ANALYSING THE RELATIONSHIP BETWEEN CRUDE OIL PRICES AND FOOD PRICES IN SOUTH AFRICA BETWEEN 2010 AND 2021

BY

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DISSERTATION

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DECLARATION 1

I, Mdungwa Maria Sherly, “declare that the dissertation hereby submitted to the University of Limpopo”, for the “degree of Master of Agricultural Management (Agricultural Economics) has not previously been submitted by me for a degree at this or any other university”; that it is my work in design and in execution, and that all material contained herein has been duly acknowledged.

Signature:

Date: 28 January 2025

DECLARATION 2 – PUBLICATIONS

Maria S Mdungwa, Mapula H Lefophane, Abenet Belete. *Analysing the Relationship Between Crude Oil Prices and Food Prices in South Africa*. *Energies* has been identified for paper publication from this dissertation.

DEDICATION

This study is dedicated to my late father, Sokadimlingene Wilson Mdungwa, and to the rest of my family: my mother, Salphie Thabi Sedibe; my brothers, Mpho, Akani, Rindzani, Tiyani, and Kurhula Mdungwa; my sisters, Dipuo Nkuna and Moipone Mayinga; and, most importantly, my son, Xilaveko, and my daughter, Amukelo.

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ABSTRACT

This study analysed “the relationship between crude oil prices and food prices in” South Africa. Data for crude oil prices were sourced from the United States (U.S.) Energy Information Administration (EIA), while data for food prices were obtained from the Food and Agricultural Organisation (FAO) for food prices. The analysis was segmented into three periods to account for structural breaks caused by global events: before March 2014, the 2014–2016 Oil Price Collapse, and the onset of the COVID-19 pandemic in February 2020.

The bound “co-integration test revealed a long-term relationship between crude oil and” food prices across all segments, achieving the first objective of the study. “The ARDL model was employed to estimate” both “the short-term and long-term” effects of crude oil prices on food prices, fulfilling the second objective. The results showed differential effects of crude oil prices on food prices, with high oil-intensive commodities like meat and dairy showing significant effects. In contrast, low oil-intensive categories like cereal, sugar, and vegetable oil exhibited minimal or delayed effects.

The Toda-Yamamoto Granger causality test was applied to determine the causal relationship between crude oil prices and food prices, achieving the third objective. Differential causality was found, with unidirectional causality for sugar, cereal, and meat, and bidirectional causality for vegetable oil during the pandemic period. No significant causal relationship was found for dairy in any segment, despite its high oil intensity, suggesting other mitigating factors in the dairy sector. Overall, the results highlight the varied impact of crude oil prices on different food categories over time, with notable distinctions between high and low oil-intensive food categories. Therefore, policy interventions should focus on managing food price inflation, ensuring energy security, and implementing commodity-specific measures to mitigate the impacts of oil price volatility.

Keywords: Crude oil price, food price, relationship, South Africa

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AIC	: Akaike information criterion
ARCH	: Autoregressive conditional heteroscedasticity
ARDL	: Autoregressive distributed lag
BBL	: Barrel
BIC	: Bayesian information criterion
BFP	: Basic fuel price
BP	: British petroleum
BPD	: Barrels per day
C	: Constant
COVID-19	: Coronavirus disease 2019
DME	: Dubai mercantile exchange
DMRE	: Department of mineral resources and energy
ECM	: Error correction Model
EIA	: Energy information administration
FAO	: Food and Agriculture organisation
FERC	: Federal energy regulatory commission
FIASA	: Fuel industry association of South Africa
FFPI	: FAO food price index
FPE	: Final prediction error
GDP	: Growth domestic product
HQC	: Hannan-Quin criterion
ICE	: Intercontinental exchange
IEA	: International energy agency

IMO	: International maritime organisation
IOSCO	: International organisation of securities commission
LM	: Lagrange multiplier
LR	: Lagrange residual
LRE	: Lagrange residual error
LWZ	: Li, Wu and Zidek
M	: Month
NATREF	: National refinery
NYMEX	: New York mercantile exchange
OECD	: Organisation for economic cooperation and development
OMV	: Osterreichische mineralolverwaltung
OPEC	: Organisation of the Petroleum Exporting Countries
PETROSA	: Petroleum Oil and Gas Corporation of South Africa
PMG	: Pooled Mean Group
PRC	: The Peoples Republic of China
RSS	: Residual Sum of Square
SAPIA	: South African Petroleum Industry Association
SBIC	: Schwarz Bayesian Information Criterion
STATSSA	: Statistics South Africa
STD.DEV	: Standard Deviation
TY	: Toda Yamamoto
UNFCCC	: United Nations Framework Convention of Climate Change
US	: United States
VAR	: Vector Autoregressive

VIF	: Variation inflation factors
WPC	: World Petroleum Council
WTI	: West Texas Intermediate

CHAPTER ONE: BACKGROUND

1.1 Introduction

Crude oil is regarded as a critical component of economic output. In its refined form, it is widely used across various sectors, such as the agricultural industry, where it powers machinery, supports fertiliser production, and facilitates the transportation of agricultural products. Moreover, crude oil significantly impacts people's lives and is an essential element in the majority of goods and services. Its wide range of applications is primarily due to its role in fuel production, benefiting households as well as the transportation, industrial, and agricultural sectors of economies (Roman et al., 2020).

In addition to being the primary energy source, oil is also used to generate electricity and produce various refinery by-products, which are utilised in manufacturing and influence transportation processes. Consequently, it holds substantial value and affects the prices of other commodities (Gulen, 2015). As crude oil is recognised as a vital input in the production of goods across all economies, fluctuations in oil prices can have an impact on economic growth and development that is both beneficial and negative (Khan et al., 2019).

Crude oil prices can influence food costs through three primary channels. First, higher oil prices increase the cost of agricultural inputs such as inorganic fertilisers (produced from natural gas) and fuel for tractors and pumps. Second, rising global crude oil prices can boost the demand for crops used in ethanol production, thereby driving up world crop prices, which are transmitted to local markets through trade links. Third, increases in oil prices raise transportation costs, which in turn affect the prices of all traded commodities, including food grains (Dillon and Barrett, 2013). Additionally, several factors contribute to fluctuations in food prices. These include load shedding (Goldberg, 2015; Naidoo, 2023), animal health issues (Aragrande and Canali, 2017; Espinosa et al., 2020), supply chain disruptions (Magagula, 2020; Njomane and Telukelarie, 2022), geopolitical events (McGrouther, 2016; Shang et al., 2023), and weak currency (Takadi, 2018).

These channels illustrate how fluctuations in crude oil prices directly influence food prices, while additional factors such as load shedding, animal health, supply chain disruptions, geopolitical events, and weak currency further contribute to price instability in agricultural markets. For this reason, the debate on the correlation between the price of food and crude oil remains unresolved due to the dynamic nature of crude oil and agricultural commodity markets. The volatility of crude oil prices and rising food costs have attracted global attention over the years, as rapid changes in these prices can adversely affect the economy (Mohamed, 2020). Therefore, this study aims to explore the connection between crude oil prices and food prices.

According to Fawthrop (2020), the world's top crude oil producers, essential to global industrialisation, play a significant role on the international stage. As of January 2022, the United States had overtaken Saudi Arabia as the world's leading oil producer. Saudi Arabia, producing 12.4 million barrels per day and accounting for 12% of global output in 2022, remains the largest oil exporter (Energy Information Administration, 2023). Russia, the second-largest producer with 10.94 million barrels per day, contributes 11% of global output and ranks just behind Saudi Arabia in crude oil exports (International Energy Agency, 2022).

Overall, major oil producers like the United States, Saudi Arabia, and Russia play a crucial role in shaping global crude oil demand, supply, and prices. Their production, geopolitical decisions, and exports drive oil price volatility, which directly impacts agricultural costs, transportation, and energy, ultimately influencing food prices (McGrouther, 2016; Shang et al., 2023; Dehshiri and Shahmoradi, 2022). Therefore, disruptions in oil supply and demand can significantly affect food price stability, underscoring the need for this study to account structural breaks due to various economic, geopolitical, and environmental factors.

Numerous global events, which occurred over the study period from 2010 to 2021, caused structural breaks in crude oil prices, contributing to higher food prices. Specifically, events such as the Arab Spring (2010-2011), the Global Financial Recovery (2010-2014), the Oil Price Collapse (2014-2016), and the COVID-19 pandemic (2020-2021), among others, caused significant shifts in crude oil markets, leading to disruptions in food prices due to the critical role of oil in agricultural production (Mead et al., 2020; Dutta et al., 2021; Dehshiri and Shahmoradi, 2022). These events underscore the necessity of this study's focus on the period 2010-2021 to investigate the connection between crude oil and food prices, while accounting for significant shifts in the data (i.e., structural breaks) caused by these global events. This approach enhances the precision and robustness of the analysis, offering a clearer understanding of the oil-food price nexus during a period of considerable volatility.

Several studies suggest a connection “between the price of food and crude oil”, with both often co-moving. Factors contributing to the “sudden spike” in crude oil and agricultural prices during 2007 to mid-2008 have been widely explored. Mitchell (2008) found that rising crude oil prices were among the key drivers of increasing food prices in the U.S. from 2002 to 2008. Similarly, Meyer et al. (2018) noted that continued food price increases were linked to changes in oil prices, suggesting that higher oil prices could lead to higher food costs. In Germany, Mohamed (2020) confirmed this “correlation between the price of food and crude oil” from 2013 to 2017, highlighting that agriculture's role in energy production strengthens the prices “between the costs of food and oil.” This body of evidence supports the view that rising oil prices contribute to food price inflation.

In South Africa, fluctuations in crude oil prices have coincided with rising prices in food categories such as meat, dairy, and cereals, with some declines in cereal, meat, and sugar prices between 2010 and 2021 (StatsSA, 2023). In South Africa, fluctuations in crude oil prices have coincided with rising prices in food categories such as meat, dairy, and cereals, alongside some declines in cereal, meat, and sugar prices between 2010 and 2021 (StatsSA, 2023). However, none of the existing studies have estimated the “short-term and long-term” effects of crude oil prices on various food categories, such as cereals, dairy, meat, sugar, and vegetable oil, while accounting for “structural breaks caused by” major global events like the Arab Spring (2010-2011), the Global Financial Recovery (2010-2014), the Oil Price Collapse (2014-2016), and the COVID-19 pandemic (2020-2021).

These events have significantly impacted both crude oil and food markets. However, previous studies, such as Fowowe (2016), Balcilar et al. (2016), and Aye (2014), did not account for these breaks, nor did they estimate both “short- and long-term effects” across comprehensive food categories. This study addresses this gap by analysing “the short-term and long-term” effects of crude oil prices on comprehensive food categories, while considering the structural breaks due to these global events. By doing so, it offers a more nuanced understanding of how global disruptions influence the crude oil-food price nexus in South Africa, providing valuable insights to help policymakers manage “price fluctuations and how they affect the availability of food.”

1.2 Problem statement

The global economy has experienced rising crude oil and food prices, sparking interest in understanding the relationship between these variables (Fasanya et al., 2019; Mohamed, 2020). Several studies attribute food price increases to crude oil price hikes through direct and indirect channels (Wang et al., 2015; Sun et al., 2021). The direct channel involves oil as an input in agricultural production, increasing production and transportation costs, which drives up food prices. The indirect channel relates to currency devaluation caused by oil price surges, affecting the cost of agricultural commodities (Fowowe, 2016).

In South Africa, rising food prices, particularly in categories like meat, dairy, cereals, and oils, and decreases in cereal, meat, and sugar prices between 2010 and 2021(StatsSA, 2023), have coincided with crude oil fluctuations. Moreover, global events during this period disrupted crude oil markets and, consequently, food prices due to oil’s critical role in agricultural production (Mead et al., 2020; Dutta et al., 2021; Dehshiri and Shahmoradi, 2022). However, no empirical studies have explored the relationship between crude oil and comprehensive food prices in South Africa for this period, while accounting for structural breaks caused by global events.

Internationally, studies on the oil-food price nexus present mixed results. While Mohamed (2020) found no long-term relationship in Germany, Taghizadeh-Hesary et al. (2019) observed a positive relationship across eight Asian countries, highlighting regional variations. Moreover, most studies identified long-term correlations (Fasanya et al., 2019; Olayungbo, 2021), but short-term dynamics vary significantly. For instance, Olayungbo (2021) reported a negative short-term relationship, contrasting with positive correlations observed in other studies (Chen et al., 2010; Pal and Mitra, 2017). While these studies reveal both patterns of “correlation” between crude oil and food prices, they cannot provide insights into South Africa's oil-food price dynamics due to country-specific factors.

Domestically, studies like Fowowe (2016) and Balcilar et al. (2016) found no significant link between crude oil prices and agricultural commodity prices in South Africa, despite accounting for structural breaks; however, they focused on limited food categories.

Similarly, Aye (2014) found no co-integration, attributing this to methods that overlooked market disruptions. These findings underscore the need for research analysing crude oil prices' impact on comprehensive food categories in South Africa from 2015 onward, while considering structural breaks from global events.

This study addresses these gaps by analysing the crude oil-food price nexus for comprehensive food categories (vegetable oil, dairy, sugar, cereals, and meat) over the period 2010–2021. Unlike previous studies, it accounts for structural breaks caused by global events and examines both short- and long-term effects of crude oil prices on food prices. The findings provide valuable insights into how crude oil price fluctuations impact food prices in South Africa, contributing to a deeper understanding of price dynamics and informing policy decisions.

1.3 Aim and objectives

1.3.1 Aim of the study

To examine the connection between crude oil price and food prices in South Africa between 2010 and 2021.

1.3.2 Objectives of the study

I. To determine co-integration relationship between crude oil prices and food prices in South Africa.
II. To estimate "the short-term and long-term" effects of crude oil prices on food prices in South Africa.
III. To determine the "causal relationship between" crude oil prices and food prices in South Africa.

1.3.3 Research Hypotheses

I. There is no co-integration relationship between crude oil prices and food prices in South Africa.
II. Crude oil prices have no significant "short-term and long-term effects" on food prices in South Africa.
III. There is no "causal relationship between" crude oil prices and food prices in South Africa.

1.4 Rationale

The study aimed to analyse the relationship between crude oil prices and food prices in South Africa. Given that crude oil prices play a significant role in determining the costs associated with food production and distribution (Dillon and Barrett, 2013), it is crucial to investigate the relationship between these two variables. To achieve this, the study focused on determining whether a cointegration “relationship exists between crude oil prices and food prices” in South Africa. Testing for cointegration involves examining whether “there is a long-term relationship between crude oil prices and food prices” (Ssekuma, 2011). The results from the cointegration analysis provide a clear understanding of whether crude oil and food prices co-moved over time, and whether the observed price increases were temporary or likely to persist.

The study also estimates both “the short-term and long-term” effects of crude oil prices on food prices in South Africa. Previous research on the oil-food price nexus in South Africa did not estimate these effects (Aye, 2014; Balcilar et al., 2016; Fowowe, 2016). This dual focus allows policymakers and stakeholders to gain a better understanding of the immediate and long-term impacts of oil price fluctuations on food prices. In doing so, the study supports informed decision-making and effective planning to mitigate the risks associated with oil price volatility. Furthermore, estimating both short-term and long-term effects helps policymakers implement policies and strategies to regulate crude oil and food prices, ultimately reducing inflation, energy insecurity, and food insecurity.

Additionally, the study examines the causal relationship between crude oil prices and food prices in South Africa. The results from the causality analysis provide insights into whether rising crude oil prices drive increases in food prices (Serfaz, 2017). If a strong causal relationship is identified, it suggests that crude oil price fluctuations directly impact food prices, particularly in commodities heavily reliant on oil for production, transportation, and distribution, such as meat and dairy. This information aids in designing effective policies to manage food price inflation, ensure energy security, and implement commodity-specific “measures to lessen the effects of fluctuations in the price of oil.”

1.5 Organisation of the study

Chapter one provides the background of the research, including the introduction, problem statement, aims, objectives, research hypotheses, and rationale. Chapter two presents the literature review, drawing on perspectives from secondary sources and relevant research. Chapter three outlines the research methodology, detailing the study area, data sources, and the analytical techniques used for the empirical analysis. This chapter also includes the methods used to validate the results. Chapter four presents the results and the corresponding discussion, while chapter five concludes the study with a summary, conclusions, policy recommendations, delimitations, and suggestions for future research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter explores the relationship between crude oil prices and food prices in South Africa. It begins by defining key terms and continues with an overview of the global crude oil market. It then examines crude oil pricing in South Africa, highlighting the impact of both international and domestic factors. Following this, the chapter discusses food production in South Africa, including regional food price variations and the factors influencing these prices. Furthermore, it analyses the pathways through which crude oil prices affect food prices, emphasising the interconnectedness of energy and agricultural markets. Finally, the chapter concludes with a literature review, offering insights into methodologies, findings, and the short- and long-term effects, cointegration, and causality between these variables.

2.2 Definition of terms

2.2.1 Crude oil prices

Crude oil, a fossil fuel refined into products like gasoline, diesel, and petrochemicals, is a finite resource since it cannot be replenished at the rate it is consumed (Chen, 2019). As one of the most in-demand commodities, crude oil significantly influences costs across all stages of the production process. “The immediate price of a barrel of benchmark oil is known as the crude oil price, and it is determined by supply and demand worldwide rather than just domestic output” (Roncaglia, 1983).

Price theory, which examines how prices are determined and their influence on individuals, firms, and markets, offers key concepts such as supply and demand, equilibrium, elasticity, marginal analysis, market structure, and price discrimination (Weyl, 2019). This framework helps economists and policymakers understand market dynamics, forecast trends, and assess the impact of economic policies.

Crude oil prices are shaped by factors such as global supply and demand, geopolitical events, OPEC decisions, and economic conditions (Hagen, 1994). In South Africa, as a net importer of crude oil, global oil prices, exchange rates, taxes, transportation costs, and infrastructure also play a crucial role in determining domestic oil prices. Any fluctuations in global oil prices, driven by factors like supply-demand dynamics or geopolitical shifts, directly impact South Africa's crude oil costs (Nkomo, 2016). Thus, crude oil price determination is a complex process influenced by both global and local factors.

2.2.2 Food prices

Food prices reflect changes in supply and demand, with current levels often indicating market imbalances (Food and Agriculture Organisation, 2021). In this study, food prices are categorised into cereals, vegetable oil, meat, sugar, and dairy, as represented by the FAO's Food Price Index. The ongoing rise in food prices has drawn attention to crude oil price changes as a potential contributing factor, with evidence suggesting that increases in crude oil prices may lead to higher food prices (To and Grafton, 2015). Additionally, the global economy has seen a rise in crude oil prices, prompting further interest in understanding the relationship between crude oil prices and food prices.

2.3 An overview of the global crude oil market

2.3.1 Brief history of global crude oil

"Petroleum, sometimes referred to as crude oil, is an unrefined, naturally occurring substance made up of hydrocarbon deposits and other organic elements" (Roman et al., 2020). It is extracted from underground reservoirs through drilling and serves as a vital source of energy globally. The modern era of crude oil exploration began in the 19^{th} century, with the first commercial oil well drilled by Edwin Drake in 1859 in Titusville, Pennsylvania, marking the start of the petroleum industry (Williamson and Daum, 1959). This discovery spurred rapid expansion of oil exploration and production in regions such as the United States, Russia, and the Middle East.

"Late 19th and early 20th century", companies like Standard Oil, founded by John D. Rockefeller, became dominant players in the oil industry. Standard Oil's aggressive business practices and vertical integration strategies enabled it to control a substantial share of the global oil market (Chernow, 1998). The Organisation of the Petroleum Exporting Countries (OPEC), founded in 1960 by oil-producing nations including Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela, was established to coordinate oil production and stabilise prices (OPEC, 2024). Since its inception, OPEC has played a significant role in the global oil market, influencing prices and production levels through its member countries.

2.3.2 Top crude oil producers

Crude oil-producing countries are pivotal in the global energy market, significantly impacting oil prices and economic dynamics worldwide. In 2023, 98 countries collectively produced around 80.75 million barrels of crude oil, with just five countries accounting for approximately 52% of this total. Table 2.1 “indicates the top five producers of crude oil and the proportion of each to the world's production.”

Table 2.1: Top 5 crude oil producers

Country	Percentage (%)
United states	14.7
Saudi Arabia	13.2
Russia	12.7
Canada	5.6
Iraq	5.5

Source: Author, based on EIA (2023)

The United States leads with 14.7%, followed by Saudi Arabia at 13.2% and Russia at 12.7%. Canada and Iraq contribute 5.6% and 5.5%, respectively. These countries' dominant roles in oil production underscore their influence on the global oil market.

2.3.3 Top crude oil exporters and importers

Imports and exports are essential components of international trade, stimulating economic growth, fostering global cooperation, and improving living standards by providing access to a diverse range of goods and services. Crude oil, as the most critical commodity, plays a central role in shaping the economic status of nations globally. The global oil export landscape experienced a slight shift between 2022 and 2023 (EIA, 2023). Table 2.2 presents the top five crude oil exporters and importers, along with their global rankings.

Table 2.2: Top crude oil exporters and importers

Exports		Imports	
Country	**Ranking**	**Country**	**Ranking**

Saudi Arabia	1st	China	1st
Russia	2nd	United states	2nd
United states	4th	South Korea	5th
Canada	3rd	Japan	4th
Iraq	5th	India	3rd

Source: Author, based on EIA (2023)

Saudi Arabia holds the top position as the largest crude oil exporter, followed by Russia and Canada. The United States ranks fourth in exports but second in imports, behind China, the world's largest importer. South Korea, Japan, and India also feature as key importers, underscoring the global interconnectedness of the crude oil trade. This highlights the pivotal role of crude oil in shaping global trade dynamics and the economic interdependence between exporting and importing nations.

2.3.4 Global crude oil market

According to Smith (2020), the crude oil market is a vital and complex system that plays a pivotal role in the global economy. It encompasses activities ranging from production to consumption, with prices shaped by various economic, geopolitical, and environmental factors. Understanding these complexities is essential for navigating the challenges and seizing opportunities within the energy sector. Crude oil is actively traded on major commodity exchanges worldwide, including the New York Mercantile Exchange (NYMEX), the Intercontinental Exchange (ICE), and the Dubai Mercantile Exchange (DME). Futures contracts for crude oil allow market participants to hedge against price volatility and speculate on future price movements.

2.3.5 Global crude oil pricing

The relationship between crude oil demand and its prices is a crucial aspect of the global economy. Crude oil prices are influenced by a complex interplay of demand, supply, geopolitical factors, and market sentiment. Typically, when demand for crude oil rises, due to economic growth or increased industrial activity, prices tend to increase. This is because the available supply may not be sufficient to meet the growing demand, causing upward pressure on prices. For example, during winter, the demand for heating oil rises in many countries, leading to higher crude oil demand and prices (Osterreichische Mineralölverwaltung, 2024). Conversely, when demand decreases, due to economic downturns, improved energy efficiency, or the adoption of alternative energy sources, prices generally fall, as reduced demand puts less pressure on the available supply.

According to the U.S. Energy Information Administration (2022), a decrease in crude oil supply, whether due to production cuts, geopolitical disruptions, or natural disasters, causes prices to rise. Reduced supply limits the amount of oil available to meet existing demand, pushing prices upward. On the other hand, when supply increases, prices typically fall. Higher production rates or the discovery of new oil fields can create a surplus of oil, driving prices down (OMV, 2024). For instance, advances in extraction technology or increases in production quotas by major oil producers can lead to greater supply, resulting in lower prices.

2.3.6 Key organisations influencing crude oil pricing

Crude oil pricing is shaped by a range of organisations, each playing a distinct role in regulating and stabilising the oil market. These organisations contribute to pricing through policy recommendations, market forecasts, regulation, and production quotas. Table 2.3 outlines the key players in crude oil pricing.

Table 2.3: Key organisations influencing crude oil pricing

Organisations	Role	Sources
Energy Information Administration (EIA)	Through its data release, forecast, and energy market analysis, the EIA influences the price of crude oil.	EIA (2024)
Federal Energy Regulatory Commission (FERC)	FERC plays a crucial role in regulating and supervising U.S. energy markets	FERC (2024)
International Energy Agency (IEA)	Provides reliable analysis, data, policy recommendations, and solutions.	IEA (2024)
International Maritime Organisation (IMO)	Responsible for the maritime industry's security and safety, as well as the prevention of ship-related air and marine pollution.	IMO (2019)
International Organisation of Securities Commission (IOSCO)	Promotes robust and productive securities regulations worldwide, enhancing the stability and operational efficiency of financial markets.	IOSCO (2024)

Organisation of the Petroleum Exporting Countries (OPEC)	Imposes production quotas and other market-stabilising measures.	OPEC (2005)
United Nations Framework Convention on Climate Change (UNFCCC)	Responsible for helping oil-producing countries adapt to cleaner energy methods	UNFCCC (2024)
World Petroleum Council (WPC)	Promotes the wise use and management of petroleum resources.	WPC (2024)

Source: Compiled by author

Key players in crude oil pricing include agencies such as the Energy Information Administration (EIA), which provides crucial data and analysis, and the Organisation of the Petroleum Exporting Countries (OPEC), which influences global oil supply through production quotas. Additionally, organisations like the International Maritime Organisation (IMO) and the United Nations Framework Convention on Climate Change (UNFCCC) shape industry practices, focusing on safety, sustainability, and the transition to cleaner energy. Collectively, these institutions influence global oil market dynamics, contributing to price stability and shaping energy policies.

OPEC, in particular, has a major impact on the world oil market by imposing production quotas and other market-stabilising measures. These actions have helped maintain stable oil prices by controlling supply. However, OPEC's production decisions and market sentiment can still lead to price fluctuations. Despite concerns about its influence on the global transition to renewable energy, OPEC remains a powerful force in the oil industry (OPEC, 2005).

2.3.7 Global crude oil market regulation

According to the International Monetary Fund (2023), market policy refers to a set of rules, regulations, guidelines, or strategies implemented by governments, regulatory bodies, or organisations to govern or influence the functioning of a specific market. These policies aim to promote competition, ensure consumer protection, foster innovation, and maintain market stability. Market policies can cover areas such as pricing, quality standards, entry and exit barriers, taxation, subsidies, and environmental regulations. Developed based on economic, legal, and social principles, these policies are periodically reviewed and adjusted to reflect changing market conditions and objectives.

Crude oil market policies encompass several key areas. First, taxation and subsidies influence crude oil production, consumption, and investment decisions. Governments may impose taxes on oil extraction, production, or consumption to generate revenue, promote energy conservation, or fund environmental programmes. Conversely, subsidies can support domestic production, enhance energy security, or stabilise fuel prices (Kaplow, 2004). Second, export restrictions and import tariffs are used by some countries to conserve domestic resources, promote refining capacity, or control the export of valuable natural resources. Import tariffs can protect domestic producers from foreign competition (Brown et al., 2014). Third, market monitoring and regulation are essential for preventing market manipulation and ensuring transparency. Regulatory agencies monitor price movements, trading activities, and market participants to maintain market integrity (Demirer and Kutan, 2010). Finally, international agreements and cooperation help countries address challenges such as price volatility, supply disruptions, and environmental concerns through trade agreements, energy partnerships, and multilateral forums (Berger et al., 1992).

2.4 Overview of South African crude oil market

2.4.1 History of South African crude oil

South Africa does not possess significant crude oil reserves, and thus, crude oil was never discovered in the country in the traditional sense (SAPIA, 2014). Instead, South Africa relies on crude oil imports to meet its energy needs and has developed a robust refining industry to process the imported crude. The country has six refineries, of which two process synthetic fuels, and four refine crude oil. Four of these refineries are located offshore, while two are inland. Figure 2.1 below illustrates the locations of these crude oil refineries.

Figure 2.1: Map of crude oil refineries

Source: Logistics cluster (2022)

The key four crude oil refineries in South Africa are as follows:

- **Sapref Refinery**: A joint venture between Shell and BP, commissioned in 1963, located in Durban. It is one of the largest refineries in South Africa.
- **Engen Refinery**: Formerly known as the Mobil Oil Refinery, it began operations in 1954 and is also located in Durban. It is one of the oldest refineries in the country.
- **Caltex (Astron Energy) Refinery**: Located in Cape Town, it started operations in 1966. Initially owned by Caltex, it is now operated by Astron Energy.
- **Natref Refinery**: The National Refinery of South Africa (Natref) is located in Sasolburg and began operations in 1971. At the time of its establishment, it was a joint venture between Sasol, Total, and the National Iranian Oil Company (SAPIA, 2022).

2.4.2 Top crude oil producers in Africa

Table 2.4 below shows the top oil-producing countries in Africa and their membership status in OPEC. Nigeria, the largest oil producer in Africa, plays a significant role in the global oil market (Omolade et al., 2019). The country's crude oil production has substantial economic and geopolitical implications both domestically and internationally. Production peaked at about 2.5 million bpd in the early 2000s but has since declined due to various factors including infrastructure issues and security concerns (Sasu, 2023). As of mid-2024, Nigeria's crude oil production hovers around 1.3 to 1.5 million barrels per day (bpd).

Table 2.4: Top oil producers in African

Country	Membership
Nigeria	OPEC
Angola	Non-OPEC
Algeria	OPEC
Libya	OPEC
Egypt	Non-OPEC

Source: author, based on OPEC (2024)

Angola is the second-largest oil producer in Africa, following Nigeria, and its oil industry is a critical component of its economy. “The nation's output of crude oil has” significant implications for both the national economy and the global oil market (Statista, 2023). Angola's oil production has seen fluctuations, peaking at around 2 million bpd in the early 2010s. The decline in production has been attributed to aging fields, reduced investment, and operational inefficiencies.

Algeria's production has been relatively stable over the years, fluctuating from 1 to 1.4 million bpd. The country peaked in production in the early 2000s and has faced challenges in maintaining those levels due to mature fields and lack of investment. Libya's oil production has experienced dramatic fluctuations, with a peak of over 1.6 million bpd in the early 2010s before plummeting during the civil conflict and rebounding in recent years as stability has somewhat improved (Statista, 2023).

2.4.3 Top importers of crude oil in Africa

Table 2.5 below presents the top African countries that import crude oil, along with their global and regional rankings. Nigeria ranks 13th globally and 1st in Africa, making it the largest crude oil importer on the continent. South Africa follows as the 18th largest global importer and ranks 2nd regionally, “demonstrating how heavily it depends on imported crude oil to meet its energy requirements.” Egypt and Morocco hold 32nd and 37th positions globally, ranking 3rd and 4th regionally, respectively. Ghana does not appear in the global rankings.

Table 2.5: Top African importers of crude oil

Country	Global ranking	Regional ranking
South Africa	18th	2nd
Morocco	37th	4th
Egypt	32nd	3rd
Nigeria	13th	1st
Ghana	-	-

Source: Author, based on EIA (2023)

For South Africa, the country's heavy reliance on imported crude oil has direct implications for food prices. Since crude oil is a key input in agriculture and food production, which affects transportation, fuel costs, and the production of agricultural inputs such as fertilisers, any fluctuations in global crude oil prices can have a significant impact on food prices. "Food prices rise as a result of higher production and transportation costs brought on by rising crude oil prices" (Chatziantoniou et al., 2021; Ike et al., 2023). Therefore, changes in South Africa's crude oil import costs, driven by global market conditions, are likely to exert upward pressure on food prices, affecting consumers and food security.

2.4.4 Retailing and wholesaling

The Petroleum Products Amendment Act of 2003 established a licensing system for the manufacturing, wholesaling, and retailing of petroleum products in South Africa. This system requires compliance with several regulatory measures and mandates the annual submission of specific data to the Department of Mineral Resources and Energy (South African Petroleum Industry Association, 2024). FIASA (Fuel Industry Association of South Africa) members are restricted to holding a limited number of retail licences, as manufacturers and wholesalers are generally prohibited from owning retail licences, except for training purposes. Typically, branded service stations operate by having FIASA members franchise the station to an independent dealer, who supplies petroleum products under a direct contract.

There are also independently owned stations that operate under a contract with oil companies, as well as independently operated unbranded stations (SAPIA, 2024). Within the South African oil industry, leading companies include BP Southern Africa, Astron Energy, Engen Petroleum, PetroSA, Sasol Oil, Shell South Africa, and Total Energies South Africa. These companies operate nationwide, with extensive distribution centres and storage terminals. Until recently, there were few non-refining wholesalers supplying petrol and diesel in South Africa, but the Department of Mineral Resources and Energy has now registered several entities (SAPIA, 2024).

2.4.5 Crude oil pricing in South Africa

According to SAPIA (2024), the South African government fully regulates the retail price of fuel, setting levies and duties that contribute to the national treasury, along with determining permissible returns across the petroleum value chain. Petroleum supplies are sourced from foreign refineries that meet South Africa's quality standards and can ensure a sustained supply. The Basic Fuel Price (BFP), which forms the foundation for South African petroleum prices, reflects the realistic, market-related costs of importing the country's liquid fuel requirements. As a result, the domestic price is influenced by factors such as the rand/dollar exchange rate and global supply and demand for petroleum products (SAPIA, 2024).

2.4.6 Crude oil price regulation in South Africa

South Africa's crude oil market policy involves several strategic and economic considerations to ensure a stable supply and manage domestic energy needs. The country relies heavily on imports to meet its crude oil requirements. There are policies made to regulate the prices of crude oil or crude oil products. Firstly, regulation of Fuel Prices, the South African government regulates fuel prices through the Basic Fuel Price (BFP) mechanism. The BFP is based on import parity pricing principles and considers factors such as international crude oil prices, exchange rates, and local taxes (Crompton et al., 2020).

Furthermore, this regulation aims to stabilize fuel prices and protect consumers from excessive price fluctuations. Secondly, petroleum product regulation, the Department of Mineral Resources and Energy (DMRE) is responsible for regulating the petroleum sector in South Africa. This includes overseeing the licensing of petroleum exploration and production activities, as well as ensuring compliance with safety and environmental standards (DMRE, 2012). Thirdly, promotion of refining capacity, the government encourages investment in domestic refining capacity to reduce dependence on imported refined petroleum products. This may include incentives for the construction or expansion of oil refineries in South Africa. Lastly, international relations and trade agreements, South Africa's crude oil market policies are also influenced by its international relations and trade agreements. The government engages in diplomatic efforts to secure favourable crude oil supply contracts and participates in regional and international forums to address energy-related issues and promote cooperation in the energy sector (DMRE, 2012).

2.4.7 Overview of food production in South Africa

The FAO Food Price Index indicates a global increase in food prices as of mid-2024, particularly in cereals, sugar, and vegetable oils. This follows a period of relative stability in early 2023, disrupted by ongoing conflicts, climate-related crop failures, and elevated energy prices (FAO, 2024). The volatility in food prices, driven by these factors, is especially concerning for developing nations where food insecurity risks are higher (FAO, 2024). In this study, food categories are classified according to the FAO Food Price Index, including cereals, dairy, meat, sugar, and vegetable oil.

Cereals are a staple in South Africa, particularly maize, which is the main source of nutrition for many households, especially low-income ones (Van Niekerk and Conradie, 2023). The Free State, North West, and Mpumalanga are key cereal-producing provinces, with the Free State leading in maize production due to its rich soils and favourable climate (Tebele et al., 2020).

Dairy products include items such as milk, cheese, and butter. South Africa's main dairy-producing regions are the Western Cape, Eastern Cape, and KwaZulu-Natal. The Western Cape, with its advanced infrastructure, leads dairy production, while the Eastern Cape and KwaZulu-Natal also contribute significantly due to their favourable climates and pasturelands (Diniso and Jaja, 2021).

Meat production in South Africa, including beef, poultry, and lamb, is concentrated in the Free State, KwaZulu-Natal, and Eastern Cape. The Free State is known for cattle farming, while KwaZulu-Natal has a booming poultry industry. The Eastern Cape is a key producer of lamb and mutton (Ncoko et al., 2020).

Sugar production is largely concentrated in KwaZulu-Natal and Mpumalanga, where the warm, humid climate is ideal for sugarcane farming. The sugar industry is a major contributor to both domestic consumption and exports, supporting local economies and job creation (South African Sugar Association, 2024).

Vegetable oils, such as sunflower and soybean oil, are mainly produced in Mpumalanga, the Free State, and North West. These provinces provide the ideal conditions for oilseed crop production, with the Western Cape also contributing to smaller-scale canola oil production (Zakari et al., 2022).

2.4.8 Regional food price variations in South Africa

There are significant regional disparities in food prices across South Africa, with notable differences between rural and urban areas, as well as among provinces. Food prices tend to be higher in urban centres like Johannesburg and Cape Town, driven by increased demand, higher living costs, and more expensive retail operations (Business Tech, 2021). In contrast, rural areas may experience lower prices for locally produced goods but often face higher costs for items that need to be transported from distant locations.

These disparities are influenced by various factors, including regional climate conditions, agricultural output, and local supply chains. Farming-friendly provinces, like the Western Cape, may benefit from lower prices for locally produced goods, while regions with less productive land or unfavourable weather conditions, which rely more on imports, tend to have higher food costs (Business Tech, 2021). Additionally, transportation costs play a significant role, particularly in remote areas. These costs are further affected by fuel prices and limited infrastructure, compounding the price differences across regions.

2.4.9 Factors affecting food prices in South Africa

Supply and Demand: The basic principles of supply and demand play a key role in determining food prices. Prices tend to rise when demand exceeds supply for a particular food item, while they generally decrease when supply surpasses demand. Variations in production levels affect supply, while shifts in consumer preferences, population growth, and income levels influence demand. For instance, if the supply cannot keep pace with increasing demand for protein-rich foods, prices for meat and dairy products may rise (de Janvry and Sadoulet, 2020).

Agricultural Production Levels: Food prices are directly impacted by production levels. Higher production typically leads to lower prices due to an abundance of food to meet demand. Conversely, reduced agricultural output or poor harvests often result in higher prices (Liliane and Charles, 2020). Factors such as agricultural yields, livestock productivity, and advancements in farming technology influence production. Innovations in farming practices, such as improved crop varieties, can boost yields and lower costs.

Climate Conditions: Weather patterns and climate significantly affect agricultural output. “Severe weather conditions like storms, floods, and droughts”, can damage crops, leading to reduced harvests and higher food prices. For example, prolonged droughts can limit water availability, negatively affecting crop growth and causing shortages (Ngcamu and Chari, 2020). In contrast, favourable weather conditions can enhance production and reduce prices.

Export and Import Policies: Trade laws and regulations impact food prices by influencing the movement of goods across borders. Tariffs, quotas, and trade restrictions can raise import costs, while trade agreements and subsidies may lower prices by promoting more efficient trade. For instance, high import tariffs on wheat can lead to higher domestic grain prices due to reduced foreign competition (Smith and Glauber, 2020).

2.5. Oil-Intensive Commodities and the Relationship Between Oil Intensity and Food Price

This section explores oil intensity of various commodities and how it influences food prices. Commodities classified as oil-intensive are those whose production, processing, or transportation depends heavily on oil or oil-derived products. These commodities, due to their reliance on oil, are directly impacted by changes in oil prices, which in turn influence their costs and market prices (Chatziantoniou et al., 2021). Among food commodities, meat is the most oil-intensive, followed by dairy, cereals, sugar, and vegetable oil. The complex, multi-step supply chains for these commodities, from farming and transportation to processing and refrigeration, require substantial energy inputs, predominantly in the form of oil. Consequently, changes in oil prices play a critical role in shaping food prices, especially for oil-intensive commodities like meat and dairy (Ike et al., 2023). Below is a discussion of the oil intensity of various commodities and how it influences the prices of food categories in this study.

Commodities such as meat, dairy, cereals, sugar, and vegetable oil vary in their oil intensity. Meat is the most oil-intensive commodity, primarily because its production process involves several oil-dependent stages. The process begins with the production of feed crops, such as corn and soybeans, which require oil for machinery and oil-based inputs like fertilisers and pesticides. Additionally, livestock farming, which involves feeding, housing, and transporting animals, consumes significant amounts of energy, further increasing the oil dependency of meat production. The processing, refrigeration, and distribution of meat also involve oil-based fuels, making it the commodity with the highest oil intensity. As a result, fluctuations in oil prices disproportionately impact the cost of meat compared to other food items (Chatziantoniou et al., 2021).

Dairy production shares similarities with meat in terms of oil usage, but it is slightly less oil-intensive. Oil is required in feed production, machinery, and energy-intensive processing stages like refrigeration. Cereals and sugar, while still oil-dependent, require less oil in comparison, mainly for farming machinery, fertilizers, and transportation. Vegetable oil production, though relatively less oil-intensive, still relies on fossil fuels for extraction and processing (Chatziantoniou et al., 2021; Ike et al., 2023).

Meat and dairy, being the most oil-intensive commodities, are more sensitive to changes in oil prices. The costs of feed, machinery, transportation, and processing all rise in response to higher oil prices, leading to a disproportionate increase in meat and dairy prices compared to less oil-intensive goods like cereals and vegetable oil. In particular, the need for large amounts of feed in livestock production compounds the impact of oil price increases on meat prices (Chatziantoniou et al., 2021).

While cereals and sugar are less oil-intensive than meat and dairy, they still experience cost increases when oil prices rise due to the use of petroleum-based fertilisers and transportation. However, these price increases tend to be less evident. Similarly, vegetable oil production is affected by oil prices, though to a lesser degree than meat or dairy (Ike et al., 2023).

In conclusion, the oil intensity of various commodities plays a crucial role in shaping their price sensitivity to fluctuations in crude oil prices. Commodities like meat and dairy, which have complex production chains that rely heavily on oil, are the most affected by rising oil prices, leading to disproportionately higher food prices in these categories. Cereals, sugar, and vegetable oil, while still impacted by oil price changes due to their reliance on petroleum-based inputs and transportation, exhibit less sensitivity compared to meat and dairy. The differential impact of oil intensity across food categories underscores the importance of accounting for these variations when analysing the relationship between crude oil prices and food prices in this study.

It is therefore necessary to conduct the analysis on individual food categories, given their distinct oil intensity. By doing so, this study accounts for the oil intensity of each category when performing unit root testing, cointegration testing, ECM modelling, and Granger causality testing. This approach ensures a more accurate and robust analysis of how crude oil prices influence food prices.

2.6 Pathways Through Which Crude Oil Prices Affect Food Prices

This section discusses pathways through which crude oil prices affect food prices. Crude oil prices influence food prices through several key pathways, each contributing to the complex relationship between the energy and food markets. These pathways include the impact on agricultural production costs, transportation and distribution expenses, the demand for biofuels, inflationary pressures, and the broader social and political stability. Each pathway highlights the various mechanisms through which shifts in oil prices affect food costs. Below is a discussion of how these pathways influence food prices.

In terms of agricultural production costs, crude oil plays a crucial role, as its refined form powers machinery and provides essential inputs like fertilisers and pesticides. When oil prices rise, the cost of these inputs increases, leading to higher overall production costs for food. This is especially true for oil-intensive commodities such as meat and dairy, where energy demands are high throughout the supply chain, that is, from feed production to processing and distribution (Chatziantoniou et al., 2021). For low-income regions, where food accounts for a significant portion of household expenses, the rise in food prices caused by increasing oil prices can severely affect consumption patterns (Nacoara and Manate, 2022).

Another key pathway is through transportation and distribution costs. Crude oil prices heavily influence fuel costs, which are essential for moving food products from farms to processing facilities, distribution centres, and retail markets (Min, 2022). Since transportation in the food supply chain relies largely on fuel derived from crude oil, any increase in oil prices directly raises transportation costs, which are then passed on to consumers (Bilal et al., 2024).

Crude oil prices also affect food prices through their impact on biofuel production. When crude oil prices rise, biofuels like ethanol often produced from crops, such as corn, become more economically viable as alternative energy sources. This increased demand for biofuels can lead to a diversion of crops from food production to fuel production, driving up the price of food crops (Nguyen, 2024). Additionally, competition between biofuel and food production for agricultural land further increases food prices by limiting the availability of land for growing food crops. Therefore, higher oil prices indirectly influence food prices by incentivising the production of biofuels, creating a complex dynamic between energy markets and agricultural commodities.

The inflationary pressure caused by rising oil prices is another critical pathway linking crude oil to food prices. When oil prices rise, they increase the costs of energy, transportation, and agricultural inputs, all of which contribute to higher food prices. These increased costs are often passed on to consumers, fuelling inflation across the broader economy (Balcilar and Bekun, 2020). Inflation erodes consumer purchasing power, disproportionately affecting low-income households, which spend a larger share of their income on food (Uyi and Demir, 2023). Therefore, examining the connection between oil prices and food prices is crucial for policymakers aiming to control inflation and maintain economic stability.

Social and political instability contribute significantly to the pathways linking crude oil to food prices. Fluctuating food prices, driven by changes in crude oil prices, can have far-reaching social and political consequences. In low-income regions, where food makes up a substantial portion of household spending, rising food prices can strain budgets and spark unrest, as witnessed during the Arab Spring (2010-2011). Political upheaval and uprisings across the Middle East and North Africa, particularly in oil-producing countries like Libya and Egypt, led to significant supply disruptions, causing global oil price fluctuations (Dehshiri and Shahmoradi, 2022). Since crude oil is a key input in agricultural production, that is, through fuel, transport, and fertiliser costs, this instability had a direct impact on food prices. This dynamic is especially evident in countries with pre-existing economic vulnerabilities.

Overall, crude oil prices influence food prices through several key pathways, each contributing to the complex relationship between the energy and food markets. These pathways include their impact on agricultural production costs, transportation and distribution expenses, biofuel demand, inflationary pressures, and broader social and political stability. Given these complexities, it is crucial for this study to analyse the relationship between crude oil and food prices. Understanding how fluctuations in crude oil prices affect food prices allows policymakers, businesses, and governments to better anticipate price shocks, design more resilient food systems, and implement strategies to stabilise food markets. Analysing this relationship provides critical insights that can help safeguard economic stability, maintain food affordability, and reduce the risk of social unrest linked to volatile energy markets.

2.7 Major global events and their impacts on food prices

Several major global events between 2010 and 2021 likely caused structural breaks in crude oil prices, contributing to higher food prices. These events are linked to economic disruptions, geopolitical tensions, and environmental factors. Some of the key events and their impacts on food prices are discussed below.

Arab Spring (2010-2011)**,** where political unrest and uprisings across the Middle East and North Africa led to significant instability in oil-producing countries such as Libya and Egypt. This resulted in supply disruptions, causing global oil price fluctuations. Since crude oil is a key input in agricultural production, particularly through fuel, transport, and fertiliser costs, this instability affected food prices (Dehshiri and Shahmoradi, 2022).

The Global Financial Recovery (2010-2014) also played a role, as the aftermath of the 2008 financial crisis saw economies gradually recover (Foo and Witkowska, 2017). This recovery increased demand for oil, leading to higher prices. As oil is integral to food production and transport, rising crude prices translated into increased food prices globally.

The Oil Price Collapse (2014-2016), driven by the oversupply from the US Shale Boom, saw oil prices fall from over $100 to below $40 per barrel. This sharp decline disrupted oil-dependent economies and caused volatility in energy markets. While lower oil prices initially reduced transport and production costs, the instability led to fluctuations in food prices, as oil is a crucial input in agriculture and the broader food supply chain (Dutta et al., 2021).

In response, OPEC and Non-OPEC Oil Cuts (2016-2017) saw OPEC and its partners, including Russia, reduce oil production to curb oversupply. This stabilised oil prices, but the resulting price recovery contributed to higher agricultural production costs, driving up food prices as a result (Hunsader et al., 2021).

The US-China Trade War (2018-2019) introduced further instability. Trade tariffs and disrupted global supply chains affected demand for oil, increasing transportation and production costs. These factors contributed to higher food prices, particularly as energy prices were impacted by strained relations between the two economic giants (Itakura, 2020).

The COVID-19 Pandemic (2020-2021) caused one of the most significant disruptions to the global economy. The pandemic led to a sharp decline in oil demand as global lockdowns halted economic activities. This resulted in a historic collapse in crude oil prices, which influenced food prices due to reduced energy costs. However, as economies reopened in 2021, oil prices rebounded sharply, pushing food prices higher as energy costs surged (Mead et al., 2020).

Finally, OPEC+ Disputes and Supply Constraints (2020-2021) exacerbated market instability. Disagreements between OPEC+ members over production cuts, coupled with rising post-pandemic demand, caused oil prices to increase rapidly. These rising energy prices, in turn, inflated food production and distribution costs, contributing to higher global food prices.

In conclusion, the period between 2010 and 2021 witnessed several major global events that caused structural breaks in crude oil prices, which in turn contributed to higher food prices. These events, linked to economic disruptions, geopolitical tensions, and environmental factors, significantly impacted the agricultural sector due to oil's critical role in fuel, transport, and fertiliser costs. Events such as the Arab Spring, the Global Financial Recovery, and the Oil Price Collapse created volatility in oil markets, with direct effects on food prices. Subsequent developments, including OPEC's production cuts, the US-China trade war, the COVID-19 pandemic, and OPEC+

disputes, further drove fluctuations in energy costs, leading to higher production and distribution expenses in the global food supply chain. Thus, the interplay between oil price instability and food prices underscores the need for this study.

2.8 Review of literature

The review of literature explores the relationship between crude oil prices and food prices, focusing on both international and national studies. Various methods and periods have been employed to examine cointegration, short-term and long-term effects, and causality between these variables, with notable similarities and differences emerging in the results.

2.8.1 Review of international literature

Chen et al. (2010) employed an Autoregressive Distributed Lag (ARDL) model to analyse weekly data from 1983 to 2010 in the United States, focusing on the relationship between crude oil prices and global grain prices. The results demonstrated a significant positive relationship between crude oil prices and soybean, corn, and wheat prices, particularly during the periods 1983-1985 and 2005-2008. This means that an increase in crude oil price resulted in an increase in the global grain prices for soybean, corn, and wheat.

Pal and Mitra (2017) used the Johansen cointegration test and a wavelet-based method to examine monthly data from 1990 to 2016 in India. Their findings confirmed a significant long-term cointegrated "relationship between crude oil and food prices", as well as a causal relationship, implying that food prices co-moved with crude oil prices over time. Similarly, Fasanya et al. (2019) found a long-term cointegration relationship between oil prices and agricultural commodities, except for groundnuts, in Nigeria using both linear and nonlinear ARDL models. This means that crude oil prices and agricultural commodity prices, except for groundnut, move together in the long term.

Taghizadeh-Hesary et al. (2019) used a Panel Vector Autoregressive (VAR) model to analyse yearly data from 2000 to 2016 across eight Asian countries (Bangladesh, China, Indonesia, India, Japan, Sri Lanka, Thailand, and Vietnam). The results identified a positive correlation between oil and food prices through price volatility, implying that fluctuations in crude oil prices are closely associated with corresponding changes in food prices.

However, Mohamed (2020), using a Vector Autoregressive model for Germany (2013–2017), found “no long-term relationship between oil and food prices”, though short-term causality was detected for wheat prices. This implies that while oil price fluctuations may not have a lasting impact on overall food prices, they can still influence specific food commodities, such as wheat, in the short term. Lastly, Olayungbo (2021) analysed data from 2001 to 2015 in Nigeria using a Panel ARDL model and found both short-term and long-term relationships between oil and food prices, indicating correlation in the long term but instability in the short term.

2.8.2 Review of national literature

Ajmi et al. (2016) found a significant “causal relationship between global oil prices and certain South African agricultural commodity prices”, particularly wheat, sunflower, and soya, using a “nonlinear Granger causality test” on daily data from 2003 to 2014. “The volatility of wheat, sunflower seed, and sorghum prices” was also linked to fluctuations in OPEC basket oil prices. This study suggests a strong link between oil prices and agricultural commodity prices, specifically highlighting the impact of oil price volatility on agricultural commodity markets.

In contrast, Aye (2016) found “no long-term relationship between” crude oil prices and food prices in South Africa using the Johansen cointegration test, although short-term causality was detected in certain periods (2002–2003, 2006, and 2010) through a time-varying approach. Aye's findings imply that oil prices may not consistently influence food prices over the long term but can affect them temporarily during certain economic conditions. This contrasts with Ajmi et al.'s conclusion of a more persistent influence of oil prices on specific commodities.

Balcilar et al. (2016) provide further complexity by using both “linear and nonlinear Granger causality tests” with daily “data from 2005 to 2014.” “The linear Granger test” found no influence of oil prices on agricultural commodity prices, while the nonlinear test revealed that oil prices Granger-caused wheat and sunflower prices. Like Ajmi et al. (2016), this study suggests a unidirectional causal relationship between oil prices and certain agricultural commodities. However, unlike Aye (2016), both studies indicated that crude oil prices affect specific commodity prices, though not uniformly across all agricultural products.

Fowowe (2016), using yearly data from 2004 to 2008, offered an even more contrasting perspective. His results, based on the Gregory and Hansen cointegration and Diks and Panchenko causality tests, indicated no long-term or short-term relationship between crude oil prices and food prices in South Africa. This finding diverges from the results of Ajmi et al. (2016) and Balcilar et al. (2016), suggesting that oil prices did not significantly affect agricultural commodity prices during the period analysed. Fowowe, however, attributed rising agricultural prices during this period to global oil prices, despite the lack of direct statistical evidence, which may point to indirect effects or other external factors at play.

Kirikkaleli and Darbaz (2021) extended the analysis to a broader energy-food nexus by examining the relationship between energy prices and food prices (including sugar, bananas, beef, chicken, and oranges) over a longer period (1980–2019). Their results from the Toda-Yamamoto and Fourier Toda-Yamamoto causality tests revealed a bidirectional causal relationship, suggesting that changes in energy prices influence food prices and vice versa. This is in contrast to the unidirectional relationships found in studies like Balcilar et al. (2016) and Ajmi et al. (2016), where food prices were affected by oil prices but not the other way around.

Furthermore, Kirikkaleli and Darbaz's study stands out by identifying that grain prices Granger-cause energy prices, highlighting the complexity of the food-energy interaction and the potential feedback mechanisms between these sectors. Their findings of bidirectional causality, particularly with the spectral Breitung-Candelon causality test, suggest that both energy and food prices are interdependent over the long term, a result that contrasts with Fowowe's (2016) conclusion of no long-term relationship between oil and food prices.

In summary, while Ajmi et al. (2016) and Balcilar et al. (2016) suggest unidirectional causality from oil prices to specific agricultural commodities, Aye (2016) and Fowowe (2016) present a more limited or conditional view of this relationship, highlighting that the impact of oil prices on food prices may vary depending on the time period and economic context. Kirikkaleli and Darbaz (2021), on the other hand, present a more complex interrelationship, finding evidence of bidirectional causality, particularly in the long term, indicating a more dynamic and interconnected relationship between energy and food prices over time. These varying results highlight the importance of considering the methodology, time period, and specific commodities studied when assessing the impact of crude oil prices on agricultural markets in South Africa.

2.8.3 Discussion of main findings

The reviewed literature revealed both commonalities and differences in the relationship between crude oil and food prices. International studies generally found evidence of long-term cointegration, indicating that oil and food prices move together over time (Chen et al., 2010; Pal and Mitra, 2017; Fasanya et al., 2019). Conversely, national studies in South Africa, such as studies by Aye (2016) and Fowowe (2016), found no such long-term relationship, suggesting a divergence in how global oil price shocks affect local food markets.

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Causality results also varied, with some studies showing a unidirectional relationship from oil prices to food prices. For instance, Mohamed (2020), using data from Germany, and Balcilar et al. (2016) in South Africa, both found unidirectional causality from oil prices to specific agricultural commodities such as wheat and sunflower, but no evidence of reverse causality. Similarly, Ajmi et al. (2016) reported unidirectional causality from global oil prices to South African agricultural commodities, including wheat, sunflower, and soya.

On the other hand, some studies reported bidirectional causality. For example, Kirikkaleli and Darbaz (2021), examining South Africa, found a bidirectional relationship between energy prices and food prices for certain commodities like sugar, bananas, beef, and chicken, suggesting that food prices can also influence energy prices. Taghizadeh-Hesary et al. (2019), analysing data from eight Asian countries, also identified bidirectional causality between oil and food prices, showing that price volatility in one market could drive fluctuations in the other.

These differences could be attributed to variations in the periods analysed, the specific commodities studied, or the empirical techniques used. While some studies focused on long-term trends using cointegration and linear causality tests, others employed nonlinear methods or time-varying approaches, which may capture more complex dynamics. This underscores the importance of considering methodological differences and context when interpreting the impact of oil prices on food markets across regions.

2.8.4 Discussion of literature gaps

The literature on the relationship between crude oil prices and food prices presents several gaps. First, while many studies have established long-term cointegration between oil and specific agricultural commodities (Chen et al., 2010; Fasanya et al., 2019), there is a lack of research on the broader range of food prices as defined by the FAO (meat, dairy, sugar, cereal, and vegetable oil), particularly accounting for their varying oil intensity. Meat and dairy, for example, are highly oil-intensive, while sugar, cereal, and vegetable oil are less so. This gap highlights the need for a more comprehensive analysis that captures the oil intensity of these diverse food categories, hence the focus of this study. By doing so, this study contributes to the literature by providing a deeper understanding of how oil price fluctuations impact a wider range of food prices, considering their differential oil intensity and the effects of global structural changes.

Second, most studies on causality (Ajmi et al., 2016; Balcilar et al., 2016) have focused on individual commodities without considering the broader structural changes in the crude oil and food markets caused by global events like the Arab Spring, the Global Financial Recovery, the Oil Price Collapse, and the COVID-19 pandemic. These events have significantly altered the relationship between oil and food prices, yet few studies have accounted for these structural breaks. This gap underscores the need for analyses that incorporate such events to better capture the evolving dynamics of oil-food price interactions. By addressing this, the current study contributes to the literature by providing a more accurate understanding of how global events affect the oil-food price relationship.

Lastly, while many studies estimate either short-term or long-term effects of oil prices on food prices (Mohamed, 2020; Pal and Mitra, 2017), few comprehensively examined both, especially in the context of structural changes in global markets. The failure to account for both short and long-term effects alongside structural shifts can lead to biased results, particularly when assessing the speed at which food prices adjust to changes in oil prices. By analysing both short-term and long-term effects within the framework of global structural changes, this study fills an important gap, contributing to the literature by offering a more complete and nuanced understanding of the oil-food price relationship.

Overall, this study contributes to the literature by addressing these gaps through testing for structural breaks in the data, examining both short-term and long-term effects, and utilising a comprehensive set of FAO-defined food prices. This approach provides a more in-depth understanding of how global events and the varying oil intensity of different food categories influence the relationship between crude oil and food prices.

2.9 Chapter summary

This chapter explored the relationship between crude oil prices and food prices in South Africa, covering a series of essential topics to achieve a comprehensive understanding of this dynamic. It began with the definition of terms, providing clear explanations of crude oil prices and food prices as fundamental concepts. Next, the overview of the global crude oil market examined the historical development of crude oil production and its top producers and exporters, highlighting the global forces that influenced oil prices. The chapter then focused on crude oil pricing in South Africa, detailing how international and domestic factors, including government regulations, impacted oil prices within the country.

A section on food production in South Africa followed, discussing regional disparities and the role of key agricultural commodities such as cereals, dairy, meat, sugar, and vegetable oil. The chapter also covered regional food price variations and factors affecting food prices, underscoring the impact of supply and demand, production levels, climate conditions, and trade policies. The chapter also discussed the pathways through which crude oil prices affected food prices, examining the oil intensity of various commodities and the effects of global events on food prices. Each section was crucial in building a thorough analysis of how crude oil prices influenced food costs, particularly in the context of South Africa, where energy and agricultural markets are closely interconnected.

Finally, the chapter concluded with a review of literature, providing insights into the different methodologies, results, and findings across various studies, offering a deeper understanding of the short-term and long-term effects, cointegration, and causality between these variables. This literature review highlighted both the similarities and divergences in results, framing the broader context of how crude oil prices influence food costs, particularly in South Africa.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter on research methodology provides a description of the study area and data sources. It also outlines the analytical techniques, which are categorised into pre-testing analysis, econometric modelling techniques, and results validation methods. The pre-testing analysis includes descriptive analysis, optimal lag determination, variance inflation factor (VIF) analysis, and unit root testing. The econometric modelling techniques cover the bound co-integration test, the Autoregressive Distributed Lag (ARDL) model, and the Toda-Yamamoto Granger causality test. The validation methods involve diagnostic tests for normality, serial correlation, heteroskedasticity, and functional form.

3.2 Study area

This study focuses on analysing the relationship between crude oil prices and food prices in South Africa. The country is bordered to the northwest by Namibia, to the north by Botswana and Zimbabwe, to the northeast by Mozambique, and to the east by Eswatini (formerly Swaziland). Lesotho, an independent country, is entirely surrounded by South African territory along the republic's eastern borders. The South African oil industry is divided into upstream and downstream activities. Upstream involves crude oil exploration and production, while downstream encompasses the processing, transportation, and marketing of final products for consumers (South

African Petroleum Industry Association, 2018). Figure 3.1 below presents a map of South Africa.

Figure 3.1: South African map

Source: Nations Online Project (2024)

South Africa ranked as the world's 64th largest exporter of crude petroleum, with exports valued at $122 million, while being the 18th largest global importer and 2nd regionally, reflecting its significant dependence on imported crude oil to meet energy demands (EIA, 2023). This heavy reliance on imported crude oil directly impacts food prices, as crude oil is a key input in agriculture, affecting transportation, fuel costs, and the production of inputs like fertilisers. Consequently, fluctuations in global crude oil prices significantly influence food prices.

Higher crude oil prices lead to increased production and transportation costs, resulting in rising food prices (Chatziantoniou et al., 2021; Ike et al., 2023). Therefore, changes in South Africa's crude oil import costs, driven by global market conditions, are likely to exert upward pressure on food prices, affecting consumers and food security. For example, the fluctuations in crude oil prices between 2010 and 2021 coincided with rising food prices in South Africa, particularly in categories like meat, dairy, cereals, and oils, as well as decreases in prices for cereals, meat, and sugar (StatsSA, 2023). This highlights the importance of this study to examine the relationship between crude oil prices and food price fluctuations in these food categories in South Africa, offering insights into how changes in global oil markets influence domestic food prices.

3.3 Description of data and data sources

3.3.1 Sample size

The study utilised secondary time-series data to analyse the relationship between crude oil prices and food prices in South Africa. Time-series data refers to an ordered sequence of observations (e.g., years) of well-defined data points at regular intervals (Wooldridge, 2020). Quantitative data for both crude oil and food prices, expressed in counts or numbers, were used, with each data set having distinct numerical values (Rudd et al., 2021). Prior to the analysis, the Bai-Perron test was employed to identify structural breaks caused by global events, such as the Arab Spring, the Global Financial Recovery, the Oil Price Collapse, and the COVID-19 pandemic, all of which impacted both the energy and food markets. The Bai-Perron test identified two significant structural breaks: March 2014, coinciding with the Oil Price Collapse of 2014-2016, and February 2020, marking the onset of the COVID-19 pandemic.

The analysis was divided into three segments: the first segment covered the period before the March 2014 break (January 2010 to February 2014); the second segment spanned from the March 2014 break to the pre-pandemic period (March 2014 to February 2020); and the third segment covered the period from the onset of COVID-19 to July 2024. To account for the increased time span in the third segment, the study analysed monthly data from January 2010 to July 2024, extending beyond the initial 2010-2021 period. This resulted in a total of 174 observations: 49 for the first segment (January 2010 to February 2014), 71 for the second segment (March 2014 to February 2020), and 52 for the third segment (March 2020 to July 2024). The overall sample size, as well as each segment, meets the recommended minimum of 30 to 50 observations for reliable time-series modelling, ensuring sufficient statistical power and robustness in the analysis (Gujarati and Porter, 2009).

3.3.2 Description of EIA crude oil price data

Crude oil price data were obtained from the U.S. Energy Information Administration (EIA), the official energy statistics of the United States Government. The EIA was chosen as the data source due to its inclusion of South Africa in its global crude oil price database. Previous South African studies, such as those by Fowowe (2016) and Chiweza and Aye (2018), also utilised EIA data for analysing the oil-food nexus in South Africa. Since South Africa is a net importer of crude oil, the EIA provides relevant and reliable data for academic research, reflecting the country's role in the dynamic and interconnected global crude oil market. While the EIA primarily focuses on U.S. oil markets, it also offers comprehensive international data, tracking crude oil imports and exports, including South Africa's, with detailed information on volumes, prices, and trade partners. Additionally, it provides historical crude oil price data, relevant to South Africa's consumption and imports, which reflect global oil price movements and trends. The EIA also compiles country-specific analysis briefs, offering insights into South Africa's oil sector, consumption patterns, refining capacity, and its role in the global oil market.

3.3.3 EIA's compilation process for crude oil price data

The EIA collects and compiles crude oil price data through a structured, systematic process, ensuring its reliability and validity. It aggregates data from multiple sources to produce average daily, weekly, and monthly prices for key benchmarks, such as Brent, West Texas Intermediate (WTI), and Dubai/Oman. This approach offers a comprehensive view of global price trends. To ensure consistency, crude oil prices are standardised in US dollars per barrel, enabling effective comparisons across different crude oil grades and regions. The EIA integrates this data into its databases using statistical software to organise and process the information, providing an accurate representation of global crude oil price trends. This rigorous process justifies the use of EIA data in this study.

3.3.4 Reliability, accuracy, and validity of EIA crude oil price data

The EIA ensures the reliability, accuracy, and validity of its crude oil price data through cross-verification, quality checks, statistical techniques, and regular audits. Data are cross-checked from multiple sources, including surveys from refineries, oil producers, customs data, trading exchange prices, and reports from agencies such as the IEA and OPEC. Rigorous quality checks identify and correct inconsistencies or anomalies, while statistical techniques, like smoothing methods and regression analysis, filter out short-term fluctuations, accurately reflecting market trends. Regular audits ensure high standards, with errors corrected in subsequent reports. This thorough process ensures the credibility of EIA crude oil price data, making it a trusted source for policymakers, analysts, and researchers.

3.3.5 FAO food price data

Food price index data were sourced from the Food and Agriculture Organisation (FAO). The FAO was selected as the data source due to its comprehensive global food price index, which includes South Africa. Studies such as those by Fowowe (2016) and Chiweza and Aye (2018) have also used FAO data to analyse food price trends in South Africa. The FAO’s global perspective allows for a comparison of South Africa’s food price trends with international trends, providing insight into how global market dynamics, such as changes in supply and demand or trade policies, affect local prices.

3.3.6 FAO's compilation of food price indices

The FAO collects information for its food price indices using a thorough, methodical procedure that incorporates a variety of sources and techniques. Specifically, FAO obtains pricing information from industry reports, market surveys, and national statistical agencies across a range of nations, including the Statistical Agency of South Africa. Most importantly, this depends on a network of contributors and partners who offer frequent updates on trade flows and market pricing. To calculate the Food Price Index, which represents volatility and trends in prices around the world, the organisation standardises and collects this data, hence its usage in this study.

3.3.7 Reliability, accuracy, and validity of FAO food price data

The FAO compiles food price indices using a systematic process, drawing from multiple sources, including industry reports, market surveys, and national statistical agencies such as Statistics South Africa. The FAO also relies on a network of contributors and partners who provide frequent updates on trade flows and market prices. This data is then standardised and aggregated to calculate the Food Price Index, which tracks price volatility and trends globally. The FAO Food Price Index is used in this study to examine food price trends in South Africa.

3.3.8 Description of food price indices

This study focuses on food price indices for five food categories: cereals, vegetable oil, meat, sugar, and dairy, as compiled and released by the FAO. The FAO Food Price Index (FFPI) is a composite measure of monthly variations in the prices of these food commodities, weighted by their average export shares. The Cereal Food Price Index monitors monthly variations in the prices of cereal grains, including wheat, rice, and coarse grains such as maize, barley, and sorghum. It is influenced by factors such as crop production levels, weather, trade regulations, and market speculation (FAO, 2023).

The Dairy Food Price Index tracks monthly variations in dairy products such as milk, cheese, and butter, influenced by supply and demand dynamics, production costs, and trade policies. The Meat Food Price Index monitors monthly price fluctuations of meats such as lamb, pork, chicken, and beef, affected by factors like disease outbreaks, feed prices, and consumer demand. The Sugar Price Index tracks monthly sugar price changes, reflecting the impact of factors such as weather, energy prices, and trade policies. Lastly, the Vegetable Oil Price Index monitors the prices of oils like rapeseed, palm, soybean, and sunflower, reflecting global market trends in vegetable oil prices (FAO, 2023). Each of these indices provides critical insights into the global and local market trends, which are essential for understanding food price volatility in South Africa.

3.4 Analytical techniques

3.4.1 Descriptive statistics

Descriptive analyses were conducted to examine the food price indexes for each category: cereals, vegetable oils, meat, sugar, dairy, and crude oil prices. Descriptive statistics were used to summarise the mean, maximum, minimum, and standard deviation of these price indexes. The aim was to provide summary statistics of crude oil prices and the price indexes for each food category, highlighting the mean, minimum, maximum, and standard deviation of price fluctuations over the study period.

3.4.2 Optimal lag determination

Optimal lag determination plays a critical role in time series analysis (Gujarati and Porter, 2009), particularly in the analytical techniques used in this study to examine the relationship between crude oil prices and food prices. For instance, the study used the Augmented Dickey-Fuller (ADF) test to check for unit roots and stationarity in the time series. Thus, the inclusion of appropriate lag lengths in the ADF test is necessary to account for autocorrelation in the residuals, ensuring reliable conclusions about the stationarity of crude oil and food prices, which is crucial for further modelling. After unit root testing, the Autoregressive Distributed Lag (ARDL) Bounds Test was employed to establish the long-term relationship between crude oil and food prices. Therefore, lag length is crucial, as it determines the ARDL model's ability to capture long-term relationships.

Once cointegration was established, an Error Correction Model (ECM) within the ARDL framework was used to estimate both the short-term and long-term effects of crude oil prices on food prices. Accordingly, the correct lag length is crucial for specifying the speed of adjustment towards long-term equilibrium, allowing for an accurate assessment of how quickly food prices respond to changes in crude oil prices in both the short and long term. Lastly, the Toda-Yamamoto Granger causality test was applied to examine the causal relationship between crude oil prices and food prices. As such, determining the lag length is essential for accurate causality determination. Additionally, data were divided into three segments due to the detection of structural breaks by the Bai-Perron test. For each segment, the optimal lag length was determined separately, accounting for the structural changes in the crude oil and food markets due to global events like the Arab Spring, the Global Financial Recovery, the Oil Price Collapse, and the COVID-19 pandemic.

Several criteria are commonly employed to determine the optimal lag length, including the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC or BIC), Hannan-Quinn Criterion (HQC), and Final Prediction Error (FPE) (Gujarati and Porter, 2009). Lag length refers to the number of previous time periods considered in the model, and it determines how much historical information is used to predict present or future values of the dependent variable. Therefore, choosing the appropriate lag length is crucial for the model's accuracy, performance, and ability to capture dynamic relationships between variables (Enders, 2014). The AIC and BIC are the most commonly used to determine optimal lag length, where "optimal" refers to the best trade-off between model fit and complexity. The AIC tends to select more lags and prioritises model fit, while the BIC is more conservative, favouring models with fewer lags to avoid overfitting (Lütkepohl, 2005). However, for this study, multiple criteria (e.g., AIC, BIC, and HQC) were applied to determine the optimal lag length for the analytical techniques, ensuring the balance between accuracy and reliability of the findings.

The choice of lag length directly affects the robustness of the results. For instance, an overly long lag structure could introduce unnecessary noise and lead to overfitting, where the model becomes too complex and less generalizable. In contrast, using too few lags might omit important historical information, resulting in biased estimates and a misrepresentation of the dynamic interactions between crude oil and food prices (Lütkepohl, 2005). Hence, optimal lag length was applied to ensure reliable analysis of both short-term and long-term relationships, as well as causality between crude oil and food prices.

3.4.3 Variance inflation factor (VIF) analysis

After determining the optimal lag structure, the Variance Inflation Factor (VIF) analysis was conducted to assess multicollinearity among predictor variables. Multicollinearity occurs when predictor variables are highly correlated, which can lead to instability in the model and inaccurate estimation of regression coefficients (Kyriazos and Poga, 2023). VIF helps identify which predictors contribute to multicollinearity, ensuring that the regression model is reliable, consistent, and interpretable (Gujarati and Porter, 2009; Wooldridge, 2013).

A high VIF value for a predictor suggests that it is significantly influenced by other predictors in the model. This may necessitate adjustments, such as adding or removing variables, to improve the model's performance and interpretability. According to Shrestha (2020), the common cut-off point for VIF is 10; a value above 10 indicates a serious multicollinearity issue. In such cases, combining or eliminating highly collinear variables should be considered. Conversely, VIF values below 5 suggest that multicollinearity is not a significant concern, while values between 5 and 10 indicate moderate but often acceptable levels of multicollinearity (Kutner et al., 2005).

3.4.4. Testing for structural breaks

The Bai-Perron test was employed to identify the existence and number of structural breaks in crude oil and food prices from 2010 to 2021. This test is particularly suitable for this study, as it detects and estimates multiple structural breaks in time series data

(Bai and Perron, 1998), which is essential given the numerous global events that impacted both oil and food prices during this period. Events such as the Arab Spring, the Global Financial Recovery, the Oil Price Collapse, and the COVID-19 pandemic, among others, caused significant shifts in crude oil markets, leading to disruptions in food prices due to the critical role of oil in agricultural production (Mead et al., 2020; Dutta et al., 2021). The Bai-Perron test allows for a precise analysis of these shifts by identifying distinct breakpoints in the data, which is crucial for understanding the underlying dynamics between oil price instability and food price fluctuations. Therefore, the test is an ideal choice for this study, as it accounts for multiple structural breaks triggered by various economic, geopolitical, and environmental factors (Bai and Perron, 1998).

The alternative structural breaks tests to the Bai-Perron test, such as the Chow Test and the Zivot-Andrews Test, are not suitable for this study for several reasons. The Chow Test, while effective in detecting structural breaks, is limited in that it requires the breakpoints to be pre-specified (Greene, 2018). This limitation makes it unsuitable for this study, where multiple structural breaks due to various unpredictable global events that occurred between 2010 and 2021. The need to account for the cumulative impact of these events, such as the Arab Spring, the Global Financial Recovery, and the COVID-19 pandemic, makes the Bai-Perron test more appropriate, as it detects multiple structural breaks without the need to pre-specify the break dates.

Similarly, the Zivot-Andrews Test, although advantageous in detecting structural breaks in the presence of unit roots (non-stationary data), is only capable of identifying a single structural break during significant disruptions (Zivot and Andrews, 1992). This limitation renders it inappropriate for this study, where the data on crude oil and food prices likely experienced multiple shifts due to various economic, geopolitical, and environmental factors. The Bai-Perron test, by contrast, is specifically designed to identify and estimate multiple structural breaks, making it a better fit for analysing real-world data like crude oil and food prices, which are influenced by numerous global events over time. Thus, given the need to detect multiple structural breaks caused by key global events, the Bai-Perron test is the most suitable method for this study, while the Chow and Zivot-Andrews tests fall short of detecting multiple structural breaks.

The Bai-Perron test precisely estimates breakpoints by minimising the residual sum of squares (RSS) across different data segments. This ensures that identified breakpoints represent genuine shifts in the relationship between crude oil and food prices over the period. Unlike other methods, the Bai-Perron test does not require pre-specifying the number of breaks, as it can infer the number directly from the data. This makes it robust for detecting structural shifts in various scenarios, such as periods of sharp price fluctuations (Bai and Perron, 1998).

Bai-Perron test involves selecting an appropriate trimming parameter and maximum number of breaks to ensure the robustness of the identified breakpoints. Trimming refers to the proportion of data excluded from each end of the time series to avoid identifying breaks in regions with too few observations. A commonly used trimming level is 0.15, meaning 15% of the observations are excluded from each end of the series. This allows for more reliable estimation of breaks in the remaining data, ensuring that enough observations exist around potential breakpoints to support valid inferences (Bai and Perron, 1998).

In the Bai-Perron test, the null hypothesis asserts that no structural breaks exist in the time series data for crude oil and food prices, while the alternative hypothesis states that one or more structural breaks exist in the data (Bai and Perron, 2003). The test uses the supremum (sup) F statistic, comparing it to a critical value to determine if structural breaks are present. If the sup F test statistic exceeds the critical value, the null hypothesis is rejected, indicating significant structural breaks in the data. This means that breakpoints should be incorporated into the analysis to account for changes in the relationship between crude oil and food prices. By using the Bai-Perron test, structural breaks can be identified and incorporated into further analyses, such as unit root testing (Bai and Perron, 1998). This ensures a more accurate assessment of unit roots and the relationship between crude oil and food prices during the study period, as the test accounts for significant shifts in the data, enhancing the precision and robustness of the overall analysis.

3.4.5 Unit root testing

After testing for structural breaks, the Augmented Dickey-Fuller (ADF) unit root test was used to check for the stationarity of the data. The ADF test is a supplement to the Dickey-Fuller test for a more extensive and intricate collection of time series models

(Bakır and Eryılmaz, 2015). The ADF test accounts for the possibility of serial correlation in the errors by adding lagged values of the dependent variable. It tests the null hypothesis that a unit root is present (i.e., the series is non-stationary) against the alternative hypothesis that the series is stationary. The ADF test involves estimating the following regression (Hamilton, 1994):

$$\triangle Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \triangle Y_{t-1} + \varepsilon_t \quad (1)$$

Where: ΔY_t represents the first difference of the time series ($Y_t - Y_{t-1}$), α is the constant (intercept) term, β_t is the trend component (optional, depending on the test), γ is the coefficient of the lagged level of the time series, δ_i represents coefficients of the lagged differences of the time series, p is the number of lags included to account for serial correlation, and ε_t is the error term. After the Bai-Perron test identified the existence and number of structural breaks, the study period was divided into subsamples. The ADF Test was then applied to each subsample to ensure stationarity within those distinct periods. This approach helps to account for potential changes in data behaviour due to structural breaks, allowing for more accurate testing of unit roots and improving the reliability of the results.

$$\triangle Y_t seg1 = \alpha_1 + \beta_1 + \gamma_1 Y_{t-1,seg1} + \sum_{i=1}^{p1} \delta 1 \triangle Y_{t-1,seg1} + \varepsilon_{t,seg1} \quad (2)$$

$$\triangle Y_t seg2 = \alpha_2 + \beta_2 + \gamma_2 Y_{t-2,seg2} + \sum_{i=2}^{p2} \delta 2 \triangle Y_{t-2,seg2} + \varepsilon_{t,seg2} \quad (3)$$

$$\triangle Y_t seg_3 = \alpha_3 + \beta_3 + \gamma_3 Y_{t-3,seg3} + \sum_{i=3}^{p3} \delta 3 \triangle Y_{t-3,seg3} + \varepsilon_{t,seg3} \quad (4)$$

In this study, unit root testing is crucial to ensure that crude oil and food price data are not integrated of order two (I(2)), as this would invalidate the bounds co-integration test, which is applied to establish the existence of a long-term relationship between these variables. Although the bounds test can accommodate both stationary (I(0)) and non-stationary (I(1)) variables, unit root testing helps verify that the data meet the necessary conditions for valid co-integration analysis. Once the long-term relationship is confirmed, the Error Correction Model (ECM) is used to estimate both short-term and long-term effects, ensuring that any deviations from equilibrium are corrected over time. Moreover, the Toda and Yamamoto (TY) Granger causality test relies on stationary or co-integrated data to accurately determine the direction of causality between crude oil and food prices. Thus, unit root testing ensures the data are suitable for accurate and reliable estimations in this study.

3.4.6 Cointegration testing

After testing for unit roots, the ARDL Bounds Test was employed to determine the existence of a long-term cointegration relationship between crude oil prices and food prices in South Africa, thereby achieving the third objective of the study. Establishing cointegration in this study is crucial to ensure that crude oil and food prices share a stable long-term relationship, even if the variables are of mixed orders of integration (I(0) or I(1)). The Bounds Test, a component of the Pesaran et al. (2001) ARDL framework, is specifically designed to handle variables that are integrated at different levels, making it suitable for this study. The test verifies cointegration by assessing the joint significance of the lagged level variables in the ARDL model.

In this approach, the F-statistic is compared to critical value bounds that account for different integration orders. If the F-statistic exceeds the upper bound, cointegration is confirmed, indicating a stable long-term relationship. If the F-statistic is below the lower bound, no cointegration exists, and results falling between the two bounds are inconclusive.

Alternative cointegration tests, such as the Engle-Granger and Johansen tests, are not appropriate for this study. The Engle-Granger test is limited because it only tests for cointegration between two variables and can identify only one cointegrating equation. Given that this study involves more than two variables, the Engle-Granger test is unsuitable. The Johansen test, while useful in detecting multiple cointegrating vectors, requires large sample sizes to yield accurate results. Since structural breaks reduced the sample size, the Johansen test's accuracy may be compromised, making it less preferred in this context.

The F-bound test, by contrast, is flexible and robust even with smaller sample sizes, making it ideal for this study. It is easier to interpret compared to the Johansen test, and it provides clear decision-making criteria by comparing the F-statistic with critical values. Additionally, the F-bound test does not require pre-testing for unit roots, though unit root testing was conducted to ensure that none of the variables are integrated of order 2 (I(2)). This was done to avoid invalidating the ARDL model and leading to spurious results, given that the F-bound test is only applicable to variables integrated of order 0 (I(0)) or 1 (I(1)).

In the F-bound test, two main hypotheses are tested. The null hypothesis (H_0) posits that no long-term relationship (no cointegration) exists between the variables, meaning that changes in one variable do not have a lasting impact on another. The alternative hypothesis (H_1) suggests that the variables are cointegrated, meaning that they maintain a long-term equilibrium relationship despite short-term fluctuations.

The ARDL Bounds Test was chosen for this study due to its flexibility in handling variables of different integration orders, its ability to work with small samples, and its simplicity in interpretation. As the study focuses on assessing both short-term and long-term relationships between crude oil and food prices, confirming cointegration through the F-bound test is crucial for proceeding to the next step of estimating the short-term and long-term effects using the Error Correction Model (ECM) within the ARDL framework.

3.4.7 Autoregressive Distributed Lag (ARDL) model

After confirming the existence of cointegration, the Autoregressive Distributed Lag (ARDL) model was employed to estimate the short-term and long-term effects of crude oil prices on food prices in South Africa, thereby achieving the second objective of the study. This model was chosen because it accommodates variables with mixed integration orders, such as I(0) and I(1), and allows for the inclusion of lagged values (Pesaran and Shin, 1998; Nkoro and Uko, 2016). Lagged values are important in economic time series, where changes in crude oil prices may not have an immediate impact on food prices, but rather a delayed effect (Enders, 2014). The general form of an ARDL (p, q) model, where *p* and *q* represent the lag orders for the dependent and independent variables, is as follows (Pesaran and Shin, 1998):

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j} + \varepsilon_t \qquad (5)$$

Where: Y_t is the dependent variable, X_t is the independent variable, α_0 is the constant term, α_i represents the coefficients of the lagged values of the dependent variable, β_j represents the coefficients of the lagged values of the independent variable, *p* and *q* are the maximum lag lengths of the dependent and independent variables, respectively, and ε_t is the error term. This ARDL formulation allows the analysis of how past values of crude oil prices and lagged values of the independent variables affect the current crude oil price (Enders, 2014), providing insights into both short-term and long-term dynamics (Pesaran et al., 2001).

Estimating both the short-term and long-term effects using the ARDL model is crucial, as it provides a comprehensive analysis of the long-term equilibrium and short-term dynamics, particularly when the variables have different integration orders (Pesaran et al., 2001; Nkoro and Uko, 2016). This approach ensures that the relationship between crude oil and food prices is thoroughly explored over both time horizons. Alternative models, such as the Pooled Mean Group (PMG) estimator, were considered but found unsuitable for this study. The PMG estimator is effective for panel data with multiple cross-sectional units (Baltagi, 2008; Hsiao, 2022). Since this study uses time series data, the ARDL model is more appropriate. Additionally, the ARDL model is easier to apply and interpret, making it ideal for understanding both long-term and short-term relationships within a single dataset (Pesaran et al., 2001; Sewar et al., 2020).

The null hypothesis for the long-term relationship posits that there is no effect of crude oil prices on food prices, while the alternative hypothesis suggests that there is a significant long-term effect. Similarly, in the short term, the null hypothesis asserts that crude oil prices have no effect on food prices, while the alternative hypothesis indicates a significant short-term effect. If the F-statistic exceeds the upper bound critical value, the null hypothesis of no long-term effect is rejected, suggesting that crude oil price fluctuations have a long-term effect on food prices. For short-term dynamics, the significance of the p-values of the lagged coefficients determines whether crude oil prices significantly influence food prices in the short term (Pesaran et al., 2001; Enders, 2014; Nkoro and Uko, 2016). This study employs a multivariate ARDL setup, incorporating a system of equations for multiple variables, including sugar, meat, dairy, cereal, crude oil, and vegetable oil. This allows for the simultaneous examination of interactions among these factors, providing a comprehensive understanding of how crude oil prices affect various food prices in both the short and long term (Pesaran et al., 1999). As a result, the general ARDL (p, q) model is converted into the particular ARDL (p, q, r, s,u,v) model in the following manner:

$$CO_T = \alpha_1 + \sum_{i=1}^{p1} \beta_{1t} CO_{t-i} + \sum_{j=0}^{q1} \gamma_{1j} CEREAL_{t-j} + \sum_{k=0}^{r1} \delta_{1k} DAIRY_{t-k} +$$

$$\sum_{l=0}^{s1} \phi_{1l} MEA\mathrm{T} + \sum_{m=0}^{u1} \psi_{1m} SUGAR_{t-m} + \sum_{n=0}^{v1} \eta_{1n} VEGOIL_{t-n} + \varepsilon_{2t} \quad (6)$$

Where: CO_t is the dependent variable (crude oil prices); x_t is the independent variable (e.g., food prices such as dairy, meat, or cereal); α_0 is the constant term; αi represents coefficients of the lagged values of the dependent variable CO_{t-l}; β_j represents the coefficients of the lagged values of the independent variable X_{t-j}; p and q are the maximum lag lengths of the dependent and independent variables, respectively; and ϵ_t is the error term, capturing random disturbances in the model. In the analysis, the food price categories are set as the dependent variables, with crude oil prices as the explanatory variable influencing changes in these categories. Therefore, the coefficients are interpreted as the effects of crude oil price changes on food prices. Subsequently, Equation (6) can be rewritten as Equation (7) below, where each food price category is set as the dependent variable, with crude oil prices as the explanatory variable influencing changes in each category.

$$FP_t = \alpha_2 + \sum_{j=0}^{q2} \gamma_{1j} FP_{t-j} + \sum_{i=2}^{p2} \beta_{1t} CO_{t-i} + \sum_{k=0}^{r2} \delta_{1k} FP_{t-k} + \sum_{l=0}^{s2} \phi_{1l} FP_{t-l} +$$

$$\sum_{m=0}^{u2} \psi_{1m} FP_{t-m} + \sum_{n=0}^{v2} \eta_{1n} FP_{t-n} + \varepsilon_{2t} \quad (7)$$

Thus, Equation (7) illustrates how crude oil prices (COt) interact with food price categories (e.g., cereal, dairy, meat, sugar, and vegetable oil) using their respective lag structures. The terms *p,q,r,s* represent the lag orders for the dependent and independent variables, allowing for a detailed analysis of both short-term and long-term relationships between these variables. In this multivariate ARDL setup, each food price category has its own lag structure, making it possible to capture the distinct effects of past values of each variable on the current value of crude oil prices or food prices, providing a comprehensive understanding of the interactions among the variables (Pesaran et al., 2001; Enders, 2014; Nkoro and Uko, 2016).

3.4.8 Granger causality testing

After estimating the long-term and short-term effects, the Toda-Yamamoto Granger causality test was employed to determine the causal relationship between crude oil prices and food prices in South Africa, thereby achieving the third objective of the study. The Toda-Yamamoto approach is a modified technique for identifying causality in time series variables, regardless of their integration levels (I(0), I(1), or even I(2)). This method adjusts the traditional Granger causality test by using a modified Vector Autoregressive (VAR) model, addressing issues associated with non-stationary or cointegrated data (Lütkepohl, 2005).

In this approach, the VAR model's lag length is set as the sum of the optimal lag length (determined by criteria like AIC or BIC) and the maximum order of integration of the system's variables. This ensures the test's asymptotic properties hold even when integrated or cointegrated variables are present (Toda and Yamamoto, 1995). Alternative causality tests, such as the Breitung-Candelon Granger causality test, were considered but found unsuitable for this study. While effective at detecting causality based on frequency components, the Breitung-Candelon method focuses on periodic data elements, which may miss time-domain causality effects. This limitation makes it inappropriate for this study, which requires time-domain analysis to assess the direct and clear causality between crude oil prices and food prices. Therefore, the Toda-Yamamoto test is the most appropriate method for this study due to its robustness in handling integrated and non-stationary data.

One of the main advantages of the Toda-Yamamoto approach is that it eliminates the need for pre-testing for cointegration or differencing to establish stationarity. The null hypothesis (H_0) states that the lagged values of crude oil prices do not Granger-cause food prices, implying that past crude oil prices cannot predict future food prices. The alternative hypothesis (H_1) asserts that lagged values of crude oil prices do Granger-cause food prices, indicating that past values of crude oil prices significantly influence food prices. The Toda-Yamamoto approach uses the Wald test to evaluate the significance of the lagged coefficients in the augmented VAR model. The null hypothesis is rejected if the p-value of the Wald test is less than the chosen significance level (e.g., 0.05), indicating a Granger-causal relationship from crude oil prices to food prices. Conversely, if the p-value is higher than the significance level, the null hypothesis cannot be rejected, suggesting no causal link between crude oil and food prices (Toda and Yamamoto, 1995). The augmented VAR model in the Toda-Yamamoto approach is expressed as follows:

$$Z_t = C + \sum_{i=1}^{k+d_{max}} A_i Z_{t-1} + \varepsilon_t \quad (8)$$

Where: *Zt* is a vector of all the variables in the system at time t; *c* is a vector of constants (intercepts); A_i represents the coefficient matrices of the lagged values; *k* is the optimal lag length of the VAR model, chosen using criteria like AIC or BIC; d_{max} is the maximum order of integration of the variables, representing the number of additional lags to account for possible non-stationarity; and *ϵt* is a vector of error terms (residuals) (Toda and Yamamoto, 1995).

This augmented VAR model includes $k+d_{max}$ lags to ensure the validity of the Wald test's asymptotic properties, even in the presence of non-stationary or cointegrated variables. The Wald test is performed on the first *k* lags of the food price coefficients to determine whether crude oil prices Granger-cause food prices. The test can result in four outcomes: unidirectional causality from crude oil to food prices, unidirectional causality from food prices to crude oil, bidirectional causality, or no causality (Toda and Yamamoto, 1995).

In this study, the multivariate Toda-Yamamoto model was employed to capture the causal relationships between crude oil prices and various food prices (cereal, dairy, meat, sugar, and vegetable oil). This model allows for the examination of causality in both directions between crude oil prices and food prices, even in the presence of non-stationary series, by augmenting the lag length with the maximum order of integration, d_{max}. Subsequently, Equation (8) is rewritten as Equation (9) to capture the causality from crude oil prices to the food price categories. In turn, Equation (9) is rewritten as Equation (10) to capture the causality from the food price categories to crude oil prices:

$$CO_t = \alpha_0 + \sum_{i=1}^{k+d_{max}} \alpha_i CO_{t-i} + \sum_{j=1}^{k+d_{max}} \beta_j FP_{t-j} + \sum_{m=1}^{k+d_{max}} \gamma_m FP_{t-m} + \sum_{n=1}^{k+d_{max}} \delta_n FP_{t-n} + \sum_{p=1}^{k+d_{max}} \lambda_p FP_{t-p} + \sum_{q=1}^{k+d_{max}} \phi_q FP_{t-q} + \varepsilon_t \quad (9)$$

$$FP_t = \eta_0 + \sum_{i=1}^{k+d_{max}} \eta_i CO_{t-i} + \sum_{j=1}^{k+d_{max}} \theta_j FP_{t-j} + \sum_{m=1}^{k+d_{max}} \chi_m FP_{t-m} + \sum_{n=1}^{k+d_{max}} \xi_n FP_{t-n} + \sum_{p=1}^{k+d_{max}} \rho_p FP_{t-p} + \sum_{q=1}^{k+d_{max}} \psi_q FP_{t-q} + \varepsilon_t \quad (10)$$

Where: COt represents crude oil prices at time t, FPt represents the various food price categories (cereal, dairy, meat, sugar, and vegetable oil) at time t, α_0,η_0 are the constant terms, αi, ηi, etc., are the coefficients of the lagged values of the respective variables, *k* represents the optimal lag length, dmax is the maximum order of integration for the series, and ϵt is the error term. This approach helps determine whether crude oil price changes cause movements in food prices (Equation 9) and vice versa (Equation 10). It accounts for the interdependencies among multiple food price categories, reducing the risk of omitting important variables and yielding more accurate estimations of how changes in crude oil prices affect food prices. By considering the complex interactions and feedback loops among these variables, the model provides a comprehensive understanding of the dynamics within the food pricing system. Additionally, the multivariate Toda-Yamamoto model handles non-stationary data effectively, ensuring reliable results despite the challenges posed by integrated time series (Toda and Yamamoto, 1995).

3.4.9 Validation of results

The diagnostic tests were conducted to ensure the validity, reliability, and robustness of the ARDL short-term (ECM) and long-term effects. Specifically, the Breusch-Godfrey Serial Correlation LM test was used to check for autocorrelation in the residuals, while the ARCH (Autoregressive Conditional Heteroskedasticity) test assessed the presence of time-varying volatility. The Jarque-Bera test evaluated whether the residuals followed a normal distribution, and the Ramsey RESET test was applied to confirm the correct specification of the model. These validation tests are crucial to prevent biased estimates of both short-term and long-term effects, ensuring that the Error Correction Model (ECM) accurately captures the adjustment process back to the long-term equilibrium without distortion from issues like heteroskedasticity or autocorrelation. By confirming the absence of such issues, the reliability of the estimated coefficients and the overall model is strengthened.

3.5 Chapter summary

This chapter on research methodology provided a description of the study area and data sources. It also outlined the analytical techniques, which were categorised into pre-testing analysis, econometric modelling techniques, and results validation methods. The pre-testing analysis included descriptive analysis, optimal lag determination, variance inflation factor (VIF) analysis, and unit root testing. The econometric modelling techniques covered the bound co-integration test, the Autoregressive Distributed Lag (ARDL) model, and the Toda-Yamamoto Granger causality test. The validation methods involved diagnostic tests for normality, serial correlation, heteroskedasticity, and functional form.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results from the descriptive analysis, optimal lag determination, variance inflation factor analysis, and structural breaks test. The structural breaks results are followed by the findings from the ADF test, bounds cointegration test, and the ARDL short-term (ECM) and long-term effects, as well as the Toda-Yamamoto Granger causality test. Additionally, the chapter discusses the results of the bounds cointegration test, the ARDL short-term (ECM) and long-term effects, and the TY Granger causality test, highlighting how the findings of this study compare with and diverge from previous literature. The chapter also includes the results of diagnostic tests, such as the Breusch-Godfrey Serial Correlation (LM) test, the Jarque-Bera test, the ARCH (Autoregressive Conditional Heteroskedasticity) test, and the Ramsey RESET test, all of which were used to validate the robustness of the ARDL short-term (ECM) and long-term effects.

4.2. Descriptive statistics results

Descriptive statistics were used to summarise the key characteristics of the crude oil and food price data in this study, providing an overview of central tendencies and variability within the dataset. Specifically, these statistics capture the mean, minimum, and maximum values for crude oil prices and various food price categories over the study period. This offers a clear understanding of the range and typical values for each variable. Additionally, the trend analysis results highlight fluctuations in crude oil and food prices, providing context for subsequent analyses of their potential relationships. By summarising these basic characteristics, the descriptive statistics and trend analysis establish a foundation for further econometric testing, including unit root, cointegration, and causality analyses. The descriptive statistics for crude oil prices (USD per barrel) and food price categories (USD per metric tonne) are presented in Table 4.1 below.

Table 4.1: Descriptive statistics results

	Crude oil	Cereal	Dairy	Meat	Sugar	Veg oil
Mean	78.164	115.963	115.136	103.147	110.626	120.854
Median	75.950	113.800	112.800	103.100	109.300	115.800
Maximum	159.050	173.500	158.200	126.000	183.200	251.800

Minimum	18.380	86.000	72.700	84.200	63.200	76.590
Std.dev	25.913	21.814	19.913	9.482	27.637	32.838
Skewness	0.154	0.415	0.236	0.213	0.541	1.159
Kurtosis	2.308	20.122	2.690	2.222	2.567	4.712
Jarqua-beta	4.185	10.656	20691	5.743	9.918	60.622
Observation	175	175	175	175	175	175

Source: Author, based on EIA (2024) and FAO (2024)

The results in Table 4.1 summarise the descriptive statistics for crude oil prices and various food price categories between 2010 and 2024. The average crude oil price was \$78.16 per barrel, with a minimum of \$18.38 per barrel and a maximum of \$159.05 per barrel. Among the food price categories, the average price of cereals was 115.96 per metric ton, with a minimum of 86.00 per metric ton and a maximum of 173.50 per metric ton. Dairy prices averaged 115.14 per metric ton, ranging from 72.70 to 158.20 per metric ton. Meat prices had an average of 103.15 per metric ton, with a minimum of 84.20 per metric ton and a maximum of 126.00 per metric ton. The average sugar price was 110.63 per metric ton, with a minimum of 63.20 per metric ton and a maximum of 183.20 per metric ton. Lastly, vegetable oil had the highest average price at 120.85 per metric ton, ranging from a low of 76.59 per metric ton to a high of 251.80 per metric ton.

Among the food categories, vegetable oil exhibited the highest mean and maximum values, indicating significant price increases during the study period. In contrast, cereals had the highest minimum price, suggesting relatively stable lower-bound pricing. The standard deviation was largest for vegetable oil (32.838), indicating greater price fluctuations compared to other food categories. Meanwhile, the other categories, including crude oil, exhibited more moderate price volatility, as reflected in their lower standard deviations.

All price series showed positive skewness, meaning that their distributions were skewed to the right, with more extreme high values (Stock and Watson, 2020). Vegetable oil had the highest skewness (1.159), indicating a greater frequency of higher prices. In terms of kurtosis, cereal and vegetable oil prices were leptokurtic (kurtosis > 3), meaning their distributions had sharper peaks and thicker tails, suggesting more frequent extreme price changes. Crude oil, dairy, meat, and sugar, on the other hand, were platykurtic (kurtosis < 3), indicating distributions with thinner tails and flatter peaks, reflecting more moderate variability in price extremes (Stock and Watson, 2020).

4.3 Optimal lag results

The determination of optimal lag lengths plays a pivotal role in ensuring the accuracy and reliability of the analytical techniques used in this study to examine the relationship between crude oil prices and food prices. For each analytical technique applied, including the ADF test, Bounds cointegration test, ARDL and ECM frameworks, and the Toda-Yamamoto Granger causality test, selecting appropriate lag lengths was essential to ensure the accuracy and reliability of each technique. Methods such as the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC) were employed to identify the optimal lag lengths, balancing model fit and complexity. The analyses were conducted across three distinct segments due to structural breaks identified by the Bai-Perron test. The optimal lag results for each segment are presented in Table 4.2 below.

Table 4.2: Optimal lag results

Lag length for first segment (January 2010 to February 2014)						
Lag	**Log L**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-376.2885	NA	47647.61	16.44733	16.52683	16.47711
1	-310.9857	122.0879*	3316.296*	13.78199*	14.02051*	13.87134*
2	-307.0072	7.092055	3323.898	13.78292	14.18045	13.93184
3	-306.4049	1.021390	3864.770	13.93065	14.48719	14.13913
4	-304.9036	2.415075	4331.873	14.03929	14.75484	14.30734
Lag length for the second segment (March 2014 to February 2020)						
Lag	**Log L**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-476.1156	NA	4387.314	14.06222	14.12750	14.08809
1	-371.3628	200.2627*	226.6179*	11.09890*	11.29474*	11.17650*
2	-368.4929	5.317718	234.3748	11.13214	11.45854	11.26147
3	-363.4738	9.004771	227.6664	11.10217	11.55913	11.28323
4	-360.4870	5.183044	234.9424	11.13197	11.71949	11.36476
Lag length for the third segment (March 2020 to July 2024)						
Lag	**Log L**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-405.0732	NA	56358.47	16.615223	16.69245	16.64453
1	-314.4195	170.2068*	1640.738*	13.07835*	13.31000*	13.16624*
2	-312.4313	3.570746	1783.142	13.16046	13.54655	13.30694
3	-308.0641	7.486551	1761.034	13.14547	13.68599	13.35055
4	-307.5964	0.763686	2043.312	13.28965	13.98460	13.55331

Source: Author, based on EIA (2024) and FAO (2024)

Note: * indicates lag order selected by the criterion.

The results in Table 4.2 indicate that all selection criteria, including the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), have selected a lag length of 1 for the analysis across the three segments. This means that the model with a lag of 1 is the most appropriate for this analysis, as it balances simplicity and accuracy by including enough historical data to explain the current behaviour of the variables without overcomplicating the model with unnecessary lags (Toda and Yamamoto, 1995; Gujarati and Porter, 2009; Enders, 2014).

In the Toda-Yamamoto (TY) Granger causality test, the optimal lag length selected by the criteria (in this case, lag 1) is augmented by an additional lag equal to the maximum order of integration (d-max) of the variables in the system (Toda and Yamamoto, 1995; Gujarati and Porter, 2009; Enders, 2014). Given that the optimal lag length from Table 4.2 is 1, and the maximum order of integration (d-max) of the variables is 1, the lag length used in the TY Granger causality test is 2 (i.e, Optimal lag+dmax = 1 + 1 = 2). This ensures that the test accounts for both the short-term dynamics and the integration properties of the variables, ensuring accurate causality testing (Toda and Yamamoto, 1995).

4.4 Trend analysis results

This section explores the relationship between crude oil prices and various food prices, including cereals, dairy, meat, sugar, and vegetable oil, using time series analysis. By examining trends over time, the aim is to identify whether fluctuations in crude oil prices have a discernible impact on food price movements. The descriptive statistics presented in the previous section provided a preliminary understanding of the variability and distribution of crude oil and food prices. Building on these insights, the trend analysis in this section allows for a deeper examination of the potential dynamic linkages between crude oil price volatility and changes in food prices, with a focus on identifying patterns that may suggest direct or indirect transmission effects. Figure 4.1 illustrates the trends of crude oil and aggregated food prices over the study period.

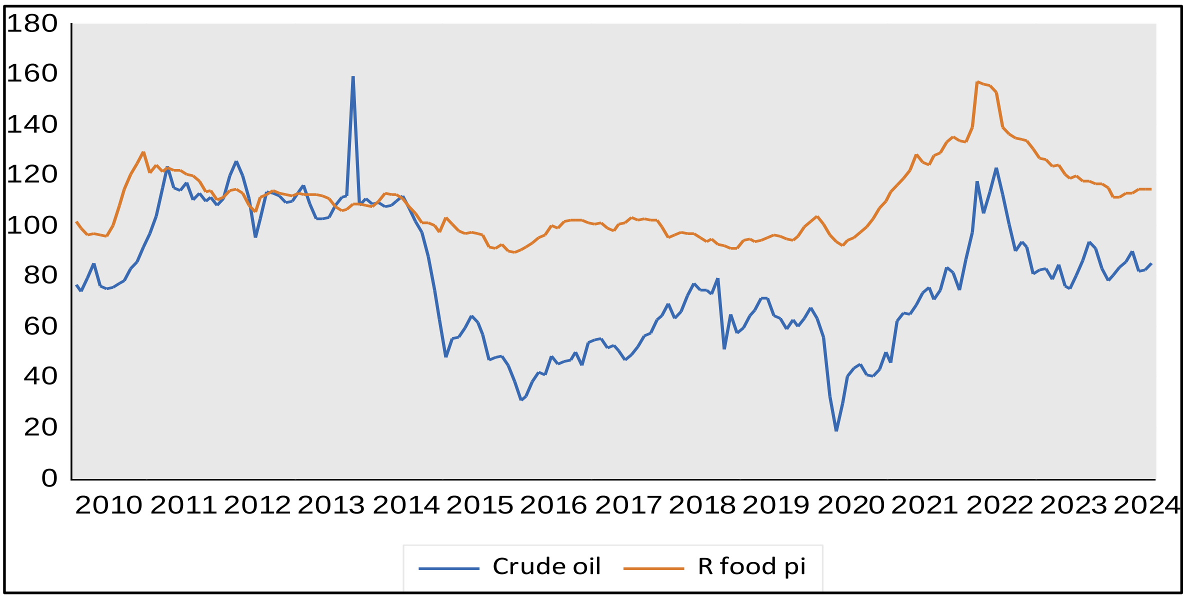

Figure 4.1: Crude oil and aggregate food price index trends

Source: Author, based on EIA (2024) FAO (2024)

Figure 4.1 shows the trends of crude oil prices and the real food price index over time. Crude oil prices exhibit sharp fluctuations throughout the period, while the food price index rises more gradually. Although there is a noticeable spike in crude oil prices midway through the graph, the food price index responds with a delayed and more gradual increase. Towards the end of the period, crude oil prices display greater volatility, while the food price index remains stable at a higher level. This suggests that food prices may not respond directly or immediately to crude oil price changes, and other factors such as supply chain dynamics and global demand are likely to play a more dominant role in food price determination.

Based on the afore-mentioned results, trend analysis for each food category is crucial to understand the varying impacts of crude oil price fluctuations. Figure 4.1 shows that while the overall food price index responds gradually to crude oil volatility, individual food categories may react differently due to specific factors like supply, demand, and production costs. Analysing trends for categories such as dairy, meat, sugar, and vegetable oil helps identify which food categories are more sensitive to crude oil changes, or if other factors, like global demand and supply chain dynamics, play a larger role. This supports more targeted econometric testing and insights into food price drivers. Figure 4.2 below shows the trends of crude oil and cereal prices.

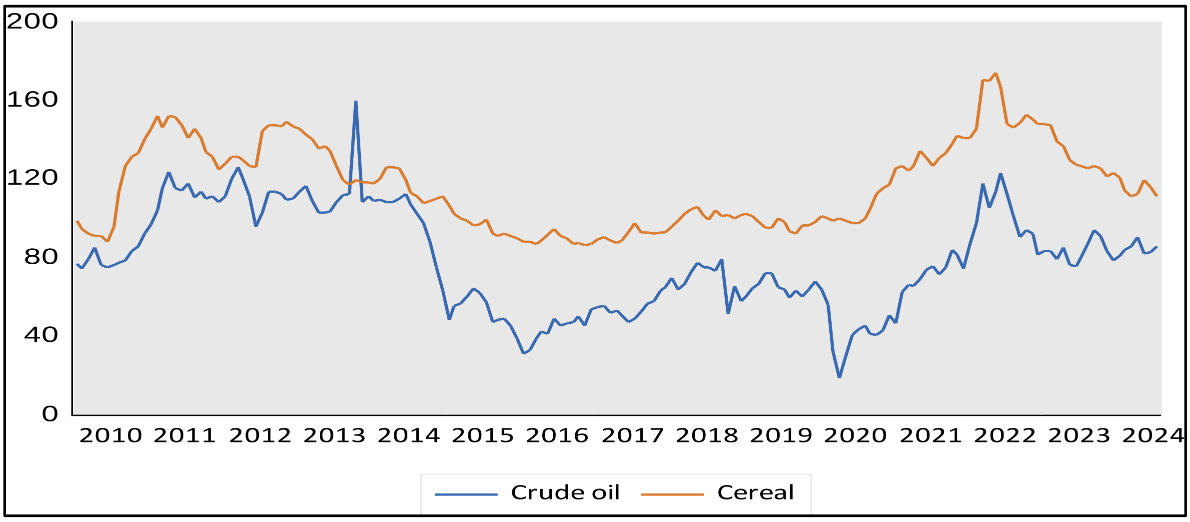

Figure 4.2: Crude oil and cereal price trends

Source: Author, based on EIA (2024) and FAO (2024)

As seen in Figure 4.2, crude oil prices demonstrate significant volatility, with sharp rises and falls throughout the period. There is a notable dip in the middle of the graph, followed by periods of recovery, though the overall trend appears downward in the latter half. In contrast, cereal prices exhibit a more stable and gradual upward trend, with fewer fluctuations. While crude oil prices show sharp swings, cereal prices rise steadily, particularly towards the end of the graph. This suggests that the volatility of crude oil prices has a limited direct impact on food prices, which are more likely influenced by factors such as agricultural production, supply, and global demand. Figure 4.3 shows the trends of crude oil and dairy prices over the study period.

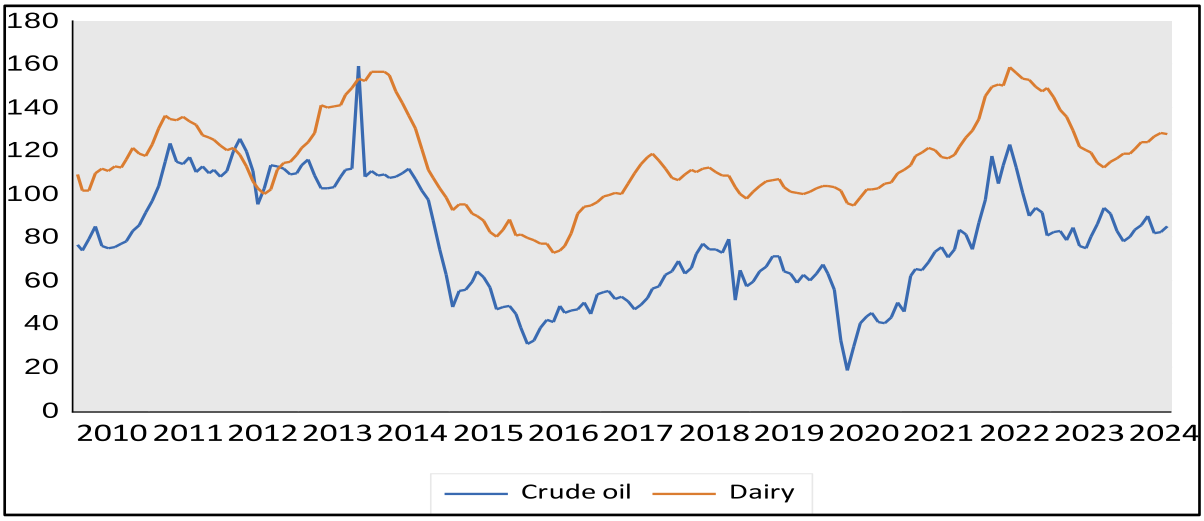

Figure 4.3: Crude oil and dairy price trends

Source: Author, based on EIA (2022) and FAO (2023)

As observed in Figure 4.3, crude oil prices again display significant volatility with sharp fluctuations, while dairy prices follow a much steadier upward trajectory. Dairy prices exhibit gradual increases with minimal fluctuations, particularly towards the middle and end of the period. Despite occasional dips in crude oil prices, dairy prices continue to rise, suggesting that dairy prices are less directly influenced by crude oil volatility. Instead, dairy prices are likely driven by factors such as agricultural production, demand, and global dairy market dynamics. Figure 4.4 compares the trends of crude oil and meat prices.

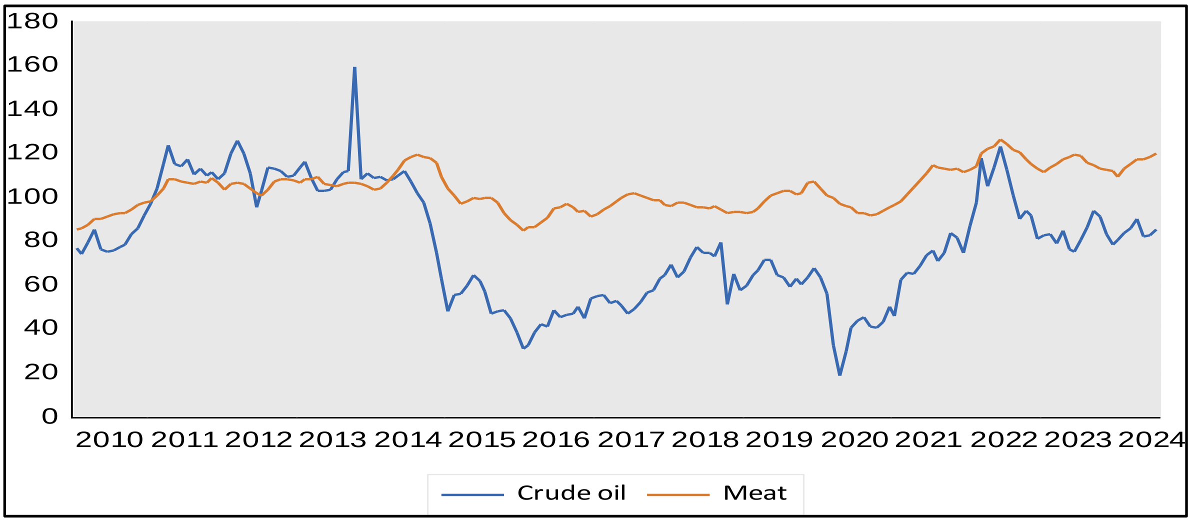

Figure 4.4: Crude oil and meat price trends

Source: Author, based on EIA (2024) and FAO (2024)

Figure 4.4 shows that crude oil prices exhibit frequent and sharp fluctuations throughout the period, whereas meat prices follow a more stable and consistent upward trend. Thus, there is minimal correlation between the two, as meat prices remain steady even during periods of significant crude oil price fluctuations. This suggests that meat prices may be influenced more by production costs, livestock supply, and market demand, with limited immediate impact from crude oil price movements. Figure 4.5 illustrates the trends of crude oil and sugar prices over the study period.

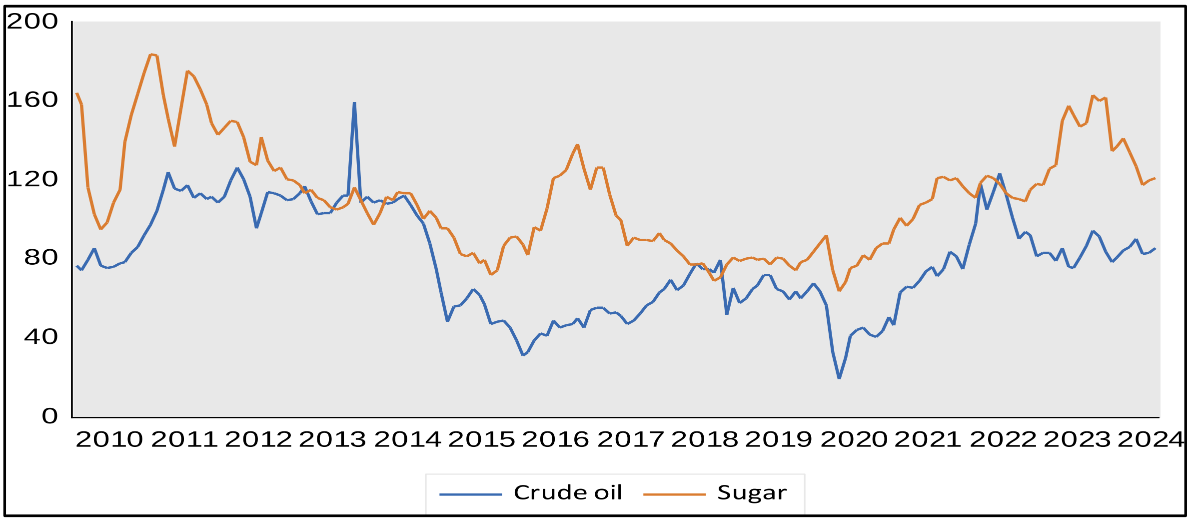

Figure 4.5: Crude oil and sugar price trends

Source: Author, based on EIA (2024) and FAO (2024)

Figure 4.5 shows that crude oil prices exhibit sharp and erratic movements, while sugar prices display more gradual fluctuations. Early in the period, sugar prices spike but eventually stabilise, showing an upward trend towards the end of the graph. Despite some volatility, sugar prices do not mirror the sharp movements in crude oil prices, indicating that factors such as supply, demand, and market-specific dynamics may be the primary drivers of sugar prices rather than crude oil price fluctuations. Figure 4.6 presents the trends of crude oil and vegetable oil prices over the study period.

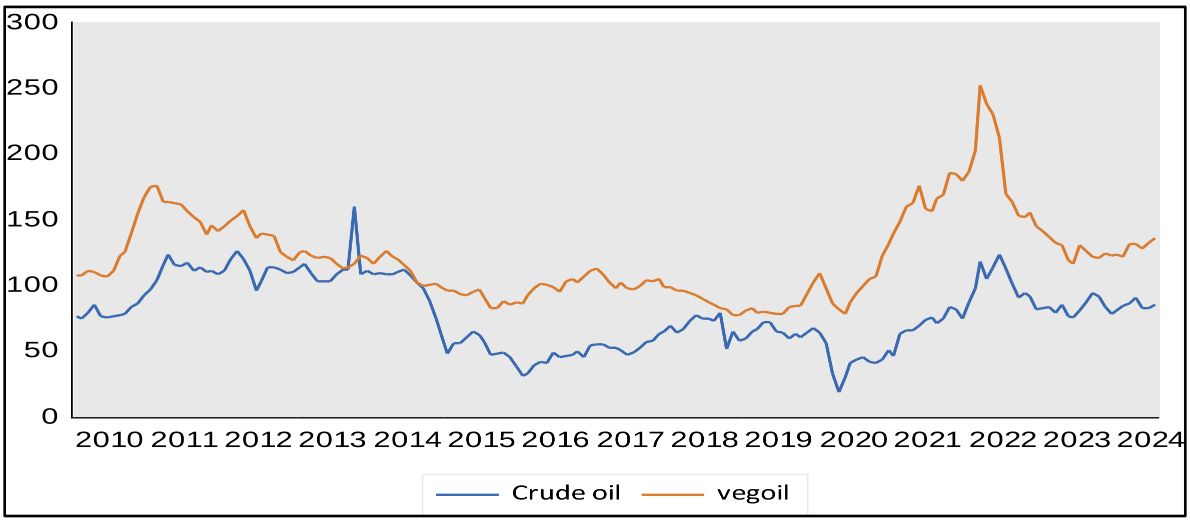

Figure 4.6: Crude oil and vegetable oil price trends

Source: Author, based on EIA (2024) and FAO (2024)

As can be seen from Figure 4.6, crude oil prices show significant volatility with frequent ups and downs, while vegetable oil prices exhibit a steadier and more consistent upward trend. Despite minor fluctuations, vegetable oil prices rise steadily, especially in the latter half of the period. This indicates that vegetable oil prices are less sensitive to crude oil volatility and are more likely influenced by factors such as agricultural production, supply conditions, and global demand for vegetable oil.

Overall, the trend analysis reveals that, while crude oil prices exhibit significant volatility, their impact on food prices is not immediate or direct across all categories. Specifically, cereal, dairy, meat, sugar, and vegetable oil prices generally show more stable upward trends, with food prices displaying resilience despite crude oil price fluctuations. This suggests that factors such as agricultural supply, demand, and trade are likely to play a more substantial role in driving food price trends than crude oil volatility. These findings complement the descriptive statistics in the previous section, which highlighted differences in variability between crude oil and food prices. This reinforces the notion by Baffes (2007) and Zhang et al. (2010) that the food sector operates with some degree of decoupling from energy market fluctuations.

4.5 Variance inflation factors results

The Variance Inflation Factor (VIF) analysis was conducted to assess multicollinearity among the predictor variables. Multicollinearity occurs when predictor variables are highly correlated, which can lead to instability in the model and inaccurate estimation of regression coefficients (Kyriazos and Poga, 2023). VIF helps identify which predictors contribute to multicollinearity, ensuring the regression model remains reliable and interpretable. A VIF value above 10 indicates a serious multicollinearity issue, whereas values below 5 suggest that multicollinearity is not a significant concern (Kutner et al., 2005; Shrestha, 2020). The VIF results for multicollinearity are presented in Table 4.3, providing insight into the degree of correlation among the predictor variables.

Table 4.3: VIF results

Variables	Coefficient variance	VIF value
C	77.60034	NA
Crude oil price	0.002297	3.155633
Dairy price	0.004192	3.401298
Meat price	0.010924	2.009934
Sugar price	0.001222	1.909658
Vegetable oil price	0.001070	2.361046

Source: Author, based on EIA (2024) and FAO (2024)

The results in Table 4.3 show that the VIF values for all predictor variables (i.e., crude oil, dairy, meat, sugar, and vegetable oil) are below 5, ranging from 1.91 to 3.40. This indicates that multicollinearity is not a significant concern in the model, as none of the variables exhibit high correlation with one another (Kutner et al., 2005; Shrestha, 2020). Consequently, the subsequent techniques employed in this study, namely, the Bai-Perron test, ADF test, bounds cointegration test, and ECM, are considered stable, reliable, and suitable for further analysis. The Bai-Perron test results are presented in the next section to identify structural breaks in the time series data, offering insights into any significant shifts that may affect the relationship between crude oil and food prices.

4.6 Bai-Perron test results

The Bai-Perron test for structural breaks was conducted following the descriptive and trend analyses to determine whether the data on crude oil and food prices from 2010 to 2021 contained structural breaks. This test, suitable for identifying and estimating multiple structural breaks in time series data (Bai and Perron, 1998), is particularly important for this study given the numerous global events that impacted both crude oil and food prices during this period. Events like the Arab Spring, the Global Financial Recovery, the Oil Price Collapse, and the COVID-19 pandemic led to significant shifts in crude oil markets, which in turn affected food prices due to oil's role in agricultural production (Mead et al., 2020; Dutta et al., 2021). The Bai-Perron test allows for the detection of these disruptions by identifying specific breakpoints, enhancing the understanding of the dynamic relationship between crude oil price instability and food price fluctuations.

The null hypothesis of the Bai-Perron test asserts no structural breaks exist in the time series data, while the alternative hypothesis posits one or more structural breaks. If the supremum F statistic exceeds the critical value, the null hypothesis is rejected, indicating the presence of structural breaks (Bai and Perron, 2003). Table 4.4 presents the results of the Bai-Perron test.

Table 4.4: Bai-Perron stuctural break results

Schwarz criterion		**2**		
LWZ criterion		**1**		
Breaks	**Sum of sq.Resids**	**Log-L**	**Scharz criterion**	**LWZ criterion**
0	20263.30	-560.50	5.153829	5.350535
1	11416.02	-519.18	4.821623	5.250223**
2	6913.62	-483.07	4.561688**	5.225041
3	4436.07	-451.12	4.359551	5.260849
4	3369.81	-431.32	4.326229	5.469058
5	3128.67	-425.98	4.493568	5.881986
Estimated break date				
1. 2014M03				
2. 2014M03, 2020M02				
3. 2013M04, 2015M03, 2020M02				
4. 2013M04, 2015M02, 2017M11, 2020M02				
5. 2011M10, 2013M07, 2015M04, 2017M11, 2020M02				

Source: Author, based on EIA (2024) and FAO (2024)

The Bai-Perron test results, presented in Table 4.4, indicate several structural breaks in the relationship between crude oil and food prices between 2010 and 2021. The Schwarz criterion (also known as the Bayesian Information Criterion, or BIC) is used to determine the optimal number of breaks by balancing model fit and complexity. It penalises models with more parameters, ensuring that only statistically significant breaks are identified (Schwarz, 1978; Bai and Perron, 2003). Using trimming at 0.15 and allowing for a maximum of five breaks, in line with Ngobeni and Muchopa (2023), the Schwarz criterion identified two key breakpoints: March 2014 (2014M03) and February 2020 (2020M02).

Therefore, despite the potential for multiple disruptions due to major global events, which disrupted both the crude oil and food markets (Itakura, 2020; Mead et al., 2020; Dutta et al., 2021), the Bai-Perron test identified and confirmed only two significant structural breaks: March 2014 (2014M03) and February 2020 (2020M02). Additionally, the Schwarz criterion, used to determine the optimal number of breaks, penalises models with excessive parameters, ensuring that only statistically significant breaks are retained (Schwarz, 1978; Bai and Perron, 2003). This explains why, despite the occurrence of several major global events during this period, the test identified only two key breakpoints.

These two structural breaks correspond to significant global events. The first break, in March 2014, aligns with the Oil Price Collapse of 2014-2016, when oversupply from the U.S. shale boom caused crude oil prices to fall sharply, impacting the broader energy and agricultural sectors. This event led to significant shifts in energy costs, which affected food prices, especially through transportation and production costs (Dutta et al., 2021).

The second break, identified in February 2020, aligns with the global onset of the COVID-19 pandemic, which caused unprecedented disruptions in both crude oil and food markets. Although South Africa reported its first COVID-19 case on March 5, 2020, and declared a National State of Disaster on March 15, 2020 (Stiegler and Bouchard, 2020; South African Government, 2020), the global impact of the pandemic began earlier. In February 2020, as the virus spread internationally, lockdowns and restrictions across major economies sharply reduced oil demand, leading to a collapse in crude oil prices. This decline affected food markets by initially lowering production and transportation costs, but later supply chain disruptions and a subsequent surge in oil prices contributed to rising food prices (Mead et al., 2021). Therefore, the February 2020 break is justified by the broader global economic shock triggered by the early stages of the pandemic.

Thus, while several global events disrupted both oil and food markets during this period, the Bai-Perron test identified these two structural breaks as the most significant. This validates its effectiveness in capturing major shifts in the relationship between crude oil and food prices. The null hypothesis of no structural breaks is thus rejected, as two significant structural breaks in the crude oil and food prices series data have been identified.

After conducting the Bai-Perron test, which identified two structural breaks in March 2014 (2014M03) and February 2020 (2020M02), the data was segmented into three subsamples corresponding to these breaks. The subsamples cover the periods January 2010 to February 2014, March 2014 to January 2020, and February 2020 to December 2021. However, the final segment, covering February 2020 to December 2021, had fewer observations, potentially compromising the reliability of the analysis. To address this issue and ensure stable and reliable results, additional data for both crude oil and food prices from January 2022 to July 2024 was incorporated into the analysis. This increased the sample size of the last segment.

As a result, the total sample covers monthly data on crude oil and food prices from January 2010 to July 2024, segmented into three periods: January 2010 to February 2014, March 2014 to January 2020, and February 2020 to July 2024. Consequently, subsequent analyses, including unit root testing, bounds cointegration testing, granger causality testing, and ECM estimation, were applied to segmented data. This approach ensures a more accurate assessment of unit roots and the relationship between crude oil and food prices during the study period, accounting for significant shifts in the data and enhancing the precision and robustness of the overall analysis. The ADF unit root test results are presented in the following section, providing an assessment of the stationarity of the crude oil and food price series data.

4.7 Unit root test results

The ADF test was applied to the segmented data to accurately assess unit roots and the relationship between crude oil and food prices, accounting for significant structural shifts, thereby enhancing the precision and robustness of the analysis (Enders, 2014; Greene, 2018). The null hypothesis of the ADF test states that a unit root is present, meaning the time series is non-stationary. If the null hypothesis is rejected, it indicates that the time series is stationary. To reject the null hypothesis, the probability value of the ADF test must be less than or equal to 5%. Following the structural break results from the Bai-Perron test, the ADF test was applied to segmented data. Table 4.5 presents the results for the first segment (January 2010 to February 2014) of the crude oil and food price series in their level and first difference forms.

Table 4.5: ADF results of the first segment (January 2010 to February 2014)

Level				
Variables	**Intercepts**	**Probability**	**Trends & inter**	**Probability**
Crude oil	-2.846	0.059**	-3.380	0.065*
Cereal	-5.042	0.000***	-2.014	0.578
Dairy	-1.162	0.683	-1.491	0.819
Meat	-2.719	0.078*	-1.999	0.586
Sugar	-1.947	0.308	-2.859	0.184
Vegetable oil	-1.968	0.299	-2.289	0.431
1st difference				
Variables	**Intercept**	**Probability**	**Trends & inter**	**Probability**
Crude oil	-9.816	0.000***	-9.812	0.000***
Cereal	-4.576	0.000***	-4.849	0.001***
Dairy	-4.942	0.000***	-4.850	0.001***
Meat	-4.810	0.000***	-5.025	0.000***
Sugar	-4.415	0.000***	-4.539	0.003***
Vegetable oil	-4.398	0.000***	-4.504	0.003***

Source: Author, based on EIA (2024) and FAO (2024)

Note: *, ** and *** show significance level at 10%, 5% and 1% levels, respectively.

H_0: There is unit root (series is non-stationary)

H_1: There is no unit root (series is stationary)

As shown in Table 4.5, the ADF test results for crude oil, cereal, and meat indicate that the null hypothesis of non-stationarity can be rejected in their level form. This suggests that these variables were stationary in their level form, indicating consistent price movements during the period from January 2010 to February 2014. Specifically, meat price series is stationary in its level form with intercepts, meaning it is integrated of order I(0). This means that meat, being highly oil-intensive, is sensitive to crude oil price fluctuations, but its stationary nature suggests it experienced consistent price movements. The cereal price series is also stationary in its level form with intercepts, meaning it is integrated of order I(0). This indicates that cereals, being less oil-intensive, are less sensitive to crude oil price fluctuations, and their stationary nature suggests stable price movements during the study period. Additionally, crude oil is stationary in its level form with trends and intercepts, also integrated of order I(0). This suggests that crude oil prices were relatively stable during this period and did not exhibit a unit root.

However, for dairy, vegetable oil, and sugar, the null hypothesis cannot be rejected at the level form, implying that these series are non-stationary in their levels. Vegetable oil and sugar are less sensitive to oil price changes compared to meat and dairy, but they exhibit non-stationarity at the level form, implying that other factors may have influenced their price trends beyond oil prices, requiring differencing to stabilise the data. The non-stationary dairy prices at the level form, due to their higher oil intensity and complex production processes, show greater variability, necessitating differencing to stabilise the data.

Upon conducting the ADF test on the first-differenced data, the results show that the price series for crude oil, cereal, dairy, meat, vegetable oil, and sugar are all stationary after first differencing. Thus, the null hypothesis of non-stationarity is rejected for the differenced data. This means that these variables are integrated of order I(1), as they became stationary in their first difference form. This suggests that while price series for dairy, meat, vegetable oil, and sugar were non-stationary at the level, they became stable when accounting for short-term changes. Table 4.6 shows the results for the second segment (March 2014 to January 2020) of the crude oil and food price series in their level and first difference forms.

Table 4.6: ADF results of the second segment (March 2014 to January 2020)

Level form				
Variables	**Intercepts**	**Probability**	**Trends & intercepts**	**Probability**
Crude oil	-2.726	0.074*	-2.525	0.315
Cereal	-3.523	0.010**	-2.635	0.266
Dairy	-2.911	0.049**	-3.286	0.077*
Meat	-3.094	0.030**	-2.926	0.159
Sugar	-2.295	0.176	-2.232	0.463
Vegetable oil	-2.611	0.095*	-3.664	0.032**
First difference				
Variables	**Intercepts**	**Probability**	**Trends & intercepts**	**Probability**
Crude oil	-8.628	0.000***	-8.789	0.000***
Cereal	-6.160	0.000***	-6.851	0.000***
Dairy	-4.588	0.000***	-4.787	0.001***
Meat	-4.693	0.000***	-4.734	0.001***
Sugar	-6.946	0.000***	-6.925	0.000***
Vegetable oil	-3.143	0.028**	-3.198	0.093*

Source: Author, based on EIA (2024) and FAO (2024)

Note: *, ** and *** show significance level at 10%, 5% and 1% levels, respectively.

H_0: There is unit root (series is non-stationary)

H_1: There is no unit root (series is stationary)

As indicated in Table 4.6, the ADF test results for crude oil, cereal, dairy, meat, and vegetable oil show that the null hypothesis of non-stationarity can be rejected for these series in their level form with intercepts, meaning they are integrated of order I(0). This suggests that these variables were stationary in their level form, indicating consistent price movements during the period from March 2014 to January 2020. Specifically, dairy and vegetable oil are stationary with trends and intercepts, meaning they were also integrated of order I(0). Dairy reflects stability despite its higher oil intensity and production complexity, while vegetable oil, being less oil-intensive, also shows consistent price movements.

However, for sugar, the null hypothesis cannot be rejected at the level form, implying that sugar prices were non-stationary in their levels. Sugar, being less sensitive to oil price changes compared to meat and dairy, still exhibited non-stationarity at the level form. This suggests that other factors influenced its price trends beyond oil prices, requiring differencing to stabilise the data.

After conducting the ADF test on the first-differenced data, the results show that the price series for crude oil, cereal, dairy, meat, vegetable oil, and sugar became stationary. Thus, the null hypothesis of non-stationarity was rejected for the first-differenced data. This indicates that all these variables are integrated of order I(1), as they became stationary after accounting for short-term changes. Table 4.7 presents the results for the third segment (February 2020 to July 2024) of the crude oil and food price series in their level and first difference forms.

Table 4.7: ADF results of the third segment (February 2020 to July 2024)

Level form				
Variables	**Intercepts**	**Probability**	**Trends & intercepts**	**Probability**
Crude oil	-1.964	0.301	-1.603	0.778
Cereal	-1.671	0.439	-0.987	0.936
Dairy	-2.474	0.127	-2.346	0.401
Meat	-1.034	0.928	-2.773	0.070*
Sugar	-1.728	0.411	-3.359	0.070*
Vegetable oil	-2.185	0.214	-1.985	0.594
First difference				
Variables	**Intercepts**	**Probability**	**Trends & intercepts**	**Probability**
Crude oil	-7.219	0.000***	-7.535	0.000***
Cereal	-5.330	0.000***	-5.686	0.000***
Dairy	-2.025	0.027**	-2.130	0.051*

Meat	-2.043	0.026**	-4.849	0.001***
Sugar	-2.596	0.010**	-2.776	0.021**
Vegetable oil	-5.460	0.000***	-5.608	0.000***

Sources: Author, based on EIA (2022) and FAO (2023)

As indicated in Table 4.7, the ADF test results for meat and sugar show that the null hypothesis non-stationarity can be rejected for these series in their level form with trends and intercepts, meaning they are integrated of order I(0). This suggests that these variables were stationary in their level form, indicating consistent price movements during the period from March 2020 to July 2024. Specifically, meat, being more oil-intensive, is sensitive to crude oil price fluctuations, but its stationary nature suggests consistent price trends despite these fluctuations. In contrast, sugar is less oil-intensive, and its stationary status suggests that other factors, beyond oil price changes, may have contributed to its stable price movements during this period.

The results for crude oil, cereal, dairy, and vegetable oil show that the null hypothesis of non-stationarity cannot be rejected for these series in their level form, as none of the variables are stationary at the level. This implies that the price series for all these commodities exhibited non-stationarity in their levels during the period from February 2020 to July 2024, meaning they were influenced by persistent shocks or trends.

Upon conducting the ADF test on the first-differenced data, the results show that the price series for crude oil, cereal, dairy, meat, sugar, and vegetable oil became stationary. Thus, the null hypothesis of non-stationarity was rejected for the first-differenced data. This indicates that all these variables are integrated of order I(1), meaning they became stationary after accounting for short-term changes.

Overall, the unit root test results provide essential insights into the stationarity of crude oil and food price series across three different segments. The ADF test results indicate that price series for all variables are either I(0) or I(1), which is crucial for further analysis, as they ensure that none of the variables are integrated of order two (I(2)), which would invalidate subsequent co-integration analysis. Given this, the bounds co-integration test can be applied to establish the long-term relationship between crude oil and food prices, helping to determine how oil price fluctuations influence food prices over time.

Once the long-term relationship is confirmed, the Error Correction Model (ECM) can estimate both short-term and long-term effects, ensuring that any deviations from equilibrium are corrected over time. Additionally, the Toda and Yamamoto (TY) Granger causality test can be used to examine the causal relationship between crude oil and food prices, further enhancing the understanding of these dynamics. In conclusion, the unit root testing results confirm that the data are suitable for accurate and reliable estimation, paving the way for more in-depth analysis using co-integration techniques and causality tests to explore the causal relationship between crude oil prices and food prices. The bounds co-integration test results are presented in the next section to establish the long-term relationship between crude oil and food prices. This analysis is crucial for understanding the extent to which changes in crude oil prices impact food prices over the long term.

4.8 Cointegration test results

After conducting unit root testing on the segmented data to ensure stability and reliability, the bounds co-integration test was performed to examine the long-term relationship between crude oil prices and food prices in South Africa across the three segments. The null hypothesis states that no co-integration relationship exists between crude oil prices and food prices, while the alternative hypothesis asserts that a co-integration relationship does exist. The decision rule is to reject the null hypothesis if the test statistic exceeds the critical value at the chosen significance level, indicating evidence of co-integration between crude oil prices and food prices. If the test statistic does not exceed the critical value, we fail to reject the null hypothesis, suggesting insufficient evidence to conclude the presence of co-integration between the variables. Table 4.8 below presents the F-bound co-integration results.

Table 4.8: F Bound Cointegration results

First segment (January 2010 to February 2014)				
Test statistics	**Value**	**Level of significance**	**I(0)**	**I(1)**
F statistic	5.745	5%	2.62	3.79
Second segment (March 2014 to February 2020)				
Test statistics	**Value**	**Level of significance**	**I(0)**	**I(1)**
F statistics	5.277	5%	2.62	3.79
Third segment (March 2020 to July 2024)				
Test statistics	**Value**	**Level of significance**	**I(0)**	**I(1)**
F statistics	6.690	5%	2.65	3.78

Source: Author based on EIA (2022) and FAO (2023)

The F-bound co-integration results presented in Table 4.8 show that the test statistic values for all three segments exceed the upper-bound critical value for I(1) at the 5%

significance level. For the first segment, the F-statistic value of 5.745 is greater than the upper-bound critical value for I(1) of 3.79, indicating the existence of a long-term relationship between crude oil prices and food prices over the period from January 2010 to February 2014. For the second segment, the F-statistic value of 5.277 exceeds the upper-bound critical value for I(1) of 3.79, which also suggests the presence of a long-term relationship between crude oil prices and food prices during the period from March 2014 to January 2020.

In the third segment, the F-statistic value of 6.690 is greater than the upper-bound critical value for I(1) of 3.78. This confirms that a long-term co-integration relationship existed between crude oil prices and food prices from February 2020 to July 2024. Overall, the results indicate that there is sufficient evidence to reject the null hypothesis of no co-integration and suggest the presence of a long-term relationship between crude oil prices and food prices for the entire period from January 2010 to July 2024. This means that crude oil and food prices co-move together over time in the long term, and the relationship between them can be observed over time.

The results in this study are similar to those of a study by Olayungbo (2021), in which the Panel ARDL model showed a positive co-integration relationship in the long term, meaning oil and food prices co-move and are stable over time. Similarly, the current study's results from the F-bound co-integration test also indicate a stable, long-term relationship between crude oil prices and food prices across all three segments. Olayungbo (2021) further identified a negative short-term relationship between crude oil and food prices, indicating an unstable and temporary link. While the current study focused on long-term co-integration through the F-bound test, it did not explicitly explore the short-term dynamics. However, the ECM used in the current study provides insights into short-term adjustments, potentially aligning or differing with Olayungbo's findings.

However, South African studies by Fowowe (2016) and Aye (2014) found no long-term co-integration relationship. In particular, Fowowe (2016) found no long-term relationship between crude oil prices and agricultural commodity prices in South Africa using the Gregory and Hansen co-integration test. This contrasts with the current study, which found evidence of a long-term relationship between oil prices and food prices across all three segments. The discrepancy may arise from different methodological approaches (Gregory-Hansen test vs. bounds co-integration test) or differences in the time periods considered.

Aye (2014) similarly found no co-integration between global oil prices and food prices in South Africa, attributing the lack of co-integration to the methods used, which did not account for structural breaks. The current study, however, found a long-term co-integration relationship, which may be due to the fact that the data was segmented into three periods to account for structural breaks, particularly capturing the Oil Price Collapse (2014-2016) and the COVID-19 Pandemic (2020-2021). Overall, the bounds co-integration test confirmed the long-term relationship between crude oil and food prices. Consequently, the ECM was applied to estimate both short-term and long-term effects, ensuring that any deviations from equilibrium are corrected over time. The results are presented in the next section.

4.9 Autoregressive distributed lag (ARDL) results

The ARDL model was employed to estimate both the short-term and long-term effects of crude oil prices on food prices, providing insights into how immediate adjustments and long-term equilibrium relationships develop. The rationale for using ARDL lies in its flexibility to handle variables of mixed integration orders, making it ideal for this analysis. After confirming the existence of a long-term relationship using the F-bound cointegration test, the Error Correction Model (ECM) was applied within the ARDL framework to capture short-term dynamics and ensure that deviations from long-term equilibrium are corrected over time.

The analysis was conducted in three segmented periods to account for structural breaks caused by global events: before March 2014, in March 2014 corresponding to the 2014–2016 Oil Price Collapse, and in February 2020, aligning with the onset of the COVID-19 pandemic. These segments provide a more precise understanding of how the relationship between crude oil and food prices evolves across different periods. Furthermore, the segmentation allows for comparison between high oil-intensive food categories (meat and dairy) and less oil-intensive categories (sugar, cereal, and vegetable oil). The focus is on how crude oil prices affect these categories in the short and long term, and which time period exhibited the strongest effects.

In the analysis, the food price categories were set as the dependent variables, with crude oil prices used as the explanatory variable influencing changes in these categories. Therefore, the coefficients are interpreted as the effects of crude oil price changes on food prices. The variables Cereal (-1), Dairy (-1), Meat (-1), Sugar (-1), and Vegetable Oil (-1) represent the lagged values of their respective food price categories. These lagged variables are included in the model to capture the effect of past prices on the current price of each category. Crude Oil (-1) represents the lagged value of crude oil prices, capturing the long-term effects of crude oil price changes on food prices, thus eliminating the need to present long-term results separately. D (Crude Oil) shows the short-term effect of changes in crude oil prices on food prices, while ECT (-1) is the error correction term, indicating how quickly short-term deviations from the long-term equilibrium are corrected. The short-term and long-term ARDL results for the first segment are presented in Table 4.9 below.

Table 4.9: ARDL results of the first segment (January 2010 to February 2014)

Variables	**Coefficient**	**Std. Error**	**T-statistics**	**Probability**
Cereal category				
C	13.98803	6.057018	2.309392	0.0256**
Cereal (-1)	-0.018154	0.056166	-0.323229	0.7480
Crude oil (-1)	-0.108075	0.065960	-1.638496	0.1083
D (crude oil)	0.021259	0.078641	0.270324	0.7881
ECT (-1)	-0.018154	0.007198	-2.522114	0.0153**
Dairy category				
C	1.470250	5.105502	0.287974	0.7747
Dairy (-1)	0.010625	0.045128	0.235451	0.8149
Crude oil (-1)	-0.017976	0.044505	-0.403902	0.6882
D (crude oil)	0.066757	0.056401	1.183617	0.2428
ECT (-1)	0.010625	0.006403	1.659384	0.1040
Meat category				
C	16.37871	3.448235	4.749883	0.0000***
Meat (-1)	-0.0233199	0.048009	-4.857390	0.0000***
Crude oil (-1)	0.074240	0.020271	3.662348	0.0006***
ECT (-1)	-0.233199	0.043571	-5.352134	0.0000***
Sugar category				
C	13.43373	12.55429	1.070051	0.2902
Sugar (-1)	-0.094966	0.063153	-1.503760	0.1395
Crude oil (-1)	-0.019538	0.098355	-0.198647	0.8434
ECT (-1)	-0.094966	0.053324	-1.780925	0.0815*
Vegetable category				
C	16.12863	7.035809	2.292363	0.0266**
Vegetable oil (-1)	-0.030708	0.047304	-0.649172	0.5195
Crude oil (-1)	-0.113059	0.060535	-1.867663	0.0683*
D (crude oil)	0.006166	0.083239	0.074076	0.9413
ECT (-1)	-0.030708	0.012484	-2.459759	0.0178**

Source: Author, based on EIA (2024) and FAO (2024)
Note: *, ** and *** show significance level at 10%, 5% and 1% levels, respectively.

The short-term results (D (Crude Oil)) indicate that changes in crude oil prices did not have a significant or strong immediate effect on any of the food price categories before the 2014–2016 oil price collapse, as evidenced by p-values all above 0.1, indicating insignificance. The lagged value for Meat (-1), a high oil-intensive category, had the strongest and most significant effect, suggesting that past meat prices exerted a stabilising influence on current meat prices. Despite being high oil-intensive, the lagged value for Dairy (-1) had no significant effect, indicating that past dairy prices had no stabilising impact on current dairy prices. Similarly, Cereal (-1), Sugar (-1), and Vegetable Oil (-1) all show insignificant effects, implying that past prices for these low oil-intensive categories did not significantly influence current prices in the first segment.

The lagged value for Crude Oil (-1) is highly significant and positive (coefficient = 0.074240, p-value = 0.0006), suggesting that past crude oil prices had a strong and lasting influence on current meat prices. As a high oil-intensive category, meat prices in the long term are significantly affected by fluctuations in crude oil prices. Despite being a high oil-intensive category, the lagged value for Crude Oil (-1) is insignificant for dairy (coefficient = -0.017976, p-value = 0.6882), indicating that past crude oil prices had no significant long-term effect on current dairy prices during this period.

The low oil-intensive categories, sugar and cereal, also showed insignificant effects, indicating that crude oil prices had no long-term influence on these categories during the first segment. However, vegetable oil, though considered low oil-intensive, showed a moderate effect (coefficient = -0.113059, p-value = 0.0683), suggesting a weak negative long-term impact of crude oil prices on vegetable oil prices. This indicates some sensitivity to crude oil prices, though less evident than in high oil-intensive categories like meat.

The ECT (-1) for meat, a high oil-intensive category, is significant and negative, indicating that deviations from the long-term equilibrium for meat prices are corrected quickly. This suggests a strong adjustment mechanism, with meat prices returning to equilibrium rapidly after short-term disturbances. Despite being a high oil-intensive category, dairy exhibited no significant correction, implying that short-term deviations for dairy persisted in the first segment. For the low-oil intensive categories, sugar showed a slower correction, while cereal and vegetable oil exhibited moderate correction speeds, though both were slower than meat. The short-term and long-term ARDL results for the second segment are presented in Table 4.10 below.

Table 4.10: ARDL results of the second segment (March 2014 to February 2020)

Variables	Coefficient	Std. Error	T-statistics	Probability
Cereal category				
C	19.32687	4.556807	4.241318	0.0001
Cereal (-1)	-0.258368	0.063266	-4.083831	0.0001***
Crude oil (-1)	0.088786	0.032897	2.698924	0.0088***
D (crude oil)	0.015033	0.050362	0.298501	0.7662
ECT (-1)	-0.258368	0.056221	-4.595574	0.0000***
Dairy category				
C	6.015949	2.572017	2.339000	0.0223
Dairy (-1)	0.000787	0.042874	0.018355	0.9854
Crude oil (-1)	-0.108508	0.040012	-2.711905	0.0085***
D (crude oil)	0.109309	0.064914	1.683902	0.0969*
ECT (-1)	0.000787	0.000139	5.674790	0.0000***
Meat category				
C	12.24532	3.240399	3.778955	0.0003
Meat (-1)	-0.179484	0.039221	-4.576237	0.0000***
Crude oil (-1)	0.087734	0.017529	5.005121	0.0000***
ECT (-1)	-0.179484	0.033618	-5.338861	0.0000***
Sugar category				
C	7.700249	4.438996	1.734683	0.0873
Sugar (-1)	-0.066278	0.040709	-1.628103	0.1081
Crude oil (-1)	-0.030262	0.039492	-0.766274	0.4462
ECT (-1)	-0.066278	0.034891	-0.899526	0.0617*
Vegetable category				
C	11.238552	3.768095	2.982547	0.0049
Vegetable oil (-1)	-0.090304	0.042404	-2.129627	0.0369**
Crude oil (-1)	-0.047696	0.027029	-1.764639	0.0822*
D (crude oil)	0.113738	0.073975	1.537531	0.1289
ECT (-1)	-0.090304	0.025121	-3.594748	0.0006***

Source: Author, based on EIA (2024) and FAO (2024)
Note: *, ** and *** show significance level at 10%, 5% and 1% levels, respectively.

During the oil price collapse of 2014–2016, the short-term effects of crude oil prices on food categories were less evident than during the pandemic. However, some significant effects were observed, particularly for high oil-intensive categories like meat and dairy. The short-term impact of crude oil prices on meat remained insignificant (D (Crude Oil) = 0.015033, p-value = 0.7662), indicating that changes in crude oil prices had no immediate effect on meat prices during this period. For dairy, the short-term effect was marginally significant (D (Crude Oil) = 0.109309, p-value = 0.0969), showing that short-term changes in crude oil prices had a weak but noticeable impact on dairy prices during the oil price collapse. The short-term effect of crude oil prices on cereal, sugar, and vegetable oil remained insignificant, with p-values well above 0.1. This suggests that crude oil prices did not have a strong immediate influence on these low oil-intensive categories during the oil price collapse of 2014–2016.

The lagged value for meat remained highly significant and negative (coefficient = -0.179484, p-value = 0.0000), indicating that past meat prices continued to exert a stabilising influence on current meat prices. This reinforces the idea that meat, as a high oil-intensive category, is strongly influenced by its price history. For dairy, the lagged value remained insignificant (coefficient = 0.000787, p-value = 0.9854), indicating that past dairy prices did not have a stabilising effect on current dairy prices during this period, despite dairy's high oil intensity. The lagged values for cereal, sugar, and vegetable oil were also insignificant, suggesting that past prices did not have a notable stabilising effect on the current prices of these low oil-intensive food categories.

In the long term, Crude Oil (-1) for meat remained highly significant and positive (coefficient = 0.087734, p-value = 0.0000), indicating that past crude oil prices had a strong and lasting impact on meat prices, consistent with its high oil intensity. This suggests that meat prices were significantly influenced by fluctuations in crude oil prices over the long term during the oil price collapse. For dairy, Crude Oil (-1) showed a significant negative long-term effect (coefficient = -0.108508, p-value = 0.0085), implying that crude oil price changes exerted downward pressure on dairy prices in the long term. This negative effect contrasts with the short-term impact, pointing to different dynamics affecting dairy prices over time.

For cereal and sugar, Crude Oil (-1) remained insignificant, indicating no significant long-term influence of crude oil prices on these low oil-intensive categories during this period. However, Crude Oil (-1) for vegetable oil showed a marginally significant negative long-term impact (coefficient = -0.047696, p-value = 0.0822), suggesting that crude oil prices had a moderate negative effect on vegetable oil prices, despite it being a low oil-intensive category.

The ECT for meat remained highly significant and negative (coefficient = -0.179484, p-value = 0.0000), showing that deviations from the long-term equilibrium for meat prices were corrected quickly during this period. This quick correction aligns with meat's high oil intensity, suggesting that the market for meat prices adjusted rapidly to changes in crude oil prices. For dairy, the ECT also became significant (p-value = 0.0000), indicating that short-term deviations for dairy prices were corrected more rapidly during the second segment compared to the first. This shows that, despite the weaker long-term impact, dairy prices became more responsive to deviations from equilibrium.

The ECT values for the low oil-intensive food categories, cereal and vegetable oil, were significant, indicating moderate correction speeds, though slower than for meat. The ECT for sugar was marginally significant (p-value = 0.0617), indicating that deviations for sugar prices were corrected more slowly during this period, reflecting its lower oil intensity. The short-term and long-term ARDL results for the third segment are presented in Table 4.11 below.

Table 4.11: ARDL results of the third segment (March 2020 to July 2024)

Variables	Coefficient	Std. Error	T-statistics	Probability
		Cereal category		
C	6.805393	6.053176	1.124268	0.2665
Cereal (-1)	-0.050587	0.071121	-0.711275	0.4804
Crude oil (-1)	-0.003306	0.061484	-0.053774	0.9573
D (crude oil)	0.229710	0.109967	2.088898	0.0420**
ECT (-1)	-0.050587	0.037478	-1.349776	0.1834
		Dairy category		
C	11.32506	3.860817	2.933332	0.0051
Dairy (-1)	-0.155462	0.046153	-3.368385	0.0015***
Crude oil (-1)	0.111256	0.035903	3.098830	0.0032***
D (crude oil)	-0.155462	0.042384	-3.667949	0.0006***
ECT (-1)	11.32506	3.860817	2.933332	0.0051***
		Meat category		
C	18.16492	4.345510	4.180159	0.0001
Meat (-1)	-0.232836	0.052370	-4.445979	0.0001***
Crude oil (-1)	0.102786	0.022761	4.515830	0.0000***
ECT (-1)	-0.232836	0.046653	-4.990801	0.0000***
		Sugar category		
C	7.231496	4.668185	1.549102	0.1279
Sugar (-1)	-0.081763	0.052526	-1.556628	0.1261
Crude oil (-1)	0.037431	0.058048	0.644829	0.5221
ECT (-1)	0.223898	0.133159	1.681429	0.0992*
		Vegetable category		
C	11.77422	5.744139	2.049779	0.0459
Vegetable oil (-1)	-0.044181	0.056851	-0.777133	0.4409
Crude oil (-1)	-0.069966	0.098396	-0.711257	0.4804

D (crude oil)	0.810917	0.207108	3.915438	0.0003***
ECT (-1)	-0.044181	0.020454	-2.160030	0.0358**

Source: Author, based on EIA (2024) and FAO (2024)
Note: *, ** and *** show significance level at 10%, 5% and 1% levels, respectively.

During the COVID-19 pandemic, the short-term effects of crude oil prices became more evident, particularly for high oil-intensive categories like meat and dairy. Meat, a high oil-intensive category, showed a significant positive effect (coefficient = 0.229710, p-value = 0.0420), indicating that short-term changes in crude oil prices had a strong and immediate impact on meat prices. Dairy, though also high oil-intensive, showed a significant negative effect (coefficient = -0.155462, p-value = 0.0006), suggesting that short-term increases in crude oil prices had a negative impact on dairy prices. Among the low oil-intensive categories, cereal and vegetable oil showed significant short-term effects, with crude oil prices having a positive effect on cereal (coefficient = 0.229710, p-value = 0.0420) and a strong positive effect on vegetable oil (coefficient = 0.810917, p-value = 0.0003). However, sugar, another low oil-intensive category, remained insignificant, indicating no immediate short-term effects on sugar prices.

The lagged value for meat remained highly significant (coefficient = -0.232836, p-value = 0.0001), reinforcing the stabilising effect of past prices on current meat prices. The lagged value for dairy became significant and negative (coefficient = -0.155462, p-value = 0.0015), suggesting that past dairy prices began to exert a stabilising effect on current prices during the third segment. The lagged values for cereal and sugar remained insignificant, while vegetable oil also showed no stabilising effect from past prices.

In the long term, Crude Oil (-1) for meat remained highly significant and positive (coefficient = 0.102786, p-value = 0.0000), indicating a strong and lasting influence of crude oil prices on meat prices during the COVID-19 pandemic, consistent with its high oil intensity. Crude Oil (-1) for dairy became positive and significant (coefficient = 0.111256, p-value = 0.0032), showing that crude oil prices had a positive long-term impact on dairy prices, reversing the negative effect seen in the second segment. Crude Oil (-1) for cereal and sugar remained insignificant, indicating no long-term influence on these low oil-intensive categories. Crude Oil (-1) for vegetable oil was also insignificant, suggesting that crude oil prices had no long-term effect on this low oil-intensive category in this segment.

The ECT for meat and dairy remained significant and negative, showing that short-term deviations for these food categories were corrected quickly during the pandemic, consistent with their high oil intensity. Cereal and vegetable oil exhibited moderate correction speeds, while sugar showed slower correction of short-term deviations, indicating that short-term deviations for low oil-intensive food categories were corrected more slowly during the pandemic.

4.10 Discussion of ARDL results

The ARDL results highlighted significant differences between high oil-intensive food categories, such as meat and dairy, and low oil-intensive categories like cereal, sugar, and vegetable oil. Throughout all segments, meat consistently showed the strongest response to crude oil prices, particularly in the long term, reflecting its high oil intensity. Increases in crude oil prices led to increases in meat prices; however, there was no clear indication that decreases in crude oil prices were equally passed through, suggesting asymmetric price transmission behaviour in meat prices. This assertion aligns with the findings of Sarwar et al. (2020), where increases in oil prices led to price increases, but decreases were not fully transmitted. In contrast, Zmami and Ben-Salha (2019) found no co-integration between the meat price index and oil prices, suggesting no long-term asymmetric relationship, as evidenced by the insignificance of long-term coefficients for both positive and negative oil price changes.

Despite its high oil intensity, dairy displayed mixed effects. Crude oil prices exerted a downward long-term effect during the oil price collapse but had a positive long-term effect during the COVID-19 pandemic. These findings are consistent with those of Zmami and Ben-Salha (2019), where the dairy price index reacted to both positive and negative changes in oil prices. Cereal and sugar remained largely unaffected by crude oil prices in the long term, in line with Ajmi et al. (2016), who found no effect of crude oil on food prices in South Africa. However, vegetable oil showed a marginal negative long-term effect during the oil price collapse, reflecting the low oil intensity of this category. Similarly, Zmami and Ben-Salha (2019) found that only negative shocks in oil prices were found to affect the vegetable oil price index in the short term.

In the short term, the effects of crude oil prices were less noticeable during the oil price collapse, with most food categories showing insignificant results. However, during the COVID-19 pandemic, the effects became more evident, especially for high oil-intensive categories like meat, which experienced immediate price increases due to rising crude oil prices. This finding differs from Zmami and Ben-Salha (2019), who found that the meat price index responded only to negative changes in oil prices in the short term, while this study shows a positive and significant effect of rising oil prices on meat prices. Additionally, low oil-intensive categories, such as cereal and vegetable oil, exhibited greater sensitivity to crude oil prices during the pandemic compared to previous periods, a result also supported by Zmami and Ben-Salha (2019), who reported that only negative oil price shocks affected the vegetable oil price index in the short term.

The Error Correction Term (ECT) values from the study showed that meat and dairy, being high oil-intensive commodities, adjusted quickly to deviations from the long-term equilibrium, particularly during the second and third segments. This contrasts with cereal, sugar, and vegetable oil, which exhibited slower correction speeds. This slower adjustment aligns with their lower oil intensity, as observed by Ajmi et al. (2016), where cereals and other low oil-intensive commodities were found to be less sensitive to oil price fluctuations. Overall, these findings demonstrate the crucial role of crude oil prices in shaping food price dynamics, particularly for high oil-intensive categories. The segmented approach allowed for a detailed understanding of how global events, such as the oil price collapse and the COVID-19 pandemic, affected the relationship between crude oil and food prices.

4.11 Validation of results

In this study, several diagnostic tests were conducted to ensure the robustness and reliability of the ECM results. Specifically, the Breusch-Godfrey Serial Correlation LM test was used to check for autocorrelation in the residuals, while the ARCH (Autoregressive Conditional Heteroskedasticity) test assessed the presence of time-varying volatility. The Jarque-Bera test evaluated whether the residuals followed a normal distribution, and the Ramsey RESET test was applied to confirm the correct specification of the model. These validation tests are crucial to prevent biased estimates of both short-term and long-term effects, ensuring that the ECM accurately captures the adjustment process back to the long-term equilibrium without distortion from issues like heteroskedasticity or autocorrelation. By confirming the absence of such issues, the reliability of the estimated coefficients and the overall model is strengthened.

4.11.1 Serial correlation LM test

Table 4.12 below shows serial correlation (LM) test results for all segments. The Breusch-Godfrey Serial Correlation (LM) test was used to examine whether the residuals from a regression model exhibit autocorrelation. The null hypothesis (H_0) posits no serial correlation, while the alternative hypothesis (H_1) suggests the presence of serial correlation. The test involves regressing the residuals on the original regressors and their lagged values. If the p-value is less than 0.05, the null hypothesis is rejected, indicating serial correlation. However, if the p-value exceeds 0.05, the null hypothesis cannot be rejected. The null and alternative hypotheses for serial correlation assumption were stated as follows:

- H_0: No serial correlation up to 2 lags.
- H_1: Serial correlation exists up to 2 lags.

Table 4.12: Serial correlation LM results

Serial correlation LM test for first segment (March 2014 to February 2020)			
Breusch-Godfrey serial correlation LM Test Null hypothesis: No serial correlation up to 2 lags			
F-statistics	0.109634	Prob F	0.8964
Observed R-square	0.273950	Prob Chi-square	0.8720
Serial correlation LM test for the second segment (March 2014 to February 2020)			
Serial correlation LM Test: Breusch-Godfrey Null hypothesis: no serial correlation at up to 2 lags			
F-statistics	0.835254	Probability	0.4394
Observed R-square	2.108359	Prob Chi-square	0.3485
Serial correlation LM test for the third segment (March 2020 to July 2024)			
Serial correlation LM Test: Breusch-Godfrey Null hypotheses: no serial correlation at up to 2 lags			
F-statistics	0.503911	Probability F	0.6078
Observed R-square	1.218539	Probability chi-square	0.5437

Source: Author, based on EIA (2024) and FAO (2024)

In the first segment, the p-values for both the F-statistic (0.8964) and the Chi-square statistic (0.8720) are greater than 0.05, indicating no evidence of serial correlation. Similarly, for the second segment, the p-values for the F-statistic (0.4394) and the Chi-square statistic (0.3485) are above the 0.05 threshold. In the third segment, the p-values for the F-statistic (0.6078) and the Chi-square statistic (0.5437) are also greater than 0.05. Therefore, for all three segments, we fail to reject the null hypothesis of no serial correlation, suggesting the models effectively capture the time-dependent structure of the data.

4.11.2 Heteroskedasticity

Table 4.13 below shows Heteroskedasticity results for all segments. The ARCH (Autoregressive Conditional Heteroskedasticity) test was used to evaluate whether there is time-varying volatility in the residuals. The null hypothesis assumes homoskedasticity, meaning no ARCH effects, while the alternative suggests the presence of ARCH effects. The null and alternative hypotheses for testing the assumption of homoskedasticity are as follows:

H_0: No ARCH effects (Homoskedasticity).

H_1: Presence of ARCH effects (Heteroskedasticity).

Table 4.13: Heteroskedasticity ARCH results for all three segments

Heteroskedasticity ARCH for first segment (March 2014 to February 2020)			
Heteroskedasticity: ARCH			
F-statistics	0.486854	Prob	0.4889
Observed R-square	0.503050	Prob chi-square	0.4782
Heteroskedasticity ARCH for second segment (March 2014 to February 2020)			
Heteroskedasticity test: ARCH			
F-statistics	0.206755	Probability	0.6508
Observed R-square	0.212355	Probability chi-square	0.6449
Heteroskedasticity for third segment (March 2020 to July 2024)			
Heteroskedasticity test: ARCH			
F-statistics	0.649528	Probability	0.4242
Observation R-square	0.667195	Probability chi-square	0.4140

Source: Author, based on EIA (2024) and FAO (2024)

For the first segment, the p-values for both the F-statistic (0.4889) and the Chi-square statistic (0.4782) are well above the 0.05 threshold, indicating no significant ARCH effects. Similarly, in the second segment, the p-values for the F-statistic (0.6508) and the Chi-square statistic (0.6449) suggest no evidence of ARCH effects. For the third segment, the p-values for the F-statistic (0.4242) and the Chi-square statistic (0.4140) are also greater than 0.05. Consequently, we fail to reject the null hypothesis across all segments, suggesting no significant time-varying volatility.

4.11.3 Normality test

Table 4.14 below shows the normality test results for the three segments. The Jarque-Bera test was used to check whether the residuals are normally distributed. The null hypothesis assumes normal distribution, while the alternative suggests non-normal distribution. The null and alternative hypotheses for testing the assumption of normality are as follows:

- H_0: Residuals follow a normal distribution.
- H_1: Residuals do not follow a normal distribution.

Table 4.14: Normality test results for all three segments

Normality test results for first segment (March 2014 to February 2020)	
Series: Residuals **Sample: 2010M04 2014M02** **Observation: 47**	
Mean	-1.08e-06
Median	-0.002734
Maximum	0.052925
Minimum	-0.069297
Std. Dev	0.027323
Skewness	0.040103
Kurtosis	2.854448
Jarque-Bera	0.054086
Probability	0.973319
Normality test results for second segment (March 2014 to February 2020)	
Series: Residuals **Sample: 2014M12 2020M01** **Observations: 62**	
Mean	-3.92e-14
Median	-0.002748
Maximum	1.503622
Minimum	-1.520382
Std. Dev	0.623889
skewness	-0.047427
Kurtosis	2.787683
Jarque-Bera	0.139696
Probability	0.962536
Normality test results for third segment (March 2020 to July 2024)	
Series: Residual **Sample: 2020M04 2021M07** **Observation: 52**	
Mean	-3.99e-14

Median	0.208816
Maximum	11.37921
Minimum	-10.22454
Std. Dev	5.139787
Skewness	-0.014393
kurtosis	2.321043
Jarque-Bera	1.000591
Probability	0.606351

Source: Author, based on EIA (2024) and FAO (2024)

In the first segment, the p-value from the Jarque-Bera test (0.9733) is significantly higher than 0.05, indicating no rejection of the null hypothesis and confirming normal distribution of residuals. The second segment also shows a high p-value (0.9625), suggesting normally distributed residuals. For the third segment, the p-value (0.6064) is again above 0.05, implying the residuals are normally distributed. Therefore, normality is supported across all segments.

4.11.4 Functional form test results

Table 4.15 below shows the functional form results for the three segments. The Ramsey RESET test was used to check whether the model is correctly specified in terms of its functional form. The null hypothesis assumes the correct functional form, while the alternative suggests a misspecified model. The null and alternative hypotheses for testing the assumption of functional form are as follows

- H_0: The model has the correct functional form.
- H_1: The model does not have the correct functional form.

Table 4.15: Functional form results for all segments

Functional form results for first segment (March 2014 to February 2020)		
	Value	**Probability**
T-statistics	0.0400	0.6909
F-statistics	0.1601	0.6910
Likelihood	0.1858	0.0666
Functional form results for second segment (March 2014 to February 2020)		
	Value	**Probability**
T-statistics	0.2875	0.7747
F-statistic	0.0826	0.7750
Likelihood ratio	0.0961	0.7565

Functional form results for third segment (March 2020 to July 2024)		
	Value	**Probability**
T-statistics	1.2052	0.2347
F-statistics	1.4527	0.2350
Likelihood ratio	1.7277	0.1187

Source: Author, based on EIA (2024) and FAO (2024)

For the first segment, the p-value for the F-statistic (0.6910) is well above the 0.05 significance threshold, meaning there is no evidence of misspecification. Similarly, in the second segment, the p-value (0.7750) indicates no evidence of an incorrect functional form. For the third segment, the p-value (0.2350) is still greater than 0.05, though marginally higher. Across all three segments, we fail to reject the null hypothesis, suggesting that the model is correctly specified in each case.

Across all diagnostic tests for serial correlation, heteroskedasticity, ARCH effects, normality, and functional form, the results indicate that the regression models for each segment are well-specified, with no significant violations of key assumptions. Specifically, the residuals exhibit no serial correlation, and there is no evidence of ARCH effects (heteroskedasticity). Moreover, the residuals follow a normal distribution, and the functional form of the model is correctly specified, all of which support the overall robustness of the models.

4.12 Granger causality results

After estimating the short-term and long-term effects, the TY Granger causality test was used to determine the causal relationship between crude oil prices and various food prices (cereal, dairy, meat, sugar, and vegetable oil) in South Africa. The rationale for using the TY test is its ability to assess causality without pre-testing for cointegration, making it suitable for time series data with varying integration levels (I(0), I(1), or I(2)). The null hypothesis (H_0) posits that the lagged values of crude oil prices do not Granger-cause food prices, while the alternative hypothesis (H_1) suggests that they do. The decision rule is to reject the null hypothesis if the p-value of the Wald test is less than the significance level (e.g., 0.05), indicating significant Granger causality.

The analysis was conducted in three segmented periods to account for structural breaks caused by global events: before March 2014, in March 2014 corresponding to the 2014–2016 Oil Price Collapse, and in February 2020, aligning with the onset of the COVID-19 pandemic. These breaks represent major global events that disrupted energy markets and influenced food prices, making it important to segment the data accordingly to examine the varying dynamics across different periods. The oil intensity of various commodities plays a crucial role in shaping their price sensitivity to fluctuations in crude oil prices. Table 4.16 presents the results for the first segment, which covers the period before the 2014 Oil Price Collapse.

Table 4.16: TY causality results of first segment (January 2010 to February 2014)

Dependent: Cereal		
Variable	**Chi-square**	**Probability**
Crude oil	1.86491	0.2760
Dependent: Crude oil		
Variables	**Chi-square**	**Probability**
Cereal	0.093735	0.7595
Dependent: Dairy		
Variables	**Chi-square**	**Probability**
Crude oil	0.155719	0.6931
Dependent: Crude oil		
Dairy	0.315322	0.5744
Dependent: Meat		
Variables	**Chi-square**	**Probability**
Crude oil	2.247599	0.1338
Dependent: Crude oil		
Meat	2.594012	0.1073
Dependent: Sugar		
Variables	**Chi-square**	**Probability**
Crude oil	4.633203	0.0314**
Dependent: Crude oil		
Sugar	1.398474	0.2370
Dependent: vegetable oil		
Variables	**Chi-square**	**Probability**
Crude oil	0.001140	0.9731
Dependent: Crude oil		
Vegetable oil	0.000318	0.9858

Source: Author, based on EIA (2024) and FAO (2024)

Note: ** shows significance level at 5%.

The results for the first segment indicate a statistically significant relationship between crude oil prices and sugar prices. The Chi-square value of 4.633203 and a p-value of 0.0314, significant at the 5% level, suggest that crude oil prices Granger-cause sugar prices during this period. This unidirectional relationship implies that changes in crude oil prices had a notable impact on sugar prices, possibly through transportation and production costs linked to energy prices. Despite sugar being less oil-intensive compared to meat and dairy, its reliance on petroleum-based inputs and transportation still makes it sensitive to oil price fluctuations.

However, no significant causal relationships were found between crude oil prices and other food categories (cereal, dairy, meat, and vegetable oil) during this period. This could reflect the lower oil intensity of cereals and vegetable oil, which are less affected by fluctuations in oil prices, while the absence of causality in meat and dairy, despite their high oil intensity, may indicate that the effects of crude oil prices on these commodities were not as evident in this specific time frame. Meat, being highly oil-intensive due to its complex production chain, followed by dairy, generally exhibits greater sensitivity to oil price changes, but this sensitivity was not captured in the first segment. Table 4.17 presents the results for the second segment, covering the period during the 2014–2016 Oil Price Collapse and the pre-pandemic years.

Table 4.17: TY causality results second segment (March 2014 to February 2020)

Dependent: Cereal		
Variables	**Chi-square**	**Probability**
Crude oil	4.090395	0.0431**
Dependent: crude oil		
Cereal	0.503570	0.4779
Dependent: Dairy		
Variables	**Chi-square**	**Probability**
Crude oil	1.877526	0.1706
Dependent: Crude oil		
Dairy	0.785985	0.3753
Dependent: Meat		
Variables	**Chi-square**	**Probability**
Crude oil	4.757170	0.0292**
Dependent: Crude oil		
Meat	0.309341	0.5781
Dependent: Sugar		
Variables	**Chi-square**	**Probability**
Crude oil	0.182595	0.6692
Dependent: Crude oil		
Sugar	1.421046	0.2332
Dependent: vegetable oil		
Variables	**Chi-square**	**Probability**
Crude oil	0.321563	0.5707
Dependent: Crude oil		
Vegetable oil	0.307927	0.5790

Source: Author, based on EIA (2024) and FAO (2024)

Note: ** shows significance level at 5%.

The results for the second segment show that crude oil prices Granger-cause cereal and meat prices, with Chi-square values of 4.090395 and 4.757170, and p-values of 0.0431 and 0.0292, respectively, both significant at the 5% level. The significant effect of crude oil prices on meat prices aligns with the high oil intensity of the meat sector, where energy is heavily used in transportation, feed production, and processing. Meat's reliance on these oil-dependent processes makes it particularly sensitive to crude oil price fluctuations. Similarly, cereals, although less oil-intensive compared to meat, also showed a significant relationship. This can be attributed to the indirect impact of crude oil on cereals through petroleum-based inputs, such as fertilisers, and transportation costs, which still make cereals moderately sensitive to oil price changes.

No significant causal relationships were found between crude oil prices and dairy, sugar, or vegetable oil prices during this period. While dairy is relatively oil-intensive, the lack of a significant relationship could suggest that other factors, such as supply chain efficiencies or market conditions, mitigated the effects of crude oil price changes on dairy prices during this period. Sugar and vegetable oil, which are less oil-intensive, would naturally show lower sensitivity to crude oil price fluctuations, consistent with the absence of significant causality. Table 4.18 presents the results for the third segment, which spans the period from the onset of the COVID-19 pandemic.

Table 4.18: TY causality results of the third segment (March 2020 to July 2024)

Dependent: Cereal		
Variables	**Chi-square**	**Probability**
Crude oil	0.000531	0.9816
Dependent: Crude oil		
Cereal	3.398350	0.0653*
Dependent: Dairy		
Variables	**Chi-square**	**Probability**
Crude oil	0.028172	0.8667
Dependent: Crude oil		
Dairy	2.017037	0.1555
Dependent: Meat		
Variables	**Chi-square**	**Probability**
Crude oil	2.368440	0.1238
Dependent: Crude oil		
Meat	2.022882	0.1549
Dependent: Sugar		
Variables	**Chi-square**	**Probability**
Crude oil	0.273738	0.6008
Dependent: Crude oil		
Sugar	0.419323	0.5173

Dependent: Vegetable oil		
Variables	**Chi-square**	**Probability**
Crude oil	1.219137	0.2695
Dependent: Crude oil		
Vegetable oil	3.872444	0.0491**

Source: Author, based on EIA (2024) and FAO (2024)

Note: ** shows significance level at 5%.

The results for the third segment show a significant relationship between vegetable oil and crude oil prices, with a Chi-square value of 3.872444 and a p-value of 0.0491, significant at the 5% level. Interestingly, the test indicates that vegetable oil prices Granger-cause crude oil prices, marking a shift in the relationship compared to earlier segments. This reverse causality might be attributed to the unique supply chain disruptions caused by the pandemic (IEA, 2021). The increased demand for vegetable oil for food production and biofuel use during the pandemic could have influenced the dynamics between these markets, leading to vegetable oil prices impacting crude oil prices. Despite vegetable oil being less oil-intensive compared to meat and dairy, its use in biofuel production and the pandemic-induced supply chain constraints could explain this unexpected relationship (IEA, 2021; Biofuels International, 2025).

No significant causal relationships were found between crude oil prices and cereal, dairy, meat, or sugar prices during this period. The broader economic shock caused by the pandemic may have overshadowed the usual oil price effects on these commodities, with disruptions in both crude oil demand and supply chains influencing food prices in more complex ways. Meat and dairy, despite being highly oil-intensive, may have been affected by other pandemic-related factors, such as changes in consumer demand or supply chain bottlenecks, which diluted the direct impact of crude oil prices.

4.13 Discussion of the granger causality test results

The Toda-Yamamoto (TY) Granger causality test applied in this study revealed varied relationships between crude oil prices and food prices across different periods, as shown in Table 4.16. The Toda-Yamamoto (TY) Granger causality test applied in this study revealed varied relationships between crude oil prices and food prices across different periods. The results align with and diverge from previous studies in terms of unidirectional, bidirectional, and absence of causality, as discussed below.

a) Unidirectional Causality from Oil Prices to Food Prices

As per Table 4.16, in the first segment (January 2010 to February 2014), the results show a unidirectional causality from crude oil prices to sugar prices (p-value = 0.0314), consistent with the findings of Mohamed (2020) and Balcilar et al. (2016), who found that oil prices influenced agricultural commodities like wheat and sunflower. However, unlike these studies, which reported unidirectional effects across a range of commodities, the current study found no significant causality for other food categories such as meat, dairy, cereal, and vegetable oil. This suggests that sugar, while not highly oil-intensive, was particularly sensitive to crude oil price fluctuations, possibly due to its reliance on petroleum-based inputs and transportation.

In the second segment (March 2014 to February 2020), crude oil prices Granger-caused cereal and meat prices, supporting the findings of Ajmi et al. (2016), who reported a unidirectional causality from global oil prices to South African agricultural commodities such as wheat and sunflower. The significant relationship between crude oil prices and meat prices is also aligned with Balcilar et al. (2016), given the high oil intensity of the meat sector, where oil is critical in transportation, feed production, and processing. However, the absence of significant causality for dairy prices contrasts with its high oil intensity, suggesting that other factors mitigated the effects of oil price changes on dairy during this period.

b) Bidirectional Causality

Interestingly, as observed in Table 4.16, in the third segment (March 2020 to July 2024), reverse causality was found between vegetable oil and crude oil prices (p-value = 0.0491), indicating that vegetable oil prices Granger-cause crude oil prices. This bidirectional relationship echoes the findings of Kirikkaleli and Darbaz (2021) and Taghizadeh-Hesary et al. (2019), who identified bidirectional causality between food and energy prices. In this case, the increased demand for vegetable oil during the pandemic, for both food and biofuel production, likely played a role in this reverse causality (IEA, 2021; Biofuels International, 2025), as disruptions in the supply chain drove fluctuations in both markets. This stands in contrast to earlier segments where no significant relationship existed for vegetable oil, suggesting a shift in dynamics due to the pandemic.

c) Absence of Significant Causality

As presented in Table 4.16, in all segments, dairy, despite its high oil intensity, showed no significant causal relationship with crude oil prices, which differs from the findings of Zmami and Ben-Salha (2019), who reported a response in dairy prices to oil price changes. This lack of significance in dairy prices could be attributed to supply chain efficiencies or market conditions that shielded the dairy sector from oil price fluctuations. Additionally, cereal and sugar prices showed no significant causal relationship with crude oil prices in the third segment, contrasting with the bidirectional relationships observed by Kirikkaleli and Darbaz (2021) in commodities like sugar. In summary, the findings of this study provide both alignment with and divergence from previous research, highlighting the complex and evolving nature of the relationship between crude oil prices and food prices across different periods and commodity categories.

4.14 Chapter summary

This chapter presented the results from the descriptive analysis, optimal lag determination, variance inflation factor analysis, and structural breaks test. The structural breaks results were followed by the findings from the ADF test, bounds cointegration test, and the ARDL short-term (ECM) and long-term effects, as well as the Toda-Yamamoto Granger causality test. Additionally, the chapter discussed the results of the bounds cointegration test, the ARDL short-term (ECM) and long-term effects, and the TY Granger causality test, highlighting how the findings of this study compare with and diverge from previous literature. The chapter also included the results of diagnostic tests, such as the Breusch-Godfrey Serial Correlation (LM) test, the Jarque-Bera test, the ARCH (Autoregressive Conditional Heteroskedasticity) test, and the Ramsey RESET test, all of which were used to validate the robustness of the ARDL short-term (ECM) and long-term effects.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study by providing a concise summary of its key aspects, including the research aims, objectives, methodologies, and main findings. It emphasises the essential outcomes, draws conclusions, and offers recommendations based on the study's findings. Additionally, it outlines delimitations and identifies potential areas for future research.

5.2 Summary

The study aimed to analyse the relationship between crude oil prices and food prices in South Africa, using secondary time-series data from January 2010 to July 2024. Data for crude oil prices were collected from the U.S. Energy Information Administration (EIA), which provides globally recognised data, including South Africa's crude oil prices. Food price data were obtained from the Food and Agricultural Organisation (FAO), which provides comprehensive global food price data, including food price indexes for South Africa.

Various analytical techniques were employed to analyse the relationship between crude oil and food prices. Descriptive statistics summarised the key characteristics of crude oil and food price data, while trend analyses highlighted fluctuations over time. The Variance Inflation Factor (VIF) confirmed no multicollinearity issues, ensuring the stability and reliability of the subsequent analyses. The Bai-Perron test identified two structural breaks: March 2014, aligning with the Oil Price Collapse of 2014-2016, and February 2020, marking the onset of the COVID-19 pandemic. Subsequent analyses were conducted in three segments: the first segment covered the period before the March 2014 break (January 2010 to February 2014); the second segment spanned from the March 2014 break to the pre-pandemic era (March 2014 to February 2020); and the third segment covered the period from the onset of COVID-19 to July 2024.

The ADF test showed that none of the variables were integrated of order two (I(2)), validating the use of further tests. The bounds cointegration test revealed a long-term relationship between crude oil and food prices across all segments, suggesting that crude oil and food prices co-move over time. The ARDL model estimated both short-term and long-term effects. High oil-intensive categories, such as meat, consistently showed the strongest response to crude oil prices, particularly in the long term. Dairy, despite its high oil intensity, exhibited mixed results, with negative long-term effects during the oil price collapse but positive effects during the COVID-19 pandemic. In contrast, cereal and sugar were largely unaffected in the long term, while vegetable oil showed marginal negative effects during the oil price collapse.

In the short term, most food categories showed insignificant results during the oil price collapse, but high oil-intensive categories, like meat, saw immediate price increases during the COVID-19 pandemic. Low oil-intensive categories, such as cereal and vegetable oil, exhibited greater sensitivity during the pandemic compared to earlier periods. Error Correction Term (ECT) values showed that meat and dairy, being high oil-intensive commodities, adjusted quickly to deviations from long-term equilibrium, particularly in the second and third segments. Cereal, sugar, and vegetable oil corrected more slowly, reflecting their lower oil intensity.

The TY Granger causality test uncovered varying causal relationships. In the first segment, there was unidirectional causality for sugar, suggesting its sensitivity to crude oil price fluctuations, despite its lower oil intensity. In the second segment, unidirectional causality was found for cereal and meat, but dairy, despite its high oil intensity, showed no significant causality, possibly due to mitigating factors. In the third segment, bidirectional causality was observed for vegetable oil, likely due to increased demand for food and biofuel during the pandemic.

5.3 Conclusion

The study has three hypotheses, which correspond with its objectives. The first hypothesis posits that there is no co-integration relationship between crude oil prices and food prices in South Africa. This hypothesis is rejected, as the co-integration results revealed a long-term relationship between crude oil and food prices across all segments, evidenced by test statistic values exceeding the upper-bound critical value for I(1) at the 5% significance level. The second hypothesis posits that crude oil prices have no significant short-term or long-term effects on food prices. This hypothesis is also rejected, as the ARDL results indicated differential and significant effects of crude oil prices on food prices, with high oil-intensive commodities like meat and dairy showing significant effects, while low oil-intensive categories like cereal, sugar, and vegetable oil exhibited minimal or delayed significant effects.

The final hypothesis posits that there is no causal relationship between crude oil prices and food prices. This hypothesis is equally rejected, as the TY causality results revealed differential and significant causality, with unidirectional causality for sugar, cereal, and meat, and bidirectional causality for vegetable oil during the pandemic period. No significant causal relationship was found for dairy in any segment, despite its high oil intensity.

5.4 Policy recommendations

The main findings of this study highlight the differential effects of crude oil prices on food prices, with high oil-intensive commodities like meat and dairy showing significant responsiveness, while low oil-intensive categories like cereal, sugar, and vegetable oil exhibited minimal or delayed effects. Additionally, differential causality was found, with unidirectional causality for sugar, cereal, and meat, and bidirectional causality for vegetable oil during the pandemic period. No significant causal relationship was found for dairy in any segment, despite its high oil intensity, suggesting other mitigating factors in the dairy sector. Based on these results, the following policy interventions are proposed to manage food price inflation, ensure energy security, and implement commodity-specific measures to mitigate the impacts of oil price volatility.

5.4.1 Subsidise energy-efficient technologies in agriculture

The results demonstrated that high oil-intensive commodities, such as meat and dairy, exhibit significant responsiveness to crude oil price fluctuations. To reduce the direct impact of oil price volatility on food prices, The South African government should incentivise the adoption of energy-efficient technologies, such as renewable energy systems (e.g., solar-powered irrigation), fuel-efficient machinery, and optimised transport methods. These subsidies or incentives would reduce dependency on crude oil, thereby mitigating the impact of oil price fluctuations on agricultural production costs and food prices.

5.4.2 Establish or expand strategic fuel reserves

Structural breaks, such as the Oil Price Collapse of 2014-2016 and the COVID-19 pandemic, demonstrated the disruptive effects of oil price volatility on food production and distribution. Therefore, establishing or expanding strategic fuel reserves can help manage energy security during periods of crude oil price spikes, ensuring a stable supply and reducing the pressure on food production and distribution. This would stabilise fuel prices during periods of high volatility, ensuring continuous agricultural activity and supply chain efficiency.

5.4.3 Promote diversification of energy sources

The reliance on crude oil exacerbates price volatility in food production, particularly in high oil-intensive commodities. Therefore, encouraging the diversification of energy sources for agriculture, including a shift towards biofuels, solar, wind, and natural gas, can reduce the sector's reliance on crude oil. This can be supported through tax breaks, grants, and low-interest loans for adopting alternative energy sources. This would increase energy security by decreasing the agricultural sector's dependence on crude oil, mitigating the effects of oil price volatility on food prices.

5.4.4 Introduce commodity-specific support programmes

High oil-intensive commodities, such as meat and dairy, exhibited greater sensitivity to crude oil price changes, while others, like cereal and sugar, showed minimal long-term effects. As such, commodity-specific interventions, such as targeted subsidies for high oil-intensive crops (e.g., meat and dairy), could help stabilise prices during periods of oil price volatility. Support programmes can focus on energy efficiency improvements in these sectors to reduce cost pressures. This would cushion high oil-intensive food categories from the direct impacts of rising energy costs, ensuring price stability.

5.4.5 Establish an energy and food price index monitoring system

The causal relationships between crude oil and food prices vary across periods, underscoring the need for proactive measures. Thus, establishing a monitoring system to track fluctuations in energy and food prices in real-time can provide early warning signals for price volatility. The system can help policymakers make informed decisions about intervention timing, such as fuel tax adjustments or releasing strategic reserves. This would enable timely policy interventions to prevent severe food price inflation caused by sudden oil price hikes.

5.4.6 Promote biofuel integration

The interconnectedness of the food and energy markets indicates that reducing reliance on imported crude oil can help stabilise both industries. To achieve this, the South African government should promote the integration of biofuels into the national energy mix. This approach would decrease dependence on crude oil while supporting the agricultural sector by increasing demand for biofuel crops. Additionally, it would enhance energy security and provide farmers with new revenue streams. However, careful planning is essential to balance the production of food and energy crops, ensuring that biofuel development does not lead to food shortages.

These policy interventions collectively aim to stabilise food prices, reduce the agricultural sector's dependency on volatile oil prices, and ensure energy security for food production and distribution.

5.5 Delimitations and areas for further analysis

The study has several delimitations, which serve as potential areas for further analysis, as follows. The study used data from January 2010 to July 2024, which included major global events but excluded potential long-term trends beyond this timeframe. Future research should extend the time horizon to include data from earlier periods or after 2024 to capture longer-term dynamics and the effects of additional global events on the crude oil-food price nexus. The analyses were limited to South Africa, which, while significant, did not fully capture regional or global variations in the crude oil-food price relationship. Comparative studies should be conducted across multiple countries in the region or globally, allowing for analysis of how country-specific factors (e.g., trade policies, supply chain efficiency) influence the relationship between crude oil and food prices.

The focus was on specific food categories, such as meat, dairy, cereal, sugar, and vegetable oil. Other important food categories, like fruits, vegetables, and processed foods, were not included. Future studies should explore additional food categories to provide a more comprehensive understanding of how crude oil price changes affect different segments of the food market, including perishable and processed foods. The analysis centred on crude oil prices, excluding other related energy inputs like electricity or natural gas, which also influence food production and transportation costs. Future research should examine the effects of other energy sources, such as electricity or natural gas, on food prices, providing a more comprehensive view of the energy-food price relationship. These delimitations highlight the focused scope of the study and suggest areas for expanding the analysis to provide a more comprehensive understanding of the crude oil-food price relationship.

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