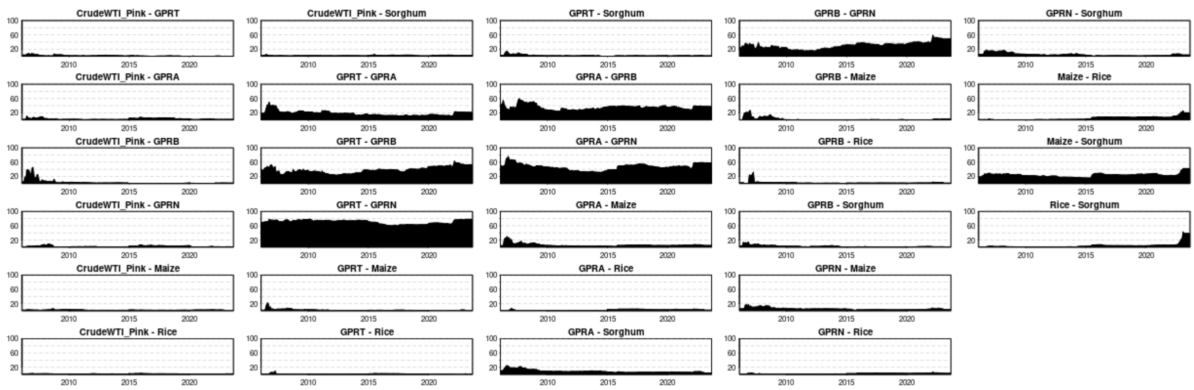
Cameroon



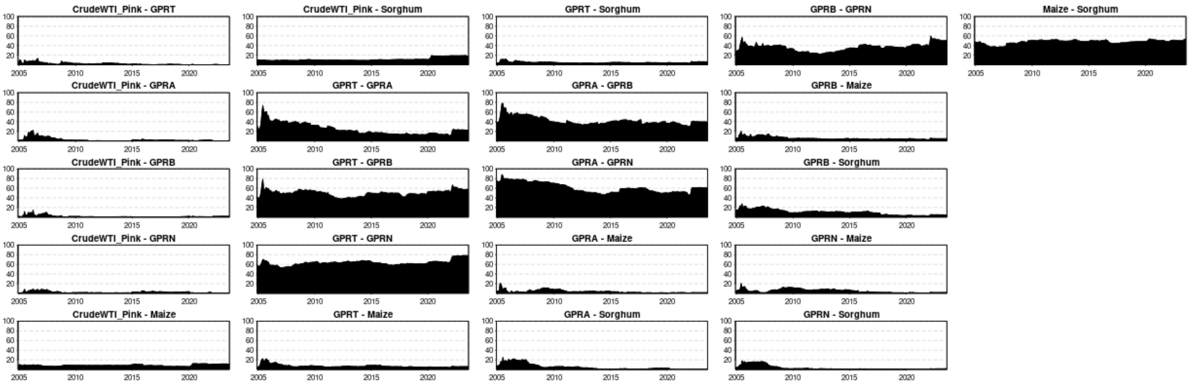
Ethiopia



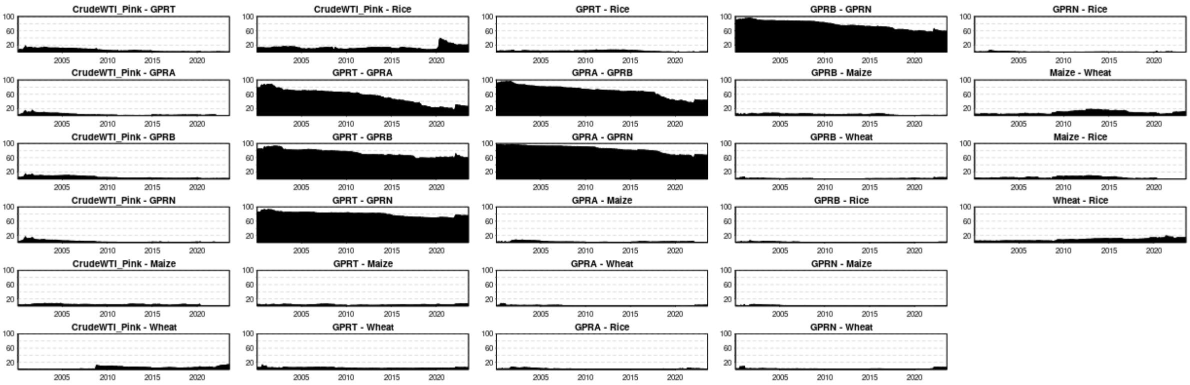
Ghana



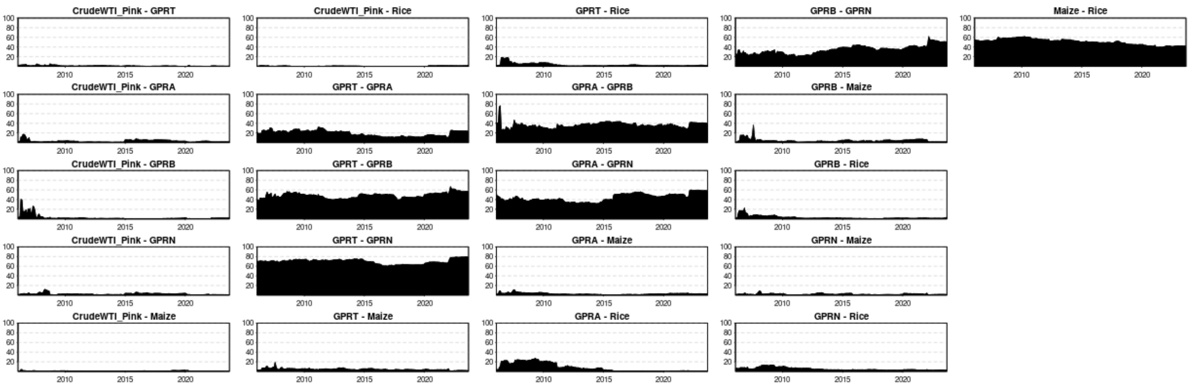
Nigeria



South Africa



Tanzania

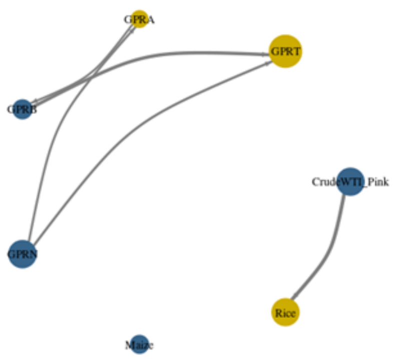


The same results can be discussed as being seen from the pairwise diagrams. Surprisingly, the different forms of geopolitical risk are connected. This also applies to the crops that are connected. This is mainly because Maize, wheat, sorghum, and rice are four of the most important cereal crops in Cameroon, Ethiopia, Ghana, Nigeria, South Africa, and Tanzania. They are all staple foods in these countries and play a vital role in food security and nutrition (Dalheimer, 2021). Moreover, they are affected by the same climatic conditions since the six countries have tropical or subtropical climates, which are well-suited for growing these crops.

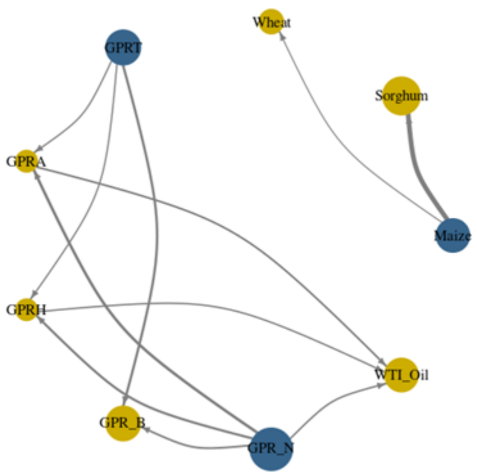
With the connectedness analysis, there are network plot figures. The nodes in the plot represent the variables, and the edges represent the spillover effects between the variables. The thickness of the edges represents the strength of the spillover effect. The plots are per specific country as shown.

Figure 3.5: Network plot

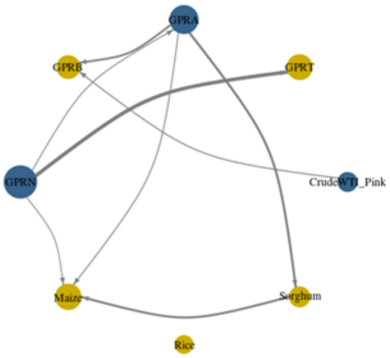
Cameroon



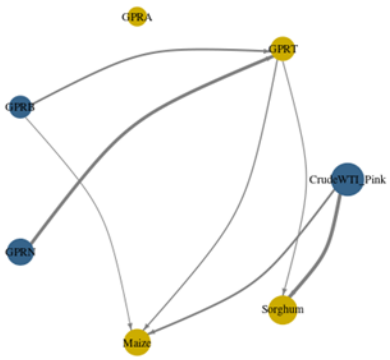
Ethiopia



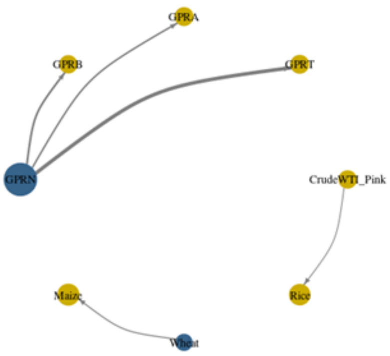
Ghana



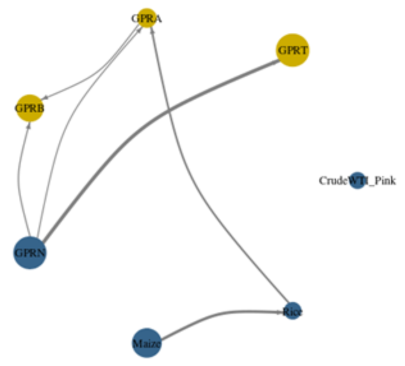
Nigeria



South Africa

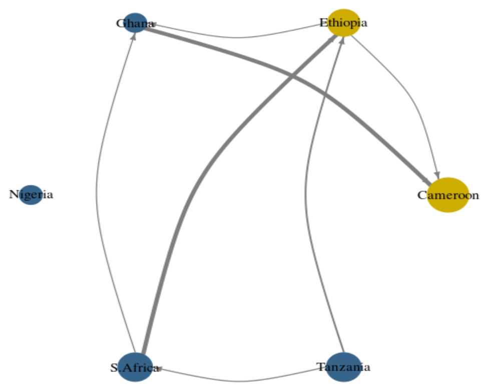


Tanzania



The analysis reveals heterogeneous spillover effects across countries and commodities. Notably, Nigeria exhibits strong spillovers from oil to maize and sorghum, aligning with theoretical postulates on the impact of geopolitical risks (GPR) on maize production and prices (Fasanya & Akinbowale, 2019). Similar spillovers from oil to rice are observed in South Africa and Cameroon, contradicting Fowowe's (2016) findings of a neutral relationship in South Africa. Ghana demonstrates significant spillovers from GPR to maize, confirming the influence of geopolitical risk on this staple food. Conversely, Ethiopia and Tanzania exhibit intra-agricultural commodity spillovers. At the same time, maize remains unconnected to GPR and oil in Cameroon and Ghana, highlighting the complex and context-dependent nature of these relationships. Additionally, bidirectional spillovers between crude oil and GPR in Ghana corroborate Huang et al.'s (2021) findings.

Whilst analyzing the connectedness, we went on to assess the network plot across countries using common maize prices. The results are so interestingly plotted below with Nigeria being not connected to the other countries. It is mainly because of the top agriculture-exporting countries, only Nigeria exports oil while the rest are oil importers.



3.6.2 Robustness Check

For robustness check, this paper used the quantile VAR (QVAR) model mainly because it is a powerful tool for forecasting and analyzing the dynamics of economic and financial variables. It has several strengths over traditional linear VAR models, including its robustness to outliers, its ability to model the tails of the distribution, and its flexibility. The results are presented in Table 3.6 below.

Table 3.6: Dynamic connectedness results using QVAR

CAMEROON									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	FROM	
Oil	95.19	0.33	0.78	0.25	0.26	0.84	2.34	4.81	
GPRT	0.11	45.70	3.92	19.15	30.70	0.30	0.13	54.30	
GPRA	0.25	5.46	60.90	11.42	21.34	0.14	0.49	39.10	
GPRB	0.09	19.09	9.48	53.62	16.71	0.46	0.55	46.38	
GPRN	0.37	22.82	15.01	14.13	47.06	0.53	0.07	52.94	
Maize	1.73	2.31	0.36	0.51	0.88	93.06	1.16	6.94	
Rice	3.87	0.38	1.73	1.15	0.24	1.15	91.48	8.52	
TO Others	6.42	50.38	31.28	46.60	70.13	3.42	4.75	212.98	
Net connectedness	1.61	-7.82	-7.82	0.22	17.19	-3.52	-3.77	**TCI=35.5**	
TANZANIA									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	FROM	
Oil	97.47	0.31	1.63	0.73	0.26	0.38	0.64	2.53	
GPRT	0.08	45.30	6.14	4.04	32.49	0.17	0.05	54.70	
GPRA	0.16	4.87	59.81	59.86	22.32	1.01	0.20	40.14	
GPRB	0.20	19.39	13.78	10.02	17.74	0.40	0.11	47.87	
GPRN	0.08	24.05	14.82	14.43	46.29	0.43	0.09	53.71	
Maize	0.55	0.59	1.17	0.22	0.39	79.17	18.40	20.83	
Rice	0.79	0.05	1.09	0.17	0.15	22.05	76.64	23.36	
TO Others	1.86	49.26	38.64	29.60	73.34	24.43	19.50	243.14	
Net connectedness	-0.67	-5.44	-1.55	-10.55	19.63	3.60	-3.86	**TCI=40.5**	
GHANA									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Rice	Sorghum	FROM

Oil	96.61	0.43	0.72	0.41	0.16	0.67	0.55	0.44	3.39
GPRT	0.08	44.91	4.24	17.80	32.33	0.18	0.27	0.19	55.09
GPRA	0.18	5.41	59.49	11.30	22.57	0.36	0.54	0.15	40.51
GPRB	0.23	18.96	10.11	52.47	17.13	0.55	0.47	0.08	47.53
GPRN	0.15	23.67	14.56	14.40	46.48	0.34	0.18	0.21	53.52
Maize	0.06	0.12	0.34	0.08	0.41	82.93	5.08	10.98	17.07
Rice	0.24	0.17	0.10	0.03	0.34	4.50	87.44	7.18	12.56
Sorghum	0.33	0.78	0.27	0.19	0.61	9.94	6.76	81.12	18.88
TO Others	1.27	49.55	30.34	44.23	73.55	16.54	13.85	19.22	248.53
Net connectedness	-2.12	-5.54	-10.17	-3.31	20.02	-0.52	1.29	0.35	**TCI=35.5**

NIGERIA

Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Sorghum	FROM
Oil	95.67	0.23	1.28	0.32	0.33	1.85	0.32	4.33
GPRT	0.12	46.03	4.08	19.04	30.54	0.04	0.15	53.97
GPRA	0.20	5.38	61.48	10.90	21.22	0.26	0.55	38.52
GPRB	0.14	18.44	10.48	53.91	15.15	0.29	1.59	46.09
GPRN	0.40	22.66	15.32	13.70	47.25	0.46	0.20	52.75
Maize	3.43	0.05	0.51	0.11	1.05	73.10	21.76	26.90
Sorghum	1.02	0.15	0.15	0.25	0.42	23.13	74.88	25.12
TO Others	5.32	46.92	31.83	44.32	68.70	26.04	24.58	247.70
Net connectedness	0.98	-7.05	-6.70	-1.77	15.95	-0.87	-0.54	**TCI=41.3**

S. AFRICA

Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Wheat	Rice	FROM
Oil	85.93	0.64	0.69	0.63	0.39	0.82	3.99	6.91	14.07
GPRT	0.31	40.09	8.06	20.59	29.20	0.66	0.71	0.38	59.91
GPRA	0.27	7.20	51.19	14.27	24.98	1.20	0.43	0.47	48.81
GPRB	0.36	17.64	12.48	47.55	19.90	1.06	0.66	0.34	52.45
GPRN	0.16	17.35	20.59	15.55	44.97	0.48	0.70	0.19	55.03
Maize	1.00	1.62	0.34	0.62	0.79	88.02	6.00	1.60	11.98
Wheat	2.77	1.47	0.84	0.88	1.42	4.21	82.40	6.00	17.60
Rice	7.78	0.69	0.81	0.39	0.82	2.65	5.40	81.46	18.54

TO Others	12.65	46.60	43.81	52.94	77.51	11.08	17.89	15.89	278.37
Net connectedness	-1.42	13.30	-4.9	0.49	22.48	-0.90	0.29	-2.64	**TCI=39.8**
ETHIOPIA									
Series	Oil	GPRT	GPRA	GPRB	GPRN	Maize	Sorghum	Wheat	FROM
Oil	93.76	0.47	0.71	0.67	0.47	1.05	0.33	2.54	6.24
GPRT	0.14	39.76	8.16	19.42	29.46	1.07	0.81	1.17	60.24
GPRA	0.20	7.93	49.52	14.45	24.40	0.95	1.86	0.69	50.48
GPRB	0.14	18.08	13.10	46.54	19.23	1.41	0.65	0.85	53.46
GPRN	0.16	18.06	20.05	14.52	43.17	0.88	2.51	0.64	56.83
Maize	1.27	0.75	0.69	0.90	0.62	70.44	8.34	16.99	29.56
Sorghum	0.56	0.75	2.00	0.34	1.95	11.23	68.36	14.80	31.64
Wheat	2.94	0.38	0.66	0.23	0.29	17.15	9.94	68.42	31.58
TO Others	5.41	46.42	45.38	50.53	76.42	33.74	24.44	37.68	320.03
Net connectedness	-0.83	-13.82	-5.10	-2.92	19.59	4.18	-7.20	6.10	**TCI=45.7**

Source: Compiled by the author

The quantile VAR (QVAR) analysis, while generally congruent with the TVP-VAR results in Table 3.5 regarding the net receiver status of most geopolitical risk (GPR) forms, reveals relatively smaller total connectedness indexes (TCIs). This discrepancy is likely attributable to the TVP-VAR's superior capacity to capture nonlinear relationships, resulting in heightened volatility. However, the QVAR analysis still demonstrates substantial interconnectedness among variables across countries, with TCIs ranging from 35.5 (Cameroon and Ghana) to 45.7 (Ethiopia). A notable finding is the net shock receiver status of oil in all countries except Cameroon and Nigeria, potentially reflecting the region's agro-based economy, wherein agricultural sector shocks can transmit to the oil sector and trigger social unrest. This is further supported by all crops' net shock giver status, underscoring the bidirectional connectedness among the three sectors.

3. 7 Conclusion and Recommendations

The role of geopolitical risk in different economic sectors is a critical macroeconomic concern that affects all nations. This has spurred numerous studies investigating its effects on financial markets and other macroeconomic indicators on a country-specific, regional, or global scale (Kumar et al., 2021; Li et al., 2021a & Salisu et al., 2022). However, few studies have examined the volatility connectedness between oil, geopolitical risk, and agricultural commodities of the Sub-Saharan region. Even more uncommon are studies that examine how the connectedness between these sectors reacts to the disaggregated indexes of geopolitical risk and oil. Recent studies have identified factors that contribute to volatility spillovers between oil and geopolitical risk, ignoring the agricultural sector.

Additionally, this study has made some methodological contributions by adopting the recent model of the TVP-VAR following Antonakakis et al., 2020. It is useful in assessing dynamic connectedness mainly due to its flexibility in capturing changing relationships in the data over different periods and adaptability in capturing structural breaks, regime shifts, and varying volatility (Gabauer & Gupta, 2018). The paper also gives insight into the connectedness between oil and agriculture due to geopolitical risk.

A summary of the findings is given below. Firstly, we find evidence of strong total connectedness between the sectors, with Ethiopia having the highest 57.6%. Assessing the net connectedness, the narrow geopolitical risk is the highest shock giver across countries, followed by oil. Therefore, oil and geopolitical risk spillovers significantly affect agricultural commodities. Secondly, there are bidirectional relationships between oil and crops. Surprisingly, there is a bidirectional relationship between the crops, mainly maize and sorghum and maize and rice. Furthermore, there is a unidirectional relationship between oil and the three different forms of geopolitical risk, except for the narrow geopolitical risk. Thirdly, according to the network plot, oil in Nigeria is not connected to the other variables mainly because Nigeria is the only oil-producing country. Notably, there are common volatility shocks around 2006 and 2022, which are periods of the global financial crisis and the Russia-Ukraine war.

This shows the disruptive effects of geopolitical risks together with oil shocks, which is crucial when formulating policies aimed at achieving stability and sustainability. The results are consistent with findings by Dahl et al. 2020, Monge et al. 2023, and Ren et al. 2023 combined since they were assessing the dual relationships instead of the trio relationship. This study demonstrates the existence of excessive spillovers during war or national conflicts. The emergence of the Russia-Ukraine war resulting in trade disruptions across the globe is key to all economic agents and policymakers. Our findings reinforce the emerging body of evidence on the susceptibility of agricultural markets to oil shocks and risks stemming from geopolitical conflicts.

Our findings yield several crucial policy implications. Firstly, the strong connections between oil, agriculture, and geopolitical risk emphasize the need for African nations to foster regional cooperation. Encourage regional cooperation among Sub-Saharan countries to share knowledge resources. This could involve sharing knowledge, resources, synchronized policies, and best practices for improving agricultural production and food security. Such collaboration would allow African countries to enhance agricultural productivity, improve food security, and achieve sustainable development. The cooperation also increases the establishment of unity across countries and enhances their ability to combat external shocks. Secondly, as Ethiopia, Nigeria, and South Africa emerged as the most connected, diversification options in agricultural production will boost the output in agricultural markets.

Policymakers should invest in agricultural research and development to develop new technologies, crop varieties, and farming practices tailored to the region’s needs. This would reduce the region's vulnerability to production disruptions and improve food security. Interestingly, the three largest economies in the region are the ones with strongly connected sectors. This is because they have more to offer on the global market, and their sectors are more dependent on each other for goods and services (Jiao, 2023). It is important to note that the region is characterized by smallholder farmers with more than 200 million people (Kapari et al., 2023). Therefore, empowering smallholder farmers through training, extension services, and access to information is crucial to enhancing their agricultural productivity and decision-making capabilities.

Thirdly, the narrow geopolitical risk is the highest net shock giver across the countries. It is, therefore, crucial for the encouragement of peace and unity across nations. Regional committees should promote dialogue, cooperation, and conflict resolution to reduce tensions and prevent conflicts if there are geopolitical threats and actions like war and social unrest. Countries must foster transparency, good governance, and respect for human rights to create a more stable, peaceful, and predictable environment conducive to investing in different sectors of the economies. For future research, it would be compelling to extend the study to the risk associated with other commodities such as green energy, bitcoin, and gold, particularly examining the spillover effects of oil and those commodities due to geopolitical risk using a higher frequency data set, which would further enrich the research.

CHAPTER FOUR

Climate Risk and the Dynamic Spillovers between Oil Prices and Food Prices: A GARCH-MIDAS Approach.

4.1 Introduction

In the face of the escalating frequency and intensity of extreme weather shocks such as droughts, floods, heat waves, hurricanes, and natural disasters, the global economy is experiencing substantial losses (Hong et al., 2019; Puertas & Marti, 2021). More frequent and severe droughts can devastate crops and livestock, leading to food shortages and economic hardships. Extreme weather events, such as increased heavy rainfall leading to flooding and crop damage or increased temperatures harming crops and reducing yields, pose significant risks to agricultural productivity, particularly for heat-sensitive staples like wheat and maize. Higher temperatures also lead to increased evaporation and transpiration, putting stress on plants and increasing the risk of drought. Additionally, warmer temperatures can expand the range of pests and diseases, potentially causing new outbreaks and damaging crops. These events directly impact agricultural, energy, and financial markets, rendering climate risk a paramount concern and a central focus for researchers and all economic agents (Ye, 2022).

Climate disasters pose a significant threat to the production and supply of agricultural and energy commodities, with potential ramifications for price fluctuations. Extreme weather events can damage or destroy crops, leading to lower yields and reduced overall production. For instance, droughts can cause crop failure, while floods can inundate fields and wash away plants. Climate disasters can damage transportation infrastructure and disrupt supply chains, making transporting agricultural products from farms to markets difficult. This can lead to shortages and price increases.

Fuel, primarily derived from fossil fuels like oil, is essential for powering agricultural machinery and transporting food products. However, burning fossil fuels is a major contributor to greenhouse gas emissions, the primary driver of climate change (Birgani et al., 2022). Thus, the reliance on fossil fuels in the agricultural sector makes food production vulnerable to oil price fluctuations and contributes to climate change that disrupts agricultural activities and further exacerbates food insecurity. When oil prices rise, food costs increase, making it less affordable and accessible, particularly for vulnerable populations. This situation is further compounded by climate change, as extreme weather events like droughts, floods, and heat waves become more frequent and intense due to the continued use of fossil fuels (Sixt &

Strzepek, 2022). These events disrupt agricultural production and energy infrastructure, increasing-price surges.

The delicate relationship between energy and food prices has long been acknowledged in the economic and agricultural spheres (Zhang et al., 2022). However, this connection is increasingly being challenged by a new and formidable threat - climate change’s uncertainty (Ye et al., 2022). The unprecedented nature of climate-induced disruptions to weather patterns, agricultural productivity, and energy resources is introducing unrivalled levels of volatility into both energy and food markets. This unusually volatile environment, characterized by a complex interplay of climate change, energy price fluctuations, and food price instability, necessitates a critical evaluation of the connectivity between these critical economic forces.

Climate disruptions, including extreme weather events and rising temperatures, are projected to disrupt agricultural production and distribution networks, potentially leading to food shortages and price hikes (Fei & Mccarl, 2023). Furthermore, the price of oil, a crucial input for agricultural production and transportation, exhibits significant fluctuations, impacting overall food production costs (Roman et al., 2022). Understanding the intricate relationship between climate risk, oil, and food prices is paramount to formulating effective policies ensuring global food security.

Despite the criticalness of climate change mitigation, including calls for an energy transition (Wuebbles & Jain, 2001) and ethical investment practices to shift away from fossil fuels (Zhang et al., 2022), the impact of climate change on fossil fuel price volatility remains under-examined. Emerging literature underscores the integration of climate risk into asset pricing (Bonato et al., 2023; Lasisi et al., 2022; Li et al., 2023; Zhang et al., 2019). This study extends this trajectory, investigating how uncertainty factoring in climate risk might affect the pricing and volatility of food prices considering oil fuels, a sector synonymous with substantial environmental externalities.

Recent observations indicate that the past century has seen a steady rise in global average temperature, accompanied by increased volatility in fossil fuel prices (Xie et al., 2022), and this period has also witnessed heightened volatility in food prices (Dahl et al., 2020). This coincidence suggests a potential link between climate change, oil prices, and food prices, prompting the need to assess how climate risk influences their connection. Climate risk, encompassing extreme weather events, temperature fluctuations, and policy shifts related to climate change, can disrupt economic systems, especially energy and agricultural markets. Oil prices are particularly sensitive to climate risk due to potential supply disruptions, such as hurricanes affecting oil rigs, and changes in demand, such as shifts toward renewable energy. Food prices, on the other hand, are directly affected by climate risk through impacts on crop yields, livestock productivity, and agricultural supply chains.

Given oil's significant role as a major input in food production and distribution (Ji et al., 2018; Luo & Ji, 2018; Dahl et al., 2020), there is a hypothesized indirect link where climate risk affects oil prices, which in turn influence food prices. This leads us to the research question: does climate risk affect the connection between oil prices and food prices? Specifically, does it alter their relationship, such as their correlation or how changes in one impact the other? Since climate risk impacts both markets, it likely strengthens their connection during high-risk periods. For instance, during heatwaves, both oil supply and crop yields may be affected, thereby increasing the correlation between oil and food price movements.

Climate risk affects oil prices, thereby indirectly influencing food prices, and also directly impacts food prices through changes in crop yields and production resulting in a dual impact. Several studies have analyzed the relationship between climate risk and fossil fuel prices (Krane, 2017; Soeder, 2020; Taskin et al., 2021; Isah & Odebode, 2023; Tumala et al., 2023). Some have assessed the impact of climate change on agricultural commodity markets (Haile, 2017; Li et al., 2023; Makkonen, 2021; Sun et al.,2023). These papers focused on these variables separately without analyzing the interplay of the three variables at once. This is key due to the dual effect of climate change, which directly affects food prices and indirectly through oil prices. The prior group focused on the commodities instead of the prices of the commodities. The usage of prices makes the analysis easier to compare across different countries and regions as they reflect a common unit. Moreover, the price data is more readily available and easier to collect. They are also a signal in a market economy.

This study exhibits conceptual similarity to Tumala et al. (2023) through its investigation of the impact exerted by climate change on fossil fuel prices. However, it advances the literature with several unique contributions. Firstly, the quantification of climate risk employs temperature changes. Temperature change quantifies the deviation of the current temperature from the previous temperature, with positive/negative values signifying correspondingly higher/lower temperatures. This metric aligns with established research demonstrating its capacity to represent climate change trends (see Li et al. 2023), offering advantages over an alternative measure like absolute temperature levels. Focusing on ten countries offers a broader analytical scope than studies that focus solely on one country. This multi-national approach facilitates an examination of potential heterogeneity in food price responses to climate change, allowing for more robust generalizations regarding the relationship.

The paper contributes to the existing literature by employing a novel approach to assess the combined effects of climate risk and oil price dynamics on food prices. We move beyond traditional static analyses by incorporating a dynamic framework that captures the temporal evolution of these relationships. This allows us to examine the immediate impact of climate events and oil price changes and the potential for lagged effects and spillover dynamics on food prices. The adoption of the GARCH-MIDAS modeling framework addresses the well-documented volatility clustering characteristic of high-frequency fossil fuel price data (Amendola et al., 2021; Salisu & Oloko, 2015).

While alternative methodological approaches exist, including FE and RE models (Lu et al., 2019; Fusco, 2022), Granger Causality (Sun et al., 2023; Taskin, 2021), and TVP-VAR models (Ye et al., 2022) – the GARCH-MIDAS framework is particularly well-suited to capture volatility dynamics within this context. The framework is employed for two compelling reasons. Consistent with other GARCH variants, it effectively addresses the inherent conditional heteroscedasticity characteristic of high-frequency data, such as daily fossil fuel prices. This aligns with established literature demonstrating the superior forecasting performance of models accounting for this effect within time series analysis (Westerlund & Narayan, 2015). Secondly, the framework's capacity to accommodate variables measured at different natural frequencies is crucial. This study's food and oil prices are monthly, while climate risk indicators are yearly. The GARCH-MIDAS model circumvents data manipulation (splicing or aggregation) necessitated by FE, RE, or TVP-VAR methodologies. This preserves the distinct temporal dynamics of food, oil prices, and climate risk, enhancing analytical rigor.

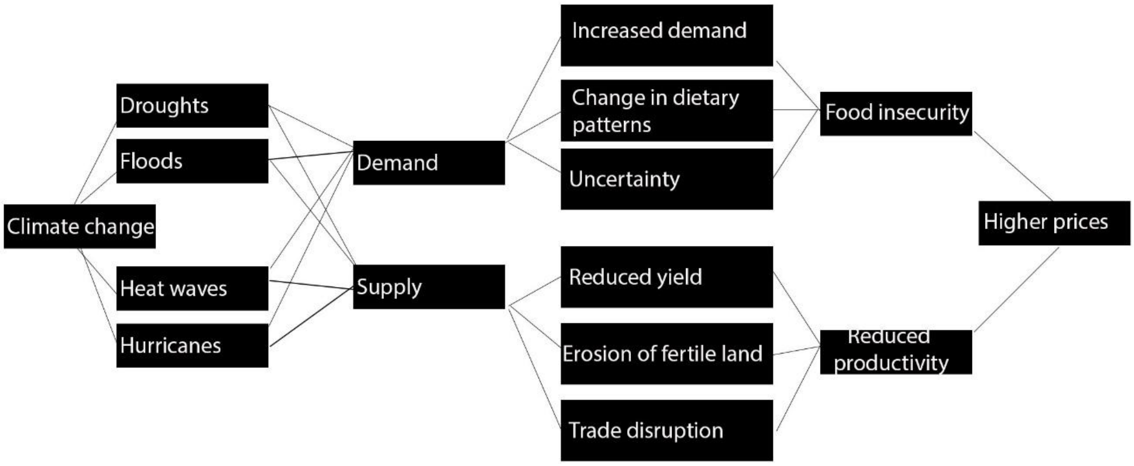
4.1.2 Transmission Mechanisms

Climate risks have profoundly and undeniably impacted economic activities, financial markets, and energy markets. Therefore, thoroughly analyzing the mechanisms by which climate risks influence these systems is crucial for policymakers to develop effective climate, energy, and agricultural policies. Moreover, such analysis provides valuable information to institutional investors in agricultural and energy markets, allowing them to optimize their climate risk management strategies. These transmission mechanisms include both the supply side and the demand side.

The transmission mechanisms on the demand side include increased demand, changes in dietary patterns, and uncertainty. Extreme weather events can lead to food insecurity and shortages in affected regions, driving up demand for staple crops and causing price hikes (Fusco, 2022). In response to rising food prices, consumers may shift their preferences towards cheaper, less nutritious food options, impacting overall market demand. Furthermore, uncertainties around future harvests and potential food shortages can trigger speculation in agricultural commodities, further exacerbating price volatility. The geographical disparities are another mechanism mainly because the impact of climate risks on food prices is not uniform and can vary significantly across regions depending on their specific vulnerabilities and adaptive capacity (Alpino, 2022). Also, government policies, such as export restrictions or subsidies, can influence how climate risks translate into price changes. The interconnectedness of the global food system can amplify the transmission of price shocks from one region to another, hence the need to focus on a region instead of a specific country.

The supply side includes reduced agricultural productivity as a result of disruptions in agricultural inputs and infrastructure, erosion of land fertility, and trade disruptions. Climate change can cause droughts, floods, extreme heat, and pest outbreaks, damaging crops and livestock and reducing yields and production. Floods, droughts, and storms can damage transportation networks, irrigation systems, and storage facilities, increasing the cost and difficulty of accessing essential inputs like fertilizers, pesticides, and water. Intense rainfall and soil erosion can deplete soil nutrients, requiring increased investments in fertilizers and amendments, ultimately raising production costs and reducing yield (Birgani et al., 2022). Lastly, climate-induced events can disrupt trade routes and logistics, making importing food from other regions difficult and expensive, particularly when multiple producing areas are affected simultaneously. Floods can result in rising sea levels and threaten coastal infrastructure, including ports and shipping lanes. This can permanently damage trade routes and make them more expensive to maintain. These disruptions are especially bad for developing countries, which often rely on exporting and importing specific resources or agricultural products. They can also create a domino effect, where problems in one part of the world ripple through the entire trading system (Arora, 2019).

Figure 4.1: Transmission mechanisms from climate risk to food prices

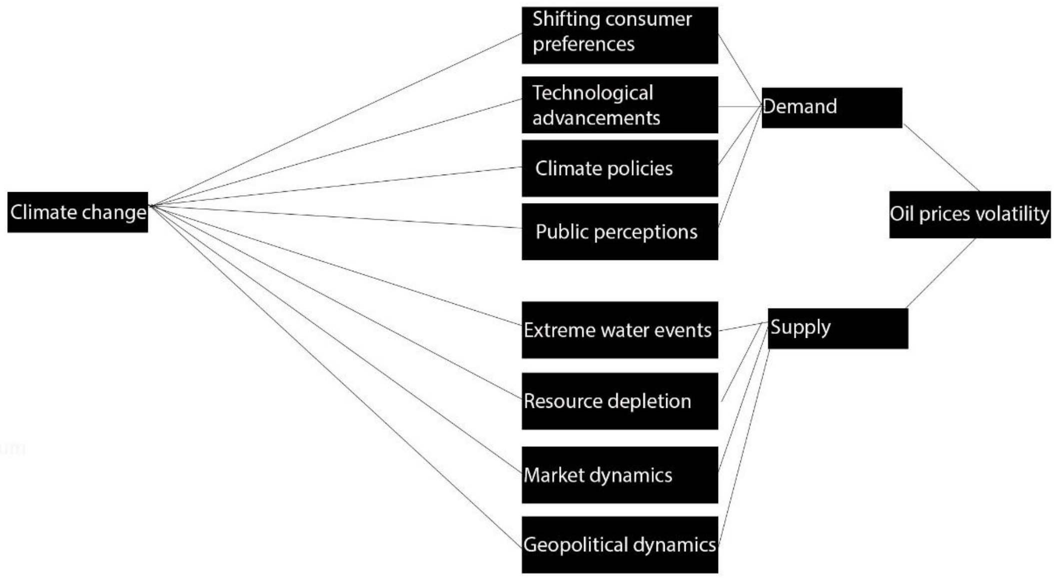


Source: Author's compilation

Climate change can also impact the oil industry through several transmission mechanisms, affecting the demand and supply, as shown in Figure 4.1 (Tumala, 2023). Demand includes shifting consumer preferences, technological advancements, climate policies, and public perception. Growing public awareness about climate change can influence consumer choices. People might opt for electric vehicles or energy-efficient appliances, reducing overall oil consumption. The development of alternative energy sources and energy-efficient technologies can gradually decrease reliance on oil for transportation and other purposes. As the urgency of climate action grows, governments may implement policies like carbon taxes or regulations on vehicle emissions (Lasisi et al., 2022). These can make oil-based transportation less attractive, leading to decreased demand for oil.

On the other hand, the supply-side mechanisms include extreme weather events, resource depletion, geopolitical instability, and market dynamics. Extreme weather events like storms and hurricanes can damage offshore oil rigs and disrupt production. Climate change might also increase the frequency and intensity of such events. Oil is a finite resource; continued extraction will eventually lead to depletion in certain regions. Climate change can exacerbate this by impacting the accessibility of some oil reserves, like those in the Arctic (Isah et al., 2023). Moreover, it can contribute to resource scarcity and regional conflicts, potentially disrupting oil production and transportation routes in some areas. Market dynamics include price fluctuations and investment decisions (Li et al., 2023). Shifts in supply and demand due to climate concerns can lead to price volatility in the oil market. While extreme weather events might disrupt supply and temporarily inflate prices, a long-term decline in demand could lead to a decrease in oil prices. Financial institutions and investors might become more cautious about investing in the oil sector as climate risks become more prominent. This could limit funding for new oil exploration and production projects, driving capital towards renewable energy sources.

Figure 4.2: Transmission mechanisms from climate risk to oil prices

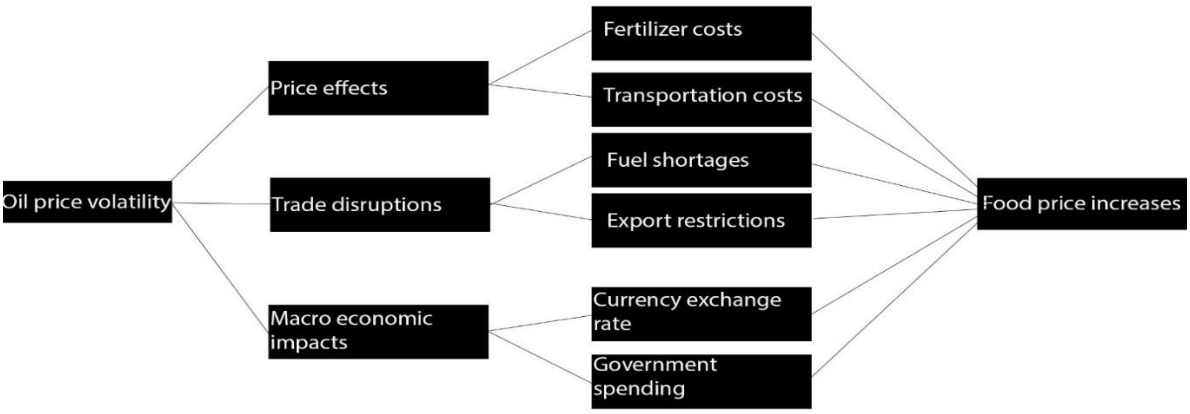


Source: Author's compilation

Justice will be done if the transmission mechanisms between oil and food are explored. Oil prices and food security are interconnected through several complex transmission channels, including price effects, trade disruptions, and macroeconomic impacts. Price effects come through increased costs of major inputs like fertilizer and transportation. Oil is a major component of fertilizers used in agriculture. When oil prices rise, fertilizer production costs increase, leading to higher fertilizer prices for farmers. This can squeeze profit margins and force some farmers to reduce fertilizer use, potentially impacting crop yields. It is also a major fuel source for transportation, including the movement of agricultural products from farms to consumers. Rising oil prices lead to higher transportation costs, which can inflate food prices for consumers, especially in regions far away from the farming regions. Trade disruptions can be in the form of fuel shortages or export restrictions. Fuel shortages can occur in extreme cases of high oil prices or supply disruptions. This can limit the transportation of food within and between countries, hindering access to food supplies and potentially leading to price spikes in affected areas (Dalheimer et al., 2021).

Furthermore, countries that rely heavily on oil revenues might restrict food exports to ensure domestic food security, especially if rising oil prices pressure their food systems. This can disrupt global food supplies and contribute to price volatility in importing countries. The macroeconomic impacts are in the form of currency exchange rates and government spending. Fluctuations in oil prices can affect currency exchange rates (Bonato et al., 2023). If a country heavily reliant on oil exports experiences a price drop, its currency might weaken. This can make food imports more expensive for that country. Oil revenue plays a significant role in the budgets of many oil-exporting countries (Hong et al., 2019). A decline in oil prices can lead to reduced government spending, potentially impacting programs that support agriculture or social safety nets for vulnerable populations.

Figure 4.3: Transmission mechanisms from oil to food prices



Source: Author’s compilation

In response to the multifaceted challenges posed by climate change, various mitigation measures have been implemented, primarily geared towards curbing greenhouse gas emissions and bolstering societal resilience to climate risks (Xie et al., 2022). These interventions encompass initiatives such as the optimization of energy infrastructure and the accelerated deployment of renewable energy sources (Ghadge et al., 2020). Notably, these mitigation efforts have demonstrably reshaped the prospects of energy markets (Li et al., 2023). However, a lot still needs to be done to curb the risks in the agricultural sector, which has affected global food prices and has led to food insecurity, mainly in the region where farming is the main source of income and food.

The intricate relationship between climate, energy, and food security is fundamental to human existence in these regions. Climate change and oil price volatility intersect, disrupting the delicate balance of global food security. This research explores this critical nexus, analyzing the interplay of these factors and their profound implications for food security and the necessity for human well-being. The overarching impact of climate risks on economic activities, financial markets, and energy markets has been unequivocal and far-reaching (Haile, 2017). Thoroughly dissecting the intricate mechanisms via which such risks intertwine with these vital economic systems is paramount for policymakers seeking to design efficacious climate policies. Furthermore, such analysis equips institutional investors in agricultural, financial, and energy markets with invaluable insights, empowering them to optimize their climate risk management strategies. Through rigorous analysis of empirical data, econometric modeling, and country-specific studies, it sheds light on the dynamics at play. It delves into the specific vulnerabilities of different regions and populations, exposing the uneven distribution of risk and the disproportionate burden of marginalized communities (Tumwesigye et al., 2019).

4.2 Background

4.2.1 Sub-Sahara Agricultural Sector

Agriculture is the backbone of most sub-Saharan African economies, contributing an average of 15% to GDP. This ranges from less than 3% in Botswana, mainly because most of its land is covered by the Kalahari Desert and South Africa, to over 50% in Chad (FAO, 2022). Chad's larger reliance on agriculture for employment, exports, and subsistence needs, coupled with limited opportunities in other sectors, leads to its higher agricultural contribution to GDP compared to other countries. It is important to note that all countries face unique challenges and opportunities in developing their economies, and the future landscape of their agricultural sectors could continue to evolve. It is also the source of employment for about 50%, primarily in small-scale farming, and a major source of exporting earnings. Despite all these, the sector has challenges of lowest productivity in the world due to factors like poor soil fertility, inadequate access to improved seeds and fertilizers, and limited irrigation (Mirón et al., 2023). Another challenge is climate change, which makes the region more vulnerable. The impacts of climate change include droughts, floods, and erratic rainfall patterns, which threaten food security and livelihoods. The impacts of climate change are taking a tour of the region mainly due to most countries being under tropical climates, which feature higher temperatures throughout the year (Arora, 2019).

It is, therefore, crucial to assess the impact of climate change on the agricultural sector to safeguard food security, economic stability, livelihoods, and environmental sustainability, as well as promote regional cooperation to address this global challenge. Understanding how climate change will affect crop yields, livestock production, and overall agricultural productivity is crucial for ensuring food security. Agriculture significantly contributes to the global economy, providing many countries with jobs, income, and exports. Millions of people worldwide, particularly in developing countries, rely on agriculture for their livelihoods (Sixt & Strzepek, 2022). Climate change can disproportionately affect these populations, pushing them further into poverty and hunger. Assessing the impact helps us develop targeted interventions to support vulnerable communities and ensure equitable access to food and resources. Agriculture also has a significant environmental footprint. Climate change can exacerbate existing problems like water scarcity and soil erosion. By understanding how climate change affects agriculture, we can develop more sustainable farming practices that minimize environmental damage and promote long-term agricultural viability.

4.2.2 Climate Change in Sub-Saharan Africa

Sub-Saharan Africa, characterized by its diverse landscapes and rich biodiversity, confronts a significant threat of climate change. The region is experiencing accelerated warming, surpassing the global average by 1.5 times, with certain areas witnessing even more pronounced temperature increases (Fusco, 2022). This climatic shift disrupts ecological equilibrium, manifesting in erratic rainfall patterns, heightened drought frequency, and devastating floods. The increasing prevalence of arid landscapes in Sub-Saharan Africa due to climate change necessitates urgent attention due to its multifaceted and cascading impacts. Arid landscapes are characterized by water scarcity, a prevalent condition in many parts of SSA. Climate change further intensifies this issue as rising temperatures increase evaporation and reduce water availability for agriculture, livestock, and human consumption (Mirón et al., 2023). This can trigger conflicts over water resources, displacement of communities, and heightened vulnerability to drought. Aridity severely hampers agricultural productivity as crops struggle to thrive in water-stressed environments. This directly threatens food security in a region heavily reliant on agriculture for livelihood and sustenance. Declining yields and crop failures can lead to food shortages, price hikes, and increased import reliance.

The agricultural sector, a cornerstone of Sub-Saharan economies, faces heightened vulnerability due to climate change. Shifting rainfall patterns and escalating temperatures contribute to diminished crop yields, jeopardizing food security for vast populations. Fields once abundant with maize and sorghum now produce scanty harvests, casting a shadow of hunger over communities. Moreover, climate change exacerbates existing water scarcity challenges, with shrinking glaciers, dwindling rivers, and diminishing groundwater reserves threatening human populations and the region's rich biodiversity (Krane, 2017). The delicate balance of ecosystems is disrupted as rising temperatures and habitat loss drive species toward extinction, endangering the vital services these ecosystems provide. Given the interconnectedness of global systems, climate change in Sub-Saharan Africa necessitates a holistic understanding of its impact across various sectors to inform effective and relevant policy interventions.

4.2.3 The Oil Sector in Sub-Sahara

The oil sector in Sub-Saharan Africa presents a complex picture with significant opportunities and challenges. Few countries produce oil in the region, the major ones being Nigeria, Angola, and South Sudan; the rest are oil importers. The sector represents a significant source of revenue, mainly for the oil producers, which will spill over to the region through regional trade. It even reduces the transportation cost since the countries will be closer to each other. It also contributes substantially to government budgets, foreign exchange earnings, and job creation (Bonato et al., 2023). However, the reliance on oil also creates vulnerability to price fluctuations in the global oil market, impacting these countries' economies. The oil reserves and production are concentrated in a few countries, resulting in uneven distribution and regional development disparities, with oil-producing countries experiencing different economic realities than non-producing ones. Oil exploration and production can have negative environmental impacts, including pollution, habitat destruction, and climate change, hence the need to assess the impact of climate change and oil on food prices (Taskin et al., 2021).

The interplay between oil prices and Sub-Saharan Africa's food security constitutes a pivotal element in comprehending the region's vulnerability to food crises. The major issue is that most countries rely heavily on imported oil for energy needs, making them acutely susceptible to global oil price fluctuations (Ji et al., 2018). This dependence translates to increased transportation costs; higher oil prices inflate the cost of transporting food and agricultural inputs, impacting consumer prices and market accessibility (Gollin & Rogerson, 2014). It also results in fluctuations in fertilizer production. Oil is a key component in fertilizer production, making fertilizer prices sensitive to oil price changes. This includes powering machinery for mining raw materials like phosphate rock and potash, operating processing plants, and transporting finished fertilizers to farms. This directly affects agricultural productivity and food production costs (Luo & Jio, 2018). Additionally, it makes the region vulnerable to global economic shocks. Historically, global economic downturns often coincide with lower oil prices, further impacting export revenues for oil-producing countries within the region, straining resources, and undermining food security initiatives. However, the degree of vulnerability to oil price fluctuations varies across the region. Countries with limited domestic oil production are more exposed than those with some production level, like Nigeria.

4.3. Literature Review

4.3.1 Theoretical Literature

The intricate relationship between energy and food prices has long been a subject of economic inquiry. However, the emergence of climate change as a major global threat necessitates a re-evaluation of this dynamic. This paper delves into the theoretical framework surrounding climate risk, its impact on oil prices, and the subsequent spillover effects on food prices. The major theory is the production theory, which focuses on how firms make production decisions to minimize costs while achieving desired output levels (Lu et al., 2019). Extreme weather events can disrupt oil production infrastructure, damage drilling platforms, and hinder the transportation of oil, leading to supply disruptions and potential price hikes. Climate change can exacerbate challenges in accessing freshwater resources for oil exploration activities like hydraulic fracturing. This scarcity can increase production costs and potentially limit supply.

Supply disruptions and scarcity of resources required to produce oil will lead to rising oil prices (Ghadge et al., 2020). This will affect several aspects of food production, mainly the major input costs. These inputs include oil and fertilizers. Oil is a key input for machinery operation, irrigation systems, and transportation. Higher oil prices translate to increased farm energy costs, impacting production costs. The same applies to fertilizer production, which is an energy-intensive process. Rising oil prices can lead to higher fertilizer costs, another significant expense for farmers. The dual increase in input cost will result in spillover effects on food prices. The production theory predicts that when firms face rising input costs like energy and fertilizers, they have two main options: reduce output or pass on the cost to the consumers. If the price increase is significant, farms might reduce production to minimize losses. This decrease in supply would put further upward pressure on food prices. More commonly, farms will likely try to maintain production levels but will need to recoup their increased costs. This is achieved by raising consumer food prices (Gollin & Rogerson, 2014).

The Dutch disease theory was developed by Corden (1982 and 1984), suggesting that a sudden influx of resource wealth, like oil revenue, can have negative consequences for other sectors of the economy. When a country discovers and starts exporting a valuable resource like oil, it experiences a surge in revenue (Fardmanesh, 1991). This can lead to a stronger currency. The stronger currency makes exports from other sectors, like agriculture, more expensive on the global market. This can lead to a decline in these sectors as they become less competitive. It, therefore, implies that less revenue in that sector leads to less investing, further reducing the supply and increasing prices (Sachs & Warner, 2001). The economy becomes increasingly reliant on resource revenue, potentially neglecting investment in other sectors and making those sectors vulnerable to future price fluctuations. Benjamin et al. (1989) studied Dutch disease in Cameroon and found that the agricultural sectors suffer more than the manufacturing sectors in oil-producing countries. He also finds that the effects of Dutch disease can be reversed mainly with the government.

The impact of climate risk leads to "Reverse Dutch Disease." In the context of climate change, the Dutch disease theory can be seen as a cautionary tale. Countries heavily reliant on fossil fuel exports might face economic challenges if they have not diversified their economies before a decline in oil prices. This "reverse Dutch Disease" scenario can be exacerbated by climate risk as it can accelerate the decline in oil revenue. Climate change can disrupt oil production and lead to future price declines as the world transitions to cleaner energy sources. If oil prices fall due to climate concerns, a nation heavily reliant on oil exports will see a decrease in revenue (Porteous, 2022). This can weaken its currency and increase unemployment as the labour is laid off. The weaker currency might not necessarily revitalize other previously weakened sector during the oil boom. Imported goods could become more expensive, putting a strain on the economy (Venables, 2016). The dependence on oil revenue might have stifled investment and development in other sectors, making it difficult for the nation to diversify its economy quickly in response to declining oil prices.

Another fundamental economic theory that can be applied also to understand the relationship between climate risk, oil prices, and food prices is supply and demand. Climate change can disrupt oil production in several ways. Extreme weather events like droughts and hurricanes can damage infrastructure and hinder extraction. Rising sea levels can threaten coastal oil fields. Resource scarcity, like limited freshwater availability for hydraulic fracturing, can make production more challenging (Jiang et al., 2018). Climate change can negatively impact food production through increased heatwaves and droughts, leading to lower crop yields. Changes in precipitation patterns disrupt water availability for irrigation. More frequent floods and storms cause damage to farmland and crops. When climate-related disruptions restrict oil supply, the basic principle of supply and demand comes into play. With a decrease in supply and a relatively stable or even increasing demand due to population growth and economic development, oil prices are likely to rise (Nkang, 2018). Like oil, climate change can lead to decreased food supply due to lower yields and disruptions. This, coupled with a steady or growing demand for food, can increase prices.

The real asset theory suggests that investors seek assets that can provide a hedge against inflation. Climate change poses an inflation risk through its impact on oil and food prices. As discussed, climate disruptions can restrict oil supply and lead to price increases. Investors might seek assets like commodities or real estate that can potentially appreciate alongside inflationary pressures on oil prices. Climate change can also lead to higher food prices due to lower yields and disruptions. Investors might consider agricultural commodities like grains or farmland as potential hedges against inflation in the food sector. When climate change threatens to increase oil and food prices, these assets become attractive as potential hedges against inflation. In some cases, investors might see oil and food as real assets. If they believe prices are likely to rise due to climate concerns, they might invest in oil futures contracts or agricultural commodities like grains to profit from the price increases (Li et al., 2023).

Portfolio Diversification theory emphasizes incorporating environmental, social, and governance (ESG) factors into investment decisions. Investors might consider climate-aware investment strategies and food security investment. The prior strategies focus on companies actively transitioning to cleaner energy sources and sustainable practices (Zhang et al., 2023). This can be relevant for the oil sector, where companies with a strong focus on renewables might be seen as more resilient in the face of climate risk and potential future oil price declines. Some investors might look toward companies involved in sustainable agriculture, alternative protein sources, or technologies that can improve crop yields despite climate challenges (Lasisi et al., 2022).

Climate change introduces uncertainty into the investment landscape for both oil and food production (Leal Filho et al., 2022). This uncertainty is best described through economic concepts like risk aversion and market volatility. Uncertainty surrounding climate change and its impact on oil and food prices can influence investment decisions in several ways. Investors might demand higher returns on investment (risk premiums) for assets exposed to these sectors. Oil companies facing an uncertain future due to climate concerns might decline their stock prices as investors demand a higher return for the increased risk (Ye, 2022). Additionally, investors might shift their portfolios towards assets perceived as less risky in the face of climate uncertainty (Kunene et al., 2023). This could lead to reduced investment in oil companies and increased investment in renewable energy or sustainable agriculture sectors. Climate change introduces uncertainty in the supply and demand dynamics of the oil and food market. This can lead to increased market volatility with more frequent and severe price fluctuations.

Uncertainties surrounding future food and oil production due to climate disruptions can lead to volatile prices. Investors and speculators might contribute to this volatility by reacting to news and events that signal potential shortages or disruptions. Climate change can lead to unpredictable weather patterns and potential crop failures, creating uncertainty in food production and market anxiety. This can cause food prices to fluctuate significantly, making it difficult for consumers and businesses to plan effectively (Hong et al., 2019). This can lead to investors demanding higher risk premiums for assets exposed to these sectors. Increased uncertainty regarding future oil prices due to climate concerns might lead investors to demand a higher return on investment for oil company stocks, which exerts pressure on the prices. The potential for climate-induced disruptions to food production can make investments in agricultural companies or farmland riskier. Investors might demand higher returns to compensate for this additional risk (Huynh et al., 2020). These frameworks highlight how investors consider climate risk, oil, and food prices when making investment decisions. Investors might seek inflation hedges, prioritize Environmental, Social, and Governance (ESG) factors, consider risk premiums, or incorporate social responsibility when allocating capital. By understanding these dynamics, we can better understand how climate change influences investment patterns and potentially shapes the future of these interconnected markets.

Economic actors do not always have perfect information, and cognitive biases can influence decision-making (Porteous, 2022). This leads to adverse selection theory that can play a role in the complex relationship between climate risk, oil prices, and food prices. Climate change introduces significant uncertainty in the production of both oil and food. Extreme weather events, rising sea levels, and resource scarcity can lead to unforeseen costs and risks for producers. Companies exploring oil might not have complete information about the potential future impacts of climate change on extraction, infrastructure damage, or stricter environmental regulations. Farmers also face uncertainty due to climate change (Porteous, 2020). They might not have complete information about the potential severity of droughts, floods, or heatwaves that could impact their crops. This can lead to two possible choices by farmers depending on whether they are in vulnerable or stable regions. Farmers in vulnerable regions might be more motivated to sell their land or intensify production (potentially depleting resources) in anticipation of future hardships due to climate change. Farmers in more stable regions might be cautious about investing in long-term improvements or expanding production due to the uncertain impacts of climate change on future yields. Understanding adverse selection (Carter et al., 2017) in this relationship is key to enacting policies that reward sustainable production methods in the oil and food sectors, creating a level playing field and encouraging long-term resilience.

Theoretical frameworks like production theory, supply and demand, and investment theory provide a foundation for understanding the complex relationships between climate risk, oil prices, and food prices. However, climate change introduces significant uncertainty that disrupts these traditional models. Adverse selection theory highlights how this uncertainty can create information asymmetry between producers and the market. This can lead to situations where companies or farms with a higher risk of climate disruption prioritize short-term gains over long-term sustainability, potentially leading to unsustainable extraction methods in the oil sector and depletion of resources in the food sector, lower investment in renewables (oil) and climate-resilient agriculture (food). Concepts like Dutch disease and reverse Dutch disease add another layer of complexity. Resource booms due to high oil prices can lead to a decline in other sectors if not managed properly. The reverse can occur if the oil sector declines due to climate concerns. By acknowledging the complex theoretical linkages and potential pitfalls of adverse selection, we can devise strategies to build a more resilient and sustainable energy and food security future in the face of climate change.

4.3.2 Empirical Literature

A well-established body of economic literature explores the potential disruptions climate change can cause to oil and food production separately. Global food security faces a multitude of challenges, with both climate change and volatile energy prices posing significant threats. Climate disruptions, including extreme weather events and rising temperatures, are projected to disrupt agricultural production and distribution networks, potentially leading to food shortages and price hikes (Birgani et al., 2022; Gupta et al., 2021; Mirón et al., 2022). Furthermore, the oil price, a crucial input for agricultural production and transportation, exhibit significant fluctuations, impacting overall food production costs (Dalheimer et al., 2021; Fasanya & Akinbowale, 2019). The literature summary is presented in the table below.

Table 4.1: Empirical Literature Summary

Author	Year	Region	Methodology	Findings
Lu et al.	2019	China	Fixed effects	Climate change significantly affects grain production
Li et al.	2023	USA	GARCH-MIDAS & DCC-GARCH	Climate risk significantly affects the volatility of energy stocks
Engle et al.	2013	USA	GARCH - MIDAS	Long-run components account for half of the predicted volatility
Isah et al.	2023	World	GARCH	Oil market volatility rises with climate risk
Taskin	2021	World	Granger Causality	Global temperature affects the expectations of agriculture and energy commodities
Fusco	2022	North & East Africa	Fixed effects and Random effects	Climate change affects food production. An increase in rainfall results in increased food production. Countries with higher income are resilient
Sun et al.	2023	World	Granger Causality	Bi-directional relationship between El Nino and agricultural commodities
Makkonen	2021	World	Quantile Regression	Temperature anomalies have both positive and negative impacts on agricultural commodities
Tumala et al.	2023	USA	GARCH-MIDAS	Strong connection between climate change and volatility of fossil fuels
Lasisi et al.	2022	World	Literature Review	Stock market volatility significantly responds to climate policy uncertainty

Mei et al.	2019	World	GARCH - MIDAS	MPU positively affects oil volatility. The impact of EPU is mixed
Lazarus et al.	2018	World	GARCH - MIDAS	Supply-side policies may increase public support for climate action
Zhang et al.	2022	China	DID and Propensity Score matching	Enterprises increase their market competitiveness by increasing strategic flexibility in the face of environmental regulation

Source: Author's compilation

Many studies have assessed the impact of climate change on food production and food prices (Alpino, 2022; Arora, 2019; Birgani et al., 2022; Fusco, 2022; Gupta et al., 2021; Haile et al., 2017; Mirón et al., 2022; Rani, 2023; Sixt & Strzepek, 2022; Tumwesigye et al., 2019). They are divided into two groups, with the first group reviewing the papers which have analysed the relationship between climate change and food production. Specifically, Alpino, (2022), Miron et al. (2022), Rani, (2023), Sixt & Strzepek, (2022), and Tumwesigye et al. (2019) in their reviews found that climate change can impact food prices through agricultural food loss and rising food prices. Climate change affects food prices by decreasing crop yields due to extreme weather events like drought and floods, leading to increased agricultural product prices. These papers conveyed that climatic conditions are changing globally, affecting food systems. Miron et al. (2022), pointed out that developing countries are more vulnerable due to their lower capacity to mitigate and address climate change impacts. This results in greater uncertainty in terms of food provision and market speculation. However, these papers only review the literature without delving into quantitative analysis, which is important because numbers speak for themselves. It allows one to test hypotheses and arrive at more objective conclusions through statistical methods. By analyzing data, quantitative studies can help establish cause-and-effect relationships between variables.

Interestingly, Sixt and Strzepek (2022) developed a new food trade and vulnerability index to assess the food security vulnerability due to climate change impacts on the food trade. The analysis shows that rising temperatures and extreme weather events are expected to disrupt agricultural productivity in many food-exporting countries, leading to food price instability and threatening rural livelihoods and sustainable food security. This is in line with Arora (2019), who pointed out that climate change is one of the most defining concerns of today's world and has greatly reshaped or is in the process of altering the earth's ecosystems. The production of major cereal crops is projected to decline by 20-45% in maize yields, 5-50% in wheat, and 20-30% in rice by the year 2100 if current GHG emissions and climate change continue. This could lead to reduced production, spiked food prices, and difficulty meeting a growing population's needs. The papers do not consider potential adaptation strategies or policy interventions that could mitigate the negative impacts of climate change on agriculture production, food trade, and security and sustainable solutions.

The second group of studies employed quantitative methodologies, including meta-analysis discussed by Birgani et al. (2022) and dynamic panel data analysis using the system GMM model (Fusco, 2022). Birgani et al. (2022) discovered that drought significantly impacts food prices. They predict that the ratio of food prices to other goods will increase substantially both before 2020 and between 2020 and 2049. This finding is especially worrisome considering the additional difficulties posed by pandemics and political unrest. Fusco (2022) examines the climate change-food security nexus in Northern and Eastern Africa, identifying a positive relationship between greenhouse gas emissions and malnourishment and a negative relationship with food security. However, this study's timeframe may not fully capture recent developments, and its assumption of linearity may not adequately represent the complex dynamics between climate change and food prices.

The paper by Gupta et al. (2021) used the General Equilibrium analysis to assess the distributional impact of climate change in India. Their results support that climate change leads to agricultural productivity losses, which causes food prices to rise. Most agents, including farmers, lose from climate change. Landless poor experience a welfare loss six times greater than the first-order impact on GDP. Like Haile et al. (2017), the results point out that climate change poses serious risks to global food systems, including crop losses, decreased yields, fluctuating food prices, and impacts on fish and aquatic resource output. They used the Fixed Effects model and found that climate change is altering the world's food systems, leading to crop losses, decreased yields, and fluctuating food prices. Nutritional quality and crop yields are declining due to climate change's impact on the growing environment. The paper highlights the vulnerability of the global food supply chain to climate change, including the risks of crop losses, decreased yields, and fluctuating food prices. The use of global prices loses specific country analysis since the impact of climate change is different across regions and countries. Additionally, the analysis is based on historical data from 1961 to 2013, which may not fully capture the potential impacts of climate change and weather extremes in the future.

The above papers focused on climate change and food. There is an extant which focuses on climate change and fossil fuels. Tumala et al. (2023) investigated the connection between climate change and the volatility of fossil fuel prices using the GARCH-MIDAS framework, which accommodates mixed data frequencies and, by extension, circumvents information loss due to splicing or aggregation of one variable for the other. The results showed that climate change significantly impacts fossil fuel prices, with a positive relationship between the two variables. The study found that an increase in global temperature leads to an increase in fossil fuel prices. The study used global prices, thereby failing to explore the regional or national-specific impacts of climate change on fossil fuel prices. Different regions or countries may experience varying effects.

Isah et al. (2023) investigates the impact of climate risk on the oil market. It aims to identify the degree to which climate risk contributes to the persistence of volatility in the oil markets. In this paper, the authors employ the classic GARCH (1,1) and its extended variant (GARCH-X) to identify the degree of oil market volatility due to climate risk. They find that climate risk increases the persistence of volatility in the oil markets. The study does not consider the specific mechanisms through which climate risk affects oil market volatility, such as the influence of extreme weather events or policy changes. The study does not account for potential regional variations in the relationship between climate risk and oil market volatility. Our study will do country analysis to account for country variations, which are key mainly due to the geographical location.

Taskin et al. (2021) examine the relationship between weather conditions, specifically temperature anomalies, and commodity futures prices, considering the significance of global warming and climate change. Suppose global average temperatures rise 4 to 6 degrees above preindustrial levels. In that case, severe disruptions of global ecosystems are expected, including self-reinforcing spirals of global warming, acidification of ocean waters, flooding of coastal regions, severe weather events, the spread of tropical diseases, and the collapse of agriculture. The paper utilizes econometric techniques, specifically vector autoregression (VAR) models, to analyze the relationship between temperature anomalies and commodity futures prices. The econometric techniques used in the study may have limitations in their assumptions and specifications. However, the study fails to account for regional variations in the impact of temperature anomalies on different commodities.

Soeder (2020) acknowledges that tapping into fossil fuels has led to a significant expansion of human enterprise and prosperity. However, it has also released toxic amounts of carbon dioxide into the atmosphere, endangering the future viability of human civilization. Suppose global average temperatures rise 4 to 6 degrees above preindustrial levels. In that case, severe disruptions of global ecosystems are expected, including self-reinforcing spirals of global warming, acidification of ocean waters, flooding of coastal regions, more frequent severe weather events, the spread of tropical diseases into temperate regions, and the collapse of agriculture in many parts of the planet. The paper does not provide a comprehensive examination of the potential economic and social impacts of the collapse of agriculture in many parts of the planet.

Krane (2017) analysed recent literature on climate action strategy and found that a new or intensified set of risks has arisen for the fossil fuel industry, including government policies and legislation, financial restrictions among lenders and insurers, hostile legal and shareholder actions, changes in demand and geopolitics, as well as the onset of new competitive forces among states and technologies. This compilation and categorization of the various forms of climate risk facing the various sectors highlights the multifaceted challenges that are not easily quantifiable. based on an analysis of recent literature. The paper does not attempt to quantify the risks or their effects on prices and revenue. Traditional models, such as ordinary least squares (OLS) or simple autoregressive models like VAR and ARCH, often fail to account for the time-varying nature of volatility in economic variables. These models assume constant variance, which can overlook significant fluctuations in data.

The GARCH-MIDAS model allows for capturing time-varying volatility and incorporating high-frequency data (Li et al., 2023). This improves the model's ability to reflect real-world economic conditions and enhances forecasting accuracy. It is also an advanced model that can accommodate asymmetries by incorporating different reaction coefficients for positive and negative shocks (Tumala et al., 2023). This provides a more nuanced understanding of the underlying relationships and improves the robustness of the findings. By addressing these limitations, advanced models like GARCH-MIDAS offer a more sophisticated and accurate approach to analyzing the dynamic relationship between oil and food prices, and climate risk This model will give consistent and unbiased results helping in providing valuable insights for policymakers and stakeholders.

4.4 Data and Methodology

Macroeconomic data is usually characterized by data with different frequencies, and this poses a challenge to the model and the results. This is like the data used in this paper where we have monthly food prices and oil prices from FAO (Food and Agriculture Organization) and World Bank Commodity Price data respectively. All countries' Climate risk data is extracted from FAO in an annual form. The temperature change is used as the proxy.

Researchers have devised ways to deal with the problem of data with different frequencies, which include up-sampling and aggregation, among others. Up-sampling is replicating lower-frequency data to create higher-frequency data. Aggregation is decomposing high-frequency data into lower-frequency data. These methods result in inaccuracies and loss of information, which might be important for understanding the dynamic linkages between the variables. Engle et al. 2013 propose the GARCH-MIDAS model (Generalized Autoregressive Conditional Heteroskedasticity with Mixed Data Sampling. This model combines GARCH (Generalized Autoregressive Conditional Heteroskedasticity), which captures volatility patterns in a time series, with MIDAS (Mixed Data Sampling), which allows incorporating information from a different data source like climate risk to explain volatility in the main variable like food prices (Jiang et al., 2017). It can effectively handle time series data with mixed frequencies. This is particularly valuable for analyzing economic and financial data, where variables can be observed at different intervals.

Converting data into return series is a valuable technique for analyzing financial and economic data (Fasanya et al., 2019), especially when dealing with non-stationary data or focusing on relative changes, normalization, risk analysis, or model building. Non-stationary means that the statistical properties, like the data's mean and variance, change over time, resulting in spurious estimates. Returns represent the percentage change between two data points, allowing for easier comparison across different assets or periods. Additionally, returns are directly related to risk. By analyzing the volatility of returns, we can assess its associated risk. The return series for oil and food prices are calculated as follows: $r_{i,t} = ln\ (P_{i,t}) - \ln\left(P_{i,t-1}\right)$ with $r_{i,t}$ representing the return series of price i in period t. $P_{i,t}$ is the price on the day i in month t with i = 1,…, N and $t = 1, \ldots, T$.

The GARCH-MIDAS has two main parts: one for the average value (mean) and another for the conditional volatility of conditional variance. The variance part is especially interesting because it is divided into short-term and long-term components (Conrad et al., 2018). Assume t to be fixed as it represents a specific month, even though it technically refers to a window of time. This window size will be chosen later based on the best model for our data. The return happens on a specific day (i) within this chosen month (t), and will be written as:

$$r_{i,t} = \mu + \sqrt{\tau_i h_{i,t}}\, \varepsilon_{i,t}, \quad \varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1), \;\; \forall_i \; i = 1, \dots N_t \qquad (1)$$

Equation 1 is the mean equation representing the average level of the data being analyzed. The return series' unconditional mean is represented by μ, $\tau_i h_{i,t}$ represents the long-term and short-term conditional volatility respectively and $\varepsilon_{i,t}$ is the error term. In $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$, $\Phi_{i-1,t}$ represents the information set up on the day $(i-1)$ of month t. The short-term component is assumed to follow the GARCH (1,1) process specified as follows:

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

Where α is the ARCH term that captures the impact of the most recent error (unexpected change) on the current volatility and is expected to be greater than zero, $\alpha > 0$. β is the GARCH term that captures the influence of past volatility on current volatility. These parameters are restricted to be positive or zero ($\alpha > 0, \; \beta \geq 0$) and their sum must be less than 1 ($\alpha + \beta < 1$) to ensure the model is stable.

The traditional approach by Merton (1980) and others used raw monthly volatility to represent long-term trends. This model does things differently for the τ_t component. Instead of using the raw monthly volatility (RV_t), this model "smooths" it out using a technique based on MIDAS regression and filtering to capture the long-term trends in volatility, providing a more nuanced picture than just using the raw numbers. The GARCH-MIDAS smoothed realized volatility is given as:

$$\tau_t = m + \theta \sum_{k=1}^{K} \vartheta_k (w_1, w_2) RV_{t-k} \qquad (3)$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \quad (4)$$

Too volatile data needs to be weighed as in equation 3 using a flexible method of Beta. This powerful tool allows you to control how much weight is given to different data points from the past. Imagine points further back in time fading in importance as you move forward. Beta weighing lets you fine-tune this fading effect. The weighing in Equation 3 can be specified as follows:

$$\vartheta_t(w_1, w_2) = \frac{(k/K)^{w_1-1}(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(j/K)^{w_1-1}(1-j/K)^{w_2-1}} \; Beta \quad (5)$$

Beta is a more advanced approach that allows for a lot of flexibility in how the data points are weighted. It considers the influence of data points from various points in the past (lags) and assigns them weights based on a beta function. This beta function can be adjusted to create different weighting schemes. The weights can be set to gradually increase or decrease over time, giving importance to older data points. The weights can be configured to create a bell-curve shape, where data points closer to the centre (present) have the most weight, and importance falls off for data points further in the past. The GARCH-MIDAS specified assumes a fixed period. This makes it parsimonious, meaning it avoids unnecessary complexity. In simpler terms, the GARCH-MIDAS model achieves good results with a fixed set of tools, unlike other models that need to keep adding more parameters for increasingly complex data. This makes it a more manageable and efficient approach. It also offers a significant benefit in that comparing different GARCH-MIDAS models that use different periods becomes easier.

Instead of a fixed monthly window, the model can use a "rolling window." With the rolling window, both τ (long-term volatility) and g (something related to the model, likely capturing short-term effects) are updated every day. This allows the model to react and adapt to changes much faster than the fixed monthly approach, making it more adaptable to changing data. Therefore, a GARCH-MIDAS model with a rolling window RV is a more dynamic version that constantly adapts to new information, making it potentially more accurate in capturing how volatility changes over time. Its rolling window RV can be expressed as:

$$RV_i = \sum_{j=1}^{N'} r_{i-j,}^2 \tag{6}$$

The GARCH-MIDAS model with rolling window RV uses daily data to capture volatility using the notation r_{i-j}. It allows us to use the return data from previous days up to j days back without explicitly storing and managing all those individual days' data. It simplifies the process without losing the information needed for the analysis. The τ component can be redefined as:

$$\tau_i = m + \theta \sum_{k=1}^{K} \vartheta_k(w_1, w_2) RV_{i-k} \tag{7}$$

The equation suggests that τ_i is influenced by past realized volatility (RV) values. Realized volatility itself can be positive or negative, depending on the data. However, the long-term volatility (τ) captured by the model needs to be non-negative, hence the need to take the log as follows:

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \vartheta_k(w_1, w_2) RV_{t-k} \tag{8}$$

The long-term component of conditional variance, denoted by τ_t is influenced by climate risk, which is an exogenous variable, denoted by X. The value of X, is constant throughout the year and repeated for each month within that year. Taking the natural logarithm of τ_t that is $\log(\tau_t)$ ensures the long-term volatility remains positive. This is because the log function is only defined for positive numbers. So, the model can be specified as:

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \vartheta_k(w_1, w_2) X_{t-k} \tag{9}$$

The GARCH-MIDAS model due to its ability to use a relatively small number of parameters, becomes generally easier to understand and work with when assessing macroeconomics data which is usually complex with different frequencies. θ is the coefficient of X. A positive θ suggest that climate change makes food prices more volatile, while a negative theta would suggest it makes them less volatile becoming stable. Table 4.2 below contains the summary statistics of the data used.

Table 4.2: Statistical Summary

Climate								
Country	Mean	Maximum	Minimum	Std.Dev	Skewness	Kurtosis	ADF	PP
Angola	0.9398	1.7520	0.1690	0.4042	0.1336	2.1011	-5.4396***	-16.876***
Cameroon	0.9093	1.4700	-0.1980	0.3279	-0.3005	2.3637	-4.5327***	-4.5384***
Congo	1.0574	1.6920	-0.3930	0.3594	-0.0303	2.1496	-5.002***	-5.1749***
Ethiopia	1.1527	1.5320	-0.5650	0.2552	-0.3626	2.3267	-5.5277***	-5.929***
Ghana	0.9738	1.4940	0.4300	0.2548	0.3992	2.9352	-4.7946***	-4.8679***
Kenya	1.0131	1.6240	0.5210	0.2986	0.2114	1.9934	-5.3129***	11.1421***
Nigeria	0.9650	1.5590	0.2250	0.3097	-0.3213	2.5787	-5.3129***	-5.2984***
Senegal	1.2718	1.7820	0.7030	0.2598	-0.0211	2.7093	-6.1172***	-8.2542***
S. Africa	0.8442	1.8110	0.2710	0.3622	0.7780	3.3182	-5.0317***	-7.0597***
Tanzania	0.9156	1.4500	0.4330	0.2432	0.0189	3.0314	-7.5560***	-7.5450***
Oil price	0.0093	0.0197	0.3290	-0.4004	0.0944	-0.5674	-11.581***	-13.2295***
Food price								
Angola	0.0229	0.2221	0.0006	0.0248	3.4018	20.1825	-5.3282***	-8.2947***
Cameroon	0.0028	0.0305	-0.0166	0.0066	0.0608	4.3345	-10.563***	-16.1489***
Congo	0.0017	0.0772	-0.0653	0.0183	0.2249	5.2417	-14.015***	-16.1489***
Ethiopia	0.0125	0.1743	-0.0914	0.0263	1.0353	10.4504	-7.8871***	-9.5615***
Ghana	0.0120	0.1095	-0.0538	0.0227	0.8724	5.9690	-8.2904***	-9.0553***
Kenya	0.0082	0.0693	-0.0319	0.0145	0.6194	5.3772	-10.522***	-10.7611***
Nigeria	0.0116	0.1260	-0.0606	0.0174	0.9977	13.6143	-10.673***	-12.1611***
Senegal	0.0031	0.0775	-0.0738	0.0216	0.0966	3.5324	-9.7084***	-11.9008***
S. Africa	0.0057	0.0248	-0.0090	0.0064	0.7713	3.1939	-6.9498***	-10.7692***
Tanzania	0.0066	0.0457	-0.0362	0.0133	0.1146	3.4823	-8.1526***	-9.2811***

Notes: ***p<0.01, ** p<0.05, * p<0.1 are levels of significance.
Source: Compiled by the author

The mean standard deviation is approximately 0.14, indicating the average spread of the data around the mean. The standard deviation values range from -0.40 to 0.40, showing variability in the dispersion of the data. The average (mean) of the "Mean" column is approximately 0.4828. The median (50th percentile) is 0.0229, significantly lower than the mean. The range of values is not wide, from a minimum of 0.0017 to a maximum of 1.2718. The mean skewness is approximately 0.42, indicating a slight positive skew on average. The skewness values range from -0.36 to 3.40, showing that some distributions are negatively skewed while others are positively skewed. The mean kurtosis is approximately 4.78, which is higher than the kurtosis of a normal distribution (3). This indicates that, on average, the distributions have heavier tails and sharper peaks. The kurtosis values range from -0.57 to 20.18, showing a variation in the tailedness of the distributions. The Augmented Dickey-Fuller (ADF) and the Philips Peron are used to test for stationarity. They are significant at a 1% level for all the countries, showing that the time series data is stationary. This is attributed to the usage of return series instead of the nominal values.

4.5 Results and Discussion

This study explores the impact of climate change on the dynamic spillovers between oil prices and food prices in different countries in the sub-Saharan region. It uses a special method called GARCH-MIDAS to do the analysis. This is important because the world is pushing for sustainability and food security, and a study like this helps guide economic decisions by businesses and governments on how to alleviate the effects and risks of climate change. The study looks at three things: firstly, how well climate change can affect the relationship between oil and food in developed economies. Secondly, climate change affects not just the production of food but even the price that the consumers will pay. Since climate change can affect the raw cost of fossil fuels, the study also considers how it might affect the price people pay at the pump.

The MIDAS (Mixed Data Sampling) regression is used to exploit data sampled at different frequencies in the modeling of economic relationships. In this particular case, it's applied to model the relationship between climate risk and the connectedness index of oil prices and food prices. The use of both rolling window realized variance (RV) and fixed realized variance provides insight into how changes in variance estimates can impact the regression results (Mei et al., 2019). The Fixed RV uses a predetermined fixed period to calculate realized variance, providing a stable measure over time. The Rolling RV uses a moving window to calculate realized variance, adapting to recent changes in volatility, and offering a more dynamic and responsive measure (Li et al., 2023). From Table 4.3, the Fixed RV parameters for Angola suggest a stable influence of the fixed realized variance on the model, with certain lagged effects captured by the coefficients. The Rolling RV parameters reflect a more dynamic response to recent changes in variance, potentially leading to different insights about the relationship between oil and food prices.

Table 4.3: Estimated Parameters with Midas Regressors

Country	Regressor	μ	α	β	θ	ω	m
Angola	Fixed RV	1.1512	0.9994	0.0006	0.1885	41.939	13.703
		[0.0001]	[0.0163]	[0.0051]	[15708]	[0.0002]	0.00001
	Rolling RV	1.1512	0.9994	0.0006	0.5951	13.257	1.7628
		[0.0001]	[0.0171]	[0.0005]	[2286.9]	[117.07]	[6773.8]
Cameron	Fixed RV	0.5539	0.9989	0.0011	0.1753	40.986	5.6607
		[0.0002]	[0.0270]	[0.0069]	[890.74]	[2.7829]	28691
	Rolling RV	0.5539	0.9998	0.0002	0.0752	40.121	2.6526
		[0.0003]	[0.0265]	[0.0056]	[88.814]	[89854]	[2953.7]
Congo	Fixed RV	4.8562	0.9990	0.0012	0.4318	25.961	31.6200
		[0.0008]	[0.0060]	[0.0060]	[196.39]	[35502]	[13574]
	Rolling RV	4.8561	0.9990	0.0011	0.2280	25.845	27.545
		[0.0010]	[0.0061]	[0.0061]	[188.87]	[55149]	[19321]
Ethiopia	Fixed RV	8.2555	0.9989	0.0011	0.3972	26.517	15.796
		[0.0013]	[0.0207]	[0.0064]	[5153.5]	[14255]	[2.0491]
	Rolling RV	5.7054	0.9978	0.0023	1.2672	3.5882	8.3265
		[0.0010]	[0.0232]	[0.0230]	[915.95]	[15.813]	[6035.9]
Ghana	Fixed RV	2.8665	1.0000	2.0772	0.0009	21.211	1.9138
		[0.0002]	[0.0131]	[0.0001]	[18.614]	[3.8415]	[270.4]
	Rolling RV	2.8665	1.0000	1.6617	0.0007	25.348	1.8667
		[0.0002]	[0.0131]	[0.0001]	[35.001]	[5.9476]	[250.99]
Kenya	Fixed RV	0.4005	0.9998	0.0002	1.6206	1.8891	0.2553
		[0.0003]	[0.0707]	[0.0078]	[27125]	[8.2738]	[4272]
	Rolling RV	0.4004	1.0000	1.3063	1.5548	49.9310	0.5640
		[0.0003]	[0.0715]	[0.0079]	[24844]	[1411.9]	[9011]
Nigeria	Fixed RV	2.4393	0.9982	0.0018	0.2601	26.6160	9.3555
		[0.0007]	[0.0483]	[0.0140]	[1366.8]	[10820]	[49192]
	Rolling RV	2.4393	0.9981	0.0018	0.3072	28.562	9.3279
		[0.0008]	[0.0482]	[0.0147]	[1644.4]	[5811.5]	[50000]
Senegal	Fixed RV	0.6408	1.5925	0.00002	1.5925	18.242	0.0022
		[0.0005]	[0.0114]	[0.0020]	[205.64]	[22.528]	[978.93]
	Rolling RV	0.6401	0.9999	0.00005	1.4660	10.668	0.0034
		[0.0005]	[0.0115]	[0.0018]	[162.96]	[3.9742]	[485.59]
S. Africa	Fixed RV	1.1948	0.9999	0.00004	0.5120	1.0010	0.8069
		[0.0006]	[0.0332]	[0.0048]	[194.22]	[0.0612]	[305.77]
	Rolling RV	1.0186	0.9999	0.00002	0.7706	2.4655	0.0043
		[0.0004]	[0.0276]	[0.0114]	[141.08]	[2.0713]	[472.96]
Tanzania	Fixed RV	2.5154	0.9999	3.7538	0.0025	15.6150	2.1876
		[0.0003]	[0.0181]	[0.0030]	[27.677]	[6.1424]	[349.96]
	Rolling RV	2.5154	0.9999	7.5560	0.0008	27.291	2.1569
		[0.0004]	[0.0159]	[0.0031]	[130.46]	[2.6247]	[295.61]

Parameter μ is the unconditional mean, α and β capture the short-term volatility dynamics in food prices, representing the ARCH and GARCH effects, respectively. θ captures the impact of the predictor with m as the corresponding decay factor and ω is the long-run average level of volatility. Standard errors are in parentheses.

Source: Compiled by the author

4.4.1GARCH-MIDAS Estimated Parameters

Table 4.4: Estimated parameters using climate risk as the predictor

Country	μ	α	β	θ	ω	m
Angola	1.1513***	0.9999***	0.00002	0.6885***	1.001***	1.2154
	[0.0001]	[0.0155]	[0.0044]	[256.23]	[0.0719]	[452.3]
Cameroon	0.6130***	0.9999***	0.00002	-0.0113	25.023	0.0144
	[2.9263]	[0.0095]	[0.0006]	[4.4041]	[5.5247]	[5.6195]
Congo	4.1722***	0.9999***	0.00003	50.2650	49.965	-52.136
	[0.0006]	[0.0078]	[0.0041]	[5360.2]	[17580]	[5559.7]
Ethiopia	5.701***	0.9973***	0.0026	73.2120	25.5520	-57.2860
	[0.0015]	[0.0352]	[0.0288]	[31597]	[87458]	[24722]
Ghana	2.8671***	0.9999***	0.00001	7.4770**	6.8874**	78.751
	[0.0002]	[0.0190]	[0.0001]	[80986]	[7.0139]	[86798]
Kenya	1.3800***	0,9981***	0,0019	0.2160***	2.5459***	0.5916
	[0.0002]	[0.0163]	[0.0107]	[112.05]	[47739]	[309.65]
Nigeria	2.2521***	0.9917***	0.0083	10.9100	25.8480	2.0851
	[0.0003]	[0.0923]	[0.0922]	[811.5]	[1.1675]	[158.51]
Senegal	0.6526***	0.9999***	4.9546	2.3708***	1.001***	-17.934
	[0.0006]	[0.0183]	[0.0133]	[3209.7]	[0.1359]	[2428]
S. Africa	1.0515	0.9996	5.1127	5.6713**	3.2584**	-2.0466
	[0.0001]	[0.0234]	[0.0069]	[317.07]	[522.32]	[114.42]
Tanzania	2.5181***	0.9999***	3.6308	9.2251**	1.001***	12.738
	[0.0002]	[0.0179]	[0.0035]	[2391.7]	[0.0345]	[3302.4]

Note: Values in parentheses are standard errors while the 1%, 5%, and 10% levels of significance are represented by ***, **, * respectively.
Source: Compiled by the author

The study uses the dynamic spillovers between food and oil as the dependent variable, with climate risk as the predictor variable. We started by running the TVP-VAR model to get the connectedness index. The parameter μ represents the long-run average level of connectedness between oil and food prices. The results show that it is significant at the 1% level, suggesting a statistically reliable baseline level of interconnectedness between these markets, independent of climate change. The agricultural sector heavily relies on oil for energy (Dahl et al., 2020; Sun et al., 2021). This includes fuel for farming machinery (tractors, harvesters, irrigation pumps), transportation of agricultural products, and the energy used in processing and packaging facilities. Trucks, trains, and ships powered by oil-based fuels are the primary modes of transportation for agricultural products. Oil is also a key raw material to produce fertilizers and pesticides. These chemicals are essential for increasing crop yields and protecting crops from pests and diseases (Albulescu et al., 2020).

The ARCH effect is captured by α, which measures how past volatility shocks in the connectedness index influence current volatility. Its significance at the 1% level indicates that past fluctuations in the oil-food connectedness are important in explaining current fluctuations. In other words, the strength of the relationship between oil and food prices tends to persist over short periods. Both μ and α are significant and positive across all countries reinforcing the strong interconnectedness between oil and food prices. Connectedness appears to be a consistent feature of the global market dynamics, regardless of specific country characteristics (Fasanya & Akinbowale, 2019; Dalheimer et al., 2021; Karakotsios et al., 2021).

This suggests that the strength of the oil-food price relationship persists, and its volatility has its own momentum. The connection is highly volatile in the past as shown by α values which are above 0.8 specifically range between 0.9917 and 0.9999 for all the countries. This means that the strength of their relationship fluctuated significantly, and it is likely to remain volatile, adding an extra layer of uncertainty. This persistence in volatility is crucial for risk management, as it implies that during periods of economic instability, such as global financial crises or geopolitical conflicts, the relationship between oil and food prices can become even more unpredictable. For instance, the global financial crisis in 2008 and the COVID-19 pandemic in 2020 both saw significant volatility in oil prices, which likely transmitted to food prices, with lasting effects, as discussed in Karakotsios et al. (2021). It also reduces the effectiveness of diversification strategies, as both markets may move together during turbulent times, increasing portfolio risk.

The lagged impact of climate risk on the volatility of the oil-food connectedness index is captured by θ. The results show positive and significant values of θ in six countries (Angola, Ghana, Kenya, Senegal, South Africa, and Tanzania), indicating that, on average, an increase in the climate change variable, like higher temperatures, is associated with an increase in the volatility of the connectedness between oil and food prices. An increase in temperatures reduces food productivity, resulting in higher food prices due to the law of demand (Shokoohi & Saghaian, 2022). The results also convey a significant positive ω indicating that recent climate events strongly influence the current volatility of the oil-food connectedness. The estimated weight is reliably different from zero, and the corresponding lagged climate value statistically impacts volatility. Notably, the insignificance of m might indicate that the relationship between climate change and the connectedness index does not follow a simple, gradually decaying pattern.

The study shows that climate risk, captured by the parameter θ, affects how much the connection between oil and food prices varies over time. In six countries—Angola, Ghana, Kenya, Senegal, South Africa, and Tanzania—higher climate risk, like hotter temperatures, makes this connection more volatile. This means the relationship between oil and food prices becomes less predictable, which can be challenging for planning. This increased volatility can make it harder for farmers to budget for oil-based costs, like fuel for machinery, and for governments to manage inflation, as food and energy prices are key factors. It suggests businesses might need better risk management, and policymakers may need flexible strategies, like subsidies, to stabilize prices. The study also finds that recent climate events, shown by a significant parameter ω, strongly influence current volatility. This means current weather events, like droughts or floods, can immediately affect how oil and food prices relate, requiring real-time monitoring to manage risks effectively.

4.6 Conclusion and Policy Recommendations

The study reveals a significant baseline interconnectedness between oil and food prices, independent of climate change (Dalheimer et al., 2021). Climate risk further amplifies his connection (Rising et al., 2022), with higher temperatures leading to increased volatility in the oil-food relationship, particularly in six African countries. This heightened volatility is driven by the agricultural sector's reliance on oil and the negative impact of climate change on food production, ultimately leading to higher food prices. Additionally, the study finds that the impact of climate change on the oil-food connectedness is not uniform over time, with recent climate events having a stronger influence than past ones.

There is a need for research and regional cooperation to ensure regional sustainable agriculture development since the sectors are connected in all the countries. Climate risk also affects the food sector, showing the necessity to reduce reliance on rainfed agriculture as mentioned by Dorinet et al. (2021) to mitigate the impact of climate risk on food-oil prices and contribute to more stable food prices. Implementing climate-resilient agricultural practices, such as drought-resistant crop varieties, efficient irrigation systems, and sustainable land management techniques, can help mitigate the impact of climate change on food production and prices.

Developing robust early warning systems is vital to monitor and forecast oil price fluctuations, climate risks, and their potential impacts on food prices. This will lead to the implementation of risk management strategies, such as hedging instruments and insurance schemes, to help mitigate the risks associated with oil price shocks and climate-related events for food producers and consumers. Investing in infrastructure, such as improved storage facilities and transportation networks, can enhance the resilience of the food supply chain to climate-related disruptions.

This study concentrates on sub-Saharan Africa characterized by a predominance of small-scale farmers facing market access and price inequity challenges, impacting their income and livelihood security (Kapari et al., 2023). Given their vulnerability to food price volatility and climate-related risks, targeted interventions are crucial. These include facilitating access to credit, extension services, and improved inputs to enhance productivity and resilience, investing in social safety nets and food assistance programs (Sasson, 2012), and promoting agricultural diversification to reduce dependence on staple crops and mitigate climate-induced shocks. Fostering alternative value chains, such as livestock and high-value crops, can diversify income sources and enhance resilience for smallholder farmers in SSA.

For policymakers, the volatility persistence means that short-term interventions, such as temporary subsidies, may not suffice; longer-term strategies to stabilize markets, such as investing in renewable energy for agriculture or diversifying energy sources, are necessary. This is particularly relevant for oil-importing countries, where volatile oil prices can lead to sustained food price increases, affecting economic stability and social welfare. For agricultural businesses, the persistent volatility implies a need for dynamic risk management strategies, such as futures contracts for oil and food commodities, to hedge against price fluctuations.

Furthermore, there is a need for policies focusing on the region since they are experiencing the same impact. The basic is regional cooperation and policy coordination among oil-producing and food-exporting countries to address the linkages between oil prices, climate change, and food price volatility. It is also important to encourage the sharing of best practices, knowledge exchange, and joint research initiatives to develop effective strategies for managing food price volatility in the face of oil price shocks and climate risks (Zhou et al., 2020).

CHAPTER FIVE

Conclusions and Recommendations

Through three interconnected studies, this research examined the role of global uncertainty, geopolitical risk, and climate risk in shaping the oil-food interactions, offering valuable insights into the challenges and opportunities facing developing countries in a rapidly changing and uncertain global environment. This study addressed key knowledge gaps in the field by employing diverse methodologies and integrating robust econometric analysis with innovative data sources, providing a deeper understanding of the underlying relationships.

5. 1 Concluding Remarks

5.1.1 Connection between Oil, Food Security, and WUI

This paper investigates the impact of global economic and policy uncertainty on the oil-food nexus in Sub-Saharan Africa using the PMG-ARDL model. The WUI is a comprehensive measure of global uncertainty derived from news media. It is the most appropriate choice as it captures the broader economic and political climate that can influence the region's oil prices and food security.

The positive and statistically significant value of oil prices indicates that increases in oil prices significantly increase food insecurity in SSA. This is likely due to several factors, including higher transportation costs for food, increased production costs for farmers, and potential indirect effects on global food markets, as proven by (Hailemariam et al., 2019; Hassan, 2022; Raza et al., 2022). Similar statistically significant positive results were obtained for world uncertainty. This means that heightened global uncertainty, which could stem from various economic, political, or environmental shocks, further exacerbates food insecurity in SSA. This highlights the vulnerability of the region to external factors.

Surprisingly, the coefficient for GDP per capita is negative and statistically significant. This suggests that higher income levels in SSA are associated with slightly lower food insecurity. This could be due to increased purchasing power and improved access to food for some segments of the population. Malik and Umar (2019) alluded that the exchange rate has a positive and significant effect on food insecurity, indicating that a depreciation of local currencies against major currencies like the US dollar can increase food insecurity in SSA. This is often due to the increased cost of imported food.

It is key to note that the initial analysis was done without considering structural breaks, and the results show that factors like oil prices and global uncertainty only seem to affect food security over long periods, not in the short term. However, when the analysis was adjusted to account for structural breaks, a different picture was realized: oil prices, global uncertainty, and income levels (GDP per capita) all have a clear and consistent impact on food security, both in the short and long term. This confirms that ignoring structural breaks can lead to misleading conclusions confirming the results (Fasanya et al., 2022). The fact that these factors consistently affect food security, even in the short term, highlights the need for Sub-Saharan African countries to reduce their reliance on oil, especially given the region's ongoing struggles with widespread undernourishment.

5.1.2 Dynamics of Extreme Spillovers between Oil, Agricultural Commodities, and GPR

This paper focuses on the specific impact of geopolitical events on the extreme spillovers between energy and agricultural markets using the TVP-VAR model. Geopolitical risk indices, which quantify the frequency and intensity of geopolitical threats and actions, are the most suitable measures as they directly capture the source of uncertainty under investigation.

The Total Connectedness Index (TCI) results for the six sub-Saharan African countries reveal varying interconnectedness between oil prices, agricultural commodity prices (maize, rice, sorghum, and wheat), and geopolitical risk factors. Ethiopia exhibits the highest TCI, indicating the strongest interconnectedness among the variables. This suggests that shocks to oil prices or geopolitical risk in Ethiopia are more likely to spill over into agricultural commodity markets and vice-versa. Cameroon shows the lowest TCI, suggesting a relatively weaker interconnectedness compared to the other countries. Nigeria and South Africa show a moderate interconnectedness, implying a significant but not overwhelming influence of oil prices and geopolitical risk on their agricultural commodity markets. Tanzania and Ghana, these countries demonstrate a relatively lower degree of interconnectedness compared to Ethiopia, Nigeria, and South Africa. However, the interconnectedness is still substantial, suggesting that shocks in one market can still spill over into others.

The high TCI for Ethiopia may indicate a higher vulnerability to external shocks, as changes in oil prices or geopolitical tensions could quickly affect food prices and availability. Policymakers in Ethiopia may need to focus on strategies to mitigate these risks, such as diversifying the economy, investing in agricultural infrastructure, and building strategic reserves. The lower TCI for Cameroon could suggest greater insulation from external shocks. However, this does not mean that Cameroon is immune to these risks. Policymakers should monitor the situation closely and be prepared to implement measures to protect food security if needed. The moderate TCI values for the remaining countries indicate a need for balanced policies that address both the opportunities and risks associated with interconnectedness.

The findings reveal significant time-variation and asymmetry in extreme spillovers, highlighting the importance of accounting for these dynamics in risk assessment and confirming the results of Tiwari et al. (2022). Geopolitical risk events significantly influence the intensity and direction of these spillovers, with specific risk categories having varying effects. The study provides valuable insights into the complex relationship between energy, agriculture, and geopolitical risk, offering implications for policymakers and market participants seeking to navigate the complexities of these interconnected markets and develop effective risk mitigation strategies.

5.1.3 Climate Risk on Dynamic Spillovers between Oil and Energy Prices

This study has illuminated the significant influence of climate risk on the dynamic spillovers between oil prices and food prices in the Sub-Saharan region. The dynamic spillovers were extracted using the TVP-VAR model. They were used as the dependent variable in the GARCH-MIDAS approach, which has proven to be a valuable tool for quantifying and modelling the impact of climate-related shocks on these markets, providing crucial insights for policymakers and market participants seeking to develop resilient strategies in the face of increasing climate-related uncertainties.

The component θ allows the model to incorporate the influence of climate risk on food and oil price volatility. The higher coefficients suggest that, on average, climate-related factors have a stronger impact on food and oil price volatility. The analysis reveals that transitory shocks associated with climate risk exhibit a higher persistence in food price and oil price fluctuations. This highlights the growing importance of climate change as a major driver of uncertainty in food production and prices. The significance of α and μ for all the countries suggests that recent shocks and past volatility have an impact on the current food-oil price volatility. The high values of α indicate that recent volatility shocks have a strong and persistent influence on current volatility. This means the market is more sensitive to short-term fluctuations, and volatility tends to cluster together. This suggests a substantial and consistent connectedness between the region’s oil markets and food security.

5.2 Implications and Policy Recommendations

This study examined how oil prices, uncertainty, and food agricultural commodities interact in SSA developing countries. Recognizing that uncertainty plays a crucial role in this relationship, the study used three proxies, including a new dataset on global uncertainty specifically for developing countries. This is particularly important because these nations have faced numerous disruptive events like trade wars, political instability, and disease outbreaks, all contributing to increased uncertainty (Ahir et al., 2022). Most studied countries rely heavily on oil for food production and distribution, making them vulnerable to oil price fluctuations. The results show a clear connection between oil prices, uncertainty, and food, with short-term and long-term impacts. This highlights the need for these countries to reduce their dependence on oil, especially considering the region's existing food insecurity challenges (Kapari et al., 2023). Strategies could include exploring alternative energy sources, promoting organic farming, and investing in new food production technologies.

The study also recommends reducing reliance on imported food and encouraging local production, especially in major importing countries. Regional trade agreements could help lower transportation costs and food prices. Collaboration among stakeholders is essential for effective policy implementation. Investing in agriculture, developing efficient technologies, and building food reserves are crucial steps. Importantly, policies must consider the significant role of uncertainty in amplifying price volatility and its potential consequences.

After using the interactive term of oil and uncertainty, this paper’s results underscore the significant vulnerability of SSA to oil price fluctuations and uncertainty when it comes to agriculture commodity prices. Policymakers in the region need to consider strategies to mitigate the negative impacts of these external factors. This could include measures such as diversification of energy sources, investment in agriculture, and regional cooperation. Reducing reliance on oil imports can help buffer against oil price shocks while improving agricultural productivity and infrastructure can enhance food security and reduce reliance on food imports (Chiu et al., 2016).

To mitigate the impacts of energy volatility and climate change, Sub-Saharan Africa (SSA) countries can reduce oil dependence by diversifying their economies. They should develop and implement comprehensive industrial policies, including incentives for non-oil sectors, to attract foreign investment and support local industries, reduce import dependency, diversify beyond oil, attract foreign investment, develop renewable energy (Mungai et al., 2022), and promote sectors like manufacturing, services, and tourism. South Africa serves as a model with its National Industrial Policy Framework (NIPF) and Industrial Policy Action Plans (IPAP) facilitating diversification since the end of apartheid. These policies have shifted the economy towards services, reducing reliance on traditional commodities, and contributing to a GDP of US$405.87 billion in 2022. Kenya has also made strides in energy efficiency through the Energy Management Regulations and promotion of solar-powered irrigation, reducing reliance on oil-based energy (Wangithi et al., 2021).

Sustainable agriculture is essential for food security and climate resilience in SSA, where smallholder farmers dominate the sector. Adopting climate-smart practices, such as conservation agriculture, agroforestry, and precision farming, can enhance productivity and resilience to climate change (Sub-Saharan Africa, 2022). Kenya's success with regenerative agriculture, which has improved yields and farmer incomes, underscores the potential of these approaches. Providing training, financial aid, and access to improved seeds and markets can empower smallholder farmers. Programs like those by Farm Africa have shown success in Kenya, enhancing livelihoods. Policies should also focus on water management and innovative technologies to enhance productivity (Economy and Environment, 2018).

Collaboration among SSA countries can improve food security through the sharing of resources and information (Gyimah et al., 2023). Governments and international organizations should closely monitor oil price fluctuations and consider policies to mitigate the impact on food prices. This could include strategic reserves, price stabilization mechanisms, or subsidies to protect vulnerable populations from food price shocks. Farmers and food companies need to manage the risk associated with oil price volatility. They can use hedging strategies or price risk management tools to minimize the impact of oil price fluctuations on their businesses and consumers (Porteous, 2020). Investors can use this information to assess the risk profile of investments in agriculture and food-related sectors. They can also consider diversifying their portfolios to mitigate the impact of oil price volatility.

Regional cooperation is vital for addressing shared challenges as discussed above. Cross-country coordination can improve early warning systems for climate disasters, facilitated by the African Union (Nalule, 2018). Trade agreements, such as The African Continental Free Trade Area (AfCFTA) can boost intra-African trade in agricultural products, reducing dependency on external markets and enhancing food security (Canton, 2021). Energy diversification can be enhanced through regional power grids like the Southern African Power Pool (SAPP), ensuring a more resilient energy future.

The results accentuate the urgency of addressing both oil dependency and climate change in strategies to enhance food security. While oil price volatility remains a significant concern, climate change emerges as a potentially even more critical factor requiring proactive mitigation and adaptation measures. Understanding these distinct drivers of food price volatility is crucial for designing effective risk management strategies. Policies and interventions should consider both the long-term influence of climate change and the persistent impact of short-term oil prices and climate shocks. Policymakers need to consider the combined effects of oil prices and climate risk when designing interventions to stabilize food markets and ensure food security. Policies should address both the direct impacts of each factor and the potential amplifying effect of their interaction. For stakeholders in the food supply chain, understanding the interactive nature of oil and climate risk is crucial for effective risk management. It highlights the need for strategies that consider both long-term climate resilience and short-term mitigation of oil prices and climate shocks.

5.3 Limitations of the Study and Avenues for Future Research

While this study offers valuable insights into the complex relationship between oil prices, global uncertainty, climate risk, geopolitical events, and food price volatility, it is not without limitations. Several factors constrain the scope and generalizability of the findings, and these limitations present opportunities for future research to build upon and extend the current body of knowledge.

5.3.1 Limitations

The major limitation of this study is the restricted timeframe of the data used, particularly for one of the main variables, food prices. While the available data provides valuable insights, longer datasets offer a more comprehensive understanding of the long-term dynamics between oil prices, climate risk, and food price volatility. Such extended datasets would facilitate the identification of structural breaks, regime shifts, and potential non-linear relationships that might not be apparent within shorter timeframes. Furthermore, the reliance on daily data, while a common practice, may not fully capture the intricate high-frequency volatility dynamics that occur within trading days. Access to intraday or tick-level data could provide a more granular view of the immediate impact of shocks, market reactions, and price discovery processes, potentially revealing subtle patterns and interactions obscured at lower frequencies.

The regional focus of the studies, particularly on sub-Saharan Africa, poses a limitation in terms of generalizability. While the findings are relevant and informative for the region, they might not be directly applicable to other regions with distinct economic structures, agricultural systems, or vulnerabilities to oil price and climate risks. Further research is needed to assess the extent to which the observed relationships hold in other contexts and to identify region-specific factors that might influence the dynamics between oil prices, climate risk, and food price volatility. Moreover, while robust, the models employed in the studies rely on certain assumptions and simplifications. For instance, the linear relationship assumed in the MIDAS component might not fully capture the potentially non-linear relationship between the variables. The models might not account for all potential factors, such as exchange rate fluctuations, trade policies, and geopolitical events, which could influence food price volatility.

5.4.2 Future Research

Given the potential impact of biofuel production on food security, particularly in Africa, further research is needed to comprehensively assess the effects of biofuel policies on food prices, crop allocation, and land-use changes across different African countries and regions. Future studies should leverage high-frequency data and explore non-linear modeling techniques to understand better the complex relationship among various sectors adding to oil prices, climate risk, and food prices. Expanding the dataset to cover recent shocks and geographical scope beyond Sub-Saharan Africa would enhance the generalizability of findings, providing a more comprehensive understanding of the global implications of biofuel policies on food security and economic stability.

In conclusion, this study has provided valuable insights into the interplay between oil prices, uncertainty, and food price volatility. However, the limitations highlighted above underscore the need for further research to expand the scope, refine the methodology, and deepen our understanding of the multifaceted drivers of food price dynamics. By addressing these limitations, future studies can contribute to more effective policies and strategies for mitigating the adverse impacts of oil prices and climate risk on food security.

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