AN ANALYSIS OF THE INTERACTION BETWEEN THE PRICES OF CRUDE OIL AND SELECTED GRAINS AND OILSEEDS IN SOUTH AFRICA (2018-2022)

BY

KGABO LUCRACIA LEDWABA

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SUPERVISOR: DR LC MUCHOPA

CO-SUPERVISOR: PROF A BELETE

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Declaration

I, Kgabo Lucracia Ledwaba, declare that the mini-dissertation titled: An Analysis on the Interaction between Prices of Crude Oil and Selected Grains and Oilseeds in South Africa (2018-2022), which is submitted to the University of Limpopo as complete fulfilment of the degree of Master of Science in Agricultural Economics, was prepared by me and has not been submitted previously by anyone else at this institution or any other higher learning institution in South Africa. All sources utilized in this study were acknowledged.

26/02/2025

Surname & Initials **Date**

Dedication

This thesis is dedicated to the memory of my late mother, Ruth Lucia Ledwaba and to my younger siblings, hoping it may encourage them to pursue their own academic endeavours.

Acknowledgements

To begin with, I would like to recognize God, for being the light and directing my path. He has been the source of my strength, the one who brought understanding and wisdom. Glory to God for the opportunity and the blessing to get this far.

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.

Abstract

The intricate interlinkage of crude oil prices, grains and oilseed prices is an ongoing topic of debate. This study delves into the interaction between crude oil and selected grains and oilseeds prices in South Africa from 2018 to 2022, focusing on maize, soybeans, and wheat. Understanding this relationship is crucial to the agricultural stakeholders given the potential influence of crude oil price fluctuations on the cost of production, transportation, and processing of agricultural products.

Employing monthly data, the study adopted a two-pronged approach. First, it evaluated the long and short-term linkages of crude oil, oilseeds and grains prices using Autoregressive Distributed Lag (ADRL) model. Second, it investigated the relationship's causal direction through Granger causality tests. The results indicated that, based on the ARDL bounds cointegration test, there exists a mixed long run cointegration between crude oil prices and selected grains and oilseed prices. Specifically, there was evidence of long run cointegration between crude oil prices and soybean and maize prices, while no such relationship was found between crude oil and wheat prices. The findings showed that the price of maize increased by 8.199 when crude oil price increased by one unit. Furthermore, although a mixed long run relationship exists, there were no short-run dynamics observed. This implies that crude oil prices do not immediately impact prices of selected grains and oilseeds. Instead, in the short-term, other factors are likely influencing the prices of these commodities in South Africa. These factors could be domestic (production costs, government policies) or global (international prices, trade flows, weather patterns).

Given the finding of no direct linkage of crude oil and grain/oilseed prices, policymakers can refocus their efforts on alternative areas to ensure food security and price stability. This could be informed by further studies to generate policy recommendations that include measures to improve domestic production efficiency through subsidies and research, diversification of import sources, and strengthening social safety nets. By challenging the assumed connection between energy and food prices, this study provides policymakers with new insights to ensure new avenues are investigated to properly address food security concerns in South Africa towards the achievement of Sustainable Development Goal (SDG) 2 of reducing hunger.

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GRAIN SA	Grain South Africa
AGRI SA	Agriculture South Africa
AGRISETA	Agricultural Sector Education Training Authority
DALRRD	Department of Agriculture, Land Reform and Rural Development
DMRE	Department of Mineral Resources and Energy
CoP	Crude Oil Prices
MzPP	Maize Prices
SbPP	Soybean Prices
WtPP.	Wheat Prices
ARDL	Autoregression Distributed Lag
ADF	Augmented Dickey-Fuller
STATS SA	Statistics South Africa
FAO	Food and Agricultural Organization
EViews	Econometric Views
SAFEX	South African Futures Exchange

CHAPTER 1: INTRODUCTION

1.1. Background

The global economy operates as a vast interconnected web, where the dynamics of one market can have far-reaching consequences on other economic variables (Lagarde, 2013). Commodity markets serve as essential channels through which interdependence and relationships between economic variables is shown. According to Mokni and Youseff (2020) the connection between crude oil with agricultural commodities stands out as a prime illustration of the connection among the many interdependencies that exist.

The South African grain and oilseeds sector, which is crucial to the nation's agricultural sector and food security, depends heavily on the energy sector, notably crude oil (Department of Mineral Resources and Energy, 2022; Venter, 2018), but the growing cost of energy, especially crude oil, presents serious concerns for the grain and oilseeds sector. According to the Department of Mineral Resources and Energy (2022), agriculture consumed 67% of South Africa's energy in 2019, with 44,384 terajoules (TJ) of liquid fuels used primarily to transport agricultural materials and products between farms and markets. This highlights the sector's heavy reliance on crude oil. Furthermore, crude oil met approximately 53.2% of the country's fuel needs during the transformation phase (DMRE, 2022). This dependence on a single fuel source, coupled with the global energy market's influence on crude oil prices, creates vulnerability for the sector. The increase in fuel prices that has been happening in South Africa (Rossouw, 2022), driven by global energy market dynamics, have exacerbated threates faced by the grain and oilseed farmers in South Africa.

The rise in fuel and other input expenses increased production costs of grain by an average of 40% (Rossouw, 2022), implying that farmers need to generate 40% more income just to cover their production costs, putting immense pressure on their profitability. The rising fuel prices also affect consumers, who are facing increased costs of food which affect their food security thus impacting on achieving the sustainable development goal 2 (SDG 2) of reducing hunger. The high costs of food to consumers can also lead to reduced spending on food, further affecting producers of the grain and oil seed industry as they face low demand.

The grains and oilseeds industry in South Africa is among the most prominent industries of agriculture, Contributing meaningfully to the gross agricultural output at the national level (Sihlobo, 2022). It encompasses the cultivation, processing, and marketing of various grains and oilseeds, including maize, wheat, soybeans, sunflower seeds, sorghum and oats. According to AgriSA's 2017 report, the grains sub-sector constitutes around 30% of the overall production in the country. The grain industry includes crops such as sorghum, oats, maize, barley and wheat, and is one of largest South African's agricultural sectors. Approximately 70% of the agricultural output serves as intermediate products, highlighting the sector's crucial role in driving the South African economy (DALRRD, 2022). Out of the total number of 26,181 employers listed in the AgriSETA employer database, the Grains sector accounts for 9.6% or 2,453 employers.

Maize remains the most significant field crop, making a notable contribution of 0.4% to the national GDP. The price of maize in the market experiences significant fluctuations compared to other grain sectors (Grains SA, 2018). As maize is a crucial food product in South Africa, it has a large number of the farmers supplying it. The cost of fuel and transportation significantly influences the price of maize, as it does for other commodities. Maize is cultivated nationwide and must be transported to storage facilities and the market. Therefore, when fuel prices increase, the price of maize increases. The maize industry has an extensive value chain that spans from the farm to the consumer, and each stage relies on fuel.

Wheat holds the second position in terms of strategic products in South Africa as reported by the Department of Agriculture, Land Reform and Rural Development in 2021. A mere fraction, less than 2%, of the local wheat consumption is allocated for seed and animal feed purposes. Significant is the observation made by Sihlobo (2021) regarding annual fuel usage, with approximately 76% of wheat transportation within South Africa occurring through road networks. This statistic highlights the complex relationship of wheat production and inputs derived from crude oil, particularly fuel, which is essential for the operation of agricultural machinery and transport.

Soybeans are a major oilseed crop in South Africa, primarily used for oil extraction and livestock feed (Dlamini et al., 2014; Khojely et al., 2018). Soybean consumption in the country is divided into three sectors: 2.67% is allocated for human consumption, 15.29% is channelled into animal feed (primarily for the broiler and egg industries), and 67.8% is directed towards oil and oilcake production (DALRRD, 2021).

Crude oil, as a vital energy source, holds a dominant position on the global energy stage, serving as a vital fuel source that has powered the world for decades (Wu and Chen, 2019). South Africa imports crude oil to meet its domestic oil needs. The majority of crude oil is imported in the country from Nigeria, Saudi Arabia, Angola, and Kuwait. South Africa imported $5.42 billion in crude petroleum in 2021, the majority of which came from Nigeria ($2.17 billion), Saudi Arabia ($2.14 billion), Ghana ($525 million), Angola ($398 million), and the United Arab Emirates ($74.2 million). Over the years, South Africa's agricultural sector has become increasingly reliant on imported energy sources, including crude oil, to power machinery and fuel transportation networks (Sihlobo, 2022).

Crude oil serves as a fundamental input for numerous industries, ranging from transportation and manufacturing to power generation. Its significance extends beyond mere energy consumption, impacting industries that depend heavily on fuel, such as airlines, plastic producers, and agricultural enterprises. In the context of agricultural enterprises and the sector in general, crude oil is important for the grain and oil seed sector in a number of ways. As already noted, firstly, crude oil is used to fuel the transportation of grain and oilseeds. Transportation is essential for the grain and oilseed sector in of South Africa. Grains and oilseed are bulky commodities that need to be transported from farms to processing facilities, ports, and markets. The transportation system also plays a vital role in assuring safety and quality of grain and oilseeds. Secondly, it is used to produce energy for grain and oilseeds processing facilities. These facilities need to be able to operate efficiently in order to process and store oilseeds. Lastly, crude oil an input in the production of fertilizers. Fertilizers are important in the production of oilseeds and grains for increasing the crop yields, and the high cost of crude oil can make it more expensive to produce fertilizers. As a result, it can be said that crude oil has become a lifeline for economies worldwide, also driving substantial import and export activities among numerous nations. The world's remarkable economic growth in recent years owes a great deal to crude oil. It has been and continues to be the driving force behind progress and success. Currently, approximately 90 million barrels of oil is consumed daily in the world (U.S Energy Information Administration, 2023). This study, therefore, attempts to address the various issues raised in the discussion about the interaction of crude oil prices and selected grains and oil seeds prices using a variety of techniques.

1.2. Problem Statement

Transportation and processing of agricultural commodities is important within the agricultural sector; therefore, crude oil plays a crucial role for the availability of food (Balcilar, 2016; Aye et al., 2021; Hung, 2021). In fact, the price relationship of agricultural commodities (including oilseeds and grains), and crude oil is complex and multifaceted (Cheng et al., 2019; Karacan, 2022). Thus, the cost of production of grains and soybeans at farm level; their processing and transportation is expected to be influenced significantly by the price of crude oil (Fowowe, 2016; Bajpai, 2022). This may affect the profitability of farmers and agribusinesses. Biofuels such as biodiesel and ethanol are made from grains and oilseeds such as, soybean, and maize. When crude oil prices rise, biofuels become more expensive, which can cause the demand for these commodities to reduce, putting down pressure on their prices. The prices of grains and oilseeds have been on the rise in South Africa (Sihlobo, 2022; Majola, 2023). The rise in these commodity prices has raised an interest in identifying the variables that affect those prices, and crude oil is hypothesised to be one such variable.

Grain South Africa (2017), states that grains and oilseeds are important crops, more especially because they contribute to food security in South Africa. Food prices have increased because of the increased agricultural commodity prices (Sihlobo, 2022). The rise in those prices keep the food inflation relatively high. This can affect the consumers in South Africa, as it is difficult to deal with rising prices due to the already existing unemployment. According to Food Forward of South Africa, almost half of South African's population is dealing with some sort of food insecurity (Esternhuizen, 2022), caused by this food inflation, leading to poor health and nutrition. Furthermore, the rising prices of crude oil have far-reaching consequences for the agricultural sector, contributing toa vicious cycle of poverty.

Though there are some factors that might have caused the price increase on agricultural commodities, this study investigated whether crude oil is a contributor.

1.3. Motivation of study

Crude oil is regarded as an essential commodity in terms of consumption and its daily trading value and is widely regarded as lifeblood of any given economy (Kumar, 2017). The relation of prices of crude oil, selected grains and oilseeds is important because they are critical commodities in the global economy, with significant impacts on food security, energy security, and overall economic stability (Roman et al., 2020). Given the importance of these commodities, it is crucial to better apprehend the interaction of crude oil prices with grains and oilseeds prices to enable better policy making and the required interventions in the markets. It is clear that every research done on these commodities offers information of advancement that can be used to their respective markets. This study analysed how prices of soybean, maize, and wheat interact with crude oil prices with reference to the South African economy. Crude oil is important in the agricultural production process, and its price might influence the selected grains and oilseeds prices (Olanrewaju, 2013). Numerous research studies, including those by Nazlioglu (2011), Kaltlalioglu and Soyta (2009), Baffes (2007), and Chenery (1975) and Hanson et al. (1993), have sought to comprehend the link of prices of agricultural commodities and oil. However, the results have been inconclusive and ambiguous in terms of findings. Studies by Reboredo (2012) and Naziloglu and Soytas (2010) for example, found no evidence that higher prices of crude oil cause a rise in agricultural commodity price. With these given examples of studies which have shown inconclusive results, it is essential for the study to be carried out.

The years 2018 to 2022 are a crucial period to study as there were various changes in both global and local economic conditions in South Africa, including the Covid-19 pandemic which led to significant decreases in commodity prices, especially prices of crude oil; trade tensions, and geopolitical risks. Additionally, the Russia-Ukraine war, whereby Russia invaded Ukraine in 2022 has caused major impacts on the global market resulting in adjustments in prices (Ray, 2023). Therefore, exploring the interaction of crude oil prices and selected grains and oilseeds during this selected time period can provide crucial insights into the agricultural sector’s dynamics and its interconnection with the broader economy. Aye (2016) mentions that assessing this interaction is crucial for making informed decisions about suitable policy options. This study contribute to literature by analysing the interaction of crude oil and selected grains and oilseed prices in South Africa by examining the causal relationship of crude oil and selected grain and oilseed prices. It contributes by providing needed information and literature on whether crude oil, soybean, wheat and maize prices in South Africa influence each other given they have been on a rise (Sihlobo, 2022). This study was carried out using a variety of analytical techniques to add to the information. Conducting the study aided in identifying the connection of prices of crude oil, selected grains and oilseeds, and, in addition, in bringing information that can be useful to policy makers developing solutions to address challenges behind the price increase in the respective markets. Policymakers, investors, farmers and other stakeholders can use the information provided by this study to make more informed decisions and take appropriate actions to ensure stability of prices.

1.4. Scope of research

1.4.1. Aim

To analyse the interaction of crude oil, selected grains and oilseed prices in South Africa from 2018 to 2022.

1.4.2. Objectives

i. To assess the existence of a short and long run relationship between prices of crude oil and prices of selected grains and oilseeds in South Africa.
ii. To analyse the causal link between crude oil prices, selected grains prices and oilseeds prices in South Africa.

1.4.3. Hypotheses

i. There is no short or long run relationship between the prices of crude oil, selected grains and oilseeds in South Africa.
ii. There is no causal link between prices of crude oil, selected grains, and oilseeds in South Africa.

1.5. Research structure

The remaining research is structured around the following chapters:

The second chapter presents an overview of South Africa's grain and oilseeds industry, highlighting its relevance and historical patterns. The third chapter focuses on analysing current literature and exploring how previous academics have tackled the topic of the interaction of crude oil prices, chosen grains, and oilseeds in South Africa and other regions of the world.

The fourth chapter describes the methods used in the study, including information about the data collection, area of study and analysis tools.

The fifth chapter encompasses the quantitative analyses conducted and the study's main findings.

Chapter six offers summary, conclusion, and potential recommendations for policymakers, stakeholders and farmers.

CHAPTER 2: AN OVERVIEW OF SOUTH AFRICA'S GRAIN AND OILSEED INDUSTRY

2.1. Introduction

This chapter offers a comprehensive understanding of the grain and oilseed industries in South Africa, highlighting the significance of the industry to the economy. The chapter starts by giving a brief background of the industry, before diving into an overview of the selected grains and oilseeds of the study. The graphical trends of prices and production are included in this chapter and are further explained.

2.2. South African grains and oilseed industry background

Although primary agriculture's portion of the overall GDP is modest, it remains a significant component of South African's economy. Among the prominent agricultural sectors, the local grain and oilseeds industry stands out as one of the largest, playing a substantial role in the nation's overall agricultural output (Agricultural Business Chamber, 2015). South Africa is a large producer of grains and oilseeds on the African continent (Sihlobo, 2023). It is a thriving industry having a substantial result on the country's economy and food security. The country produces a variety of crops including maize, wheat, soybean.

2.2.1. Soybean Industry in South Africa

Soybeans play a modest yet significant part in South Africa's agricultural sector (Dlamini et al., 2014). There has been a growing focus on soybean products due to their health advantages. A percentage of 14.24 of soybeans is processed into specialised oil products for application in the food industry. Soybean is produced all over the country, but it is notably produced in larger quantities in the Free State (42%) and Mpumalanga (33%) provinces (Sihlobo and Kapuya, 2016). The amount of soybean produced has fluctuated over time, often exceeding the local demand. South African soybean production fluctuates between an estimated 900,000 and 1,000,000 tons annually. Under dryland conditions, the average yield falls within the range of 1.7 to 2 tons per hectare (DALRRD, 2021).

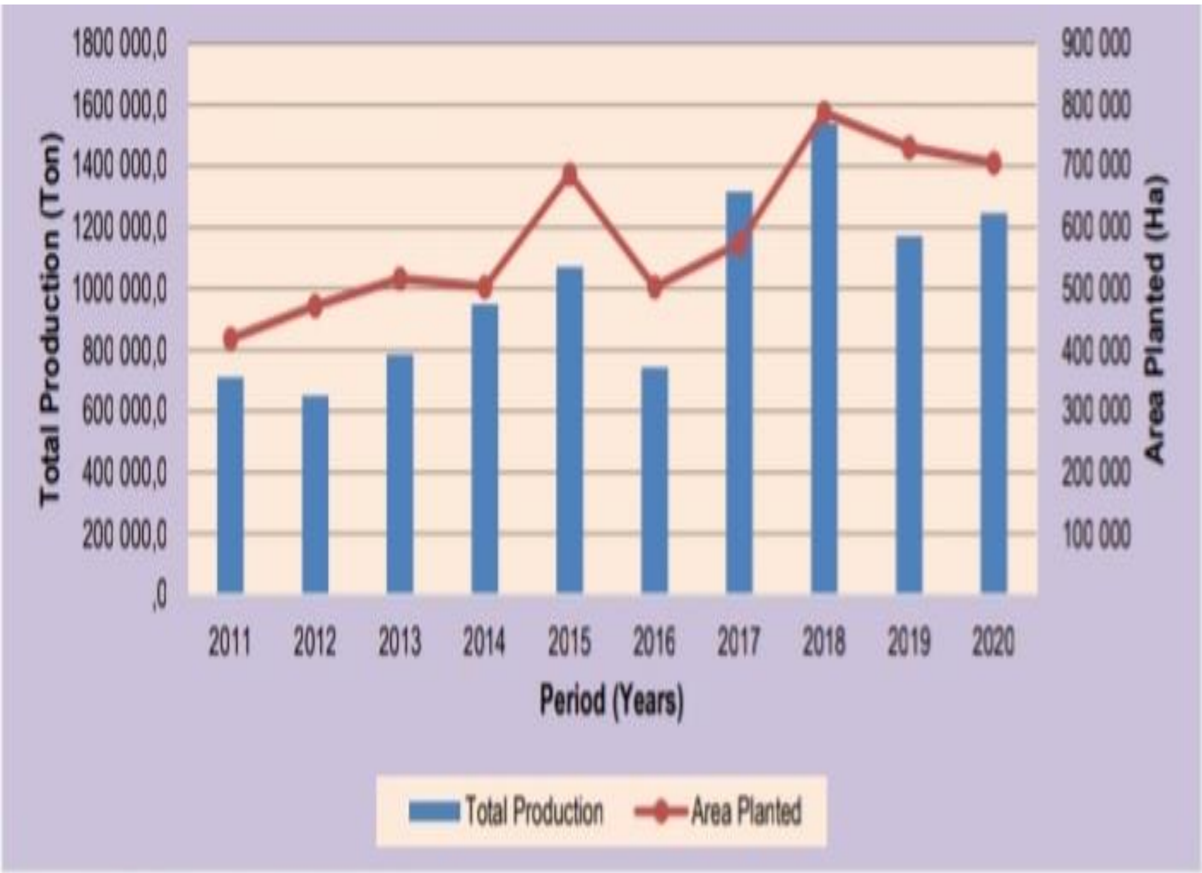


Figure 1. The Total Production of Soybean and Area Planted

Source: DALRRD, (2021).

Figure 1. shows the area planted has exhibited some changes from the 2010/11 to the 2019/20 seasons, with notable variations. There was a significant decline in the 2015/2016 season. The quantity of soybean production has also been uneven, influenced by the fluctuations in the area devoted to soybean production. Notably, there was a marked rise in soybean production from the 2012/2013 to the 2017/18 seasons. The production of soybean experienced a slight increase in the 2014/15 season, likely due to larger areas being devoted to soybean cultivation in key producing regions and improved yields. However, production declined in the following 2015/16 season. The soybean production increased in the 2017/18 season with the highest recorded crop. There was a decrease in both areas planted and soybean production during the 2019/20 season as shown in Figure 1.

According to Maluleke (2020), South Africa experienced a significant rise in soybean prices during the 2020/21 season. This increase was attributed to the weakening of the country's currency, the rand, against the US dollar. Rising prices are a result of the local currency's decline and the increasing demand for soybeans from China and other Asian markets (NAMC, 2020). Since South Africa relies heavily on soybean imports, its prices are influenced by global trends. The country imports around 0.5 million tons of soybean meal annually, making it vulnerable to swings in worldwide soybean prices. This is why the recent rise in global soybean prices has led to higher domestic soybean prices in South Africa.

Figure 2. Local Soybean Prices and Import Price

Sources: Grain SA, (2021).

Figure 2 shows the soybean prices locally and the import prices. In reference to Figure 2., the prices of soybeans dropped by 3.2% when comparing this quarter to the previous one, but over the course of a year, it increased by 15.3%. The price of soybeans within the region was 27% higher than the price of imported ones.

2.2.2. South Africa’s Maize Industry

Maize holds the status of being the primary grain crop in South Africa, with its harvest and production significantly affecting the country's economic growth and food security (DALRRD, 2021). The maize industry is closely interconnected with various manufacturing sectors. From 2008/09 to 2017/18, the gross value of maize seed was notably higher compared to other agronomic seeds (DALRRD, 2021). This can be related to the fact that maize is South Africa's principal food source.

Following the deregulation of maize prices in 1991, market dynamics such as supply, and demand have predominantly shaped the market. Approximately 66% of the maize grown in South Africa is utilized within the domestic market, either as maize-based goods for human consumption or as animal feed (Ala-Kokko et al., 2021). Maize is cultivated in every province of South Africa, with the most notable production occurring in the North-West provinces (18%), Mpumalanga (21%) and Free State 45%) (DALRRD, 2021). Typically, the country plants around 2.8 million hectares of commercial maize yearly. The total maize supply in South Africa is determined by three factors: domestic production during a specific season, imports from other regions, and supplies from preceding seasons. In South Africa, most of the maize, around 98%, comes from commercial farms, with the remaining 2% coming from smaller, developing farms. The amount of maize produced each year has varied a lot, hitting its lowest point in 2015/16 and reaching its highest yield in the 2019/20 season as illustrated in Figure 3.

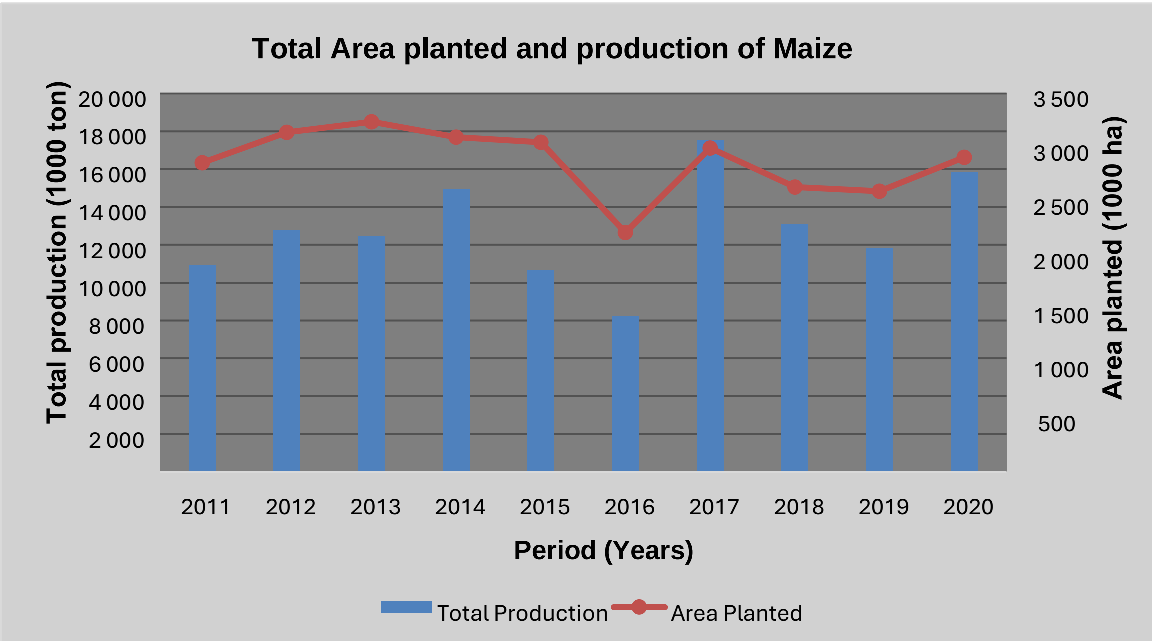


Figure 3. Total Area Planted and Production of Maize

Source: DALRRD, (2021).

The Figure 3 shows the production trend of maize from 2011 to 2020 and the production area. For the most part, the maize production area has consistently exceeded the total production. The land dedicated to producing maize has experienced notable fluctuations. At the start of the 2011/20 season, maize area was planted at a moderate rate, with comparable overall production. The extent of land devoted to maize cultivation seemed to be influenced by the moderate average prices that maize producers received during that season. These prices encouraged farmers to keep cultivating maize to benefit from higher market prices. However, there was a notable 9.86% increase in the area planted during the 2010/11 season, which led to a substantial 16.8% rise in overall maize production compared the previous season. The following 2011/12 season witnessed a greater volume of maize in the market due to improved yields and higher-than-usual rainfall during that period. the 2015/16 season saw a sharp drop in maize production due to a decrease in the planted area, attributed primarily to a drought induced by El Niño. In contrast, during the 2016/17 growing season, conducive weather in key maize production areas led to both record-breaking yields and an expansion of maize plantings. In addition, the 2019/20 growing season witnessed a decline in maize planted areas, leading to a subsequent decrease in total maize production.

According to Maluleke (2019), the price of maize in the market tends to fluctuate significantly, making it one of the most unstable among various grain sectors. As a vital staple crop in South Africa, its price fluctuations have a substantial impact on a significant portion of the country's farmers. The primary determinant affecting the cost of maize each season is the balance between its availability and the level of demand. Around 75% of the maize harvested during a season is utilized within South African’s local market. This usage encompasses both maize-derived food products for people and animal fodder. In essence, when experiencing a prosperous growing season resulting in high maize production, the cost of maize drops due to the surplus supply. during more challenging drought years with diminished yields, the price of maize rises in response to heightened demand. The price of maize is greatly influenced by the fuel and transportation cost, just like it affects other goods. Maize is grown across the country and has to be transported to storage locations and markets. When fuel prices rise, the cost of producing maize increases. This leads to lower prices for the end product, as buyers consider these added expenses. The journey of maize from the farm to the consumer involves multiple stages, each requiring fuel for transportation.

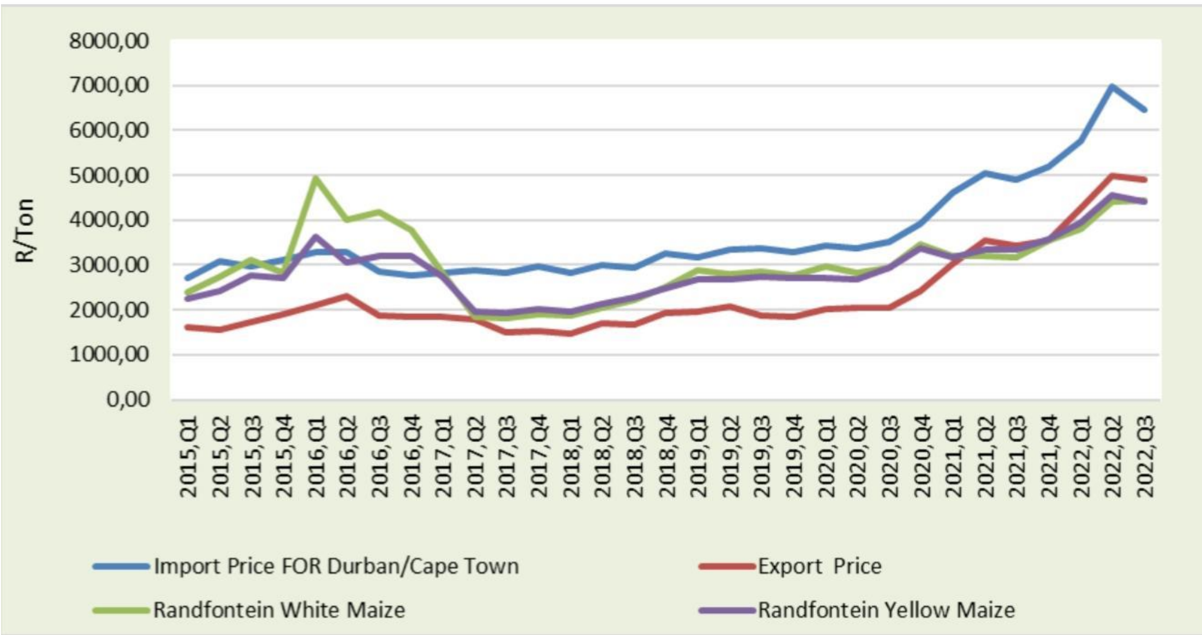


Figure 4. Maize Prices

Source: Grain SA, (2021).

In Figure 4, price of maize showed a yearly increase of 40% for white maize and 32% for yellow maize. Looking at shorter periods, the price of white maize went up by 1.1% on a quarter-to-quarter basis, while the price of yellow maize decreased by 3.3%. Both white and yellow maize prices were 31.3% and 32% lower than the import price, and they remained competitive when compared to export parity during the quarter.

2.2.3. Wheat Industry in South Africa

According to the DALRRD (2021), wheat holds the position of being the second largest significant cereal crop cultivated in South Africa. In this country, wheat serves primarily as a vital source of food for humans. Additionally, some of the harvested wheat is allocated for planting purposes and animal feed. Additionally, some of the harvested wheat is allocated for planting purposes and animal feed.

In South Africa, wheat production stands out due to its distinctiveness in having three separate wheat production regions. These regions each come with their own set of challenges and specialized needs. In South Africa, the Northern Cape (13%), Free State (20%) and Western Cape (52%) seem to be the major wheat producer provinces contributing to a significant portion of the nation’s total wheat production (DALRRD, 2021). South Africa holds the position of the largest wheat producer within the SADC area and stands as Africa’s sixth largest producer. On a global scale, South Africa's wheat production ranks at number 30, with China holding the leading position in worldwide wheat production.

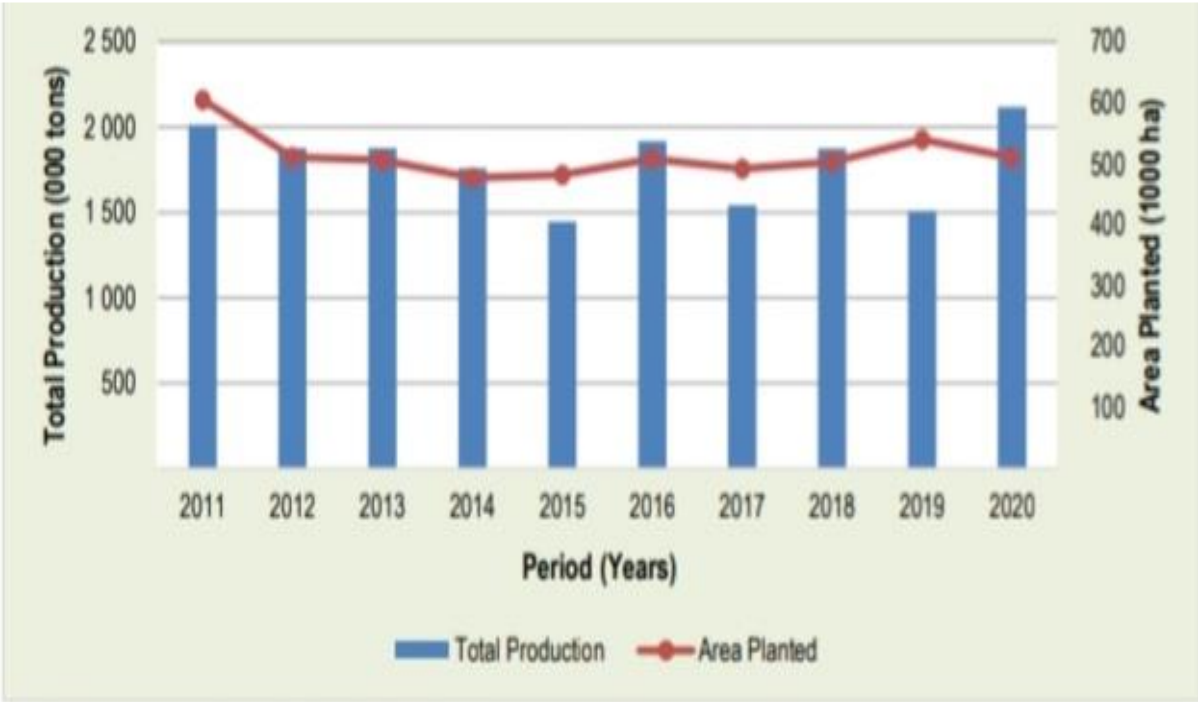


Figure 5. Total Production and Area Planted of Wheat

Source: DALRRD, (2021)

In Figure 5 between 2011 and 2020, the area of land used for producing wheat in South Africa has remained fairly consistent, averaging around 513,000 hectares each year. In 2011, there was a particularly positive start to the wheat production season, with the highest area of land, over 600,000 hectares, being planted. The subsequent years saw a significant decline in production from 2012 to 2015. Production volumes rebounded in 2016. The period concluded with a peak wheat production of in 2020, which was the highest achieved during the analysed timeframe. This production level was higher than the previous peak in 2011.

South Africa imports more wheat from other countries than it produces locally. This means that the prices of wheat in South Africa are influenced by changes in global wheat prices, the strength of South African Rand relative to other currencies and shifts in the costs of transporting wheat.

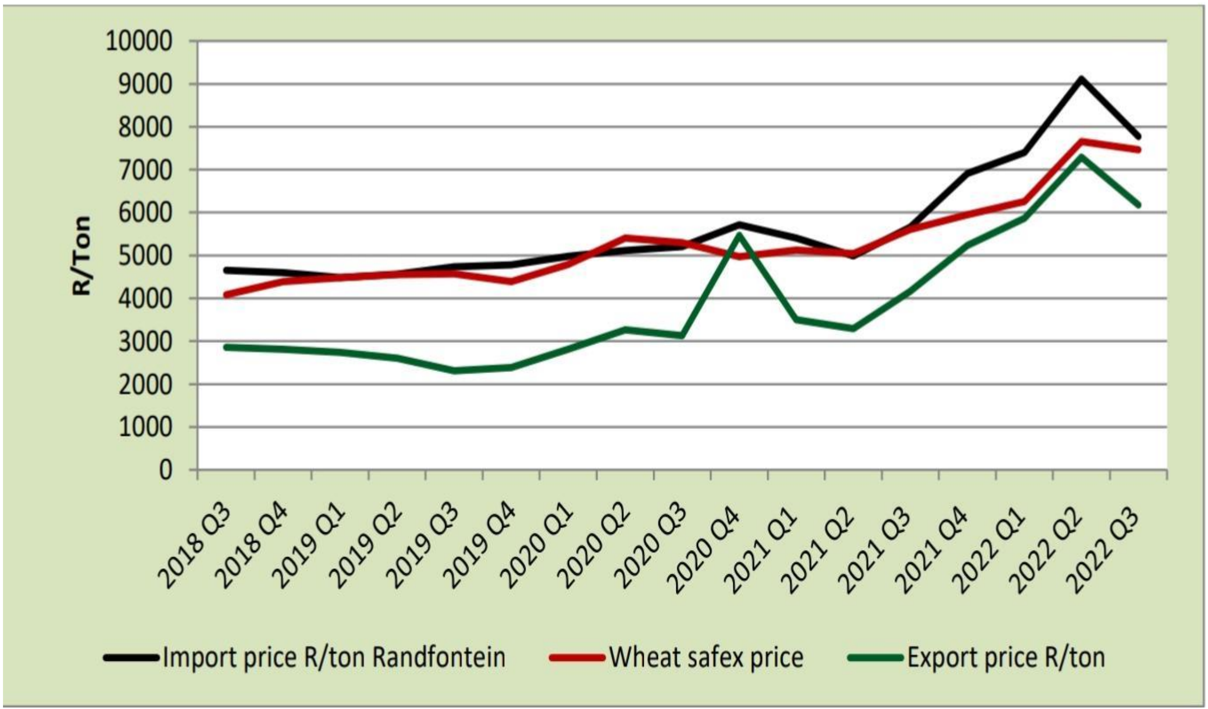


Figure 6. Wheat Prices

Source: Grain SA, (2021).

The Figure 6 displays the price patterns of local wheat prices and global parity prices from the third quarter of 2018 to the third quarter of 2022. In the third quarter of 2022, the South African domestic wheat price was R7,464.26 per ton, marking a 2.5% decrease compared to the preceding quarter. During the same period, the wheat imports parity price stood at R7,768.41 per ton, witnessing a 14.8% reduction in price, and the wheat export parity price was R6,176.70 per ton, experiencing a price decrease of 15.3%, as indicated in Figure 6.

2.3. Summary

This chapter provided a brief look at the grain and oilseed industry in South Africa. It highlighted key trends, production volumes, and market dynamics of soybean, maize, and wheat. The analysis included the impact of climatic conditions that affected the industry and other factors.

CHAPTER 3: LITERATURE REVIEW

3.1. Introduction

This chapter gives an overview of examination of earlier research studies aimed at comprehending the underlying principles governing the interaction of crude oil prices and specific grains and oilseeds. Additionally, this chapter presents an overview of previous investigations carried out in South Africa and globally concerning crude oil, grains, and oilseeds.

3.2. Key concepts definitions

3.2.1. Crude oil

According to the Simanzhenkov and Idem (2003), crude oil can be defined as unprocessed oil that is located deep below the Earth's surface. However, the Encyclopedia of Energy (2004) defines crude oil as a natural mixture of mainly hydrocarbons, typically yellowish black in color and found in geological formations.

3.2.2. Grains

Grains are grass seeds (caryopses) that are edible and starchy (Nesbitt, 2012). Babcock (1976) describes grain as a small, tough, and dehydrated fruit (known as a caryopsis) that can be consumed by humans or animals, either with or without an outer layer called the hull.

3.2.3. Oilseeds

Oilseeds are seeds primarily cultivated for the purpose of producing edible oils. In a broader context, peanuts and soybeans can be classified as oilseeds (González-Pérez et al., 2009). According to Sarwar et al. (2013), oilseed are crops cultivated largely for the oil found in their seeds.

3.2.4. Soybean

Based on Britannica (2024), the soybean is a legume that belongs to the pea family (Fabaceae) and has a seed that can be consumed. It holds significant economic value globally, serving as the most crucial bean by providing vegetable protein for millions of individuals and serving as an ingredient in numerous chemical products. According to Dwevedi and Kayastha (2011) soybean is a widely popular legume with Asian origins, known for its high protein content and versatility in preparation and consumption.

3.2.5. Maize

Benz (2001) states that maize is a type of cereal grain that was cultivated around 10,000 years ago by the indigenous people in the southern Mexico. Maize belongs to the grass family, Poaceae, which includes other vital agricultural grasses such as rice, wheat, oats, sorghum, and rye.

3.2.6. Wheat

Wheat is type of grass extensively grown for its seed, which is a cereal grain and serves as a staple food worldwide (Beldrok et al., 2000; Shewry 2009). According to Grain SA (2015), it is considered one of the earliest domesticated plants, originating in the Fertile Crescent region in south-eastern Turkey around 9,500 years ago.

3.3. Review of empirical studies on the interaction between prices of crude oil and selected grains and oilseeds in South Africa

Balcilar et al. (2016) investigated the causal link of South African agricultural commodity prices (soybeans, corn, sunflower, wheat) and oil prices using daily data from 2005 (19 April) to 2014 (July). The test showed no significant effects, however, the quantile approach revealed impacts that vary across different quantiles. The prices of oil had a more significant effect on sunflower and wheat prices and therefore indicating a link under various market conditions. Bakhat and Würzburg (2013) utilized threshold cointegration analysis which allowed the identification of co-movements that had remained undetected in earlier research utilizing linear cointegration analysis. In the short-term, findings revealed asymmetric response to negative and positive deviations from the long-term equilibrium for agricultural raw products and food. While the price Granger causalities aligned with expectations for agricultural commodities prices, food prices exhibited distinct behaviour. Overall, the study emphasized the significance of consistently examining nonlinear cointegration and highlights the intricate interactions observed among other commodity markets and oil market.

According to Fowewe (2016), an empirical analysis was conducted to examine the impact of oil prices on agricultural commodity prices in South Africa. Through the use of structural breaks cointegration tests, it was determined that there is no sign of a long-term connection of agricultural commodity prices and oil. Additionally, no evidence of a relationship where changes in prices of oil would affect commodity prices when using non-linear causality test.

Examining the existing body of South African empirical literature concerning the connection of crude oil prices with specific grains and oilseeds presents a difficulty. The reviewed studies have focused on different inputs and agricultural commodities, rather than specifically investigating the influence of crude oil as an input. There is a shortage of empirical research on this topic. Thus, the aim is to examine the interplay of crude oil prices and selected grains and oilseeds in South Africa, thereby contributing to the existing knowledge gap in this area of study within the country.

3.4. Review of empirical studies on the interaction of prices of crude oil and selected grains and oilseeds in the world

Numerous published studies have explored the price interaction of these commodities, where most of them primarily focused on the one-way causal relationship.

Vo et al. (2019), examined the effect of agricultural market disruptions on crude oil price dynamics in the United States through the analysis of monthly spot commodity prices. The researchers used the impulse response functions, variance decomposition approach and structural vector autoregressive model. The study's empirical results demonstrated that not every oil shock causes the same variations in crop prices. Similarly, aggregate demand shocks have varying consequences on the agriculture market.

Kapusuzoglu and Ulusoy (2015) demonstrated prices of soybeans, wheat and maize can be impacted by crude oil prices. Similarly, Fernandez-Perez, Frijns, and Tourani-Rad (2016) determined maize, wheat, soybeans and oil prices can have a granger-causality relation and have an immediate impact on soybeans and wheat. On the other hand, Wang et al. (2014) investigated prices of agricultural commodities response to oil prices between May 2006 and December 2012, and the findings indicated that a substantial number of examined commodities exhibited price sensitivity to oil price fluctuations. This is demonstrated by impulse response obtained from the SVAR. Additionally, Wang et al. (2015) analysed how crude oil prices impact rice prices in China using data from 1998 to 2013, and findings, based on ARDL bounds testing, suggest a significant link between the two commodities in the long and short term. This implies crude oil price fluctuations can influence rice prices in China.

Vimal and Tripathi (2019) analysed the long-term relation in India and found a bilateral causal linkage showing significant interactions in the long-term between agricultural commodities and energy prices. Papież (2014), investigated the causal connections of maize, crude oil, and ethanol prices. The study analysed weekly data from 2007 to 2014 using a rolling regression technique. The study revealed that these relationships are dynamic and change over time. The results showed that corn prices can influence energy prices (both crude oil and ethanol). Additionally, it was discovered that prices of maize and ethanol are causally related to prices of crude oil.

Zafeiriou et al. (2018) examined the interaction of crude oil prices and the prices of maize and soybean, using the ARDL cointegration approach. The analysis, encompassing periods of both high and low oil prices, revealed a significant influence of crude oil prices on these agricultural commodities. This finding reinforces the interconnectedness between agricultural and energy markets, suggesting that biofuels may not provide a complete substitute for crude oil nor shield economies from energy price fluctuations.

Gokmenoglu et al. (2021) employed panel data analysis on monthly observations from 2006 to 2015, and established a positive association between agricultural and oil prices, suggesting that oil price fluctuations impact demand for Nigerian agricultural crops. Additionally, a granger causality test incorporating heterogeneity and differencing revealed a two-way causal connection, signifying that oil prices both affect and are affected by agricultural commodity prices.

Several studies have yielded limited evidence supporting the idea that of direct impact of oil prices on agricultural commodities. For instance, Nazlioglu and Soytas (2011) employed Toda-Yamamoto approach to investigate the long-term causality interaction, however, the outcomes did not reveal a Granger causal interaction of both prices of oil and commodity. Moreover, there was no evidence that prices of agricultural commodities were affected by spikes in oil prices, whether through direct impact or through the exchange rate. In a similar vein, Chiu et al. (2016) conducted research in the United States using VAR and VECM models, and their results indicated that while there was evidence that corn price fluctuations Granger-caused oil price movements, the reverse relationship was not observed.

Additionally, Zhang et al. (2010) found no long-run equilibrium relationship of agricultural product prices and energy prices. Notably, prices of sugar were found to be capable of Granger-causing oil prices, whereas oil prices were unable to Granger-cause any agricultural commodity prices. A study by Meyer et al. (2018) investigated how food prices in oil-exporting developing countries reacted to changes in oil prices over time, finding an asymmetry in the long-term response. While increases in oil prices led to significant increases in food prices, reductions in oil prices did not have a corresponding effect. Arshad and Hameed (2009) examined the long-term association of cereal and oil prices, revealing a cointegrated connection and unidirectional causality where oil prices changes influenced cereals prices in the long term. Zhang et al. (2009) addressed impact of rising ethanol demand on agricultural commodity prices. The findings suggest that there was no evidence for a long-term link of fuel and agricultural product prices in recent years.

Saghaian (2010), point to the connection of agricultural and energy markets, particularly the rise of biofuels, as a potential driver of price volatility. While Saghaian (2010) finds strong correlations between commodity and oil prices, the evidence for a direct causal linkage from oil to food prices is inconclusive, suggesting a more complex relationship. Obadi and Korcek (2014) utilize Granger causality tests to explore the long-term connection. The findings suggest a long-run influence of oil prices on food prices, implying that oil price fluctuations can have a substantial influence on cost of food in the long term. Further research by Harri et al. (2009) investigates specific commodity linkages and a cointegrated was found between corn and oil prices, with oil price shocks impacting corn prices. No causal effect is found in the opposite direction for corn or wheat, but linkages are identified between oil and soybeans and cotton prices. Esmaeili and Shokhoohi (2011) delve into the possibility of indirect effects. The study suggests that oil price fluctuations can indirectly impact food prices by influencing food production costs. In conclusion, the literature reveals a multifaceted relation between oil and food prices.

3.5. Chapter Summary

Chapter three reviewed existing literature of the prices interaction of crude oil, grains and oilseeds. It covered both international and national studies, identifying the key findings and methodologies used in previous research. The review explored how fluctuations in crude oil prices influence agricultural commodity prices, focusing on the mechanism driving these interactions. It also highlighted gaps in literature and relevance of these studies to the South African setting.

CHAPTER 4: RESEARCH METHODOLOGY AND ANALYTICAL TECHNIQUES

4.1. Introduction

An overview is provided regarding the research methods employed for conducting this study in this chapter. It outlines the area of study, data collection, and analytical techniques used.

4.2. Study area

The study relied on an examination of selected grains and oil seeds prices in South Africa and crude oil prices, seeking to understand how fluctuations in the global crude oil markets influence the grains and oilseeds market in South Africa, given that understanding the price interaction can be crucial for assessing economic stability and food security. The countries that share a border with South Africa are Mozambique, Namibia, Botswana and Zimbabwe. South Africa has a coastline that stretches 2,798 km along the Indian and South Atlantic oceans. The country has nine provinces namely, Kwa-Zulu Natal, Limpopo, Gauteng, Eastern Cape, North West, Western Cape, Mpumalanga, Northern Cape, and Free State. The population of South Africa is 60,6 million as estimated by STATS SA (2022). Geographical coordinates of South Africa are, 30.5595°S, 22.9375° E (STATS SA, 2022).

4.3. Data collection

The study utilised the secondary time series data from the World Bank commodity price data, the pink sheet (World Bank, 2023) and Statista, covering a period of five years (2018-2022). The dataset comprises 60 monthly observations of prices for crude oil, soybean, wheat, and maize. Following Balcilar et al. (2016), to prevent the capturing influence of currency rate on oil, oilseeds and grains, the prices of crude oil are kept in dollars rather than South African Rand. That is, crude oil prices are in US dollars (USD) on the global market, not local currencies like the South African Rand (ZAR). This practice aims to isolate the price of oil itself from fluctuations in exchange rates. Currency fluctuations can introduce unnecessary volatility into oil pricing. Keeping it in its origin currency simplifies price comparisons across borders.

The study utilized a list of variables, and their corresponding descriptions are listed Table 1.

Table 1: Description of variables

Variable Code	Variable Name	Variable Description	Unit of Measurement
CoP	Crude oil Prices	The monthly crude oil prices	Dollar/Barrel
SbPP	Soybean Producer Prices	Monthly producer prices of Soybean	Rand/Metric ton
MzPP	Maize Producer Prices	Monthly producer prices of Maize	Rand/Metric ton
WtPP	Wheat Producer Prices	Monthly producer prices of wheat	Rand/Metric ton

Source: Computation by author, 2024.

4.4. Analytical Techniques

This study included both descriptive and econometric analyses. The descriptive analysis was utilized to describe pricing trends. The econometric analysis was employed to determine the presence of a short term and a long-term relations and causal relationship of selected oilseed, grain prices with crude oil prices. The analysis was carried out using EViews 12 Student Version downloaded in 2023.

The study first tested the stationarity of the study variables data. The bounds cointegration test was used to test whether the variables are cointegrated or not. As Tu et al. (2019) point out, cointegration analysis is crucial in economics for uncovering long-term equilibrium relationships between time series data, even if these relationships are weak or absent in the short-term. This justifies the application of the bounds cointegration test in this instance. By employing this test, the study aimed to determine whether the variables under investigation exhibit cointegration, implying a stable long-run association despite potential short-term fluctuations. In essence, the bounds test allows an assessment of the presence of a unifying force that compels the variables to return to a balanced state in the long run. To ensure an accurate specification of the Vector Autoregressive (VAR) model, an optimal lag length test was administered prior the Granger causality analysis. In exploring the potential connection between prices of crude oil, and selected oilseeds and grains, a Granger causality examination was conducted. The investigation utilized a multivariate linear autoregressive model to explore the potential long-term and short-term interaction of the prices of crude oil, grains, and oilseeds in South Africa, which Pesaran et al. (2001) proposed:

$$CoP_t = \beta_0 + \beta_1 SbPP_t + \beta_2 MzPP_t + \beta_3 WtPP_t + \varepsilon_t \quad (1)$$

$$\Delta CoP_t = \beta_0 + \sum_{i=1}^{p} \beta_1 SbPP_{t-1} + \sum_{i=0}^{p} \beta_2 \, MzPP_{t-1} + \sum_{i=0}^{p} \beta_3 WtPP_{t-1} + \varphi_1 SbPP_{t-1} + \varphi_2 MzPP_{t-1} + \varphi_3 WtPP_{t-1} + \varepsilon_{it} \quad (2)$$

Where:

CoP is crude oil prices; SbPP is soybean producer prices, MzPP is maize producer prices, WtPP is wheat producer prices, and p is the highest number of lagged data allowed in the model. The dependent and independent variables are crude oil prices, selected grain, and oil seed prices respectively and the error term ε. The coefficients are β and φ.

4.4.1. Unit Root Test for Non-Stationarity and Stationarity

First, using the unit root test, stationarity was observed before proceeding with examining the short term and the long-term relationships and testing for causality. In the context of statistical inference using time series models, a unit root presents a distinct characteristic within stochastic processes. This characteristic can lead to complications during statistical inference, particularly when analysing time series data (Gonzalo & Montesinos, 2002; Purutcuoğlu, 2004; Phillips, 2010). A non-stationary variable is said to contain a unit root while a stationary variable has no unit root. According to Gujarati and Porter (2009) the following equations can be used to analyse unit roots:

$$Y_t = \partial Y_{t-1} + u_t \quad (3)$$

$$-1 \leq \partial \leq 1$$

If the coefficient of Y_{t-1} namely, $|\partial|$ is equal to 1, then Y_t is non-stationary.

4.4.2. Augmented Dickey-Fuller (ADF) test

The unit root was tested according to the following hypotheses based on Dickey and Fuller (1979):

I. Null hypothesis was stated as there being a unit root.

II. Alternative hypothesis was stated as there being no unit root.

4.4.3. Auto-Regressive Distributed Lag Model

The autoregressive distributed lag (ARDL) model was employed in order to empirically analyse if the variables exhibit relation for either the short or long run. The ARDL model is suitable when analysing time series that are either non-stationary, stationary or with a mixed integration order (Shrestha and Guna, 2018). Nasrullah et al. (2021) suggests this model as the most suitable econometric method for cases where variables exhibit stationary behaviour at I(0) and I(1) levels. In the context of the present investigation, this model offers a superior approach for capturing the dynamic relationships between variables in short term and long term.

The technique autoregressive distributed lag cointegration has become widely used in applied econometrics to analyse the relationship between non-stationary series (Nkoro and Uko, 2016). By reformulating the data within the framework of Error Correction Model (ECM), the analysis can capture the short-term dynamics and the long-run equilibrium link of the variables under investigation.

Following Pesaran et al. (2001) which is also related to Engle and Granger (1986) as well as Granger (1981), the equation of ARDL model is as follows:

$$Y_t = y_0 + \beta_1 X_{t-1} + \beta_2 X_{2t-1} + \beta_3 X_{3t-1} + \varepsilon_t \text{ ....} \quad (4)$$

Where:

From equation 4, Y_t is a vector and the variables in X_t are allowed to be /(0) or /(1) or cointegrated. The β's in the equation are parameters and y_0 is a constant.

$$\Delta CoP_t = \beta_0 + \sum_{i=1}^{p} \beta_1 SbPP_{t-1} + \sum_{i=0}^{p} \beta_2\, MzPP_{t-1} + \sum_{i=0}^{p} \beta_3 WtPP_{t-1} + \varphi_1 SbPP_{t-1} + \varphi_2 MzPP_{t-1} + \varphi_3 WtPP_{t-1} + \varepsilon_{it} \text{..} \quad (5)$$

The second equation in the ARDL model (equation 5), serves as the method for correcting errors. It separates the equation into two key parts that explain how the independent variables (SbPP, MzPP, WtPP) influence CoP as the dependent variable over time. One part, represented by the terms with φ coefficients, captures the long-run equilibrium relation. These terms show how deviations from the long-term balance between variables (represented by lagged error term) are corrected over time. The other part, represented by the β coefficients, and the differenced independent variables, describes the short- and long-term impacts of the independent factors on the dependent variable. The β coefficients show the immediate impact (short-term) of the independent variables changes on the dependent variable.

To check if a model's estimates are valid, statisticians use a special test called the joint F-statistic. Its expected distribution deviates from the norm when there is no long-term association of the prices of the commodities such as soybean, crude oil, wheat, and maize selected for this study. The equation 6 and 7 indicate how the prices can be connected.

$$H_0: \varphi_1 = \varphi_2 = 0 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots ..6$$

The alternative hypothesis:

$$H_1: \varphi_1 \neq \varphi_2 \neq 0 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 7$$

The H_0 is be deemed valid when it is above the upper critical limit, and the opposite otherwise.

4.4.4. Granger Causality Test

According to Granger (1969), the study examined if the prices of soybean, wheat, maize, and crude oil are causally connected. In a linear granger causality, predictability can be used to determine causality between two stationary series, y_t and x_t. According to Ajmi et al. (2013), if using previous occurrences of y_t leads to better forecast of x_t compared to using only historical x_t data, then y_t is considered to granger cause factor for x_t.

The test based olinear vector autoregressive VAR(p) is structured as follows: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \varphi_{11,1} & \varphi_{12,1} \\ \varphi_{21,1} & \varphi_{22,1} \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} \varphi_{11,p} & \varphi_{12,p} \\ \varphi_{21,p} & \varphi_{22,p} \end{pmatrix} \begin{pmatrix} x_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$

Where: The process ε_t, is a white nose processes made up of ε_{1t}, ε_2 with covariance matrix Σ and mean of zero. A sequential likelihood ratio test was utilised to determine the ideal lag order of the process, with constants α_1 and α_2, and parameters represented by φ.

4.5. Chapter Summary

This chapter detailed the methodology used in the study. It describes the study area and the data set of crude oil, wheat, soybean, and maize prices between 2018 to 2022. The analytical methods are outlined starting with the unit root test, the Augmented Dickey-Fuller (ADF) test to ensure data stationarity. The chapter then explained the use of Autoregressive Distributed Lag (ARDL) model to analyse both short-run and long-run relationships between variables. Finally, to determine the direction of causality between crude oil prices and grains and oilseed prices, Granger causality was discussed.

CHAPTER 5: RESULTS AND DISCUSSION

5.1. Introduction

This chapter contains the findings and discussions of the regression models used to analyse data for this study. The analysis used 60 observations of crude oil prices, as well as soybean, maize, and wheat producer prices. It is designed as follows: The initial section analyses the descriptive analysis of the variables, including the description of graphical trends. The following sections present findings meeting objective 1 and 2. Firstly, the stationarity of the price data across time is given using the Augmented Dickey-Fuller tests. The lag order selection results are then presented, followed by the examine short run and long run relationships using the Autoregression Distributed Lag Model and Granger Causality Tests to determine causality direction.

5.2. Descriptive Analysis

The descriptive statistics on monthly prices of four commodities: crude oil, maize, wheat, and soybeans are presented in this section. Crude oil prices are included for comparison, while maize, wheat, and soybean prices are specific to South Africa. The data covers a monthly period from 2018 to 2022 (60 observations). This analysis will provide an initial understanding of the central tendency, dispersion, and potential skewness in the price distributions of these commodities. The subsequent table will present the descriptive statistics in detail, and discussion of the key outcomes which follows and any notable patterns observed in the price data.

To provide a summary of the descriptive analysis, Table 2 depicts the outcomes.

Table 2: Descriptive Statistics

Variables	Mean	Median	Minimum	Maximum	Standard Deviation	Skewness
CoP	69.53417	67.24500	23.34000	120.0800	20.47024	0.295570
SbPP	7366.606	6564.965	4759.400	11636.52	2276.582	0.615576
MzPP	3277.70	2698.820	1904.100	6226.970	1168.117	0.875759
WtPP	4238.595	3784.145	2272.760	8299.070	1643.524	0.961405

Source: Computation by author, 2024.

The average price of crude oil in from 2018 to 2022 is approximately 69.53 dollars per barrel. This gives an idea of the central value around which the prices tend to cluster. The median price of crude oil is around 67.25 dollars. As the median is a bit lower than the mean, this suggest that the distribution may be slightly positively skewed. The lowest price of crude oil between 2018 and 2022 was recorded as 23.34 dollars/barrel, on the other hand maximum is at 120.08 dollars/barrel. That marks the peak price for crude oil prices. There is a standard deviation of approximately 20.47 dollars, indicating that prices do not vary too far above or below the mean price and are spread out evenly. The skewness value of 0.295 indicates a minor positive skewnes, which is consistent with the assumption that a few relatively higher prices are driving the mean upwards.

Observations in the study period covered by this present study shows that the average soybean price in the dataset is 7366.60 Rands/ton, while the lowest soybean prices is 4759.40 Rands/ton and highest is 11636.53 Rands/ton. Given that a higher standard deviation denotes higher price volatility, the 2276.58 Rand/ton standard deviation illustrate the degree of variability in Soybean prices close to the mean. The positive skewness value of 0.615576 indicates that soybean price variations follow a positively skewed distribution. This means that while the majority of prices are piled towards the bottom, some higher elements lead the distribution to have a longer tail on the right.

The mean of 3277.70 represents the average price of maize Rands/ton for the period of 60 months. The middle price of maize is 2698.82 Rands, which is the point when maize prices are arranged from lowest to highest and acts as an indicator for affordability within the South African market. With the standard deviation of 1168.12 Rands, suggest more volatile price movements for maize. The lowest prices recorded for maize from 2018 to 2022 was 1904.10 Rands, whereas the highest price was 6226.97 Rands. Since the skewness of maize is positive, indicates more frequent lower prices.

The average price of wheat from 2018 to 2022 in South Africa was recorded as 4238.59 Rands, with the lowest price at 2272.76 and highest price at 8299, which was the second highest price for the selected grains and oilseeds in South Africa. The wheat is volatile as indicated by the standard deviation, and its prices are fluctuating more significantly around the average price. Note that the standard deviation is relatively high for all four commodities, indicating significant variation in prices around the mean. Soybean prices have the highest standard deviation (2276.58), followed by wheat (1643.52), maize (1168.12), and crude oil (20.47). This suggests that soybean prices fluctuate the most over time.

5.3. Graphical Trends

The graphical trends of the prices of soybean, maize, wheat and crude oil are presented in Figure 7, with a detailed graph for crude oil prices in Figure 8.

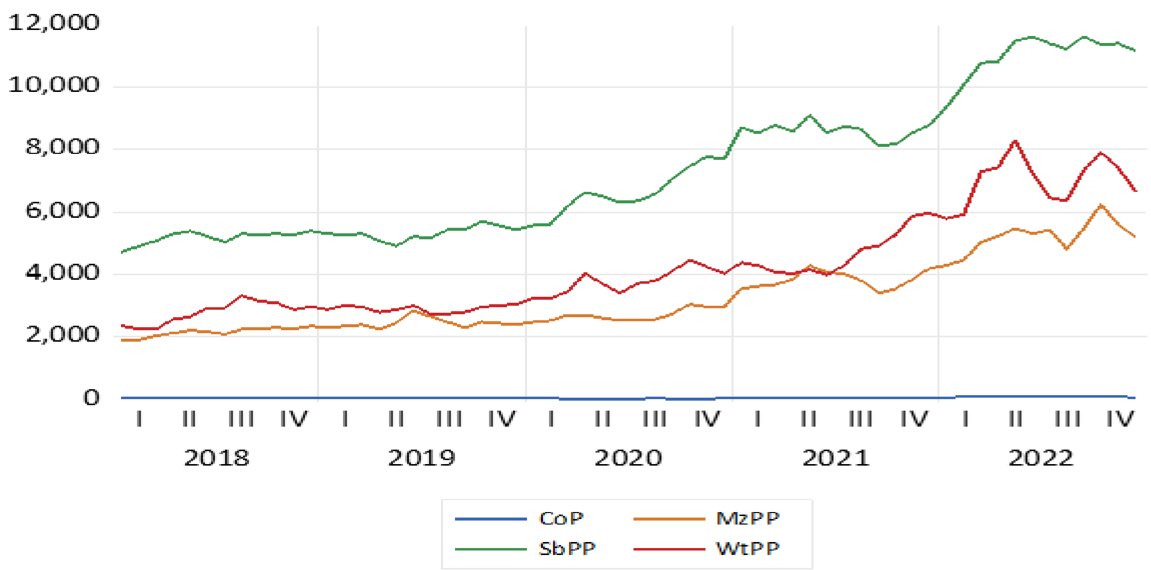


Figure 7. Monthly Price Trends of Soybean, Maize, Wheat and Crude Oil in South Africa from 2018 to 2022

Source: Author Computation, 2024

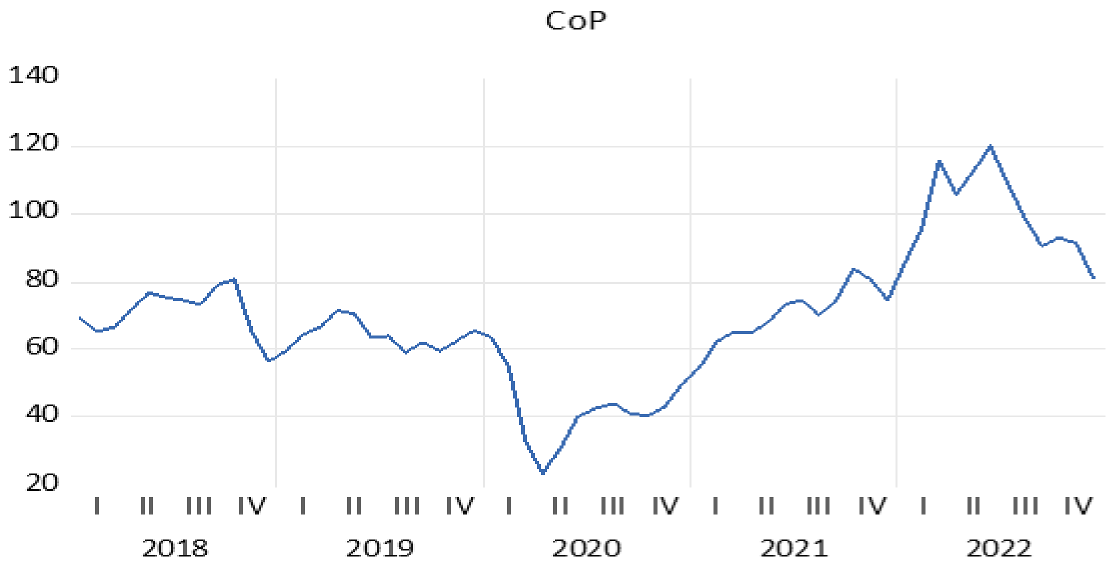


Figure 8. Monthly Price Trends of Crude Oil from 2018 to 2022

Source: Computation by author, 2024

Figure 7 displays the price movements of observed monthly prices of crude oil, maize, wheat, soybean in South Africa, from January 2018 to December 2022, whereas Figure 8 shows crude oil prices only. Crude oil (CoP) prices exhibit the most volatility, with notable peaks in 2018, late 2021, and early 2022. Maize (MZPP) and soybean (SBPP) prices have an upward trend, with price surges in late 2020 and early 2022. Wheat (WTPP) prices are the most susceptible to change, with major rises in 2018, late 2020, and early 2022. Crude oil prices follow a cyclical pattern, with peaks and troughs occurring over a five-year period (60 months). This is consistent with how crude oil prices often trend on the worldwide market as a result of variables such as international wars and pandemics (Le et al., 2021; Energy Information Administration, 2023; Chen et al., 2024). A rise in maize, soybean, and wheat prices over time could be attributed to a variety of factors, including global supply and demand dynamics, production costs, or internal market conditions in SA.

5.4. Augmented Dickey-Fuller (ADF) Test

Assessing stationarity is a crucial first step as it influences the choice of appropriate statistical methods. This study employs a two-pronged approach to stationarity analysis. Initially, graphical analysis provides a preliminary assessment of stationarity.

Subsequently, the Augmented Dickey-Fuller (ADF) test is employed to statistically confirm graphical findings. This approach aligns with the methodology outlined by Shrestha and Bhatta (2018) for time series analysis. The following sections will present the graphical representations of the price series for both crude oil and the selected grains and oilseeds, followed by a detailed examination of the ADF test results.

5.4.1. Graphical Representations of Stationarity

To gain preliminary insights on stationarity, graphical representations of the data at their original level are presented (Figure 9) and after first differencing (Figure 10).

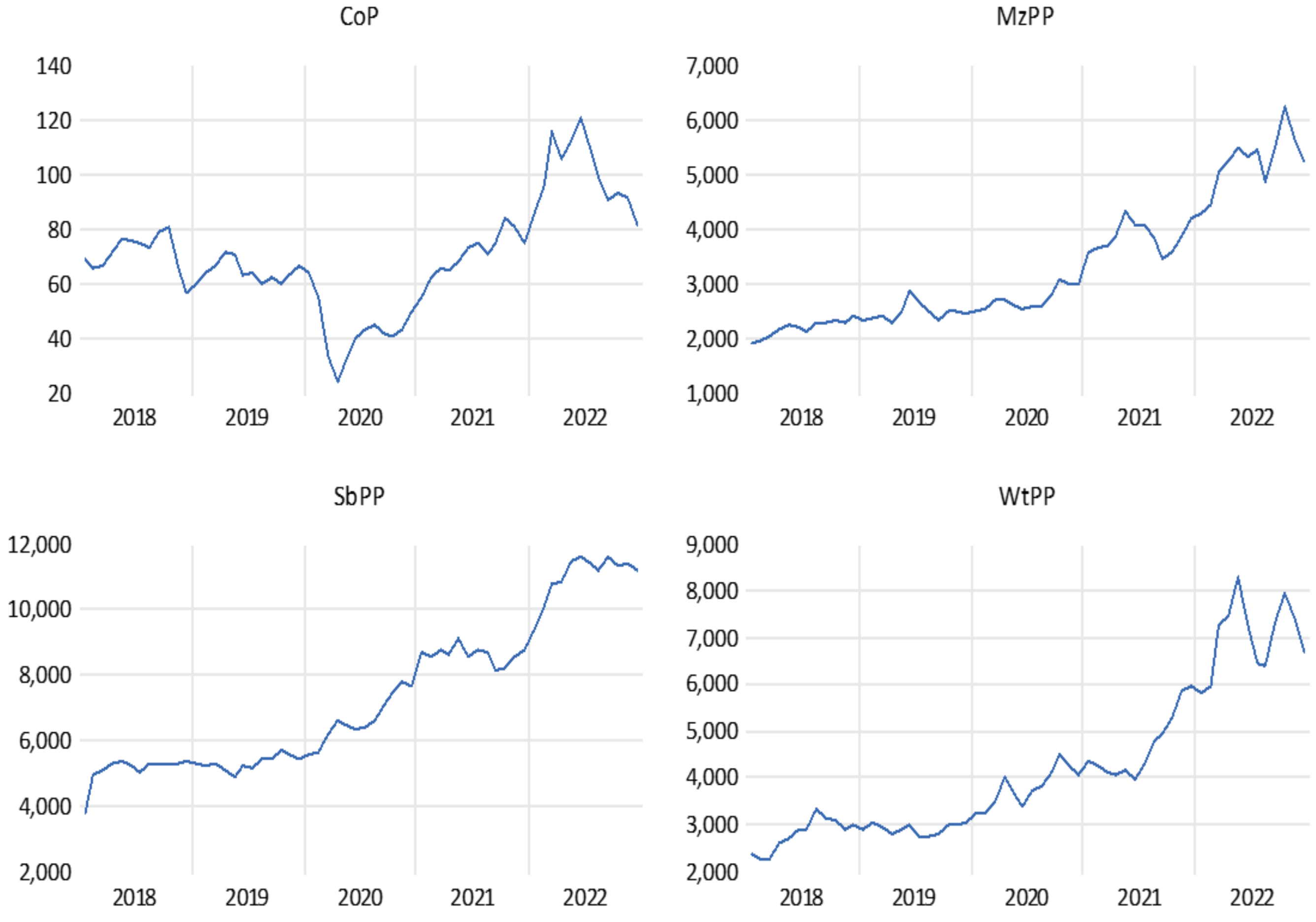


Figure 9. Graphical representation of the variables at level

Source: Author's computation, 2024

Figure 9 shows non-stationary time series data for four variables: COP, MzPP, SbPP, and WtPP. As Shrestha and Bhatta (2018) indicate, non-stationary time series exhibit strong upward or downward trends over time. This is evident in all four of the series plotted in the graph.

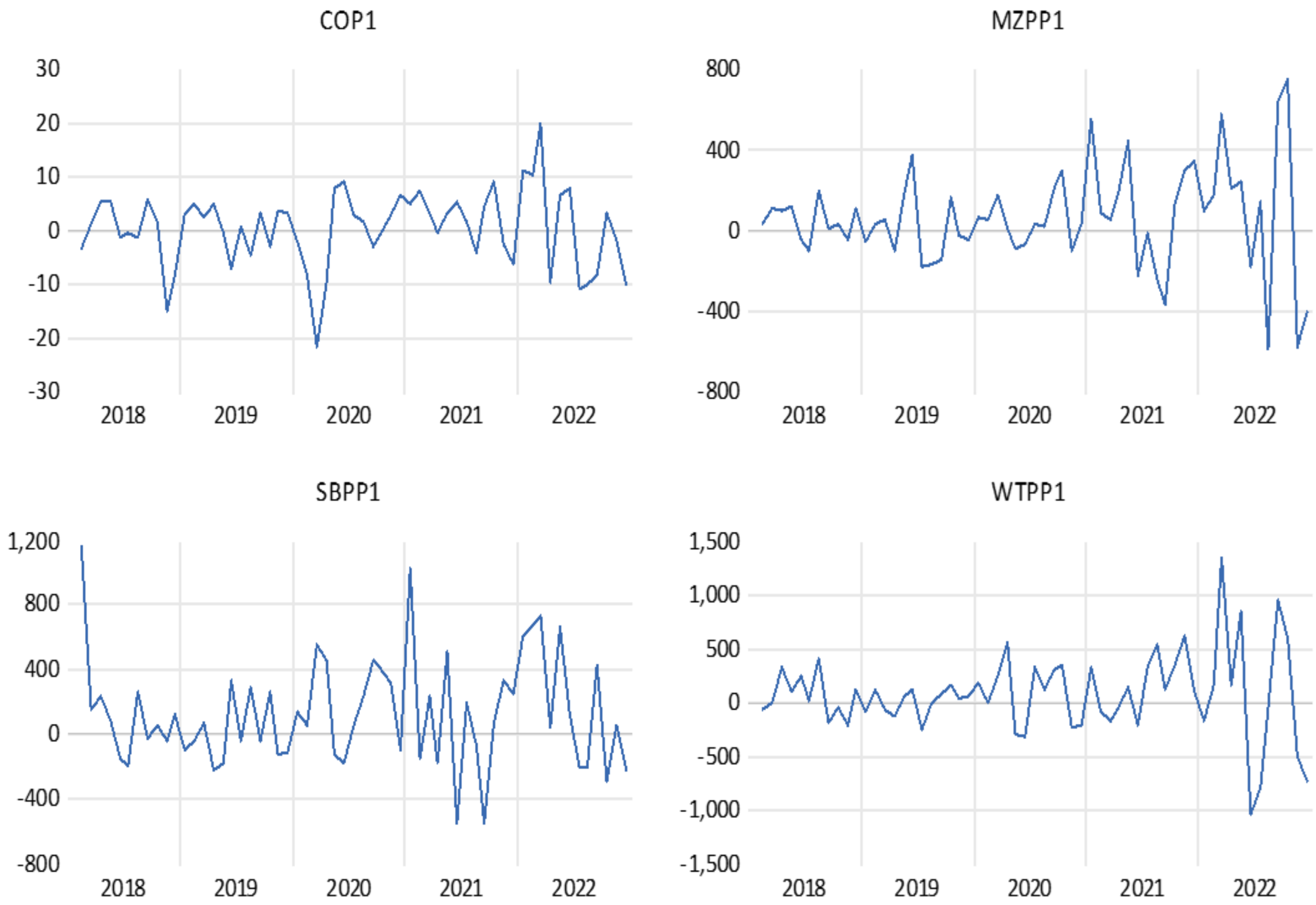


Figure *10*. Graphical representation of variables after 1st Difference

Source: Author's computation, 2024

Figure 10 shows graphs of the same variables after 1st differencing, which means that for each data point, the value of the previous time step has been subtracted. In Figure 9, the variables all exhibited a strong upward trend, which is a characteristic of non-stationary data. After 1st differencing, the trends have been removed, and the graphs appear more stationary. This is because differencing removes the constant change over time (the trend) by focusing on the change between time steps. Crude oil prices series, each data point likely showed a higher value than the previous one. After differencing, the series focuses on the difference between those values. The important aspect is that the differenced series no longer shows a consistent upward or downward trend, but rather fluctuates around a central value, which is a sign of stationarity. Similarly, the differenced series for maize prices, soybean prices, and wheat prices also show fluctuations around a central value, with no clear upward or downward trends. This suggests that after differencing, these time series are now more stationary.

5.4.2. Statistical test of Stationarity

Prior to investigating the dynamic interactions between the price series, it is crucial to assess their stationarity properties. This is achieved by employing unit root tests. Table 3 presents the Augmented Dickey-Fuller (ADF) test results for the prices of crude oil, maize, wheat, and soybean.

Table 3: Augmented Dickey-Fuller (ADF) Unit Root Test

Variables	**Intercept**				**Intercept and Trend**			
	Level		**First Difference**		**Level**		**First Difference**	
	t-stat	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**
COP	-1.813	0.371	-5.487	0.000	-2.030	0.573	-5.418	0.000
MzPP	-0.400	0.902	-6.661	0.00	-2.248	0.455	-6.755	0.000
SbPP	-0.411	0.900	-7.971	0.000	-1.716	0.732	-8.002	0.000
WtPP	-0.653	0.85	-6.629	0.000	-2.261	0.448	-6.692	0.000

Source: Author computation, 2024

Table 3 displays results of the unit root tests on the variables, indicating non-stationarity of all variables at levels, meaning that at the 5% significant level the null hypothesis is accepted. This suggests that the time series data exhibit a unit root. This means that variance and mean of the time series are not consistent over time. Since a unit root can be a problem, in order to analyse the data further, differencing was applied to the data. At the 1st difference it was found that all variables are stationary, therefore at 5% significance level the null hypothesis is rejected. The study can infer that the 1st was sufficient to make all variables stationary. The fact that all variables became stationary following the first differencing suggests that the original non-stationarity was caused by a unit root. This is a common occurrence in time series data, and differencing is a standard technique of dealing with it. With the variables being stationary, further analysis can proceed with more reliable results.

5.5. Lag Order Selection Criteria

In order to find the ideal lag length, a standard unrestricted VAR framework was employed. This allowed the assess the optimal lag structure of the time series data. The selection of the optimal lag length was guided by information requirements; Hannan-Quinn Criterion (HQ), Akaike Information Criterion (AIC), and Final Prediction Error (FPE), as presented in Table 4.

Table 4: Vector Lag Order Selection

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-1527.140	N/A	1.78e+19	55.667783	5582381	55.73428
1	-1333.225	352.5734	2.773e+16	49.20818	49.93811*	49.49045*
2	-1317.347	26.55602	2.18e+16	49.21269	50.52658	49.72078
3	-1302.206	23.12806	2.97e+16	49.24384	51.14168	49.97775
4	-1269.825	44.74426*	1.71e+16*	48.64818*	51.12997	4960791
5	-1254.771	18.61220	1.92e+16	48.68258	51.74832	49.86813
*indicates the optimal lag length chosen by criterion						

Source: Author's computation, 2024.

According to the data in Table 4, lag length of four is the most suitable. The analysis of lag selection revealed that lag 4 is a suitable choice due to its higher Log Likelihood, stronger explanatory power, lower Final Prediction Error, and better overall fit. Both AIC and SC information criteria favour lag 4, balancing model fit with complexity, with the HQ criterion slightly favouring lag 2. This selection is backed up by econometrics literature by Hanck et al. (2021), Gutierrez et al. (2009) and Ozcicek and Mcmillin (1999).

5.6. Autoregressive Distributed Lag Model

The study follows the procedure by Nkoro and Uko (2016), Zafeiriou et al. (2018) and Govdeli (2022) in analysing the long and short run linkages within the ARDL framework. This includes the bounds test, long run estimates, and short-run dynamics in this order.

5.6.1. Bound Cointegration Test

As a preliminary step (Zafeiriou et al., 2018), the bounds cointegration test is conducted to determine long-term link between variables. This test is crucial in establishing the validity of ARDL model for further analysis. By confirming or rejecting cointegration, the bounds test ensures that the model is appropriately specified, allowing for interpretation of long-run and short-run dynamics. Table 5 displays the outcomes of this test.

Table 5: ARDL Bounds Cointegration Test

Variables	F-Statistic Value	I(0)	I(1)
CoP	1.0453	2.79	3.67

SbPP	8.9929	2.79	3.67
MzPP	4.4329	2.79	3.67
WtPP	2.1678	2.79	3.67
Significant at 5% level			

Source: Computation by author, 2024

Table 5 shows the cointegration bounds test which analyse whether a long-run dynamic of the variables is present. The hypothesis is that there is no long relationship if the F-statistic is lower than the upper and lower bounds at 5% significance level. Each variable was tested separately as a dependent variable in the model to determine the presence of long-term relationship of these variables for each specified model. The outcome indicated that when crude oil is a dependent variable, no long-term cointegration between prices of crude oil, selected grains and oilseeds exist, since the F-statistic was found to be lower than the lower and upper bounds. The same was analysed with wheat as the dependent variable, showing no long run relationship, concluding that the crude oil prices are not a factor in the increase or decrease in the long run. Furthermore, no long run cointegration between wheat, soybean and maize, that is, price changes in maize, soybean, and crude oil have no lasting impact on wheat prices. Implication of no long-run relationship between the wheat, soybean and wheat prices is that there is independence of the two prices. Even though wheat, maize and soybean, fall under the same industry in South Africa, soybean and maize prices cannot be used as the predictors that are reliable to forecast the wheat prices. Contrastingly, with soybean and maize prices as dependent variables, the test indicates a long run cointegration with wheat prices. This shows that the relationship is multifaceted, in addition an asymmetric relationship is highlighted. An asymmetric relationship shows the dependency of the other markets on the one for wheat, meaning the factors that affect the wheat prices in South Africa also influence the soybean and maize prices in a long term, but the factors that affect soybean and maize prices do not influence the wheat prices. The long run coefficients of maize and soybean with other variables will further be analysed, since both variables passed the bounds cointegration test as the dependent variables.

5.6.2. Long run estimates

The step that follows involves explaining long-run estimates of the variables that showed long-term relation in the bounds cointegration test, and the estimates are shown in Table 6.

Table 6: Long run estimates

Dependent Variables	**Regressors**	**Coefficients**	**Standard Error**	**t-Statistic**	**Probability**
MzPP	CoP	8.199	2.797	2.932	0.006
	WtPP	0.119	0.125	0.959	0.344
	SbPP	0.382	0.077	4.993	0.000
	C	-543.144	199.598	-2.721	0.000
SbPP	CoP	-26.134	5.067	-5.158	0.000
	WtPP	0.603	0.172	3.508	0.001
	MzPP	1.431	0.225	6.352	0.000
	C	1918.128	241.178	7.953	0.000

Source: Computation by author, 2024

The findings show the estimations of coefficients for the long run interactions. At 5% significance level, the coefficient of prices of crude oil, soybean and constant are significant, since their p-values are less than 0.05. However, the coefficient of wheat prices has a p-value that is greater than 0.05, which means that it is insignificant. This suggests that short-term fluctuations in wheat prices do not necessarily lead to predictable changes in maize in the long-term. Furthermore, it implies that the observed long-term link that was observed could be due to a random chance than a true linkage. Additionally, in the linkage between soybean and wheat prices, the coefficient of wheat price is significant due to its p-value (0.001) which is greater than 0.05. This contrast with Camp's (2019) findings, which highlighted a positive cointegration between price changes for maize, soybean, and wheat, suggesting that prices for these major commodities in the United States trend together, between December 2001 and December 2017, due to common price-determining factors. The difference in findings could be attributed to the difference in time periods analysed, the specific market conditions. While Camp (2019) emphasizes the long run interconnectedness of these commodity prices, this study suggests that the long run price relationship involving wheat prices may not be as robust.

Crude oil price is shown to significantly influence both maize and soybean prices, as indicated by a p-value of less than 0.05, therefore the study confidently observes the relationship further. There is a strong positive relationship between maize and crude oil prices, whereas there is a negative linkage between soybean and crude oil prices. The negative coefficient of crude oil prices indicates that when the prices of crude oil increase by one unit, the price of soybean decrease by about 26.13 units. This means that in the long run, a substitution can take place especially in oil making. Soybean is known to produce biofuel and also bioplastic, which can also be produced using crude oil. When there is an increase in crude oil prices, the soybean prices will decrease, then soybeans will be used as a substitution. According to Engelbrecht et al. (2020) as well as Gasparri et al. (2016), South Africa is the highest producer of soybean, which can be an advantage to them when the prices of crude oil increases. If there is a good support system of soybean producers and also an encouragement of biofuel production, this can bring development in South Africa, investment opportunities, trade opportunities for biofuel, which can in return improve the GDP of the country. While the decrease in soybean prices when prices of crude oil might seem beneficial for consumers leading to food security, this can harm agribusinesses and farmers by reducing their profitability, which may potentially lead to lower agricultural investment and productivity. Therefore, this shows the importance continuous support to farmers financiallyand subsidies to farmers who experience challenges with the low prices of soybean. Famers are encouraged to also diversify their crops, in addition invest in value-adding processes to help them mitigate the price fluctuations in soybean.

The positive crude oil prices coefficient when the dependent variable is maize prices, means that when crude oil increases or decreases by one unit, the prices of maize are to increase or decrease by 8.199 units. The crude oil prices influence maize prices to increase through production cost and transportation, meaning when crude oil prices increase, producers in South Africa are likely to increase the prices of maize, to make it up for the cost incurred during production. All in all, this will affect food prices, due to maize producer prices increasing. This will affect the affordability of food in South Africa, leading to an increase in food insecurity. To avoid this, policy makers should subsidize inputs during the rise of prices of crude oil to reduce the cost of production for farmers. There should be further research and investment on alternatives to fertilizers avoiding crude oil fertilizers. The production and use of biofuels should also be encouraged to avoid much dependence on crude oil. The overall model indicates that maize prices' important determinants are crude oil and soybean prices, while the prices of wheat are not significantly influencing maize prices in the long-term. Soybean prices on the other hand, are significantly influenced by all variables. This aligns with the study by Tessmann (2022) in Brazil, found a long-term influence of other agricultural commodity prices on the soybean prices, showing a stronger dependency of soybean prices. The study also found that maize prices are influenced by prices of agricultural commodities, but soybean prices have a higher dependency than maize prices.

The long-term price interaction of agricultural commodities and crude oil has been well-documented across various studies. This study analysis revealed that in South Africa, maize and soybean prices are significantly influenced by crude oil prices. Similarly, Zafeiriou et al. (2018) validate the existence of a long-run price linkage of agricultural commodities (mainly maize) and crude oil, emphasizing the role of maize in ethanol production. The findings suggest that high crude oil prices consequently lead to higher maize prices. This dynamic underscore the interconnectedness of agricultural and energy markets on a global scale. Further supporting these conclusions, Fasanya et al. (2018) found cointegration between crude oil prices and most agricultural commodity prices in Nigeria, including maize, wheat, palm oil, and soybean, except for rice and ground nut. This study found no cointegration between crude oil prices and wheat prices, whereas Fasanya et al. (2018) found a relationship, it could be that there is a difference in wheat market in Nigeria and the one in South Africa. The study of Fasanya et al. (2018) further suggests that periods with more pronounced crude oil prices movements may lead to stronger cointegration signals, indicating that the trends and price increases in crude oil are crucial in determining the strength of this relationship. Nazlioglu and Soytas (2012), and Nazlioglu (2011) extend this analysis to a global context, finding the link between crude oil prices and a broad range of agricultural commodity prices, including maize, wheat, and soybean. These studies collectively prove that the linkage between agricultural commodity prices and crude oil prices is consistent across different regions and commodities, particularly in recent years.

5.6.3. Short term Relationship

To conclude on the short-term dynamics of the variables, results are displayed in table 7.

Table 7: Short term Relationship

Dependent Variables	Regressors	Coefficients	Standard Error	t-Statistic	Probability
CoP	SbPP	-0.006	0.006	-0.874	0.388
	MzPP	0.002	0.008	0.036	0.971
	WtPP	0.009	0.005	1.799	0.080
	C	1.433	8.167	0.176	0.861
SbPP	CoP	-3.754	4.296	-0.873	0.388
	MzPP	0.697	0.812	3.835	0.001
	WtPP	0.0448	0.109	4.111	0.002
	C	662.454	181.942	3.641	0.001
MzPP	CoP	0.119	3.336	0.036	0.972
	SbPP	0.416	0.108	3.835	0.001
	WtPP	0.059	0.102	0.579	0.566
	C	-352.263	153.572	-2.294	0.028
WtPP	CoP	9.443	5.248	1.799	0.080
	SbPP	0.713	0.173	4.111	0.002
	MzPP	0.157	0.271	0.579	0.566
	C	-437.929	258.458	-1.694	0.099

Source: Computation by author, 2024

The study analysed the price relationship between crude oil, selected grains and oilseeds in the short-run, with the findings shown in table 7. Firstly, crude oil was analysed as a dependent variable with wheat, soybean and maize being the independent, to check their short-term impact on crude oil. The results indicated no short run impact of grains and oilseeds on crude oil. The absence of the cointegration is expected because crude oil markets are influenced by large producers such as the Organization of the Petroleum Exporting Countries (OPEC) (Breitenfellner et al., 2009; Olimb and Odegård, 2010), which South Africa is not forming part. Secondly, the analysis was on the impact of crude oil prices on the grains and oilseeds. The results revealed no statically significant effect of crude oil in the short term, that is, the prices in crude oil do not immediately influence prices of maize, soybean and wheat at 5% significance level. The study fails to accept the hypothesis that there is a short run relationship between crude oil and maize prices.

Additionally, the analysis revealed a significant and asymmetric linkage between soybean and wheat prices, with soybean prices exerting a substantial influence on ‘the prices of wheat, as proven 0.713 coefficient and 0.002 p-value. In contrast, the influence of wheat prices on soybean prices is relatively small, with a coefficient of 0.0448, despite being statistically significant with the same p-value. This shows that fluctuations in soybean prices are likely to cause notable changes in wheat prices, while the reverse effect is considerably weaker. This emphasizes the importance of closely monitoring soybean markets and consider price support measures to indirectly stabilize prices of wheat. Furthermore, strengthening the supply chain of soybean and encouraging crop diversification could reduce the impact of soybean fluctuations on wheat. The same is observed with prices of maize and soybean, where maize is showed to exert a substantial influence on the soybean prices. This shows the interconnectedness of these grains and oilseeds.

With the result indicating no short-term linkage, these results align with Meyer et al. (2018), Zhang et al. (2009), and Arshad and Hameed (2009) findings. Meyer et al. (2018) found no evidence of an asymmetric relationship between oil prices and food prices in the short run, suggesting that neither oil price increases nor decreases significantly impact food prices in the short term. Similarly, Zhang et al. (2009) observed an absent relationship between oil prices and global food prices in the short run. Arshad and Hameed (2009) further corroborated this notion, reporting a lack of short-run association between oil prices and cereal prices in Thailand and the United States. Although, Meyer et al. (2018), Zhang et al. (2009) their focus is on food prices, which differs from the commodity prices in this study, it is important to remember that food prices reflect the grains and oilseed prices. However, the findings of this study are in contrast with what is usually said that oil prices are a major driver of agricultural commodity prices. The study by Wang et al. (2015) used the same method to test the short-run relationship and the results contrasted with the ones found in this study. Wang et al. (2015) discovered, using the ARDL model, that rice prices in China and crude oil have a short-term relationship. The difference in the results could be due to difference in commodities. Even though rice is also a grain, it is possible that the changes in prices could be different from those of wheat, and it is possible that the connection between prices of crude oil and rice could be different from other grain prices. Additionally, differences between countries can significantly affect the results of studies investigating the interaction of crude oil prices and grain prices. Countries have distinct trade policies, production structures, and reliance on imported grains.

The absence of a significant short-term relationship of crude oil and the selected grains and oilseeds prices in South Africa suggests that other factors are likely playing a more prominent role in driving up grains and oilseed prices. These factors could be domestic in nature, such as production costs, government policies, or inefficiencies in storage and transportation (Grain SA, 2018; Sihlobo, 2022). Alternatively, global influences like international grain and oilseed prices, trade policies, weather patterns in major producing regions, and broader economic trends could be at play.

The policy implications of these results where crude oil price fluctuations are not directly impacting grain and oilseed prices in the short term are that policymakers should focus their efforts on addressing alternative factors to ensure food security and mitigate rising grain and oilseed prices in South Africa. Investing in domestic production is crucial, and this could involve subsidizing essential inputs like fertilizers, supporting research into drought-resistant crops, and upgrading storage and transportation infrastructure.

5.7. Granger Causality

To delve deeper into the potential causal link between crude oil prices and the selected grains and oilseeds, a Granger causality test was employed. This statistical technique assesses whether the past values of one variable can statistically improve the prediction of the current value of another variable compared to a model that only uses its own past values. The results of the Granger causality test, summarized in Table 8.

Table 8: Granger Causality Test Results

Null Hypothesis	**Observations**	**F-statistics**	**Probability**
SbPP does not Granger cause CoP	56	1.235	0.309

CoP does not Granger cause SbPP	56	0.831	0.512
MzPP does not Granger cause CoP	56	0.915	0.463
CoP does not Granger cause MzPP	56	0.343	0.831
WtPP does not Granger cause CoP	56	0.760	0.557
CoP does not Granger cause WtPP	56	2.117	0.094
SbPP does not granger cause MzPP	56	3.254	0.0195
MzPP does not Granger cause SbPP	56	0.369	0.830
WtPP does not Granger cause MzPP	56	8.183	4.E-05
MzPP does not Granger cause WtPP	56	1.192	0.327
WtPP does not Granger cause SbPP	56	0.955	0.441
SbPP does not granger cause WtPP	56	0.380	0.822

Source: Author computation, 2024.

According to the results in Table 8, it was found that prices of crude oil does not granger cause prices of the selected grains and oilseeds in South Africa. This is shown by the p-values being greater than 0.05, thus it is necessary to conclude that the null hypothesis which is there is no causal relation between prices of crude oil and selected grains and oilseeds in South Africa from 2018 to 2022 is accepted. There is no statistically significant evidence to suggest that past values of crude oil prices can be used to predict future values of soybean, maize, and wheat, and so does the prices of soybean, wheat, and maize to crude oil prices. In other words, prices of these commodities appear to be independent of each other.

Several implications arise from this observation. Firstly, it challenges the often-assumed positive connection between energy and food prices. Traditionally, rising oil prices are thought to increase production costs for agricultural goods (e.g., fertilizers, transportation), leading to higher food prices. However, in the South African context, these price linkages seem weaker, suggesting that other factors might be driving fluctuations in grain and oilseed prices. These could include domestic production costs, global supply chain disruptions, or regional weather patterns. Secondly, the lack of Granger causality between crude oil and selected grains and oilseeds presents opportunities for targeted policy interventions. If oil price fluctuations are not primary driving the grains and oilseeds price movements, policymakers can focus on other areas to ensure food security and price stability. This could involve promoting domestic production efficiency, diversifying input sources (e.g., fertilizers), or improving storage and transportation infrastructure to minimize disruptions.

The research also explored Granger causality between the chosen grains and oilseeds themselves. The results indicate that the past price movements in Soybeans (SbPP) were found to Granger cause future price changes in Maize (MzPP) (p-value = 0.0195). This suggests a potential influence of Soybean prices on Maize pricing strategies within the South African agricultural market. Additionally, Wheat (WtPP) price movements were shown to Granger cause future Maize prices (p-value = 4.E-05). This indicates that fluctuations in Wheat prices might also influence pricing decisions for Maize. However, no significant causal relationships were detected in the other directions (Wheat-Soybean, Maize-Soybean, Maize-Wheat). These findings highlight potential market dynamics within South African agriculture. The observed causal relationships between Wheat, Soybeans, and Maize suggest some level of interdependence between these commodities. Price movements in one grains and oilseed could influence planting decisions or substitution strategies for others, impacting their future prices. Understanding these internal market dynamics can inform policy decisions. The Granger causality between Wheat, Soybeans, and Maize prices suggests that monitoring all three commodities could be beneficial for anticipating price fluctuations in the South African market. By implementing measures to stabilize the prices of any one of these grains/oilseeds, policymakers might indirectly influence the stability of the others. This could involve strategies such as import quotas, production subsidies, or improved storage facilities for Wheat, Soybeans, and Maize. Additionally, policies promoting crop diversification among these grains/oilseeds could help mitigate risk and reduce price shocks in the market.

The conclusions of the current study, contradict the findings of Vo et al. (2019), Papież (2014), and Gokmenoglu et al. (2020), who discovered a causal relation of agricultural commodity prices and crude oil prices. Vo et al. (2019) found that crude oil prices play a major role in explaining fluctuations in the prices of these commodities in the United States, Gokmenoglu et al. (2020) found that oil prices drive agricultural commodity prices and in return the agricultural commodity prices drive oil prices in Nigeria and Papież (2014) found evidence of mutual Granger causality of corn and crude oil prices in the United States, implying that changes in one price can influence the other.

The difference in the results could be due to a number of possible reasons. The difference in time periods can be a reason as to why the result in this study are different from that of other studies. This study examined the period from 2018 to 2022, while Vo et al. (2019) examined the period from 2000 to 2018 monthly, Gokmenoglu et al. (2020) examined the period from 2006 to 2015 monthly, while Papież (2014) focused on weekly data from 2007 to 2014. It is possible that the price connection of crude oil and commodity has changed over time. The difference in the data set can be another reason for the difference in results. This study used monthly data for South Africa for the three grains and oilseeds (soybean, maize, and wheat), while Vo et al. (2019) used monthly data for 15 commodities which includes the selected grains and oilseeds of this study, and Gokmenoglu et al. (2020) used monthly data for six agricultural commodity prices, which includes only wheat and soybean from this study. Papież (2014) study analysed weekly data, focusing on corn prices, and ethanol. It is also possible that the relationship between crude oil prices and agricultural commodities is different for different commodities and different countries. Since these countries use different currencies from South Africa, it can also have an effect on the outcomes.

The findings of this study are corresponding with those of Fowewe (2016) who also conducted the study in South Africa, which revealed no causality relation of agricultural commodity prices and oil prices. The study employ data from South Africa and concluded no existence of causal linkage between crude oil prices and the chosen commodity prices. Although Fowewe (2016) analysed weekly data from January 2003 to January 2014, which is a longer period than this study, the results still align. This alignment strengthens the argument that the influence of crude oil prices on South African agricultural commodities might be negligible.

It is important to acknowledge that other thesis, such as Gokmenoglu et al. (2020), Vo et al. (2019), and Papież (2014), have identified causal relation between crude oil and agricultural commodities in different regions. This highlights the potential for regional variations in this relationship. By comparing these studies, the importance of considering regional and temporal factors when analysing the interaction between agricultural commodity and crude oil prices is appreciated. Future research that incorporates a broader range of commodities and employs a comparative approach across different regions can offer a more comprehensive understanding of this complex relationship.

5.8. Diagnostic test

Following Norat (2005), diagnostic tests were used to evaluate model adequacy and detect any misspecification. These tests, which includes the heteroskedasticity test, serial test, and stability test, assess the robustness of the predicted coefficients and guarantee that the model is complies to its underlying assumptions (Shrestha and Bhatta, 2018). A well-specified model should pass all of the diagnostic tests in this section.

5.8.1. Heteroskedasticity Test

One of the fundamental assumptions of linear regression analysis is the homoscedasticity, which means that the variance of error components (residuals) remains equal across all data (Gogoi, 2014). Violation of this assumption, known as heteroskedasticity, can result in inefficient estimates and incorrect standard errors. To validate the validity of the regression results, the Breusch-Pagan-Godfrey test as recommended by Gogoi (2014) was used to assess the presence of heteroskedasticity. The findings are summarized in Table 9.

Table 9: Heteroskedasticity Test

Dependent Variable	Null Hypothesis	Statistic	p-value	Decision
CoP	No heteroskedasticity	F-statistic	0.7351	Accept
		Chi-square	0.9207	
MzPP		F-Statistic	0.578	Accept

	No heteroskedasticity	Chi-square	0.513	
WtPP	No heteroskedasticity	F-Statistic	0.213	Accept
		Chi-square	0.224	
SbPP	No heteroskedasticity	F-Statistic	0.933	Accept
		Chi-square	0.881	

Source: Author's computation, 2024.

Table 9 conveys the findings of heteroskedasticity test. Based on the high p-valued for both F-statistics and chi-square tests of all variables as dependent variables, the study fails to reject the null hypothesis of no heteroskedasticity. There is no evidence of heteroskedasticity in the data, implying that the variance of residuals is likely constant across all levels of the independent variables.

5.8.2. Serial Correlation Test

The Breusch-Godfrey Serial Correlation LM test was used to determine the presence of serial correlation in the residuals of the model. This violation, also known as autocorrelation, occurs when errors at one period are dependent on errors at previous time periods, which can result in inefficient estimates. Table 9 displays the test results.

Table 10: Serial Correlation test

Dependent variable	Null-Hypothesis	Statistic	P-value	Decision
CoP	No serial correlation	F-Statistic	0.9507	Accept
		Obs*R-square	0.8807	
MzPP	No serial correlation	F-Statistic	0.447	Accept
		Obs*R-square	0.274	
WtPP	No serial correlation	F-Statistic	0.343	Accept
		Obs*R-square	0.183	
SbPP		F-Statistic	0.259	Accept

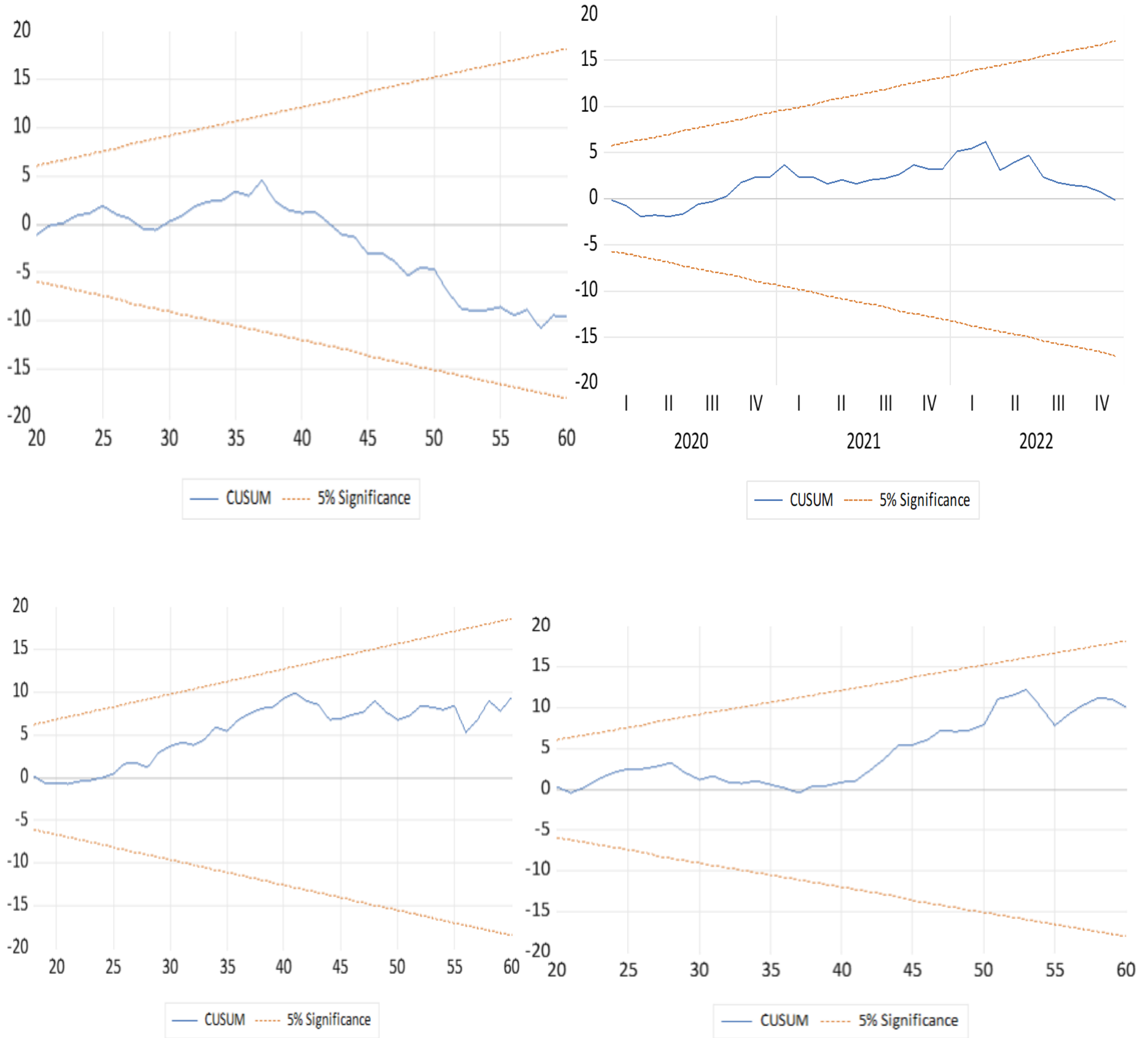
	No serial correlation	Obs*R-square	0.118	

Source: Computation by author, 2024

The Breusch-Godfrey Serial Correlation LM test findings in table 10 show that there is no statistically significant serial correlation in the model's residuals. This is demonstrated by high p-valued in the F-statistic and Obs*R-square, which exceed the generally used 5% significance level.

5.8.3. Stability Test

The results of the stability test are displayed in Figure 11.



Top: Soybean, Crude Oil

Bottom: Maize, Wheat

Figure 11. CUSUM Test of Stability Test

Figure 11 of the Stability test shows a model that is stable for all the variables as dependent variables. The CUSUM line is entirely within the critical bounds, indicating no statistically significant deviation from the null hypothesis of parameter stability throughout the estimation period. This suggest that the coefficients of the model remain consistent overtime, lending evidence to the reliability of the estimated relationships and validity of using the models for future analysis and forecasting.

5.9. Chapter summary

In this chapter, the findings of the econometric study were presented and discussed, compared to the findings of other studies. The chapter has achieved the objectives of the study where the results on the short run and long run relationship, causality relationship were demonstrated in the tables. Furthermore, in the first part of the chapter, the descriptive analysis of the variables was provided and discussed in detail. In addition, a diagnostic test was conducted to check model adequacy and detect any misspecification. More information about the data and the analysis tables are provided in the appendix.

CHAPTER 6: SUMMARY, CONCLUSION, AND RECOMMENDATIONS

6.1. Introduction

This section condenses key findings of the thesis that analysed the interaction between prices of crude oil and selected grains and oilseeds in South Africa from 2018 to 2022. The chapter also provides conclusion based on the findings, offers recommendations, suggests areas for future researchers, and outlines the limitations of the study.

6.2. Summary

The study analysed the interaction between the prices of crude oil and selected grains and oilseeds in South Africa from 2018 to 2022. Furthermore, it gave an overview of the crude oil, soybean, maize and wheat industry in detail.

The aim was to investigate the long-term and short-term linkages of crude oil prices with selected grains and oilseeds in South Africa, specifically maize, soybean and wheat. This was the first objective of the thesis. To achieve this objective, the Autoregressive Distributed Lag (ARDL) model was employed. The analysis began with bounds cointegration test to determine the presence of long-term cointegration between the variables, which is essential for further analysis of long-term estimates. The findings revealed a long run cointegration where soybean and maize acted as dependent variables, while no long run cointegration was found for wheat as the dependent variable. In the long-run estimations, it was discovered that crude oil prices negatively influence soybean prices, whereas there was a positive relationship between maize prices and crude oil prices, but this linkage does not extend to all grains and oilseeds, as evidenced by the lack of influence on wheat prices. Further analysis of the short-term dynamics indicated no significant interaction between crude oil, selected grains and oilseed prices. This finding aligns with the results of Zafeiriou et al. (2018), who suggested that the interaction between energy and agricultural markets evolve over the long-term rather than short-term.

To ensure the accuracy of the results, the Augmented Dickey-Fuller test was employed to check the stationarity of the time series data, since it can be a problem and can give misleading results. From the test results, it was indicated that crude oil, soybean, maize and wheat were non-stationary at level, meaning there is a unit root. After the 1st differencing, all the variables became stationary. VAR was used for the lag order selection to assist in accurately capturing the dynamic relationship between the variables and avoid misleading conclusions. Based on the results, the lag length four was selected

The study also addressed the second objective, which was to analyse the causality price relation between crude oil, and selected grains and oilseeds in South Africa. The analytical tool that was used to analyse the causality was the Granger Causality Test. The study followed the procedure and explanation that was used by Ajmi et al. (2013), and results indicated that, the previous occurrence of crude oil prices does not lead to the forecast of soybean, maize, and wheat prices, therefore there was no granger causality connection in prices of crude oil and selected grains and oilseed in South Africa from 2018 to 2022. In addition, the research found that past price movements in soybeans and wheat have a granger causality, affecting future price changes in maize. This suggests that soybean prices may influence maize pricing strategies in the South African agricultural market. Wheat prices also influence maize prices. The findings suggest that understanding these internal market dynamics can inform policy decisions, suggesting monitoring all three commodities to anticipate price fluctuations and implement measures to stabilize prices.

Furthermore, the study conducted a diagnostic test, to assess if a model is well-specified. To conclude on whether the model was well-specified, Heteroskedasticity test, Serial Correlation and Stability test were utilised, and it was concluded that at 5% significance level, the model is well-specified.

6.3. Conclusion

This study examined the potential short-term and long-term connection of crude oil prices and the prices of soybeans, maize, and wheat in South Africa from 2018 to 2022. The investigation was motivated by concerns regarding rising grain and oilseed prices, with some attributing this increase to higher prices of crude oil. However, the findings of this research suggest a mixed influence of crude oil on these agricultural commodities.

The study had two hypotheses, and both were tested. The first hypothesis stated that the selected grains and oilseeds prices in South Africa and crude oil prices do not have a short or long run relationship, and it was only accepted for the short run relationship. However, the study concludes that there is a noticeable a mixed long-term relationship between crude oil prices and selected grains and oilseeds prices in South Africa, whereby no cointegration was found in all the grains and oilseeds prices. The prices of maize and soybean in South Africa, as dependent variables, show a long term cointegration with prices of crude oil, whereas no such relationship exists for wheat price as a dependent variable. The second hypothesis stated that no causality relationship exists between prices of crude oil, selected grains, and oilseeds in South Africa. Thus, this hypothesis was accepted since the outcome from the granger causality test indicated no causality in the prices of crude oil, selected grains, and oilseeds from 2018 to 2022. Additionally, the study also analysed the granger causality interaction between the prices of grains and oilseed. The findings revealed a unidirectional causality between soybean and maize, and wheat with maize. That is, wheat and soybean prices cause the prices of maize, but maize prices do not granger cause wheat and soybean prices.

In conclusion, the research findings suggest the interaction between energy and South African agricultural markets is more pronounced over a long term, rather than the short-term. With no short-term relationship between crude oil prices and selected grains and oilseeds prices found, and also a granger causality interaction, this highlights the need for further investigation into alternative factors influencing these agricultural commodity prices.

6.4. Recommendations

Based on the findings of this study, which revealed a mixed long-term interaction, where long run cointegration was found with prices with soybean and maize prices as dependent variables, but no long run link for wheat prices as dependent variable was found, and no significant short-term, and Granger causality relationships, several recommendations can be made to mitigate the crude oil prices impact on the grain and oilseed industry sector in South Africa over the long run period. Research, investment, and promotion of alternative energy sources such as biofuels, wind, and solar, can reduce the agricultural sector's dependency on crude oil, making it less prone to the changes of crude oil. Encouraging local investors to invest in South African biodiesel manufacturers can be beneficial, reducing the agricultural sector’s dependency on crude oil by providing a stable renewable energy source. Not only will this help mitigate the impact of crude oil prices fluctuations on production cost of maize and soybean, but it supports sustainable agricultural practices and promotes economic growth within the country. Policymakers should consider implementing measures of price stabilization and provide financial support to the famers. Furthermore, improving infrastructure to reduce transportation and logistics costs, which heavily influenced on crude oil prices, can help the overall cost structure of agricultural production. Implementing these recommendations can create a more resilient agricultural sector capable of withstanding the impacts of crude oil prices, thereby contributing to a greater food security and economic stability in South Africa.

6.5. Limitations

It is crucial to acknowledge the study's limitations. The analysis focused on a specific timeframe (2018-2022) and might not capture the influence of crude oil prices during periods of significant price volatility. Additionally, the study only considered a limited set of variables. Further research that incorporates a broader range of variables, explores alternative timeframes, and utilizes more sophisticated econometric techniques might yield more nuanced insights. Despite the limitations, this study can also add to the literature that is already limited in South Africa by adding to knowledge and providing other researchers with different view of the relationship of prices of crude oil, selected grains, and oilseeds between 2018 and 2022.

6.6. Suggestions for further studies

In order to add to more literature in the energy industry, grains and oilseeds sector, future researchers investigate the outcome of the relationship between crude oil prices and grain and oilseeds prices on food security in South Africa or any other countries. Further research could explore alternative methodologies to strengthen the analysis. Additionally, investigating the role of other factors, such as global market trends, weather patterns, and government policies, on South African grain and oilseed prices could offer a more thorough with insight of market dynamics.

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Appendix

Null Hypothesis: COP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.812879	0.3708
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COP)
Method: Least Squares
Date: 05/27/23 Time: 23:56
Sample (adjusted): 2018M03 2022M12
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COP(-1)	-0.080985	0.044672	-1.812879	0.0753
D(COP(-1))	0.331907	0.130421	2.544882	0.0138
C	5.756642	3.217184	1.789342	0.0791

R-squared	0.130420	Mean dependent var	0.266897
Adjusted R-squared	0.098799	S.D. dependent var	7.230555
S.E. of regression	6.864084	Akaike info criterion	6.740821
Sum squared resid	2591.360	Schwarz criterion	6.847395
Log likelihood	-192.4838	Hannan-Quinn criter.	6.782334
F-statistic	4.124449	Durbin-Watson stat	1.855662
Prob(F-statistic)	0.021430		

Null Hypothesis: D(COP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.486653	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COP,2)
Method: Least Squares
Date: 05/27/23 Time: 23:51
Sample (adjusted): 2018M03 2022M12
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(COP(-1))	-0.715325	0.130375	-5.486653	0.0000
C	0.158524	0.920853	0.172149	0.8639

R-squared	0.349619	Mean dependent var	-0.113793
Adjusted R-squared	0.338005	S.D. dependent var	8.606871
S.E. of regression	7.002815	Akaike info criterion	6.764376
Sum squared resid	2746.207	Schwarz criterion	6.835425
Log likelihood	-194.1669	Hannan-Quinn criter.	6.792051
F-statistic	30.10336	Durbin-Watson stat	1.831863
Prob(F-statistic)	0.000001		

Null Hypothesis: SBPP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

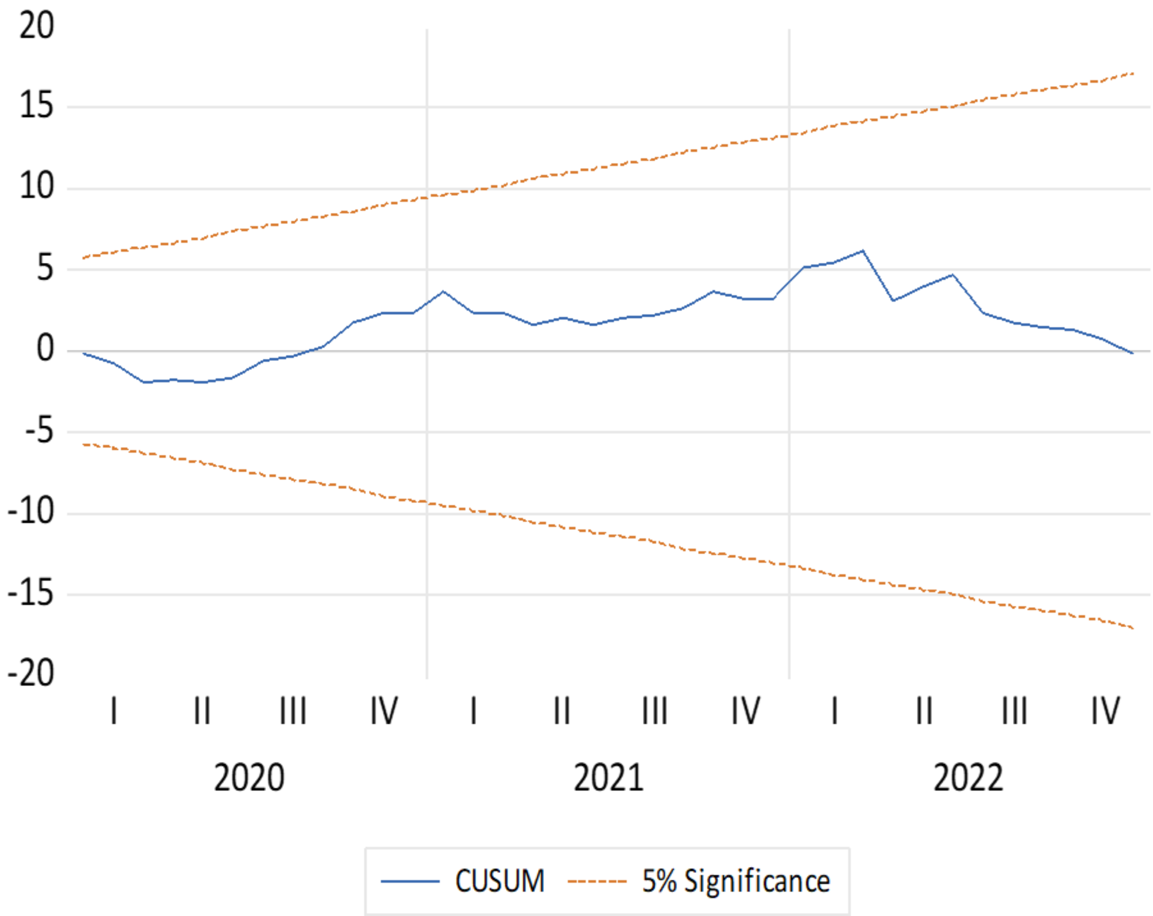
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.217485	0.9716
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SBPP)
Method: Least Squares
Date: 05/28/23 Time: 00:28
Sample (adjusted): 2018M02 2022M12
Included observations: 59 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SBPP(-1)	0.003993	0.018361	0.217485	0.8286
C	79.76097	140.1356	0.569170	0.5715

R-squared	0.000829	Mean dependent var	108.9197
Adjusted R-squared	-0.016700	S.D. dependent var	310.6140
S.E. of regression	313.1969	Akaike info criterion	14.36485
Sum squared resid	5591262.	Schwarz criterion	14.43528
Log likelihood	-421.7631	Hannan-Quinn criter.	14.39234
F-statistic	0.047300	Durbin-Watson stat	1.965316
Prob(F-statistic)	0.828607		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5% Significance

Null Hypothesis: D(SBPP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.320619	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SBPP,2)
Method: Least Squares
Date: 05/28/23 Time: 00:30
Sample (adjusted): 2018M03 2022M12
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SBPP(-1))	-0.987596	0.134906	-7.320619	0.0000
C	106.4608	44.27675	2.404441	0.0195

R-squared	0.489011	Mean dependent var	-6.701034
Adjusted R-squared	0.479886	S.D. dependent var	438.1433
S.E. of regression	315.9841	Akaike info criterion	14.38314
Sum squared resid	5591373.	Schwarz criterion	14.45418
Log likelihood	-415.1109	Hannan-Quinn criter.	14.41081
F-statistic	53.59146	Durbin-Watson stat	1.987521
Prob(F-statistic)	0.000000		

Null Hypothesis: MZPP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.400328	0.9019
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MZPP)
Method: Least Squares
Date: 05/28/23 Time: 00:37
Sample (adjusted): 2018M02 2022M12
Included observations: 59 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MZPP(-1)	-0.011771	0.029402	-0.400328	0.6904
C	94.66635	101.1083	0.936286	0.3531

R-squared	0.002804	Mean dependent var	56.47661
Adjusted R-squared	-0.014691	S.D. dependent var	255.4719
S.E. of regression	257.3416	Akaike info criterion	13.97200
Sum squared resid	3774809.	Schwarz criterion	14.04242
Log likelihood	-410.1739	Hannan-Quinn criter.	13.99949
F-statistic	0.160262	Durbin-Watson stat	1.861139
Prob(F-statistic)	0.690412		

Null Hypothesis: D(MZPP) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.661151	0.0000
Test critical values:	1% level	-3.550396	
	5% level	-2.913549	
	10% level	-2.594521	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MZPP,2)
Method: Least Squares
Date: 05/28/23 Time: 00:40
Sample (adjusted): 2018M04 2022M12
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(MZPP(-1))	-1.329670	0.199616	-6.661151	0.0000
D(MZPP(-1),2)	0.347706	0.141847	2.451273	0.0175
C	81.37280	36.12698	2.252411	0.0284

R-squared	0.520947	Mean dependent var	-8.847368
Adjusted R-squared	0.503204	S.D. dependent var	356.0014
S.E. of regression	250.9231	Akaike info criterion	13.93937
Sum squared resid	3399969.	Schwarz criterion	14.04689
Log likelihood	-394.2719	Hannan-Quinn criter.	13.98116
F-statistic	29.36122	Durbin-Watson stat	1.971842
Prob(F-statistic)	0.000000		

Null Hypothesis: WTPP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.652869	0.8501
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WTPP)
Method: Least Squares
Date: 05/28/23 Time: 00:44
Sample (adjusted): 2018M02 2022M12
Included observations: 59 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WTPP(-1)	-0.020678	0.031673	-0.652869	0.5165
C	160.4270	142.3933	1.126647	0.2646

R-squared	0.007422	Mean dependent var	73.64136
Adjusted R-squared	-0.009991	S.D. dependent var	390.1358
S.E. of regression	392.0799	Akaike info criterion	14.81412
Sum squared resid	8762420.	Schwarz criterion	14.88454
Log likelihood	-435.0165	Hannan-Quinn criter.	14.84161
F-statistic	0.426238	Durbin-Watson stat	1.653790
Prob(F-statistic)	0.516466		

Null Hypothesis: D(WTPP) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.628575	0.0000
Test critical values:	1% level	-3.552666	
	5% level	-2.914517	
	10% level	-2.595033	

*MacKinnon (1996) one-sided p-values.

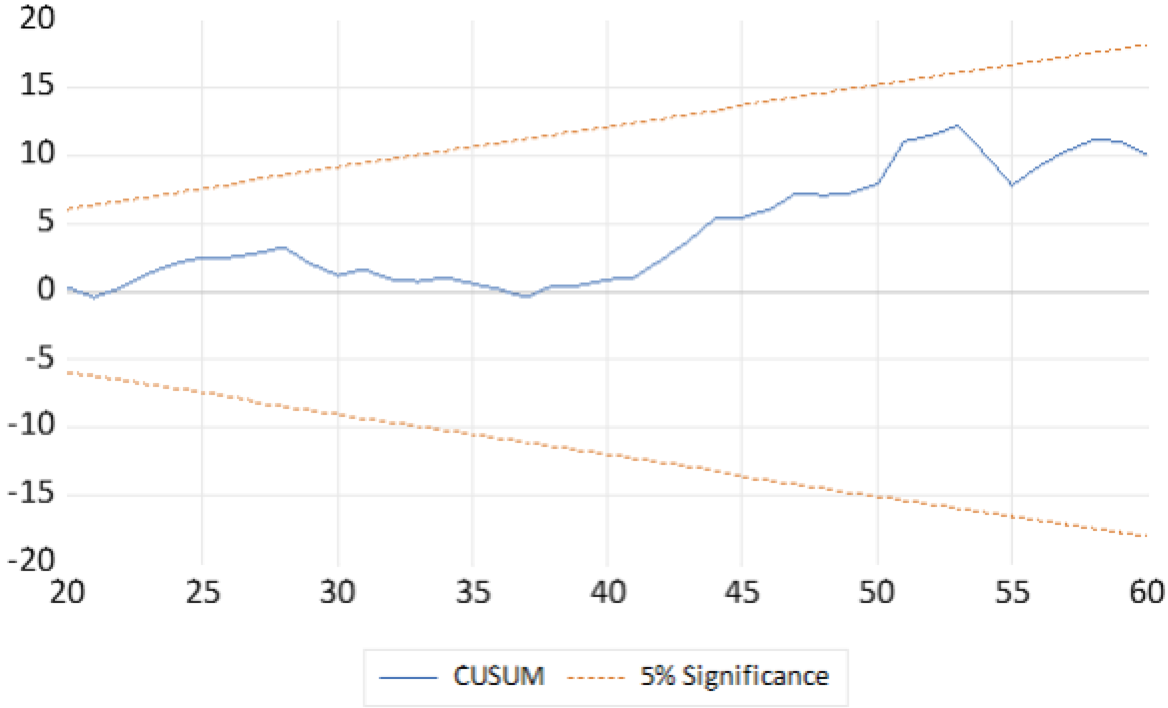
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WTPP,2)
Method: Least Squares
Date: 05/28/23 Time: 00:46
Sample (adjusted): 2018M05 2022M12
Included observations: 56 after adjustments

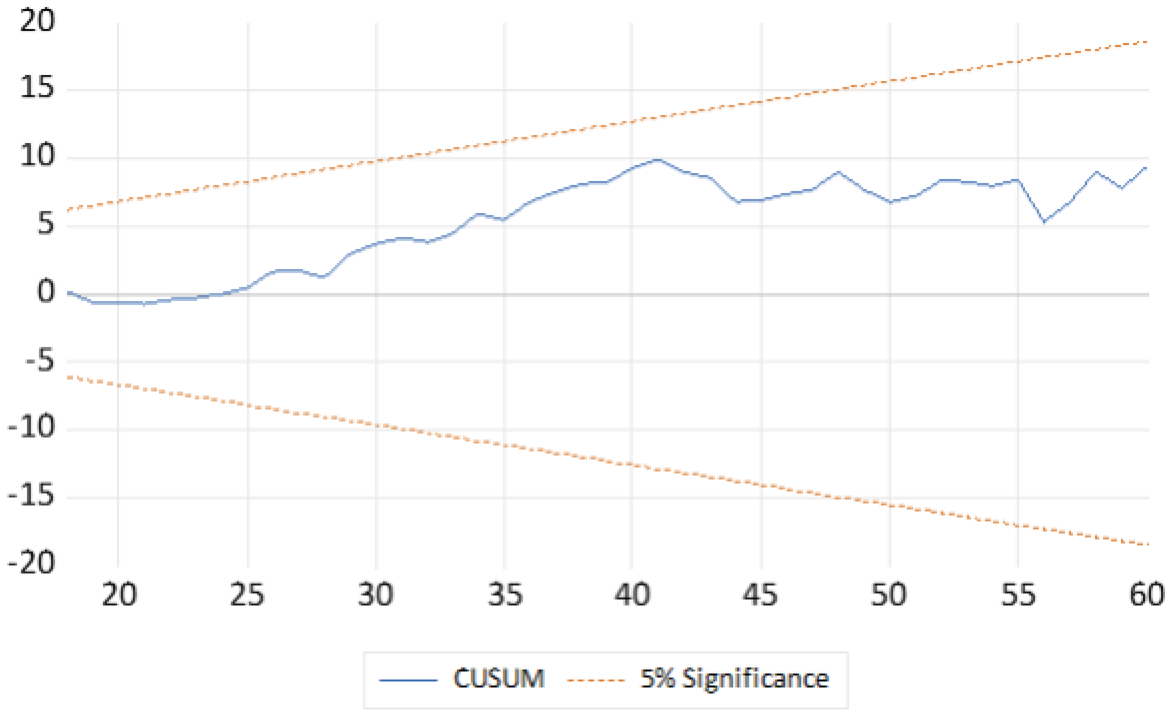
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(WTPP(-1))	-1.543585	0.232868	-6.628575	0.0000
D(WTPP(-1),2)	0.614518	0.177773	3.456756	0.0011
D(WTPP(-2),2)	0.375412	0.138088	2.718632	0.0089
C	124.3784	53.48456	2.325501	0.0240

R-squared	0.525439	Mean dependent var	-18.81036
Adjusted R-squared	0.498061	S.D. dependent var	516.1941
S.E. of regression	365.7115	Akaike info criterion	14.71032
Sum squared resid	6954737.	Schwarz criterion	14.85498
Log likelihood	-407.8888	Hannan-Quinn criter.	14.76640
F-statistic	19.19166	Durbin-Watson stat	1.961715
Prob(F-statistic)	0.000000		

Pairwise Granger Causality Tests
Date: 05/14/24 Time: 11:28
Sample: 2018M01 2022M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
MZPP does not Granger Cause COP	56	0.91455	0.4634
COP does not Granger Cause MZPP		0.34256	0.8478
SBPP does not Granger Cause COP	56	1.23505	0.3089
COP does not Granger Cause SBPP		0.83085	0.5124
WTPP does not Granger Cause COP	56	0.75950	0.5569
COP does not Granger Cause WTPP		2.11654	0.0936
SBPP does not Granger Cause MZPP	56	3.25432	0.0195
MZPP does not Granger Cause SBPP		0.36839	0.8299
WTPP does not Granger Cause MZPP	56	8.18280	4.E-05
MZPP does not Granger Cause WTPP		1.19158	0.3269
WTPP does not Granger Cause SBPP	56	0.95469	0.4411
SBPP does not Granger Cause WTPP		0.38042	0.8215





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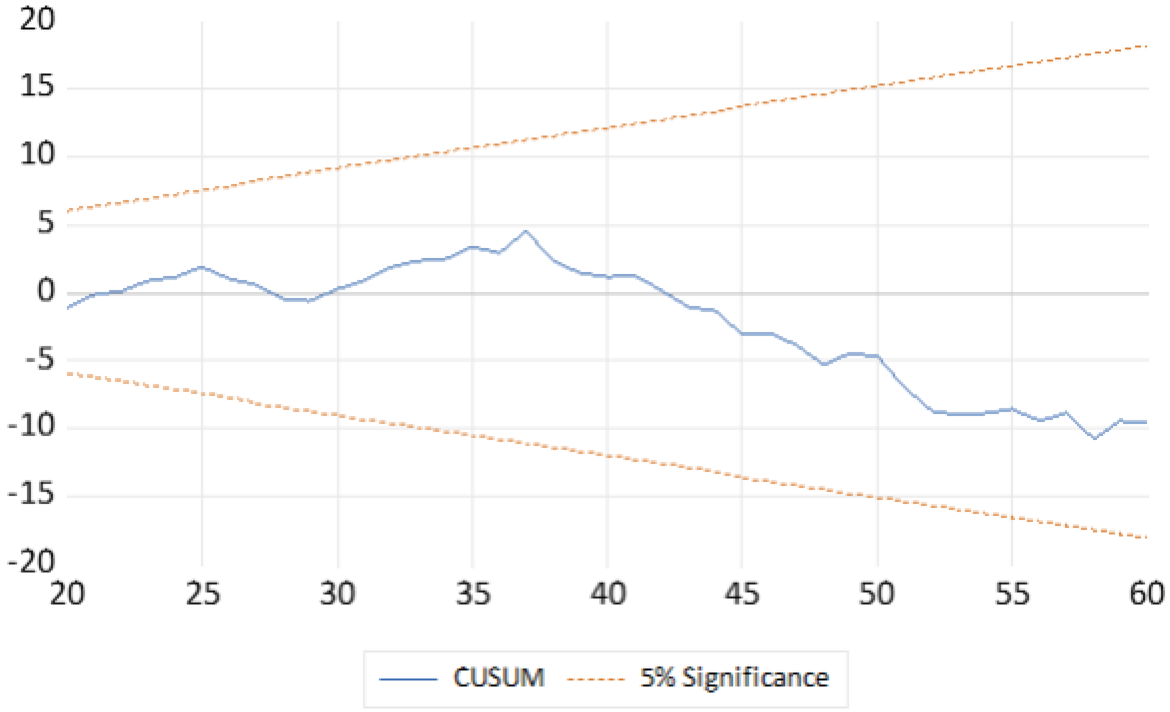

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Dependent Variable: COP
Method: ARDL
Date: 07/03/24 Time: 10:02
Sample (adjusted): 5 60
Included observations: 56 after adjustments
Dependent lags: 4 (Fixed)
Dynamic regressors (4 lags, fixed): MZPP SBPP WTPP
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
COP(-1)	1.281255	0.177608	7.213967	0.0000
COP(-2)	-0.734839	0.313736	-2.342222	0.0248
COP(-3)	0.451229	0.337295	1.337786	0.1894
COP(-4)	-0.086785	0.218806	-0.396631	0.6940
MZPP	0.000296	0.008282	0.035688	0.9717
MZPP(-1)	0.004538	0.008943	0.507385	0.6150
MZPP(-2)	-0.006114	0.008599	-0.710983	0.4817
MZPP(-3)	0.002779	0.010569	0.262919	0.7941
MZPP(-4)	-0.004342	0.008669	-0.500856	0.6195
SBPP	-0.005533	0.006332	-0.873908	0.3880
SBPP(-1)	0.008362	0.006746	1.239565	0.2232
SBPP(-2)	0.001472	0.006140	0.239694	0.8119
SBPP(-3)	-0.002506	0.006022	-0.416140	0.6798
SBPP(-4)	0.000185	0.004389	0.042143	0.9666
WTPP	0.008740	0.004857	1.799506	0.0803
WTPP(-1)	-0.010298	0.007271	-1.416399	0.1653
WTPP(-2)	0.005189	0.006825	0.760233	0.4521
WTPP(-3)	-0.000394	0.006802	-0.057862	0.9542
WTPP(-4)	-0.003784	0.005257	-0.719732	0.4763
C	1.439323	8.166809	0.176241	0.8611

R-squared	0.921838	Mean dependent var	69.63500
Adjusted R-squared	0.880585	S.D. dependent var	21.18795
S.E. of regression	7.321798	Akaike info criterion	7.092042
Sum squared resid	1929.914	Schwarz criterion	7.815382
Log likelihood	-178.5772	Hannan-Quinn criter.	7.372479
F-statistic	22.34631	Durbin-Watson stat	2.015810
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

ARDL Long Run Form and Bounds Test
Dependent Variable: D(COP)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 07/03/24 Time: 10:07
Sample: 1 60
Included observations: 56

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.439323	8.166809	0.176241	0.8611
COP(-1)*	-0.089140	0.115710	-0.770369	0.4461
MZPP(-1)	-0.002843	0.009523	-0.298598	0.7670
SBPP(-1)	0.001980	0.004699	0.421374	0.6760
WTPP(-1)	-0.000548	0.003961	-0.138257	0.8908
D(COP(-1))	0.370395	0.195667	1.892990	0.0664
D(COP(-2))	-0.364444	0.195280	-1.866262	0.0702
D(COP(-3))	0.086785	0.218806	0.396631	0.6940
D(MZPP)	0.000296	0.008282	0.035688	0.9717
D(MZPP(-1))	0.007677	0.008429	0.910783	0.3685
D(MZPP(-2))	0.001563	0.008226	0.190026	0.8504
D(MZPP(-3))	0.004342	0.008669	0.500856	0.6195
D(SBPP)	-0.005533	0.006332	-0.873908	0.3880
D(SBPP(-1))	0.000849	0.005361	0.158406	0.8750
D(SBPP(-2))	0.002321	0.005006	0.463639	0.6457
D(SBPP(-3))	-0.000185	0.004389	-0.042143	0.9666
D(WTPP)	0.008740	0.004857	1.799506	0.0803
D(WTPP(-1))	-0.001011	0.005135	-0.196912	0.8450
D(WTPP(-2))	0.004177	0.004171	1.001435	0.3233
D(WTPP(-3))	0.003784	0.005257	0.719732	0.4763

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MZPP	-0.031899	0.137336	-0.232272	0.8176
SBPP	0.022211	0.076765	0.289333	0.7740
WTPP	-0.006143	0.048314	-0.127147	0.8995
C	16.14682	75.00224	0.215285	0.8308

EC = COP - (-0.0319*MZPP + 0.0222*SBPP -0.0061*WTPP + 16.1468)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	1.045280	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	56		Finite Sample: n=60	
		10%	2.496	3.346
		5%	2.962	3.91
		1%	4.068	5.25
			Finite Sample: n=55	
		10%	2.508	3.356
		5%	2.982	3.942
		1%	4.118	5.2

Dependent Variable: WTPP
Method: ARDL
Date: 07/03/24 Time: 12:02
Sample (adjusted): 5 60
Included observations: 56 after adjustments
Dependent lags: 4 (Fixed)
Dynamic regressors (4 lags, fixed): MZPP SBPP COP
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
WTPP(-1)	1.183268	0.146323	8.086677	0.0000
WTPP(-2)	-0.507738	0.209705	-2.421208	0.0206
WTPP(-3)	-0.125630	0.222632	-0.564293	0.5761
WTPP(-4)	0.156630	0.172075	0.910246	0.3687
MZPP	0.157010	0.270989	0.579397	0.5659
MZPP(-1)	-0.653708	0.274170	-2.384312	0.0225
MZPP(-2)	0.174372	0.283146	0.615837	0.5419
MZPP(-3)	0.090791	0.347425	0.261325	0.7953
MZPP(-4)	0.291226	0.281800	1.033448	0.3083
SBPP	0.713295	0.173499	4.111232	0.0002
SBPP(-1)	-0.568329	0.205669	-2.763323	0.0090
SBPP(-2)	0.025472	0.201955	0.126129	0.9003
SBPP(-3)	0.082421	0.197942	0.416387	0.6796
SBPP(-4)	-0.099333	0.143329	-0.693046	0.4927
COP	9.442998	5.247550	1.799506	0.0803
COP(-1)	-21.55565	8.393316	-2.568192	0.0145
COP(-2)	37.52165	9.135237	4.107354	0.0002
COP(-3)	-36.10993	9.634142	-3.748121	0.0006
COP(-4)	16.39509	6.670015	2.458030	0.0189
C	-437.9296	258.4577	-1.694396	0.0988

R-squared	0.985555	Mean dependent var	4371.959
Adjusted R-squared	0.977932	S.D. dependent var	1620.109
S.E. of regression	240.6739	Akaike info criterion	14.07722
Sum squared resid	2085261.	Schwarz criterion	14.80056
Log likelihood	-374.1620	Hannan-Quinn criter.	14.35765
F-statistic	129.2768	Durbin-Watson stat	2.147948
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

ARDL Long Run Form and Bounds Test
Dependent Variable: D(WTPP)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 07/03/24 Time: 12:04
Sample: 1 60
Included observations: 56

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-437.9296	258.4577	-1.694396	0.0988
WTPP(-1)*	-0.293469	0.120688	-2.431629	0.0201
MZPP(-1)	0.059691	0.313252	0.190552	0.8499
SBPP(-1)	0.153525	0.152696	1.005428	0.3214
COP(-1)	5.694164	3.715434	1.532570	0.1341
D(WTPP(-1))	0.476738	0.149042	3.198682	0.0029
D(WTPP(-2))	-0.031001	0.138915	-0.223163	0.8247
D(WTPP(-3))	-0.156630	0.172075	-0.910246	0.3687
D(MZPP)	0.157010	0.270989	0.579397	0.5659
D(MZPP(-1))	-0.556388	0.264448	-2.103960	0.0424
D(MZPP(-2))	-0.382017	0.262919	-1.452982	0.1549
D(MZPP(-3))	-0.291226	0.281800	-1.033448	0.3083
D(SBPP)	0.713295	0.173499	4.111232	0.0002
D(SBPP(-1))	-0.008559	0.176263	-0.048561	0.9615
D(SBPP(-2))	0.016913	0.165016	0.102492	0.9189
D(SBPP(-3))	0.099333	0.143329	0.693046	0.4927
D(COP)	9.442998	5.247550	1.799506	0.0803
D(COP(-1))	-17.80682	6.056151	-2.940286	0.0057
D(COP(-2))	19.71483	5.864622	3.361655	0.0018
D(COP(-3))	-16.39509	6.670015	-2.458030	0.0189

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MZPP	0.203398	1.062870	0.191366	0.8493
SBPP	0.523138	0.480685	1.088319	0.2837
COP	19.40293	12.33577	1.572900	0.1245
C	-1492.250	795.8061	-1.875143	0.0689

EC = WTPP - (0.2034*MZPP + 0.5231*SBPP + 19.4029*COP - 1492.2502)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	2.167818	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	56		Finite Sample: n=60	
		10%	2.496	3.346
		5%	2.962	3.91
		1%	4.068	5.25
			Finite Sample: n=55	
		10%	2.508	3.356
		5%	2.982	3.942
		1%	4.118	5.2

Dependent Variable: SBPP
Method: ARDL
Date: 07/03/24 Time: 11:39
Sample (adjusted): 5 60
Included observations: 56 after adjustments
Dependent lags: 4 (Fixed)
Dynamic regressors (4 lags, fixed): MZPP WTPP COP
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
SBPP(-1)	0.709322	0.134984	5.254867	0.0000
SBPP(-2)	0.173440	0.157440	1.101624	0.2779
SBPP(-3)	-0.163465	0.154856	-1.055593	0.2982
SBPP(-4)	-0.037965	0.114159	-0.332557	0.7414
MZPP	0.697095	0.181786	3.834710	0.0005
MZPP(-1)	-0.200569	0.231387	-0.866812	0.3918
MZPP(-2)	0.182674	0.223490	0.817372	0.4191
MZPP(-3)	-0.370119	0.268581	-1.378053	0.1767
MZPP(-4)	0.109436	0.225863	0.484524	0.6309
WTPP	0.447921	0.108950	4.111232	0.0002
WTPP(-1)	-0.511893	0.174897	-2.926827	0.0059
WTPP(-2)	0.162489	0.177140	0.917292	0.3651
WTPP(-3)	0.417107	0.162995	2.559020	0.0148
WTPP(-4)	-0.300226	0.128522	-2.335992	0.0252
COP	-3.754338	4.296032	-0.873908	0.3880
COP(-1)	3.134193	7.215987	0.434340	0.6666
COP(-2)	-14.50455	8.433204	-1.719934	0.0940
COP(-3)	21.90990	8.227725	2.662936	0.0115
COP(-4)	-15.69741	5.077543	-3.091536	0.0038
C	662.4543	181.9426	3.641006	0.0008

R-squared	0.995358	Mean dependent var	7533.996
Adjusted R-squared	0.992908	S.D. dependent var	2264.673
S.E. of regression	190.7194	Akaike info criterion	13.61194
Sum squared resid	1309461.	Schwarz criterion	14.33528
Log likelihood	-361.1342	Hannan-Quinn criter.	13.89237
F-statistic	406.2652	Durbin-Watson stat	2.274177
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

ARDL Long Run Form and Bounds Test
Dependent Variable: D(SBPP)
Selected Model: ARDL(3, 0, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 07/03/24 Time: 11:55
Sample: 1 60
Included observations: 56

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	783.7845	142.1130	5.515222	0.0000
SBPP(-1)*	-0.408619	0.066285	-6.164580	0.0000
MZPP**	0.584877	0.123194	4.747623	0.0000
WTPP(-1)	0.246479	0.081793	3.013456	0.0044
COP(-1)	-10.67886	2.125205	-5.024858	0.0000
D(SBPP(-1))	0.093160	0.098254	0.948157	0.3486
D(SBPP(-2))	0.279949	0.098638	2.838151	0.0070
D(WTPP)	0.481539	0.084857	5.674736	0.0000
D(WTPP(-1))	-0.337087	0.101465	-3.322189	0.0019
D(WTPP(-2))	-0.083239	0.096867	-0.859311	0.3952
D(WTPP(-3))	0.240973	0.094867	2.540109	0.0150
D(COP)	-3.884228	4.125878	-0.941431	0.3520
D(COP(-1))	11.52181	4.454730	2.586422	0.0133
D(COP(-2))	-5.832439	4.693868	-1.242566	0.2211
D(COP(-3))	18.93797	4.298324	4.405897	0.0001

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MZPP	1.431348	0.225351	6.351633	0.0000
WTPP	0.603200	0.171951	3.507980	0.0011
COP	-26.13399	5.066877	-5.157810	0.0000
C	1918.128	241.1778	7.953170	0.0000

EC = SBPP - (1.4313*MZPP + 0.6032*WTPP -26.1340*COP + 1918.1284)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	8.992935	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	56		Finite Sample: n=60	
		10%	2.496	3.346
		5%	2.962	3.91
		1%	4.068	5.25
			Finite Sample: n=55	
		10%	2.508	3.356
		5%	2.982	3.942
		1%	4.118	5.2

Dependent Variable: MZPP
Method: ARDL
Date: 07/03/24 Time: 10:51
Sample (adjusted): 5 60
Included observations: 56 after adjustments
Dependent lags: 4 (Fixed)
Dynamic regressors (4 lags, fixed): SBPP WTPP COP
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
MZPP(-1)	0.686749	0.139711	4.915511	0.0000
MZPP(-2)	-0.388041	0.161801	-2.398263	0.0218
MZPP(-3)	0.519609	0.194479	2.671802	0.0113
MZPP(-4)	-0.466879	0.156808	-2.977385	0.0052
SBPP	0.416028	0.108490	3.834710	0.0005
SBPP(-1)	-0.276085	0.130758	-2.111412	0.0417
SBPP(-2)	-0.073519	0.123052	-0.597463	0.5539
SBPP(-3)	0.045345	0.121233	0.374032	0.7106
SBPP(-4)	0.136178	0.085361	1.595316	0.1194
WTPP	0.058842	0.101558	0.579397	0.5659
WTPP(-1)	-0.008111	0.150325	-0.053954	0.9573
WTPP(-2)	0.085810	0.137695	0.623190	0.5371
WTPP(-3)	-0.421442	0.117499	-3.586781	0.0010
WTPP(-4)	0.362398	0.087773	4.128829	0.0002
COP	0.119690	3.353771	0.035688	0.9717
COP(-1)	6.537679	5.481912	1.192591	0.2408
COP(-2)	-2.948789	6.759443	-0.436247	0.6653
COP(-3)	-3.556245	6.928749	-0.513259	0.6109
COP(-4)	5.165592	4.327833	1.193575	0.2405
C	-352.2626	153.5715	-2.293802	0.0277

R-squared	0.989364	Mean dependent var	3368.978
Adjusted R-squared	0.983751	S.D. dependent var	1155.822
S.E. of regression	147.3364	Akaike info criterion	13.09577
Sum squared resid	781488.8	Schwarz criterion	13.81911
Log likelihood	-346.6815	Hannan-Quinn criter.	13.37620
F-statistic	176.2490	Durbin-Watson stat	1.748972
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

ARDL Long Run Form and Bounds Test
Dependent Variable: D(MZPP)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 07/03/24 Time: 10:44
Sample: 1 60
Included observations: 56

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-352.2626	153.5715	-2.293802	0.0277
MZPP(-1)*	-0.648563	0.158517	-4.091433	0.0002
SBPP(-1)	0.247947	0.085298	2.906824	0.0062
WTPP(-1)	0.077498	0.078667	0.985144	0.3311
COP(-1)	5.317927	2.173807	2.446366	0.0194
D(MZPP(-1))	0.335311	0.162198	2.067301	0.0460
D(MZPP(-2))	-0.052730	0.165373	-0.318852	0.7517
D(MZPP(-3))	0.466879	0.156808	2.977385	0.0052
D(SBPP)	0.416028	0.108490	3.834710	0.0005
D(SBPP(-1))	-0.108004	0.106397	-1.015106	0.3168
D(SBPP(-2))	-0.181523	0.096399	-1.883038	0.0678
D(SBPP(-3))	-0.136178	0.085361	-1.595316	0.1194
D(WTPP)	0.058842	0.101558	0.579397	0.5659
D(WTPP(-1))	-0.026766	0.103301	-0.259112	0.7970
D(WTPP(-2))	0.059044	0.084529	0.698500	0.4894
D(WTPP(-3))	-0.362398	0.087773	-4.128829	0.0002
D(COP)	0.119690	3.353771	0.035688	0.9717
D(COP(-1))	1.339442	4.122670	0.324897	0.7471
D(COP(-2))	-1.609347	4.106571	-0.391896	0.6974
D(COP(-3))	-5.165592	4.327833	-1.193575	0.2405

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SBPP	0.382302	0.076576	4.992468	0.0000
WTPP	0.119492	0.124512	0.959681	0.3436
COP	8.199558	2.796927	2.931631	0.0058
C	-543.1435	199.5979	-2.721189	0.0100

EC = MZPP - (0.3823*SBPP + 0.1195*WTPP + 8.1996*COP - 543.1435)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	4.432884	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	56		Finite Sample: n=60	
		10%	2.496	3.346
		5%	2.962	3.91
		1%	4.068	5.25
			Finite Sample: n=55	
		10%	2.508	3.356
		5%	2.982	3.942
		1%	4.118	5.2

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.907522	Prob. F(19,36)	0.5781
Obs*R-squared	18.13581	Prob. Chi-Square(19)	0.5134
Scaled explained SS	8.392918	Prob. Chi-Square(19)	0.9823

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/05/24 Time: 07:23
Sample: 2018M05 2022M12
Included observations: 56

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	50742.17	22324.76	2.272910	0.0291
MZPP(-1)	40.12415	20.30979	1.975606	0.0559
MZPP(-2)	-33.29656	23.52106	-1.415606	0.1655
MZPP(-3)	35.92418	28.27146	1.270687	0.2120
MZPP(-4)	-22.00319	22.79531	-0.965251	0.3409
COP	-345.2845	487.5393	-0.708219	0.4834
COP(-1)	488.9258	796.9080	0.613528	0.5434
COP(-2)	-404.2580	982.6233	-0.411407	0.6832
COP(-3)	737.0312	1007.236	0.731737	0.4691
COP(-4)	-1161.410	629.1390	-1.846030	0.0731
SBPP	-20.60012	15.77124	-1.306183	0.1998
SBPP(-1)	-11.55507	19.00839	-0.607893	0.5471
SBPP(-2)	10.69685	17.88812	0.597987	0.5536
SBPP(-3)	0.633384	17.62370	0.035939	0.9715
SBPP(-4)	7.131107	12.40897	0.574673	0.5691
WTPP	12.75969	14.76354	0.864270	0.3932
WTPP(-1)	-12.57641	21.85287	-0.575504	0.5685
WTPP(-2)	3.341638	20.01682	0.166942	0.8684
WTPP(-3)	1.762950	17.08084	0.103212	0.9184
WTPP(-4)	6.065505	12.75955	0.475370	0.6374

R-squared	0.323854	Mean dependent var	13955.16
Adjusted R-squared	-0.033001	S.D. dependent var	21073.46
S.E. of regression	21418.36	Akaike info criterion	23.05434
Sum squared resid	1.65E+10	Schwarz criterion	23.77768
Log likelihood	-625.5215	Hannan-Quinn criter.	23.33478
F-statistic	0.907522	Durbin-Watson stat	2.041254
Prob(F-statistic)	0.578052		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.351811	Prob. F(19,36)	0.2129
Obs*R-squared	23.31752	Prob. Chi-Square(19)	0.2236
Scaled explained SS	5.613090	Prob. Chi-Square(19)	0.9987

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/05/24 Time: 07:27
Sample: 2018M05 2022M12
Included observations: 56

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7932.318	41124.40	0.192886	0.8481
WTPP(-1)	-31.75567	23.28216	-1.363949	0.1811
WTPP(-2)	-1.901920	33.36706	-0.057000	0.9549
WTPP(-3)	54.16499	35.42398	1.529048	0.1350
WTPP(-4)	-48.00924	27.37960	-1.753468	0.0880
SBPP	20.74769	27.60623	0.751558	0.4572
SBPP(-1)	10.49416	32.72491	0.320678	0.7503
SBPP(-2)	4.885890	32.13394	0.152048	0.8800
SBPP(-3)	-34.29674	31.49552	-1.088940	0.2834
SBPP(-4)	-8.011393	22.80571	-0.351289	0.7274
COP	990.6990	834.9620	1.186520	0.2432
COP(-1)	-419.3907	1335.499	-0.314033	0.7553
COP(-2)	791.7718	1453.550	0.544716	0.5893
COP(-3)	-1471.999	1532.933	-0.960250	0.3433
COP(-4)	758.2792	1061.297	0.714483	0.4795
MZPP	51.76882	43.11836	1.200621	0.2377
MZPP(-1)	-39.65974	43.62452	-0.909116	0.3693
MZPP(-2)	-15.51014	45.05259	-0.344267	0.7326
MZPP(-3)	5.052728	55.28037	0.091402	0.9277
MZPP(-4)	39.84539	44.83856	0.888641	0.3801

R-squared	0.416384	Mean dependent var	37236.81
Adjusted R-squared	0.108365	S.D. dependent var	40555.10
S.E. of regression	38294.74	Akaike info criterion	24.21647
Sum squared resid	5.28E+10	Schwarz criterion	24.93981
Log likelihood	-658.0610	Hannan-Quinn criter.	24.49690
F-statistic	1.351811	Durbin-Watson stat	2.010436
Prob(F-statistic)	0.212873		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.522929	Prob. F(19,36)	0.9329
Obs*R-squared	12.11252	Prob. Chi-Square(19)	0.8808
Scaled explained SS	7.646464	Prob. Chi-Square(19)	0.9899

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/05/24 Time: 07:32
Sample: 2018M05 2022M12
Included observations: 56

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	84160.95	43050.35	1.954942	0.0584
SBPP(-1)	-53.10642	31.93917	-1.662736	0.1050
SBPP(-2)	38.89471	37.25277	1.044076	0.3034
SBPP(-3)	7.606221	36.64130	0.207586	0.8367
SBPP(-4)	-18.23940	27.01180	-0.675238	0.5038
COP	537.3875	1016.505	0.528662	0.6003
COP(-1)	-145.6292	1707.410	-0.085292	0.9325
COP(-2)	-876.2469	1995.422	-0.439129	0.6632
COP(-3)	70.88684	1946.803	0.036412	0.9712
COP(-4)	-507.7810	1201.423	-0.422650	0.6751
MZPP	55.62644	43.01319	1.293242	0.2042
MZPP(-1)	-6.123963	54.74967	-0.111854	0.9116
MZPP(-2)	-24.89476	52.88111	-0.470769	0.6406
MZPP(-3)	21.71146	63.55031	0.341642	0.7346
MZPP(-4)	3.689755	53.44249	0.069042	0.9453
WTPP	-18.65250	25.77930	-0.723545	0.4740
WTPP(-1)	22.22139	41.38327	0.536966	0.5946
WTPP(-2)	-24.09044	41.91399	-0.574759	0.5690
WTPP(-3)	31.41943	38.56705	0.814670	0.4206
WTPP(-4)	-5.493964	30.41020	-0.180662	0.8576

R-squared	0.216295	Mean dependent var	23383.22
Adjusted R-squared	-0.197327	S.D. dependent var	41241.15
S.E. of regression	45127.07	Akaike info criterion	24.54481
Sum squared resid	7.33E+10	Schwarz criterion	25.26815
Log likelihood	-667.2545	Hannan-Quinn criter.	24.82524
F-statistic	0.522929	Durbin-Watson stat	2.488363
Prob(F-statistic)	0.932858		