TRADE DISRUPTION AND COMMODITY-PROGRAM PAYMENTS: A PANEL GARCH MODEL

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

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ABSTRACT

Trade disruption has reduced the economic gains countries enjoy from great trade relationships. This disruption stems from trade wars, exchange rate volatility, and rare events. However, the gravity model, mainly used to investigate this problem, is plagued with heteroscedasticity, omitted variables, and zero trade flow. This makes it difficult for farmers, policymakers, and investors to predict how the international market behaves. The study assesses how commodity-program payments help mitigate shocks from trade disruptions using a panel GARCH model. Hence, the study examines the source of trade disruption, the intensity of trade disruption on soybean and corn export, the risk associated with trade disruption, and how effectively existing farm payments have mitigated the risk. The results indicated that the price loss coverage effectively mitigates the risk of trade disruption for soybeans and corn.

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DEDICATION

I dedicate this work to my parents, siblings, my son Ezra Onell Owusu-Asante, and my dear wife, Sandra Hagan.

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LIST OF ABBREVIATIONS

PLC ………………………………………...Price Loss Coverage

SEM ………………………………………...Structural Equation Model

USDA……………………………………….United States Department of Agriculture

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CHAPTER ONE: INTRODUCTION

1.1. Background

The fundamental truth that great trade relationships among countries lead to economic gains has, in recent years, been muddied by trade disruption (Glick & Taylor, 2010). These disruptions stem from trade wars through tariffs, exchange rates, and rare events such as financial crises, war, pandemics, and policy uncertainty. An example is the trade war between the US and China following the increase in tariffs by the Trump Administration, which reduced the US' total agricultural export to China by 58% (Grant et al., 2019). Furthermore, Arita et al.(2021) reported that Covid-19 reduced US agriculture exports by 9% in the second quarter of 2019.

Investigating these disruptions, scholars have focused on creating a model to detect and prove the causes of trade disruption and its impact. The prominent model researchers use is the gravity model, which predicts trade flow among countries. Although true, the gravity model suffers from misspecification, heteroscedasticity, and miscued inference. (Westerlund & Wilhelmsson, 2011). Furthermore, the model does not account for latent variables causing trade disruption due to some observations with zero trade (Westerlund & Wilhelmsson, 2011). This makes it difficult for the model to holistically detect the cause of trade disruption. This has led to contradictory results using the same model (Glick & Taylor, 2010).

To correct these problems, Cheng and Tsai (2008) employed panel data, which allowed for the use of log-linear fixed effect least square. Also, Helpman et al. (2008) used the two-stage estimation selection, which is identical to the sample selection model, to reduce the zero trade observation. Although the result from these modified gravity models did not eliminate the errors, scholars (including Westerlund & Wilhelmsson, 2011 Sheng et al., 2014; Glick & Taylor, 2010.;

Goldstein,1989; Martin & Pham, 2020) used the gravity model in determining the impact of trade disruptions on trade.

To correct this issue, the study will develop a near holistic model, free from biasedness and econometric problems, and incorporate latent variables. This is because policymakers and agents in international trade need a model that will capture the source of trade disruption and calculate the intensity of the source in order to make the decision. The study will use a panel GARCH model to investigate the source of disruption to USA soybean and corn international trade.

1.1.1. Why Soybean and Corn?

Crop production in the US is an essential agricultural sector in the US economy subsector. This is because it accounted for a cash receipt of about $192 billion, most of which comes from corn and soybean production, accounting for 40% (46.7 billion and 36 billion dollars) in 2020 (USDA ERS, 2021). In addition, the USA was ranked the second-largest soybean producer, with a trade export of $25.7 billion in 2020 (U.S. Agricultural Exports, 2020). Although corn and soybean production enjoy all these statistics, their production is without risk and uncertainties, with the significant hit coming from trade disruptions (Adjemian et al., 2021a). Statistical trends from the USDA suggest that shocks emanating from trade impediments have reduced corn and soybean exports during the USA-China Trade War and the COVID-19 pandemic. This statistic is presented in Figure 1.1 and 1.2.

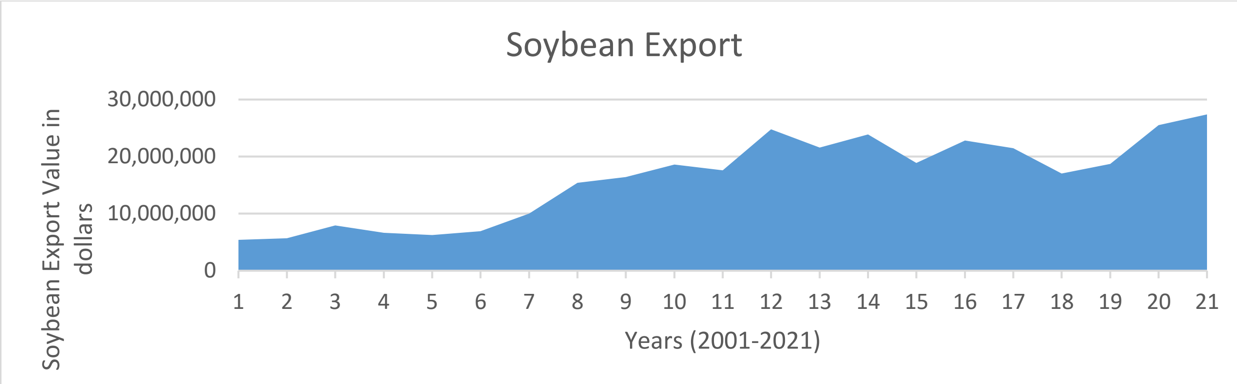

Figure 1.1: USA Soybean Export Trend

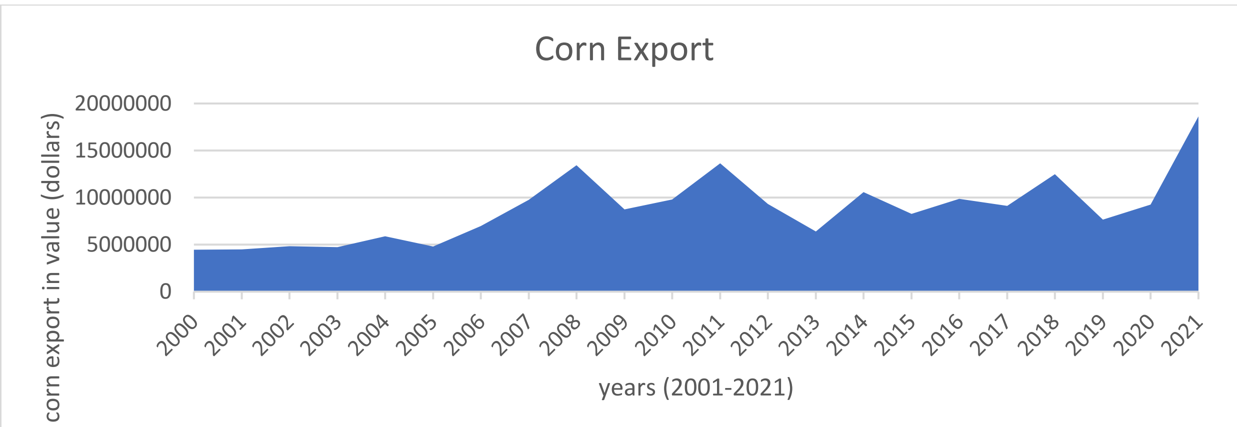

Figure 1.2: USA Corn Export Trend

Figures 1.1 and 1.2 show the USA corn and soybean export trends worldwide. As shown in figure 1a, soybean export experienced a 20.5% decrease in soybean export in 2017-2018. The 2018-2019 exports increased but did not equal the 2016-2017 exports. From the trends in Figure 1b, it is demonstrated that 2018-2019 and 2019-2020 realized a decrease in the export of corn compared to 2017-2018. In terms of percentages, corn exports recorded a 28.5% decrease in 2018-2019. Although the 2019-2020 exports increased, the increase was not as significant as the 2017-2018 corn exports. These trends are also consistent with the findings of Arita et al.(2021) and (Grant et al., 2019).

Figures 1.1 and 1.2 imply that soybean and corn exports decrease during rear events and trade wars. This will reduce the USA's cash receipt from exporting these commodities, affecting the agriculture sector's contribution to the country's GDP. This also suggests a need to know the intensity of these trade shocks on corn and soybean exports so that the government can formulate the appropriate farm policy and absorb this shock during disruptions and volatility.

Furthermore, previous research generally examines the impact of trade disruption on US exports with little consideration given to corn and soybean exports. This leaves a gap in investigating the reduction in soybean and corn exports and how it can be mitigated. This gap is what the study seeks to fill through the development of a holistic model that will help to detect the source and intensity of the cause of the disruption and how to mitigate it through existing farm policy.

1.2. Problem Statement

The shocks emanating from trade disruption hamper the free flow of goods and services across international borders (Grant et al., 2019). This has caused soybean and corn prices to fluctuate in the commodity futures market with significantly volatile prices (Turvey et al., 2022). This has made researchers concentrate more on the financial market volatility without giving credence to the source of the shock. Studies, which include Sanjuán-López and Dawson (2017), Hernandez et al. (2021), Zhu et al. (2021), and An et al. (2021), focused on contagion on the commodity futures price. The gap these studies leave is that they could not holistically investigate the cause of the contagion and the intensity each source has on the futures market price volatility.

Furthermore, shocks from trade disruption reduce diversification benefits and increase the risk management process producers face (Yip et al., 2020). This problem is because investors cannot predict future agriculture trade prices and costs. As a result, investors will prefer to invest in a stable future market (Mensi et al., 2017).

Also, agricultural trade disruptions adversely affect policymakers' ability to design an optimum policy for price stabilization (Hernandez et al., 2021). This is because policymakers find it difficult to make predictions about shocks. This implies that various models need to be more holistic to detect the source of the shocks and the risk these shocks have on farmers and assess the impact of how existing policies help to mitigate these shocks in the short and the long run.

Finally, methods used by researchers have made it difficult to investigate the sources of agricultural trade disruptions holistically, the effect it has on crop prices, the related risk on the farmers, and how existing policy is mitigating risk. This makes it difficult for farmers to adequately know the demand for their products. This creates a disincentive for the farmer to expand production and increase revenue.

These problems exist because finding the source of the trade disruption in the soybean and corn trade and creating a model that will help the farmers assess the impact of existing policies in mitigating the shocks has received little attention. Therefore, this study aims to create a model that will holistically unearth the source and intensity of the trade disruption in the soybean and corn trade and assess the risk it has on farmers and how existing federal policy (farm bill) mitigates these shocks.

1.3. Research Questions

The study will seek to answer the following research questions.

1. What are the effects of trade disruption on the US and global soybean and corn exports?
2. What are the intensities of these sources on the US and global soybean and corn export?

3. Does these trade disruption pose any long-lasting risk to Soybean and corn farmers' income?
4. Are farm policies (price loss coverage) sufficient in mitigating the shocks from trade disruptions?

1.4. Research Objectives

This study analyzes the mitigative effect of farm policies on risk associated with trade disruption on farm income.

1.4.1. The Specific Objectives is to:

1. Identify the effects of trade disruptors on soybean and corn exports.
2. Estimate the intensity of trade disruption on soybeans and corn exports.
3. Compute the risk of trade disruption on soybean and corn farmers' income.
4. Determine the mitigative effect of price loss coverage on risk associated with trade disruption.

1.5. Justification

Research on trade disruption in soybean and corn on the trade war and exchange rate volatility has generally been done at the national and international levels. This has left little information about how other sources disrupt the soybean and corn trade. There is a need to use a holistic model that also captures disruptions caused by latent variables.

Furthermore, though there is information about trade disruption at the national and international levels, the effects of trade disruption vary from state to state and by commodities. Therefore, it is essential to have this study because it will provide more information on the soybean and corn trade in the Midwest of the USA, including North Dakota. States like North

Dakota often suffer from port bias effects and are neglected in some key studies (Addey & Nganje, 2023).

Also, the existence of asymmetric information about the source and effect of trade shocks on soybean and corn has made it difficult for investors to understand the causality pattern of the concepts of trade disruption. This study will create a holistic model providing accurate information about the source, intensity, effect, and commodity-program payment that can mitigate shocks.

Finally, many researchers have used different models to detect trade disruption. Although their model revealed some shocks, it was plagued with econometric problems and biases. This study will use the structural equation model and a panel GARCH model to help capture the latent variables causing trade disruption. This model is superior to the other models because it uses large data and will help determine the appropriate econometric model, which will be free from the problems faced by the previous models used by researchers.

1.6. Research Contribution of the Study

The study will fill research gaps by providing information about trade disruption in the soybean and corn trade. Understanding the source, intensity, and risk from trade disruption, the soybean and corn trade at the national level will help farmers predict the price, expand production, and increase farm revenue. It will also help farmers' interest groups to negotiate better farm risk mitigation incentives for their members.

Also, the study will help investors understand the causality pattern of trade disruption on soybean and corn, which will help them make appropriate investment decisions to increase returns (e.g., logistics).

Furthermore, the study's model will help correct other models' econometric problems when analyzing the agriculture trade disruption.

1.7. Organization of the Other Chapters

The study's introductory chapter provides background information about the topic. This will serve as the background for the research and as a summary of the problem. This chapter addresses the study's research questions, objectives, and rationale for the study. Chapter two is a literature review that summarizes the work's primary themes. This includes an overview of the USA's corn and soybean exports, its agriculture policy, trade disruption, and how it is measured. This section delves into both empirical analyses of other research. Academic journals and published books were consulted for this purpose.

Chapter 3 addresses the theoretical framework, the work's empirical model, and the data collection and analysis approach. The penultimate chapter, Chapter 4, includes the results and accompanying discussion. Chapter 5 has a summary, conclusion, and suggestions of the study.

CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

This chapter introduces the literature review of the study. This chapter has been subdivided into seven sections. The first section talks about the overview of Trade Disruption. The second section talks about factors causing trade disruption. Methods of measuring trade disruption follows. The USA trade policies and Agriculture trade will then follow. The study will also review strategies used by the USA through The Farm Bill. The sixth section of this chapter discusses empirical analysis, while the final section concludes this chapter.

2.2. Trade Disruption

There is no single definition of trade disruption. In defining trade disruption, scholars define it in the contest with their choice of study. Eichengreen and Irwin (1995) and Irwin (1996) described trade disruptions as those policies that discourage the flow of trade internationally. They defined trade disruption based on the contest with which they analyzed trade. They realized that government trade policies sometimes attract unilateral retaliation from their trading partners, and these retaliations restrict trade.

Trade disruption was defined in a Congress report as a ban on imported goods from exporting countries (Langton, 2008). Their definition of trade disruption was in contest with the Avian flu pandemic and how to mitigate it.

Furthermore, Glick and Taylor (2010), when analyzing the effect of trade war, defined trade disruption as disturbances that hinder trade flow internationally. In the context of trade restriction, trade disruption is defined as a restriction imposed on exporting countries that prevents the exportation of specific goods and services and, in return, causes a trade war (Amiti et al., 2019). Adjemian et al. (2021) and Fajgelbaum & Khandelwal (2022) further simplified the definition of trade disruption as a trade war among countries that act as a barrier to the free flow of importing and exporting goods and services.

This study aims to have a holistic view of trade disruption. Due to this, the study defines trade disruption as factors that hinder the flow of goods and services from one country to the other. Defining trade disruption from this angle will help the study to conceptually assess and analyze all the significant factors (observed and latent) that affect international trade. Furthermore, this definition explains how the study's objectives will be examined.

2.3. Determinants of Trade Disruption

There are several factors causing trade disruption directly and indirectly. The study identified four main factors causing trade disruption in reviewing the literature. These factors are tariffs, war, exchange rate, and financial market contagion.

2.3.1. Tariffs

Most scholars have defined tariffs as taxes on imported goods (Gandolfo, 2014; Stiglitz & Rosengard, 2015). Tariffs have historically been used to control imports to protect the welfare of the citizens and producers, protect industries from unnecessary competition, and even generate revenue for the country. (Horwell, 1966; Johnson, 1953, 1969; Gardner & Kimbrough, 1992). As a result, scholars argue that determining the optimum use of tariffs will benefit the state (Johnson, 1953, 1969). Although this assertion from scholars is accurate and used by Waverman (1972), Neary (1998), Nunn and Trefler (2010), and Amiti (2019), there is an argument that tariffs have a repelling effect on production and prices of goods and services through tariff retaliation (Fajgelbaum & Khandelwal, 2022; Grant et al., 2019: Amiti, et al., 2019). A contemporary example was the reduction in the export of goods by the USA when the Trump administration imposed high tariffs on imported goods, which attracted retaliation from the exporting countries (Fajgelbaum & Khandelwal, 2022). It was estimated that exports reduced from $1.67 trillion to $1.65 trillion, equalling about a 1.192% decline in good exports alone (www.census.gov/foreign-trade). The effect is that revenue will decrease while unemployment increases (Grant et al., 2019).

2.3.2. Exchange Rate Volatility

Exchange rate volatility is the frequent increase or decrease in the exchange rate (McKenzie, 1999; Kandilov, 2008; Hatzenbuehler et al., 2016). Over time, exchange rate volatility has impacted trade through export and import prices (Eichengreen & Irwin, 1995; McKenzie, 1999; Cho et al., 2002). The argument is that a volatile exchange rate makes it difficult for the actors in international trade to decide how much to produce and the quantity of goods to be exported since it makes export prices very expensive and unpredictable (Kroner & Lastrapes, 1993). Furthermore, Bacchetta and Wincoop (2000) also asserted that exchange rate volatility negatively affects the cost of production. Apart from this, it also decreases demand for export since it makes it expensive (Kandilov, 2008: Greenaway et al., 2010). Although the effect of exchange rate volatility is unclear because it makes imports to the USA cheaper, one cannot undermine its impact on exporting goods (Campa & Goldberg, 2005).

2.3.3. Rare Event and Contagion

The study categorized rare events as international events that transmit shocks from one country to another and hinder trade flow (Hernandez & Valdes, 2001). The study uses rear events and financial contagion because of the study's definition of the rear event. This is because these events have an immediate severe effect on international trade, and it takes longer for trade to come to normalcy even after the event has been taken care of (Glick & Taylor, 2010). Typical events are the financial crises of 2007-2009, the covid-19 pandemic, and the Russian-Ukraine war. The effects of these trade disrupters are either direct or indirect (Anderton & Carter, 2001; McKibbin & Stoeckel, 2009; Glick & Taylor; Grant et al., 2019).

2.3.3.1. Financial Crisis

McKibbin and Stoeckel (2009) identified that financial crisis affects the trade of goods and services from one country to the other. Financial crises force countries to ban exporting goods and services to keep domestic prices low and stable (Dorsey et al., 2011). The reason for Dorsey et al. (2011) assertion is that domestic companies cannot compete. Furthermore, financial crises lead to a demand shortage. The reason is that exporters cannot access bank loans to pay for goods in the international market (Aikins, 2009).

Evidence of the effect of the financial crisis on trade was seen in the USA agriculture export during the 2007-2009 financial crisis period, reducing from 83 billion dollars to 68 billion dollars, indicating a 17% decrease in exports as revealed by USDA ERS(2021). Furthermore, Grant et al. (2019) identified that during the financial crises in 2007-2009, agricultural trade was reduced by 20%.

2.3.3.2. Covid-19 Pandemic.

Several works of literature revealed the effect of covid-19 on international trade. Scholars including Grant et al. (2019), Mallory (2021), and Mena et al. (2022) in assessing the effect of covid-19 on international trade, realized that the pandemic did not just lead to a shortfall in exports but led to a shortage of goods which increase the prices of goods and services of goods and services. Furthermore, Mena et al. (2022) identified that pandemics also increased transaction costs, which hindered international trade. The shutting of borders by most countries also distorted the supply chain Mallory (2021). This was seen in the USA 2019 data when exports fell from 1.6 trillion to 1.4 trillion dollars (https://www.usitc.gov).

2.3.3.3. Wars

War always affects trade directly or indirectly. War reduces exports and makes the importation of goods costly (Rohner et al., 2013). The most economically depressing problem with war is that it takes many years for the economy to recover (Anderton & Carter, 2001; Glick & Taylor., 2010; Rohner et al., 2013). Furthermore, it increases production costs and reduces production since it affects other input factors (Orhan, 2022). Although recent events in Russia and Ukraine have not economically hit the U.S. economy, most studies agree that it has increased oil prices and indirectly affected the economy (Orhan, 2022).

2.4. Measuring Trade Distortion

Most literature used the gravity model introduced by Tinbergen (1963) and Leibenstein (1966) to measure trade distortion. It is the most populous model in assessing trade distortion because apart from its empirical specification of bilateral trade flow, it also considers the characteristics of the trading countries (Oguledo & Macphee, 1994; Anderson & Wincoop, 2003; Helpman et al., 2008.; Anderson, 2011; Westerlund & Wilhelmsson, 2011). Furthermore, using other microeconomic theories, the gravity model has been praised for accurately explaining the flow of goods from one country to another (Anderson, 2011). The model successfully incorporates fixed effect, two-stage least squares, log-linear fixed effect, and sometimes OLS (Westerlund & Wilhelmsson, 2011).

The major criticism is that the gravity model only analyzes positive trade flow among countries (Helpman et al., 2008). It also ignores the zero trade flow among countries, which results in bias in the estimates (Westerlund & Wilhelmsson, 2011). Scholars (including Cheng & Tsai, 2008; Helpman et al., 2008; Anderson, 2011) tried to modify the model to do away with the biasedness in the estimator, but their results showed inefficient estimates because of the presence of heteroscedasticity (Westerlund & Wilhelmsson, 2011).

Finally, the gravity model does not account for latent variables affecting trade flow. This affects the model's ability to identify factors affecting trade flows sufficiently. The probable explanation for why the model does not give attention to latent variables is that the model does not consider the hindrance of international trade (Helpman et al., 2008). As a result, this study has resolved to use a more dynamic model to help holistically determine the causes of trade disruption. Accordingly, the study will use the structural equation model and a panel GARCH model. The structural equation model is superior to the gravity model because it will allow the study to consider latent variables that affect trade and predict the appropriate estimation technique.

2.5. USA Trade Policies and Agreements

Trade economics in the USA are formulated and implemented through trade policies and agreements to create opportunity for Americans by protecting producers and contributing to the economy's growth (USA International Trade Administration www.trade.gov/free-trade-agreements). The policy specifies the rules for companies in the U.S. that want to engage in world business by reducing barriers to U.S. export, protecting the state interest, and ensuring the rule of law in the trade agreement with partners (USA International Trade Administration). These policies affect the price of goods in the domestic market and protect consumers. With trade policies, there are four basic policy strategies taken by policymakers (Irwin, 2020). These four tools include import tariffs, export subsidies, import subsidies, and export taxes. In the American trade policy, the constitution prohibits the use of import subsidies and export taxes (Canto et al., 1986; Rodrik, 1995).

The two primary trade tools the USA uses to control trade are import tariffs and export subsidies, with import tariffs being the most widely used tool (Irwin, 2020). The use of import subsidies by the USA dates back to 1789 to protect domestic producers, restrict imports, and retaliate against policies that prevent American exports (Baldwin, 1989).

Trade policies significantly affected the U.S. economy following the 1934 GATT agreement (Canto et al., 1982). The purpose is to increase U.S. exports and trade balance (Baldwin, 1989). The GATT agreement has been reviewed several times to prevent discrimination, protect domestic companies through tariffs, ensure stable trade, solve problems, waive, and take emergency action, which is an exception to general rules (Canto et al., 1982). Assessing trade agreements has been one of the main goals of the U.S. trade policy. As a result, there have been changes in the U.S. trade agreement, from the Kennedy round and Tokyo round to the Trump Administration import tariffs, which aimed to protect the USA's steel and aluminium industry (Irwin, 2020).

Import tariffs imposed on imported goods also attract retaliatory action from importing countries (Grant et al., 2019). A typical example is the retaliatory trade action taken by China on exported U.S. goods (Adjemian et al., 2021). As a result, USDA identified that the US export of goods alone declined by 1.192% (www.census.gov/foreign-trad). This also increased domestic prices and led to unemployment in the export sector (Grant et al., 2019). To mitigate this government used the Market facilitating program due to the losses incurred by producers because of the retaliation.

2.5.1. U.S. Agriculture and Trade

The USA's agriculture sector provides food for domestic and international markets. It is an important economic sector with a cash receipt of 525 billion in 2022 (USDA ERS, 2022).

Among all the crops, the 2021 data has shown that corn and soybeans contribute more than 40%, accounting for $72 billion and $49.2 billion of the cash receipt (*USDA ERS, 2022*). In the international market, the USA is the highest corn-producing country. Concerning soybeans, it was ranked second (*World Agricultural Production 2020/2021*, 2021). Regarding cash receipts from crop exports, corn and soybean exports recorded $18.6 billion and $27.4 billion, as recorded by the USDA in their 2022 agricultural export report (U.S. Agricultural Exports, 2022). This indicates that any shock on crop production will cause a significant scar on the U.S. economy.

An example is the high decline in US agricultural exports because of the trade war between the USA and China. The tariff trade war between the two countries led to a decline of 58% in export value from June 2018-July 2019 (Grant et al., 2019).

As a result, the federal government has instituted policies to deal with some of the shocks (Rausser & Zilberman, 2014). However, whether or not these agricultural policies have achieved the intended aim has always been a question to answer.

2.5.2. The USA Farm Bill

Farmers' revenue is dependent on the future price of the crop. This is because crop farmers' decision to expand production is induced by their prediction of future crop prices (Houston et al., 2015). This means reducing crop futures prices becomes a considerable risk for the farmer. As a result, if the fall in farm prices is uncontrolled, it will lead to a foreclosure of farms. This is one of the classical explanations for the 1933 USDA agricultural bill (Glauber, 2016). The Farm Bill mostly administers the agricultural policy of the USA.

The Farm Bill, as defined by Monke and Johnson (2010), governs the federal farm and food policies in the USA, covering an array of agricultural production programs and activities that undergo review and renewal every five years. This means that the farm bill is a law covering all activities on agricultural production, agricultural marketing, and the use of natural resources to improve the welfare of household farmers by stabilizing farm revenue and agricultural commodity prices. The majority of the Farm Bill also covered nutritional programs.

Before 1933, US agricultural policies covered land tenure systems intending to increase individuals' ability to access land for farming and increase production quickly (Young, 2000). This was achievable because the government sold public land to private individuals at a lower price (Young, 2000). After the industrial revolution, agricultural manufacturing companies expanded, and agricultural production increased, leading to growth in the sector (Glauber & Effland, 2016). However, during World War 1, food production decreased in the world. For the U.S. government to take advantage of the situation, federal intervention was introduced to increase farm production (Glauber and Effland, 2016, p.8: Dimitri, Effland and Conklin, 2005). The collapse of the global food demand resulted from the European agricultural recovery and the use of protective trade control tariffs from countries to protect their economy and industries, which reduced agricultural prices (Ikerd, 2020). This reduced farm revenue and profit and increased loss, increasing farm foreclosure.

In solving the problem, the United States government, through Congress, passed the Agricultural Adjustment Acts of 1933 to improve the value of crop production (Ikerd, 2020). This was the first intervention from the government in the form of income-support subsidies and production control for crops. The Agricultural Act of 1933 created the farm bill. The Agricultural Act of 1933 established the need to review and renew, if necessary, every five years leading to the creation of the Federal Corp Insurance Corporation (Young, 2000). The farm bill of the United States has undergone several changes from when it was established to now. The changes in the farm bill are to develop sustainability and efficiency in the production of crops, crop marketing, and conserving the land. As a result of this, the farm bill covers 11 titles. This includes commodity, conservation, nutrition, credit, rural development, research, extension, related market, forestry, energy, horticulture, crop insurance, and miscellaneous (Monke & Johnson, 2010).

The 2014 farm bill made some significant changes. The New Agriculture Risk Coverage and the Price Loss Coverage replaced the Direct and Counter-Cyclical guaranteed payment program (USDA News Report, *2020*). The Price Loss Coverage program is a payment program issued when the effective price of a covered commodity is less than the reference price of that commodity (*ARC/PLC Program*, 2019). The effective price is the highest of the average market price of a covered commodity. In contrast, the reference price is less than 85% of the average market price (*USDA Commodity for Credit Corporation, 2019*). Introducing these programs allow producers to select the best option to subscribe to when selecting a program that helps and keeps them in production. This is because it gave the farmers a flexible program (*ARC/PLC Program*, 2019). It also allowed the farmers to assess their shock variables and select which policies would benefit them.

2.6. Empirical Studies

Most literature focused on specifics instead of aggregates in measuring the factors affecting trade flows. First, Grant et al. (2019) assessed the impact of the 2018-2019 trade conflict between the USA and China on US agricultural exports. Their study aims to analyze the impact of the retaliatory tariff on USA agriculture exports. They used a fixed-effect bilateral trade flow model. Their model identified that U.S. exports to China from January 2019 to July 2019 reduced by 71%. They also revealed that the tariff retaliation hit seven agriculture products, with soybeans being the most affected. They also revealed that the USA lost some of its market share to other countries because of the retaliation.

Also, Amiti et al. (2018) used the fixed effect to measure the impact of the 2018-2019 tariff retaliation on price and welfare. Their findings revealed that although the tariff impacted the prices, it was insignificant. They also discovered a positive impact of tariff retaliation on export prices. The study also revealed that U.S. consumers and exporters bore the tariffs.

Adjemian et al. (2021) study on trade disruption analyzed the effect of the trade war on soybeans. They used the Relative Price of a Substitute method and the error-correction model to test whether the trade war affected soybean prices. Interestingly, they revealed that the USA soybean price adjusted at 0.04% daily while that of the Brazilian soybean had to adjust by 3% if the same tariff was imposed. They also discovered that the China retaliatory tariff stressed the USA soybean price by 0.75$/Bu. Their state analysis revealed North and South Dakota as the most hit states during the tariff retaliation.

In analyzing the effect of rare events on trade, Mallory (2021) analyzed the effect of COVID-19 on the mid-term export prospects for soybean, corn, beef, pork, and poultry. The study used trend analysis to estimate the impact. It was revealed in the study that the meat sector had a considerable shortfall in the USA, with Brazil filling the gap. Also, they revealed a decline in soybean exports.

In analyzing the effect of war on trade, Anderton and Carter (2001) used a multiple uninterrupted time series model to estimate the impact of war on trade. They used war trends and war levels as well as trends to measure the trade trends. It was revealed that war from a major or non-major economy negatively impacted trade and disrupted trade. Although the evidence revealed by their study seems to be weak, they acknowledged that war creates trade disruption.

Glick and Taylor (2010) also estimated how war causes trade disruption and the economic impact of war. They used the gravity model to identify the important variables and the fixed effect model to estimate the impact of war on trade. Their result revealed a significant effect of war on trade. The result also indicated a negative impact of war on GDP and global economic welfare. Their study also revealed a higher cost related to the war on trade.

Mena et al. (2022) analyze international trade resilience and the covid 19 pandemic. They used the fuzzy set qualitative comparative static analysis for their analysis. The variables they used were government response, health care, income level, and economic globalization. Their finding identified that the factors influenced trade resilience during the pandemic.

Louati et al. (2022) analyzed the effect of covid-19 on trade and financial trade flow as a market contagion. They used graph theory, information theory, and the Markov chain for their analysis. The study revealed that systematic trade risk increased during the lockdown period, and it was significant. Also, they discovered a change in commercial and financial dynamics. Their result revealed an extreme contagion risk of covid 19 on trade and financial trade when they used the Markov chain.

Cho et al. (2002) analyzed the effect of exchange rate uncertainty on agricultural trade. They used the gravity model as the base model in determining the variables necessary for the analysis. In addition, they used the fixed and random effect as the method of analysis. Their study revealed that exchange rate uncertainty negatively impacted agricultural trade over the period compared to other sectors.

Dimitri et al. (2016) used the GARCH model to analyze the effect of exchange rate volatility on international trade. First, they used Granger causality to find the causal relationship between the long-term linkage of exchange rate volatility and trade. The result indicated that exchange rate volatility has an impact on international trade. The result from the GARCH model indicated that in the short run, the intensity of the exchange rate volatility is small, but if it persists, in the long run, it is high.

Nicita (2013) also looked at the impact of exchange rate volatility on international trade and how trade policies can solve these issues. Their estimated mode is the fixed effect model. The study's result revealed that the effect of the exchange rate on international trade is minimal in the short run. As a result of this, their result also indicated that an appropriate trade policy would mitigate this effect.

2.7. Conclusion

Agricultural trade and export have been a major revenue-generating sector for the US economy (nationally and domestically). This has made the US agricultural trade more integrated into the international market. As a result, it is assumed that little disruption in the international market will cause a contagion to the US agricultural futures market. This calls for finding an appropriate farm model to investigate and assess trade disruption's impact on the USA soybean and corn international market. Furthermore, there is a need to develop a tool to assess the impact of the various policies (Price Loss Coverage) generated by the farm bill on soybean and corn trade. In other to achieve this, the study reviewed works of literature on agricultural production and trade concerning soybeans and corn, the USA agricultural policies, farm models, and trade disruption (definition, causes, how it is measured), generating a more efficient approach in measuring it, and finally did an empirical review of other articles.

CHAPTER THREE: METHODOLOGY

3.1. Introduction

This chapter introduces the methodology for the paper. The first part describes the data sources and descriptive statistics. This entails the source of data and the behavior of the data. The second section deals with the model specification and the econometric model, which will be used for the data analysis.

3.2. Data

The study provided a brief overview of the data collection process, which included the data's source, descriptive statistics, and data tests for corn and soybeans.

3.2.1. Data Source

The study used historical harvest area, feed use, production, yield, import demand, and domestic consumption carry-over stock, food, seed and industry (FSI) data for the USA, China, Brazil, Argentina, EU, and the rest of the world from the Production, Supple and Distribution (PS&D) database from the Economic research service for the years 1977-2022. The study also obtained data on Exchange rates taken from the Federal Reserve Economic Database. For data on war, the study adopted the style Miljkovic and Mostad (2007) used. By adopting this data model, the study relied on the frequency of newspaper reports on war from 1977 to 2022 and used it as a proxy for the war index. This is a proper proxy because it is reasonable to assume that variables that play an essential role in popularly explaining another variable can be used to measure it. They assumed that newspapers and magazines report and information from the public on news defines current happenings of the specific and timely event. This implied that the frequency of war in newspapers indicates how severe war is to humans and the world's economy. The study collected annual reports from 1977 to 2021. As a result, we resorted to

NEWSBank Inc (infoweb.newsbank.com) for this information. In addition, the study collected data on tariffs, trade membership, and trade policies from the World Integrated Trade Solution (wits.worldbank.org).

3.2.2. Data and Variable Description

Table 3.1: Descriptive Statistics of Data for Soybean

Variable	Mean	Standard deviation	Min	Max	Kurtosis
Production (1000 metric tons)	40207.61	48887.4	0	149000	2.969368
Beginning stock (1000 metric tons)	5626.214	8059.79	0	33342	4.692628
Crush (1000 metric tons)	18833.67	20926.54	0	95000	4.443244
Domestic consumption (1000 metric tons)	21471.81	23677.66	0	115589	5.499127
Feed waste (1000 metric tons)	1482.826	1574.463	0	7250	5.159057
Industrial use (1000 metric tons)	528.0994	953.4123	0	5443	8.598535
War (news items on Russian War)	747176.7	620067	0	1861020	1.398146
Covi-19 (dummy)	.068323	13.33076	0	1	12.7097
Tariff (tariff charges from China)	14.07547	34.48246	0	114	7.506765
Exchange rate (rate of exchange)	6.347628	.252692	4.6e-12	94.99074	17.72179
Export (1000 metric tons)	8875.932	16995.02	0	92135	9.886502

Table 3.2: Descriptive Statistics of Data for Corn

Variable	Mean	Standard deviation	Min	Max	Kurtosis
Production (1000 metric tons)	173082.1	147816.7	16002	566788	2.527541
Beginning stock (1000 metric tons)	52061.44	88692.81	596	468075	11.30522
Domestic consumption (1000 metric Tons)	153412.4	140220.7	9345	623850	3.417518
Feed Consumption (1000 metric tons)	72877.98	61863.66	3241	262550	2.459768
Industrial use (1000 metric tons)	60245.28	57937.2	4645	213524	3.041706
Export (1000 metric tons)	26315.55	29873.4	0	114413	3.664169

The data set is the panel data with (variables like production, beginning stock, crush, domestic consumption, feed waste, industrial consumption, war, covid-19, Tariff, exchange rate, and export) collected for the USA, Brazil, Argentina, Chinese, Ukraine, and Russia.

The descriptive data gives the mean, minimum, maximum, kurtosis, and standard deviation of the data. While the mean gives the average value of the data set, the minimum and maximum values describe the dataset's range. The standard deviation explains how the variables are spread away from the mean. Finally, as defined by Groeneveld and Meeden (1984), kurtosis measures the degree of flatness of a distribution.

From Table 3.1, it is observed that the panel data has a positive Kurtosis value. This indicates that the distribution for the panel data is more peaked than the normal distribution and with more variance due to extreme values.

3.2.2.1. Supply Side Variables

Production: The study defines production as the total number of soybeans and corn produced in 1000 metric tons. The study used production as a determinant of soybean and corn supply. This is because production has a direct relationship with supply, which is proportional, as reported by the USDA soybean and corn supply and demand updates. This suggests that when soybean and corn production increases, the soybean and corn supply in the year will increase, and vice-versa. Because of this, the study hypothesized that soybean and corn production would positively affect supply.

Table 3.1 shows that soybean production has a mean value of 40207.61 (1000 metric tons), which indicates an average value of around 40207.61 (1000 metric tons). The standard deviation of 48887.4 (1000 metric tons) indicates that the value in the production data set is spread out of the mean, with most of the value falling within one standard deviation of the mean. The minimum value for production was zero, and the maximum value of 149000 (1000 metric tons) indicates that the dataset has a wide range of values. Furthermore, Table 3.1b indicates that corn production has a mean value of 173082.1(1000 metric tons). The minimum and maximum values were 16002 (1000 metric tons) and 566788 (metric tons). The kurtosis value for soybean production and corn production were 2.939 and 2.528. This indicates that the data distribution is more peaked and has heavier tails than a normal distribution. This suggests that the data for the production variables has some extreme values or outliers, contributing to the deviation from the normal distribution.

Figure 3.1 presents the relationship between soybean supply and production. The figure shows a positive linear relationship between soybean supply and production. This confirms the hypothesis drawn by the study.

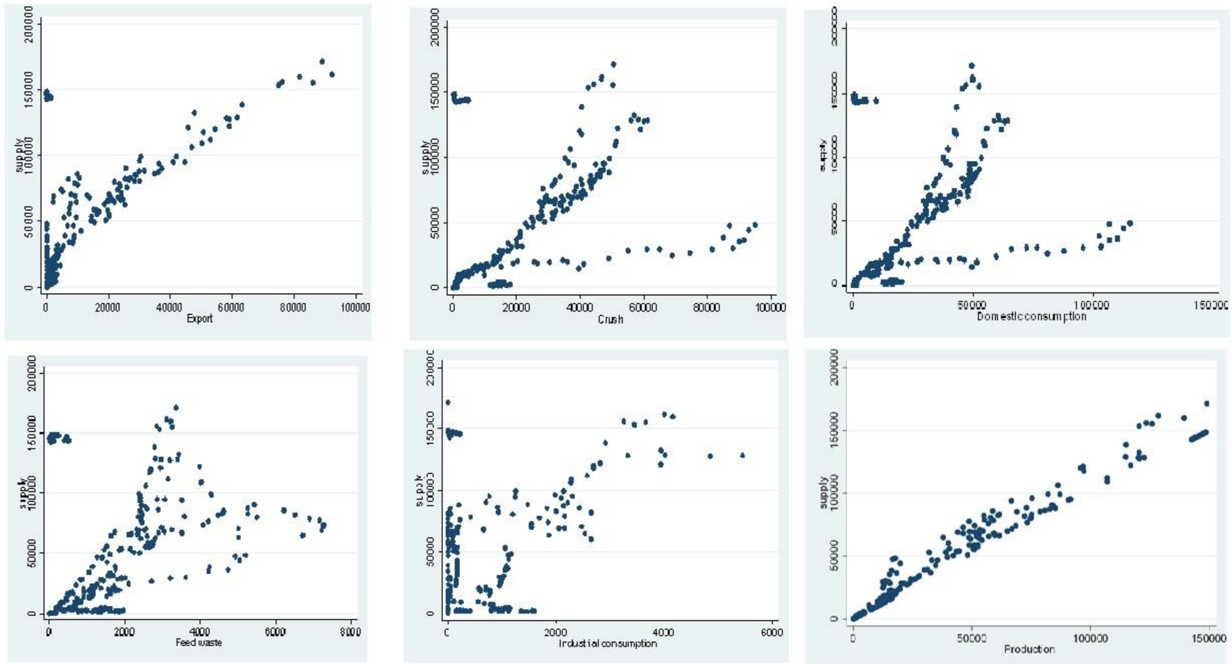

Figure 3.1: Scatter Plot of Data

Beginning Stock: The study defines beginning stock according to the USDA definition. The study defined the quantity of crops held in storage at the beginning of every marketing year (USDA ERS - Food Availability Documentation, 2023). The beginning stock is an essential determinant of soybean and corn supply. This is because the soybean and corn supply is calculated by adding production to the beginning stock. As a result, it has a proportional relationship with soybean and corn supply in the marketing year. As observed from Table 3.1, the beginning stock for soybeans has a mean value of 5626.214 (1000 metric tons), which indicates an average value of around 5626.214 (1000 metric tons). The standard deviation of 8059.79 (1000 metric tons) indicates that the value in the beginning stock data set is spread out of the mean, with most of the value falling within one standard deviation of the mean. The minimum value for production was zero, and the maximum value of 33342 (1000 metric tons) indicates that the dataset has a wide range of values. However, the mean value for corn, as shown in Table 3.2, indicated a mean value of 52061.44 (1000 metric tons) with a standard deviation of

88692.81(metric tons). It was also indicated that the soybean and corn data is more peaked and has a heavy tail than the normal distribution. This is because the kurtosis value for soybean and corn were 4.693 and 11.305, respectively.

3.2.2.2. Demand Side Variables

Soybean Crush: Soybean crush represents a significant portion of soybean demand since the soybean industries use this to produce soybean oil and meal for human and animal consumption. The level of soybean crush activities also has a significant impact on supply. If soybean crush increases, the study expects that the demand for soybean production will increase and vice-versa. Therefore, the study hypothesized that there would be a positive relationship between soybean crush and supply.

Table 3.1 shows that soybean crush has a mean value of 18833.67 (1000 metric tons). The standard deviation of 20926.54 (1000 metric tons) indicates that the value in the production data set is spread out of the mean. The minimum value was zero, with a maximum value of 95000 (1000 metric tons) and a kurtosis of 4.443.

Feed Waste and Feed Consumption: The study defines feed waste as the by-product of soybean and corn processing for animal and human consumption. Because of this, soybean and corn feed waste does not directly impact the supply. However, it affects supply indirectly through demand. Due to this, the direction of how feed waste can affect corn and soybean supply, as the study hypothesized, can be negative or positive.

Table 3.1 shows that soybean feed waste has a mean value of 1482.826 (1000 metric tons), which indicates an average value of around 1482.826 (1000 metric tons). The standard deviation of 1574.46 (1000 metric tons) indicates that the value in the production data set is spread out of the mean, with most of the value falling within one standard deviation of the mean.

The minimum value for production was zero, and the maximum value of 7250 (1000 metric tons) indicates that the dataset has a wide range of values. Feed consumption for corn had a mean value of 72877.98 and a standard deviation of 262550 (1000 metric tons). The kurtosis value for soybean and corn were 5.159 and 2.560. This suggests that the data for soybean feed waste and corn feed consumption has some extreme values or outliers, contributing to the deviation from the normal distribution.

Domestic Consumption: the definition of domestic consumption was in line with the USDA PSD definition. The study defines domestic consumption as the total soybean and corn consumed for human and animal purposes. Therefore, domestic consumption will proportionately increase soybean and corn supply through the demand. The hypothesis is that an increase in soybean and corn for domestic consumption would increase the demand for soybean and corn, encouraging farmers to produce more to meet the demand.

Table 3.1 Indicates that the average value for domestic consumption was around 21471.81(1000 metric tons). The standard deviation, which explained the spread away from the mean, was 23677.66 (1000 metric tons). Additionally, Table 3.1b indicated a mean value of 153412.4 (1000 metric tons) and a standard deviation of 140220.7 (1000 metric tons). The positive kurtosis value for corn and soybean shows a peaked and heavy tail of the distribution.

The scatter plot presented in Figure 3.1. shows a linear and positive relationship between domestic consumption and soybean supply.

Industrial consumption: The study defines industrial consumption as the total use of soybean and corn for non-food applications and other industrial products. For soybean, this includes paper coatings, wood veneer adhesive, and printing inks Johnson and Myers (1995). For corn, it includes Ethanol. Therefore, the study hypothesized that industrial use of soybean and corn would positively impact corn and soybean supply.

Export: The study defines export as the shipment of goods from one country to another. Export is a demand side in the study's conceptual framework. The study conceptualizes that an increase in export demand incentivizes farmers to produce more crops to meet the demand. Because of this, the study hypothesized that increasing export demand would increase corn and soybean supply.

Tables 3.1 and 3.2 showed that the average soybean and corn export values were around 8875.932 (1000 metric tons) and 26315.55 (1000 metric tons). The standard deviation were 16995.02 (1000 metric tons) and 29873.4 (metric tons) whiles the kurtosis was 9.887 and 3.664.

Trade Disruption: The study defined trade disruption as any regulatory policy and unforeseen occurrences that disturb the exports of goods from one country to the other. This can be tariff retaliations, pandemics, wars, and exchange rate volatility. The study treated trade disruptions as a latent variable affecting the observed variable directly or indirectly. The main disruptions to trade the study looked at were War, Tariffs, the Covid-19 pandemic, and exchange rate volatility.

War News from Russia: The study seeks to limit its scope to the Russian war affecting the USA soybean and Corn export. From the study of (Glick & Taylor, 2010), war negatively affects trade. The war variable was represented with a proxy, the frequency of newspaper reports on war from 1977-2021. The effect of war is primarily indirect on the supply of soybean and soybean export. For example, most Russian wars, especially the war between Russia and Ukraine, according to Smutka and Abrhám (2022), reduced soybean export from the USA and

EU to Russia through tariff retaliation from Russia. Although this effect is indirect, the study expects that war will negatively impact the world and US soybean export.

The descriptive data on war revealed an average number of 747176.7 news reports, a standard deviation of 620067 news reports, and a kurtosis of 1.398. This explains that war data collected has a heavy tail compared to the normal distribution.

Covid-19: The study also examined how covid-19 affected soybean and corn production and export. While other studies revealed that covid-19 negatively impacted export globally, Beckman and Countryman (2021) and Grant et al. (2021) discovered that covid-19 did not affect the USA soybean export. Because of this, the study hypothesis is that covid-19 influence export positively. Also, Elleby et al. (2020) indicated that Covid-19 did not have a long run effect on corn. They further explained that the reason is because Covid-19 was a short duration shock.

Tariffs: The study defines tariffs as taxes on imported goods in the Chinese economy. The study used tariffs from China because China is the highest global soybean and corn importer(Fedoseeva & Zeidan, 2022). Tariffs directly affect export (Johnson, 1953a). As a result, the study hypothesis is that tariffs would negatively influence soybean and soybean supply.

Exchange Rate: The exchange rate affects soybean and corn export through international demand for these commodities by making them cheaper or expensive. The study sees exchange rate volatility as destruction to trade flow from one country to another because it affects the price of the imported commodity (Chambers & Just, 1979). The study defines the exchange rate using the dollar as the base of exchange. This is because the dollar is the main currency of international exchange (Anderson & Garcia, 1989). As a result of this, the study hypothesizes that there is an inverse relationship between exchange rate and export.

3.2.3. Data Testing

The study conducted a test on the panel data. This is to ensure that the data is suitable for analysis. The test includes a stationarity test. To achieve this, the study used the Fisher-type unit root test proposed by Choi (2001). The Fisher-type unit root test combines the p-values from the unit root of the groups. This test was conducted following Choi (2001) assumptions. The purpose of this test is to ensure stationarity. Furthermore, the study will validates the stationarity test by Choi (2001) using Pedroni (2004) test.

3.3. Model Specification

Most literature used the gravity model introduced by Tinbergen (1962) and Leibenstein and Tinbergen (1966) to measure trade distortion. The model assumes that the trade volume between two countries is directly proportional to the size of their economies and inversely proportional to the distance between them (Paniagua, 2015: Oguledo & Macphee, 1994). It is the most populous model in assessing trade distortion because apart from its empirical specification of bilateral trade flow, it also considers the characteristics of the trading countries (Oguledo & Macphee, 1994:Anderson & Wincoop, 2003; Helpman et al., 2008.; Anderson, 2011; Westerlund & Wilhelmsson, 2011). Furthermore, the gravity model is praised for accurately explaining the flow of goods from one country to another using microeconomic theories (Anderson, 2011). The model has been successful with fixed effect, two-stage least squares, log-linear fixed effect, and sometime OLS (Westerlund & Wilhelmsson, 2011) because trade data are mostly panel data.

The major criticism is that the gravity model only analyzes positive trade flow among countries (Helpman et al., 2008). It also ignores the zero flow of trade among countries, which results in bias in the estimates (Westerlund & Wilhelmsson, 2011). Scholars including Cheng and Tsai (2008), Helpman et al. (2008) and Anderson (2011) tried to modify the model to do away with the biasedness in the estimator, but their best results could not yield efficient estimators due to the presence of heteroscedasticity (Westerlund & Wilhelmsson, 2011).

Finally, the model does not account for latent variables affecting trade flow. This affects the model's ability to identify factors affecting trade flows sufficiently. The probable explanation why the model does not give attention to latent variables is that the model does not consider detailed hindrances of international trade (Helpman et al., 2008).

3.3.1. Preliminary Model

The study used pooled OLS regression model as the preliminary model to test the gravity model as used by Taylor and Koo (2015) report. With the preliminary model, the study assumed a stabilized political system, unchanged weather conditions, and no changes in agriculture policy, as assumed by Taylor and Koo (2015). Furthermore, the study used the four-period weighted moving average used by Dhuyvette and Kastens (1998) as a forecasting technique. This is because the four way weighted moving averages to provide a more accurate prediction (Hatchett et al., 2010; Taylor et al., 2006; Dhuyvette and Kastens, 1998). Thompson et al. (2019) argued that the reason is because the four way weighted moving average captures planting and harvesting seasons as well as the supply and demand dynamics of soybean and corn trade. They also argued that it smooths out long term trends.

To ensure that the study's model meets the Gauss-Markov assumptions of linear regression, the Durbin-Watson test was conducted to check for serial autocorrelation (Durbin & Watson, 1971). Furthermore, a heteroscedasticity test was performed. Finally, the study used the adjusted R-squared and the Akaike Information Criteria to determine the model's fitness.

3.3.2. The Structural Equation Model

The structural equation model is a causal inference method that unveils the correlation between variables. Since its inception by Wright (2022), the structural equation model has been classified as a univariate, bivariate, and multivariate data analysis technique. It combines regression, factor, or path analysis using observed and latent variables (Hox and Bechger, 1999*)*. The observed variables are from the data (Fox, 2008). The observed variables are variables that can be measured with ease. The latent variables are hypothetically constructed variables or variables that are not directly measured by the data (Kline,2016) and are very difficult to measure but indirectly affect the dependent variable.

The study used the structural equation model because it provides the basis for testing theoretical models that hypothesize how variables (observed and latent variables) define construct and how they relate to each other (Schumacker & Lomax, 2004). That is, SEM helps to explain how a set of sample data explains a theoretical model. Furthermore, the structural equation model is suitable for a large sample size. Using SEM in dealing with a large sample size helps reduce omission errors and makes the econometric model used for data analysis robust (Hox and Bechger, 1999). Also, the structural equation model helps to make econometric interpretation very easy and accurate. This is because it puts less importance on statistical testing (Kline, 2016). With the Structural equation model, one can either evaluate the whole model or significant individual effects to conclude. Furthermore, it gives the model the advantage of accommodating the latent variable that will not be captured if a different model is used. Finally, the structural model also shows the pathway using a path diagram which shows the relationship between the observed variables and the latent variables and how they cause the dependent variable (Wang & Sun, 2017).

To determine the expected satisfaction a farmer gets from producing some crops, the study used the structural equation model to determine how the demand (domestic and international demand) for the crop determines the aggregate supply of the crops that farmers will be willing to produce. To achieve this, there is the need to collect data on the observed and latent variables and understand the path through which these variables affect domestic and international demand and how it subsequently affects the aggregate supply of soybean.

Using the structural equation model, the study adopted and modified the model as suggested by Eichler (2007) to determine the causal relationship between the variables. Eichler (2007) model used Granger causality to determine the causal relationship among variables. This model helped in visualizing the theory on which the study was built. It also helps to show the direct and indirect causal link between the exogenous and endogenous variables using a directional arrow and the relationship between the latent and observed variables (Hoyle, 2012). Finally, the study used the Dumitrescu and Hurlin (2012) Granger causality model to determine the global causal relationship among the variables. The Dumitrescu and Hurlin (2012) Granger causality model is:

$$Y_{it} = a_1 + \sum_{k=1}^{k} \gamma_i^k Y_{i,t-k} + \sum_{k=1}^{k} B_i^k X_{i,t-k} + \varepsilon_{it} \quad (1)$$

X and Y are two stationary variables for N individuals on T period. For simplicity, we assume that a_1 is fixed in the time dimension. We also assumed that the lagged order K is identical for all cross-section units in the panel and that the panel is balanced.

Specifically, the study used the time series Granger causality Eichler (2007) used to determine the causal relationship among variables for USA soybean export and corn production. Furthermore, the study employed a simple VAR model for the impulse response of the variables on US corn and soybean export and production. The path diagram represents the observed variables in rectangles, while the latent variables are eclipse-shaped. The arrow shows the directional link between the dependent and the independent variables (Kline, 2016). The path analysis for the study is demonstrated in Figure 3.2.

The path diagram in Figure 3.2 shows the relationship between farmers' decision to Supply and the demand (domestic and international demand) for their products. The model indicated that soybean and corn supply is determined by aggregate demand. Furthermore, the diagram also showed production of soybean and corn is affected by the yield and the harvested acreage. The Yield, however, is affected by the fertilizer prices and farm policy (Price Loss Coverage).

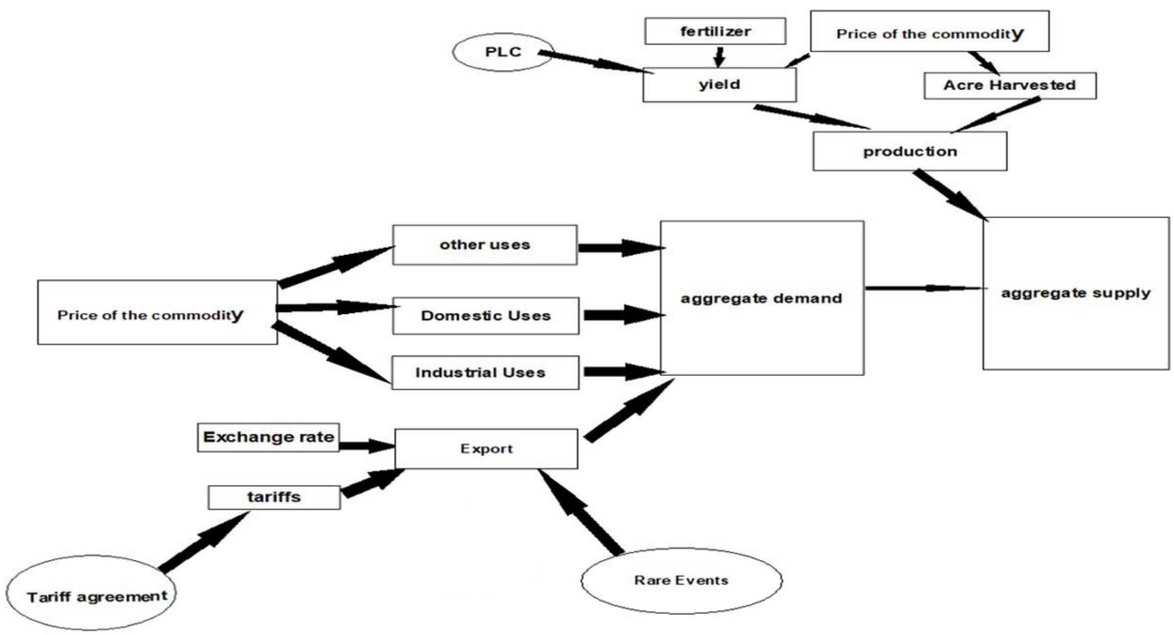

Figure 3.2: The Path Diagram

The path diagram also indicated that the aggregate supply of soybean is determined or caused by aggregate demand for soybean. This means that the farmer will supply more of his commodity when he knows that higher demand exists. Figure 3.2 also shows that the net export, the industrial use of the commodity, the domestic use, and the other uses determine the aggregate demand. The exchange rate, tariffs, and rear events also determine net Export. Finally, the tariff is determined by the trade agreement between countries. From the demand side, trade agreements, world economic policy uncertainty, and rear events are latent variables that indirectly determine aggregate demand through net export.

3.4. Econometric Model of the Structural Equation Model

The econometric model for the study was a modification of Won Koo (2012) model developed to forecast the outlook of US soybean and corn production. The behavioral equation model derived an equilibrium between aggregate supply and aggregate demand. The study modified this model using the structural equation model to capture domestic and external shocks. These shocks in the model were captured as latent variables. This is because of the difficulty in measuring them.

In Won Koo (2012), for the farmer to determine the response to traders' demand for their products, they must equate the aggregate supply to the aggregate demand. The farmer should first have their production equation, Yield equation, domestic demand and use of the crop, and net export equation. This is presented as;

$$Pd_t^n = f(HA_t^n, Y_t^n) = HA_t^n * Y_t^n \tag{2}$$

Y^n_t is the total yield of soybean, and HA^n_t is the harvested area of crop n in time t. From the path diagram, the yield is affected by the fertilizer price and the Farm policy (PLC). Therefore, the study based on the literature assumes a negative effect on the fertilizer price and the yield (Brunelle et al., 2015), while the farm policy PLC has a positive relationship with yield (Thompson, 2005).

In the study, yield is a function of fertilizer price, the price of the commodity, and the farm policy and the trend. The yield equation is;

$$Y_t^n = f\left(p_t^n, F_t^p, FarmP, T_t\right) \tag{2a}$$

$Y^n{}_t$ is the total yield of soybean or corn in time t, $P^t{}_n$ is the soybean price, T_t is the trend variable, $F^p{}_n$ is fertilizer price, and FarmP is the farm policy over time. Furthermore, harvested acreage is determined by the harvested area of crop n in time t-1, the price of soybean or corn in time t, soybean or corn price in time t-1, and their substitute.

$$HA_t^n = f(HA_{t-1}, P_{t-1}^n, P_{t-1}^m) \tag{2b}$$

$HA^n{}_t$ is the harvested area of crop n in time t, $P^n{}_{t-1}$ is the real soybean or corn price in time t-I, and $PA^n{}_t$ is the real soybean or corn price in time t. $PA^w{}_{t-1}$ is the price of its substitute. Furthermore, HA_{t-1} is the harvested area of crop n in time t-1. The lagged variable measures dynamics in production as assumed by (Nerlove, 1972).

Furthermore, modifying the demand model for soybeans and corn used by Won Koo (2012), we estimate the demand for soybeans or corn as follows:

$$QTY_t^{sc} = f(p_t^{sc}, Y_t) \tag{3}$$

$QTY^s{}_d$ is the quantity demanded of soybean or corn, $P^{sc}{}_t$ is the real price of soybean or corn, and Y_t is the income of the economic agent.

To know the quantity of soybean demanded, there is a need to know the various reasons economic agent's demand for soybeans, domestically and internationally. From literature, soybeans and corn were demanded for Industrial use, Carry-Over stock, and export demand.

The domestic demand for soybean and corn is a function of the commodity's price and the trend. The assumption is that there is a negative relationship between domestic demand for soybeans and the price of soybeans. The equation for domestic demand for is:

$$Dd_t^{sc} = f(p_t^{sc}, T_t) \tag{3a}$$

Where Dd^{sc}_t is the domestic demand for soybean or corn, P^{sc}_t is the real soybean of corn price, and T_t is the trend variable.

Furthermore, domestically, soybean or corn is demanded for industrial purposes. Because of this, the study estimated the industrial demand for these commodities. Therefore, the equation for industrial demand is:

$$ID_t^{sc} = f(p_t^n, T_t) \tag{3b}$$

IDd^{sc}_t and P^n_t is the real soybean or corn price, and T_t is the trend variable.

The study classifies the other uses of soybean or corn as the use of for seed and bio-energy. The function of other uses is:

$$OD_t^{sc} = f(p_t^n, T_t) \tag{3c}$$

The study also estimated the international demand for soybean and corn by estimating the net export. First, the equation for net export is a function of the exchange rate, tariffs, rear events, and price of the commodities. The study assumes a negative relationship between price and net export (Adjemian et al., 2021b), exchange rate, and rear events. Therefore, the equation for net export is:

$$NX_t^d = f(p_t^{sc}, Tf, RE\ T_t) \tag{3d}$$

Where Er, Tf, WEPU, RE, and P^{sc}_t are exchange rates, tariffs, rear events, and the price of soybean and corn.

Therefore, from the path analysis of the structural equation model, the tariff is a function of a trade agreement among the nations and their membership. As a result of the difficulty in getting data, the tariff agreement or membership is measured as a dummy variable. Therefore, the tariff equation will be a function of the tariff agreement of membership and the quantity demanded by the country.

$$Tf_{ij} = f(QTY^s, T_t) \tag{3e}$$

Where $Tf_{ij}$the tariff agreement or membership, and QTY is the quantity imported.

Finally, for the farmer to be in equilibrium, the soybean supply should be equal to the Domestic demand and international demand for soybean and corn.

So the Farmers Aggregate Utility will be:

$$U_s(S) = f(ID_t^s, OD_t^s, CS_t^n, NX_t^s) \tag{4}$$

The extended equation will be:

$$PD_t^n - ID_t^s - \ OD_t^s - CS_t^n - NX_t^s \tag{5}$$

Furthermore, from the path diagram shown in Figure 2, net export in the international market is determined by Exchange rate, trade agreement (tariffs) and rear events (war). Therefore, the study used a fixed effect model as the base model to determine how these factors affect export.

3.5. Fixed Effect Model

The fixed effect model was used to identify the effect of the trade disruptors of corn and soybean exports. The reason for adopting this model as the base model is the existence of the time variable and the cross-sectional variables. The cross-sectional variables are the tariffs and the counter-tariffs imposed on US export by the importing countries and soybean production from competing countries. Further, war is a cross-sectional variable. The time variable is the year. This model has successfully been used by most literature on trade because of the gravity model (Adjemian et al., 2021a; J. E. Anderson, 2011; Disdier et al., 2008; Glick & Taylor, 2010; Goldstein, 1989; H. G. Johnson, 1953b; Kandilov, 2008; McKenzie, 1999; Rohner et al., 2013; Orhan,2022; Richards et al., 2022). The study adopts the fixed effect model used by Anderson and Wincoop, (2003) and Anderson and Nelgen (2012).

The model specification is:

$$\ln X_{it} = a_i + a_2 lny_{it} + a_3 lnwar + a_4 lntariff + a_5 lnExrate + a_6 Covid19 + \varepsilon_{it} \qquad (5)$$

Where X_{it} is the US export, and it is the dependent variable, y_{it} production from the countries lnwar is the war variable, the tariff is the tariff retaliation from imported countries, and Exrate is the exchange rate while ε_{it} is the error term.

Despite the advantages of the fix effect model, the fixed effect model have been criticized because of the presence of heteroscedasticity, autocorrelation and zero trade flow. Furthermore, trade disruption make export volatile. Therefore, there is the need to use a model which will capture the volatility in export as a result of the trade disruption. Because of this the study used the panel GARCH model for this purpose.

3.5.1. Panel GARCH Model

The study used the Panel GARCH model to analyze the intensity of trade disruptions on soybean and corn export globally. The study used the Panel GARCH model because the data for the analysis is panel data. This method combines panel data analysis with the generalized Auto-regressive Conditional Heteroscedasticity model. First, the study tested whether soybean production from other countries affects USA corn and soybean production using fixed effect. The panel data analysis helps provide more information on how the production from other countries affects USA soybean and corn export by clearly evaluating the relationship among them. It also helps to check for random walk. The panel fixed effect analysis is indicated by equation 5. The second step is to model the panel GARCH model using the estimates from the fixed effect analysis.

With the GARCH model, we adopt and modify the model used by (Borkowski et al., 2021; Lee, 2010) by using the conditional mean estimated in equation 5 with the fixed effect panel data, which has zero mean and normal distribution. The conditional moment, which these assumptions follow, is:

$$E\left[\varepsilon_{it}\varepsilon_j\right] = 0\ for\ i\ \neq j\ and\ t \neq s \tag{6}$$

$$E\left[\varepsilon_{it}\varepsilon_j\right] = 0\ for\ i = j\ and\ t \neq s \tag{7}$$

$$E\left[\varepsilon_{it}\varepsilon_j\right] = \sigma_{ij,t}^2\ for\ i \neq j\ and\ t = s \tag{8}$$

$$E\left[\varepsilon_{it}\varepsilon_j\right] = \sigma_{ij}^2\ for\ i = j\ and\ t = s \tag{9}$$

The first and second conditions assume no non-contemporaneous cross-sectional correlation and no autocorrelation. The third and fourth assumption defines the general condition for the conditional variance-covariance process. This is assumed to follow the GARCH model. The GARCH model will follow the GARCH model originally proposed by (Bollerslev, 1986), which was then modified by (Borkowski et al., 2021; Lee, 2010). The GARCH model is:

$$\sigma_{it}^2 = \varphi_i + \gamma\sigma_{it-i}^2 + \delta\varepsilon_{it-1}^2, \quad i = 1, \dots, N, \tag{10}$$

$$\sigma_{ij,t}^2 = \varphi_{ij} + \omega\sigma_{ij,t-1} + \rho\varepsilon_{it-1}\rho\varepsilon_{jt-1} \quad i \neq j \tag{11}$$

Because ε_j is the conditional heteroskedasticity and cross-sectionally correlated, the study used the Maximum loglikelihood method as used by Davidson, MacKinnon (1993), and Zinde-Walsh (1995).

To measure the magnitude of risk imposed by trade disruption on export, the study used the GARCH-Value at Risk model. The VaR model is a risk analysing tool which measures the volatility of an asset or portfolio. It measures the maximum possible loss an asset or portfolio can have in a period given the confidence interval (Huang et al., 2009). Since the inception of the VaR model, there have been some modifications in the model which enables and advanced and efficient way of measuring risk. For example the copula VaR and the GARCH-VaR. the GARCH-VaR is one of the most widely used model in calculating the risk of a portfolio. This is because it has been identified to be superior to the traditional VaR model (Engle & Kroner, 1995). The reason is that they have the capacity for depicting volatility-clustering phenomena efficiently. Furthermore the GARCH-Var model is flexible in dealing with distributional assumptions. It help to accommodate various distribution assumptions, for example normal distribution, t-distribution or skewness (Gao & Song, 2008). Finally, Huang et al. (2009) argued the GARCH-VaR ensures computational efficiency. This is because they realized that it involved fewer computations and efficiently measures risk of a portfolio.

Other researchers also used the Copula-VaR model in calculating the risk of a portfolio (Lu et al., 2014; Chen & Tu, 2013; Hsu et al., 2012; Bianchi et al., 2010). This is because it captures the joint distribution of returns. The advantage the GARCH-VaR model have on the Copula Model is that, apart from having the flexibility in dealing with the distributional assumption, the GARCH-VaR is efficient in capturing time-varying volatility when dealing with asset with changing volatility.

Furthermore, the study used the GARCH model and the Value at Risk to examine the risk these trade disruptors had on USA soybean and corn farmers' income. The essence of using GARCH Value at Risk in this study is that the GARCH-VaR helps to capture extreme events in the lower tail of the portfolio return distribution (Manfredo & Leuthold, 1999). Also, it is simple to use in estimating risk. Finally, the VaR can be easily used with other models, especially the GARCH model, in estimating risk.

The VaR model used was the variance-covariance approach propounded by JP Morgan's Risk Metric (1996). This is written as;

$$VaR = Portfolio\ Value \times (1 - confidence\ Interval) \times volatility \times z - score \tag{12}$$

$$VaR = Portfolio\ Value \times (1 - confidence\ interval) \times \sqrt{H_T} \times z - score \tag{13}$$

The portfolio value is the total portfolio being analyzed (corn and soybean), the H_T is the conditional variance at time t, and the Z-score is the standard deviation corresponding to the desired confidence level.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1. Introduction

This chapter presents the results of the study. The chapter begins with a summary of worldwide statistics on soybean and corn production, export, and Import. Furthermore, the chapter presents the preliminary results from the OLS estimates, and the moving averages forecast. This is followed by the estimations for the path diagram, which showed the causal relationship between the observed and the indirect variables. In addition, the VAR and Granger causality estimates of production and export were estimated. Finally, the panel GARCH model which captures trade disruption's intensity and risk on income were also estimated and presented.

4.2. Global Production and Export of Soybean and Corn

The Global soybean and corn characteristics from 1977-2021 are presented in Figure 4.1 and Figure 4.2 through to Figure 4.7. Figure 4.1 indicates the production trends of soybeans in the USA, Brazil, and Argentina. The major reason to select these countries is that they produce more than 50% of the world's soybean.

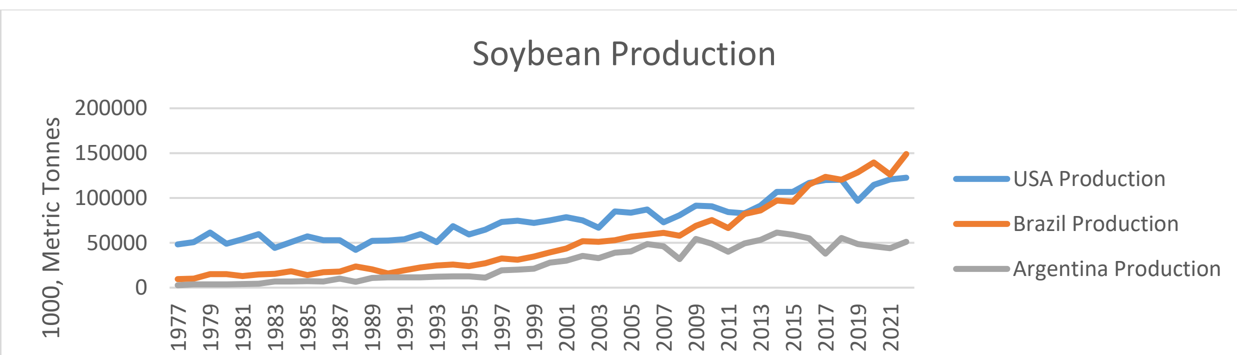

Figure 4.1: Trend of Soybean Production

From Figure 4.1, Brazil topped soybean production worldwide from 2016-2022. Followed by the USA and Argentina. Figure 4.1 shows that in 2018-2019, the USA experienced a decrease in soybean production. Arita et al. (2021) explained that such a decrease in soybean is because of the trade war between USA and China. However, the production of soybean in Brazil and Argentina increased, as indicated in Figure 4.1.

However, during the covid-19 period, Soybean production in the USA increased. This is because of the soybean export increase in 2020-2021 (USDA, 2021). On the other hand, during the same period, the production of soybean in Brazil and Argentina reduced.

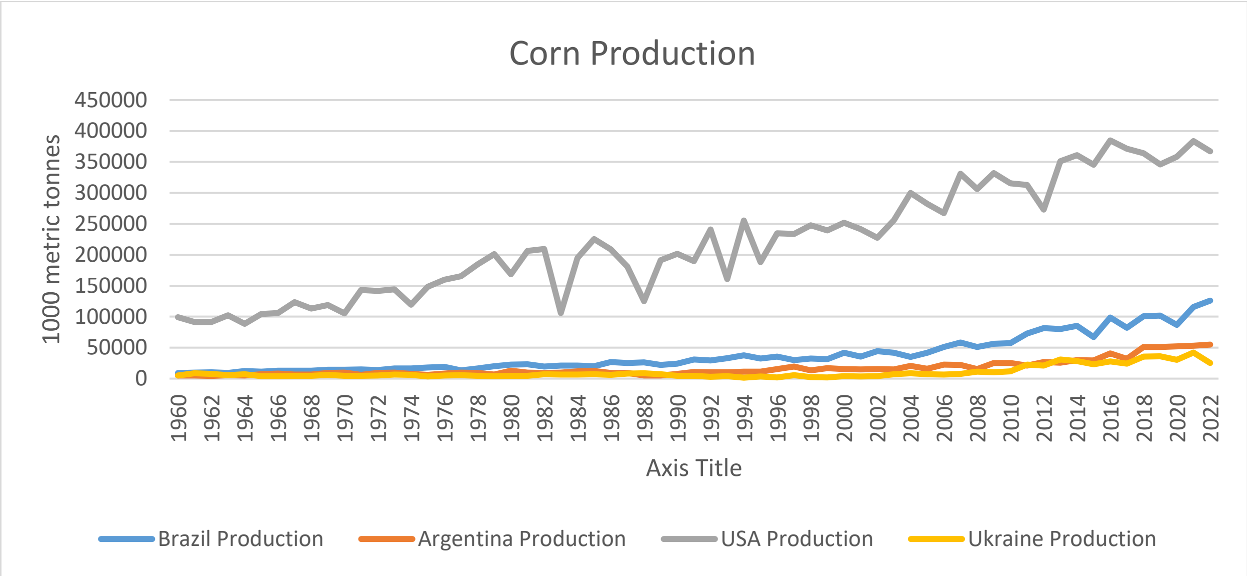

Figure 4.2: Trends of Corn Production

Figure 4.2 shows the corn production trends for Brazil, Argentina, USA, and Ukraine. The trend indicated that the USA is the leading producer of corn, followed by Brazil, Argentina, and Ukraine in that order. The trend indicated that US corn production reduced during the 2018-2019 market year. This was caused by a planting delay, as reported by the USDA. On the other hand, Brazil experienced an increase in corn production in that same period. The reason is the area expansion for the Safrinha crop (USDA, 2019). The trend in Figure 4.2 also indicated a fall in USA corn production in 2022. The USDA (2022) reported that the decline is because of an increase in the cost of input.

4.2.1. Soybean and Corn Export

The study plotted a soybean export trend for the USA, Brazil, and Argentina. The reason is that exports from the USA, Brazil, and Argentina are about 80% of the world's soybean exports. From Figure 4.3, Brazil was the largest soybean exporter from 2016-2022, with an export value of 89 million metric tons of the world's soybean export. However, the USA exported 59 million metric tons of soybeans in 2022. Figure 4.3 revealed that USA soybean exports reduced in 2018 and 2019. The probable explanation for this, as posited by Arita et al.(2021) and Grant et al. (2019), was the trade war between the USA and China. Within the same period, soybean exports from Brazil and Argentina Increased.

During the Covid-19 pandemic period, soybean exports from the USA increased. This confirms the USDA report on soybean exports in 2020-2021. The reason for this increase is the increase in USA soybean exports to China, followed by the relaxation of the trade restriction between the USA and China (USDA ERS, 2022). On the other hand, soybean exports from Brazil and Argentina decreased within the same period.

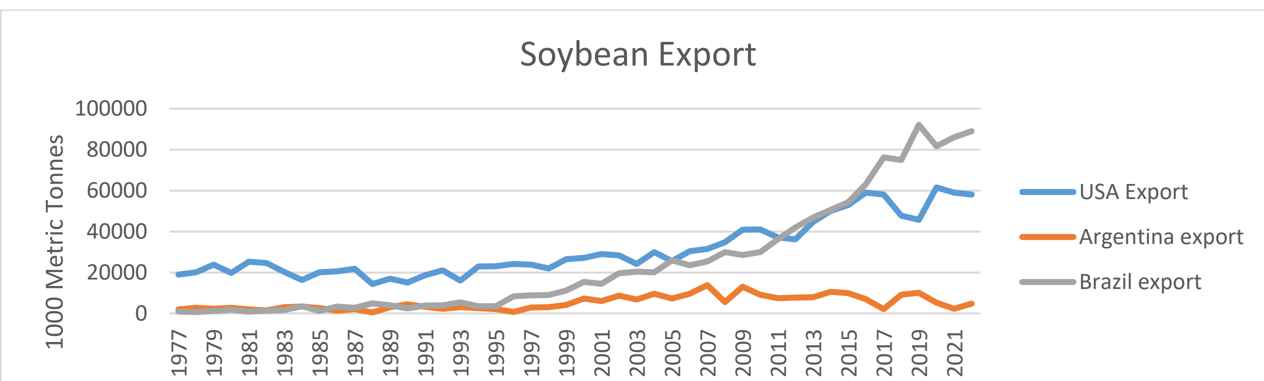

Figure 4.3: Trends of Soybean Export

Figure 4.4 shows the corn export trends for the USA, Argentina, Brazil, and Ukraine. The trends indicated that the US is the leading corn exporter, followed by Brazil, Argentina, and Ukraine. Figure 4.4 indicates that during the 2018-2019 marketing year, the USA realized a decrease in corn exports. The probable explanation is the tax retaliation from China (Arita et al., 2021). Also, the USDA (2019) reported another reason for the decline is price competition from their major competitor. Furthermore, the USA experienced a decline in corn exports in 2022. The reason for this, as reported by the USDA (2022), is due to competition from their exporters.

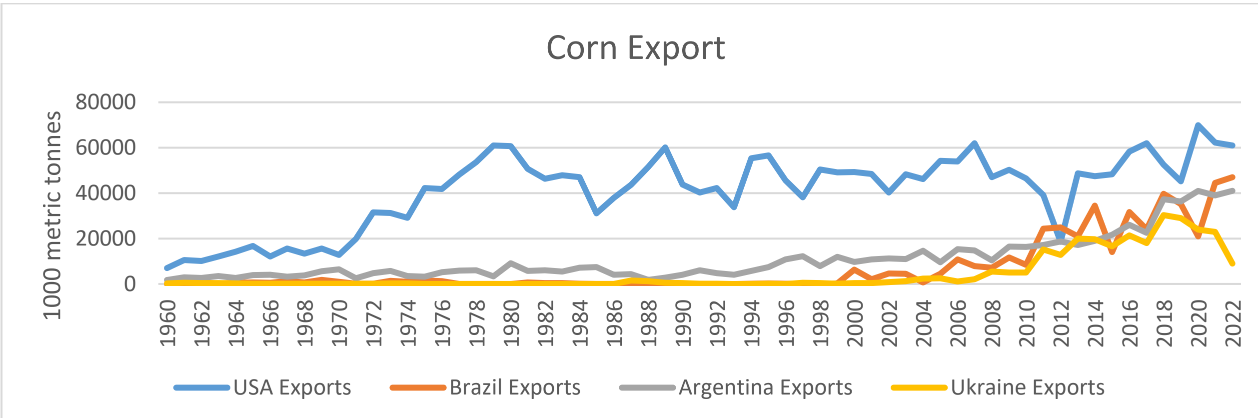

Figure 4.4: Trends of Corn Export

4.3. Soybean Consumption

Figure 4.5 shows the world's soybean consumption. Over the last five years, world soybean consumption has increased (*USDA ERS - Soybean Market Outlook*, 2022). Figure 4.5 revealed that China consumes more of the world's soybean produced. Followed by the USA, the rest of the world, Brazil, Argentina, and the EU, in that order. Taylor (2016) report indicated that soybean consumption in the USA increased by 11% from 2001 to 2016.

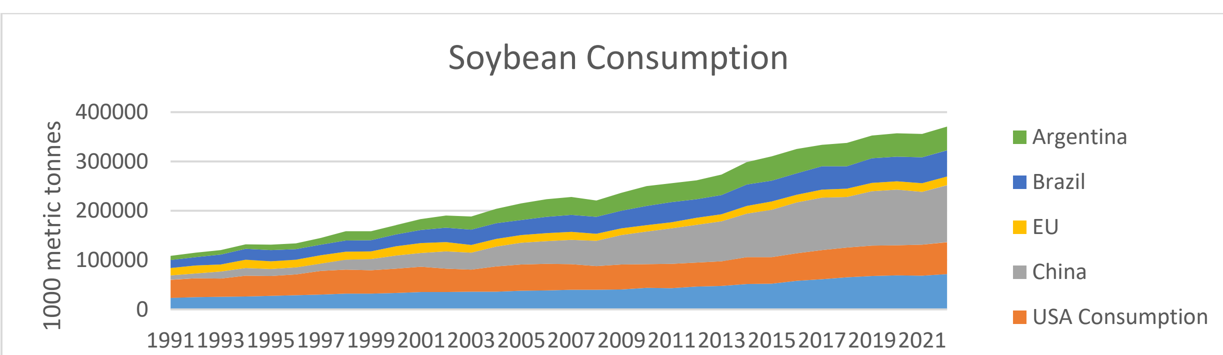

Figure 4.5: Soybean Consumption Trends

4.3.1. Soybean and Corn Import

Figure 4.6 indicates the world's soybean import. The study focused on soybean imports from China and the EU. They import more than 50% of the world's soybean exports. The trends from Figure 4.6 indicated a reduction in soybean imports in 2021. In China, the USDA report suggested that the reason for this is China's recovery from the African Swine Fever and Covid-19

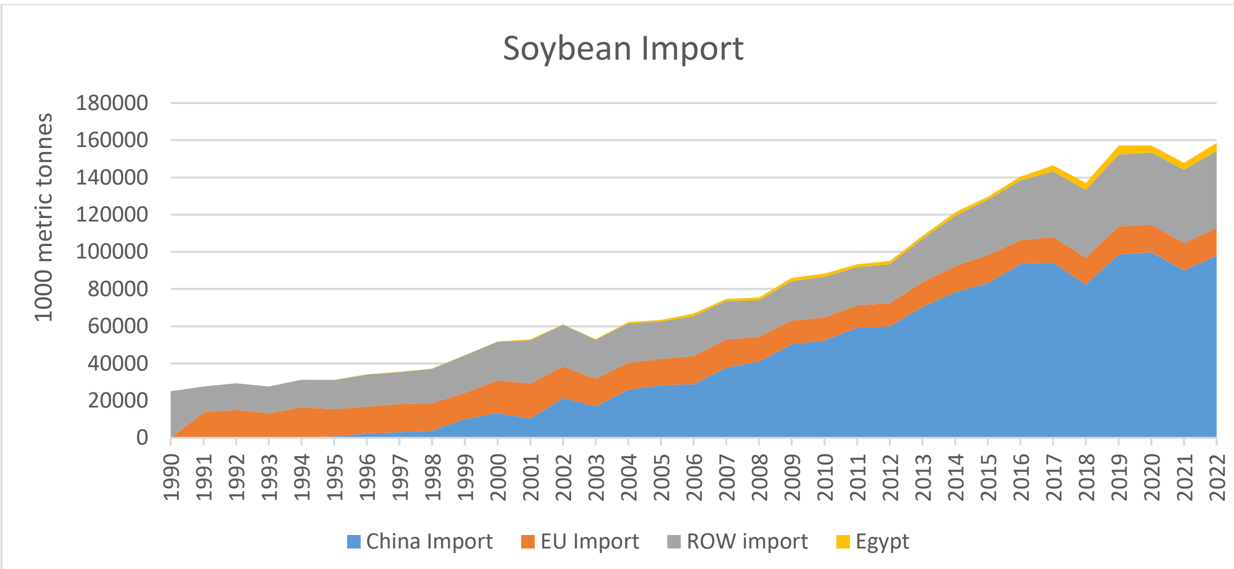

Figure 4.6: Soybean Import Trend.

Figure 4.7 indicates the corn import trend for the EU, China, Egypt, Mexico, Japan, and the rest of the world. Figure 4.7 indicates that the rest of the world imports more corn, followed by China, the EU, Japan, Mexico, and Egypt. The trend also indicated that during the COVID-19 period and in 2022, corn imports by these countries decreased.

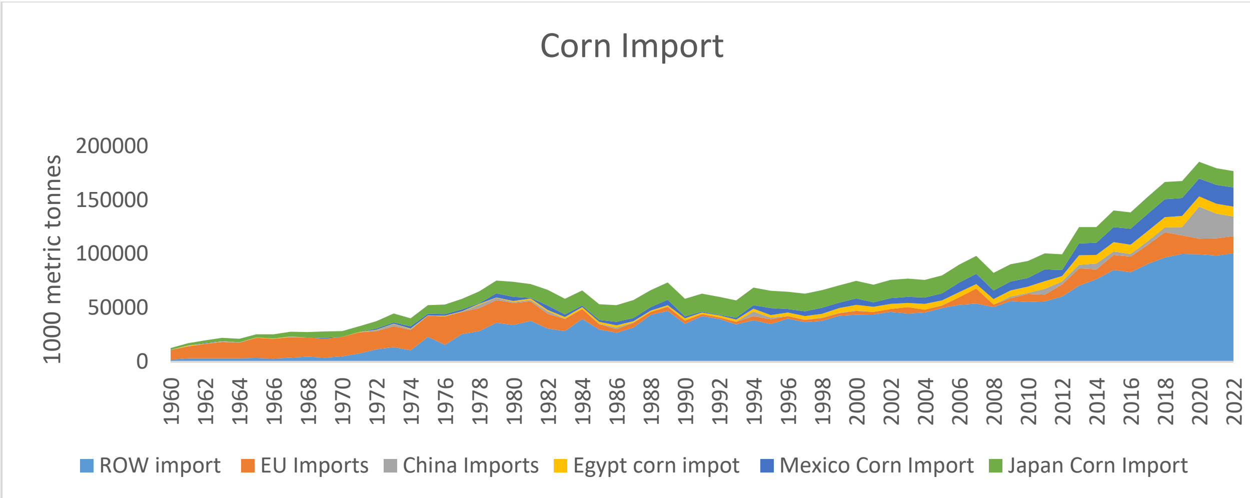

Figure 4.7: Corn Import Trend.

4.4. Data Testing, Preliminary Model Results, and Soybean and Corn Forecast

The study first tested for unit root to ensure that the data for the analysis were stationary. Next, the study used the Augmented Dickey-Fuller test to test for stationarity. With the Augmented Dickey-Fuller test, the null hypothesis suggests that the data is not stationary, while the alternative hypothesis states that there is stationarity of the variable. From the unit root test, most variables became stationary at a p-value of 0.05% after the first differencing. The result of the Augmented Dickey-Fuller test is presented in Table 4.1.

Table 4.1: Unit Root test

Variables	Without differencing (p-value)	First Differencing
Export	0.9083	0.0000
Beginning stock	0.0020	
Crush	0.7592	0.0000
Domestic consumption	0.8911	0.0000
Feed waste	0.0127	0.0000
Industrial consumption	0.9783	0.0000
Production	0.6932	0.0000
China Domestic consumption	0.9991	0.0000
China Production	0.0005	
Argentina Export	0.0303	
Brazil export	0.9986	0.0000
EU Domestic consumption	0.5710	0.0000
EU Production	0.8898	0.0000
Brazil production	0.9983	0.0000
Ukraine Export	0.7490	0.0000
Russia Export	0.9682	0.0000
Population	0.0001	

The study used ordinary least squares and four-period weighted moving averages for the forecast. The four-period weighted moving averages provide a more accurate prediction (Hatchett et al., 2010; Taylor et al., 2006; Dhuyvette and Kasten, 1998).

The result from the OLS model is presented in Tables 4.2 and 4.3. The results from the OLS estimations were subjected to an autocorrelation test, heteroscedasticity test, and multicollinearity test. The Durbin-Watson test and the variance inflation factor revealed negative autocorrelation and multicollinearity. However, the test for heteroscedasticity revealed that the variables were homogeneous when the Breuch-Pagan Lagrange multiplier test was conducted.

Table 4.2: OLS model Results for Soybean and Corn

Variables	Brazil		Argentina	
	Soybean	Corn	Soybean	Corn
Beginning stock	0.68***	0.24**	0.55***	0.99***
Crush	7.25***		2.57	
Domestic consumption	-7.81***	-2.13***	-3.23	-1.25***
Feed waste/ consumption	6.15***	1.79***	2.14	0.87
Industrial consumption	7.58***	1.68**	0.23	0.28
Production	0.51***	0.65***	0.52***	0.99***
Multiple R	0.9960	0.9842	0.9709	0.9999
R Square	0.9920	0.9745	0.9426	0.9999
Adjusted R Square	0.9903	0.9723	0.9303	0.9987

***, **,* means 1%, 5% and 10% significant respectively

The results from the OLS from Table 4.3 revealed that Brazil's soybean export, China's soybean consumption, Argentina's soybean export, Ukraine's soybean export, industrial consumption, and USA production significantly influenced USA soybean export. On the other hand, Brazil's soybean exports, Argentina's soybean exports, and Ukraine's soybean exports negatively influenced USA exports. The reason is that these countries, especially Brazil, are the major soybean competitors to the USA in the international market, and they compete for the market share in the world. (Montanía et al., 2021). Therefore, from the OLS result in Table 4.2, a 1% increase in Brazil's soybean export will lead to a 0.31% reduction in the US soybean export.

Furthermore, a 1% increase in the exports from Ukraine and Argentina will lead to 3.8% and 0.65% in US soybean exports, respectively.

Table 4.3: Regression Analysis of the USA Soybean and Corn Exports

Variables	Soybean	Corn
Beginning stock	0.228536	0.11***
Crush	-79.21	
Domestic consumption	79.48907	3.64
Feed waste	-81.804	-4.07
Industrial consumption	-4.19891***	-4.06
Production	0.375477***	0.19***
ChinaDomesticconsumption	0.704352***	0.37**
ChinaProduction	-0.264	0.02
Argentina Export	-0.64829***	0.11
Brazilexport	-0.31422**	-0.06
EUDomesticconsumption	0.052035	0.48**
EUProduction	1.953549	-0.06
Brazilproduction	0.073423	-0.26
UkraineExport	-3.83878**	-0.33
RussiaExport	-2.35154	
Population	-0.00025*	0.7E-03
Multiple R	0.991119	0.9096
R Square	0.982318	0.8274
Adjusted R Square	0.972562	0.7675

***, **,* means 1%, 5% and 10% significant respectively

Furthermore, the result indicated that production positively influenced US exports. This shows that a 1% increase in USA production will lead to a 0.4% increase in US soybean export. However, from Table 4.3, US corn export is influenced by beginning stock, China's domestic consumption, EU domestic consumption and the US corn production.

4.5. Production Forecast

Figure 4.8 shows the production forecast for Brazil, the USA, and Argentina from 2022 to 2029. The forecast revealed that soybean production would experience an increase in 2021/2022 in Brazil and USA. However, the forecast also indicated that the US soybean production in the 2022/2023 market season was reduced. The probable explanation for the reduction in soybean production in 2022 is because of poor weather conditions in soybean-producing states in the United States and the increase in the cost of production, especially fertilizer. The USDA Reports(2022) revealed that soybean production in the US reduced by 4% due to unfavorable weather conditions in August. The forecast is consistent in the Ates (2022) oil crop report of the USDA.

Furthermore, Brazil's soybean production reached its peak in 2022. The reason is the increase in their export due to the devaluation of their currency to the dollar (*USDA ERS, 2022*). This made them competitive with the USA. However, Argentina, on the other hand, experienced a decline in soybean production in 2022. The primary reason is poor weather conditions ('UPDATE 2-Argentina's Soy Crop Forecast, 2023). Furthermore, the Argentine government's increase in soybean export taxes discouraged farmers from growing soybeans (Bloomberg, 2022).

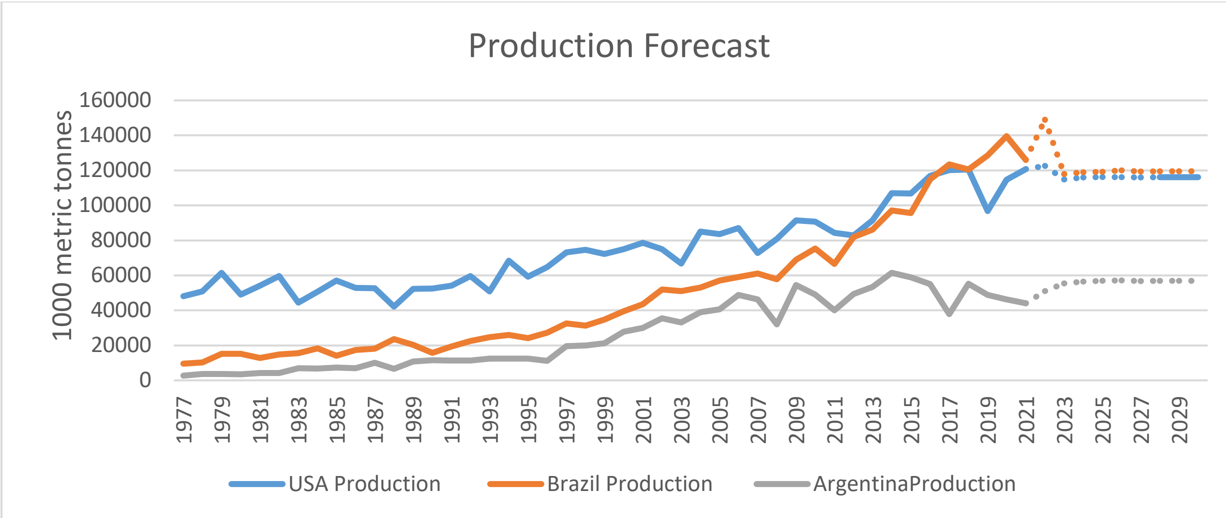

Figure 4.8: Soybean Production Forecast

Figure 4.9 presents the corn forecast for the USA, Brazil, Argentina and Ukraine. From Figure 4.9, it was forecasted that corn production would decline in the USA, Brazil and Argentina. The decline in the US production forecast is caused by increased input costs (USDA, 2022). Also, Argentina and Brazil's forecast declined because of poor weather. The forecast for Brazil is inconsistent with the USDA (2022) corn forecast, which predicted an increase in Brazil's Corn Production. This disparity is because our forecast model did not capture the Brazil-China 2022 contract, which induced an increase in corn production in the second season.

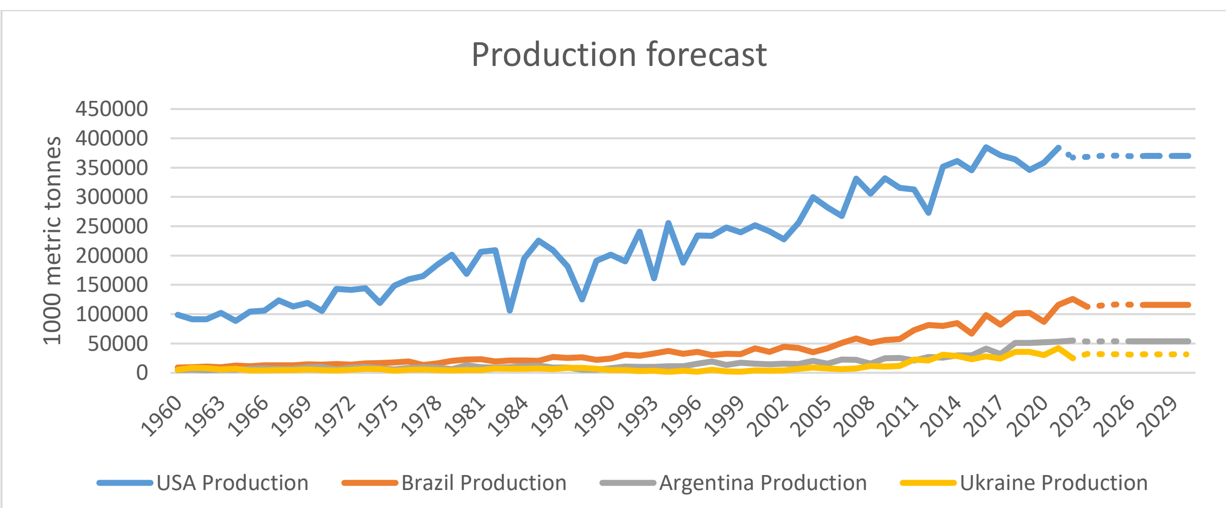

Figure 4.9: Corn Production Forecast

4.5.1. Soybean and Corn Export Forecast

Figure 4.10 shows the soybean export forecast for the USA, Brazil, and Argentina from 2022-2029. The forecast from Figure 4.10 indicated a reduction in the USA soybean exports. The decline in soybean exports in 2022 is because of a reduction in China's soybean imports and the flattening of soybean imports from the EU. China's import reduction is due to increased soybean prices (USDA Soybean Export Highlights, 2021).

Comparatively, soybean exports from Brazil increased in 2022. However, according to the USDA, the increase was not as high as compared to 2021. The reason for the increase is the price competitiveness of Brazil's soybean with the US soybean (USDA Soybean Export Highlights, 2021). This result is consistent with the USDA soybean export report. However, Argentina's soybean exports reduced in 2022. The reduction of soybean exports is due to the reduced soybean production in 2022, as reported by ('UPDATE 2-Argentina's Soy Crop Forecast Cut Again as Extreme Weather Bites', 2023). The reason is due to poor weather conditions.

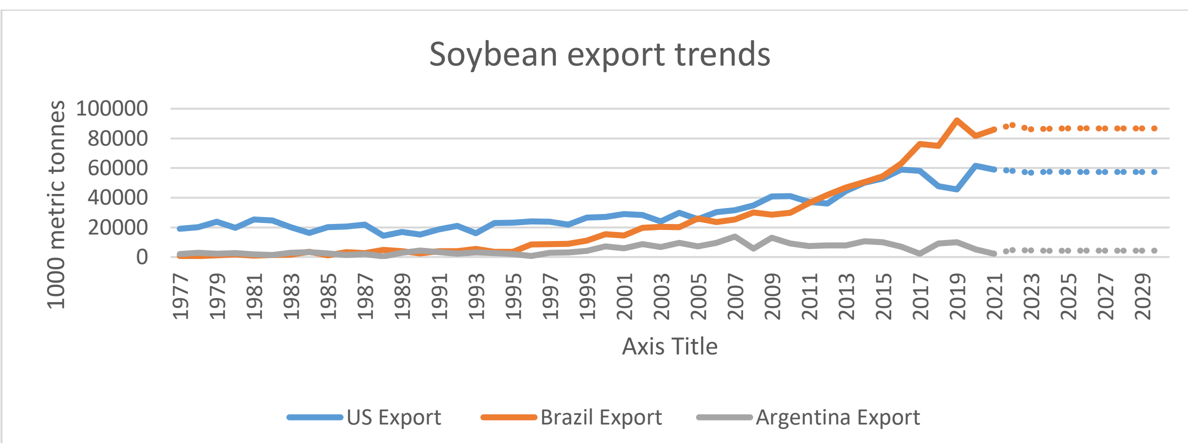

Figure 4.10: Soybean Export Forecast

The inconsistency in China's soybean import behavior should worry soybean exporters. This suggests that soybean exporting countries must search for a new market partner and be flexible when dealing with tariffs imposition on China's exports to their economy.

Furthermore, Figure 4.10 shows the corn export forecast for the USA, Brazil, Argentina, and Ukraine from 2022 to 2029. From Figure 4.11, the forecast indicated a decline in USA corn exports in 2023. However, the forecast indicated an increase in Ukraine's corn exports in 2023. The reason for the decline in the US corn export is price competition from their major competitor (USDA, 2019). Furthermore, our forecast for Brazil's corn export in 2023 declined. Our forecast is inconsistent with the USDA's (2022) corn export. The reason is that the USDA adjusted their forecasts to capture the Brazil-China contract in October 2022.

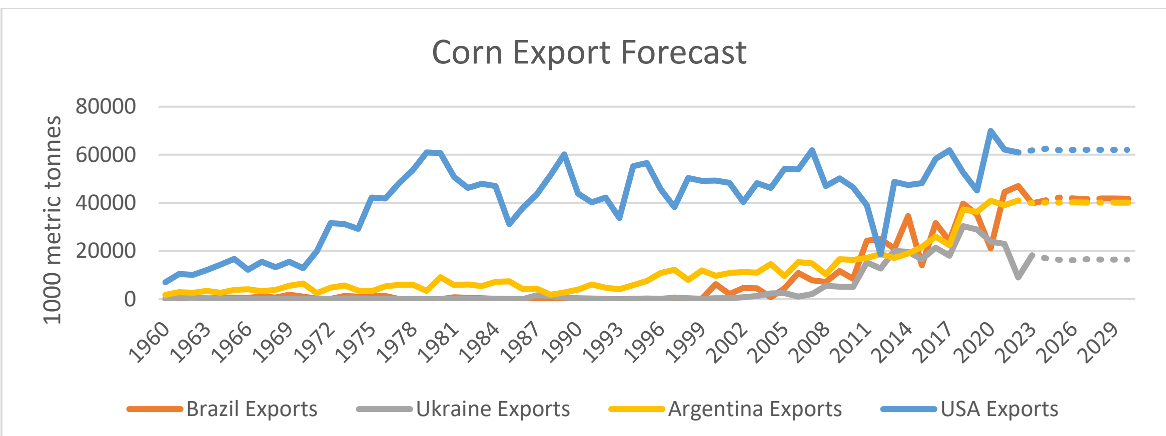

Figure 4.11: Corn Export Forecast

4.6. Empirical Results and Discussion

The econometric results are organized into two sections. First, we examine the source of trade disruption at the international and national levels using the structural equation model. Second, we estimate the intensity of trade disruption on soybean and corn exports at the international and state level.

4.6.1. Identifying the Effects of Trade Disruptors on Soybean and Corn Export

The study used the Eichler (2007) Granger causality model to examine the source of trade disruption at the national level. Furthermore, the study used the Dumitrescu and Hurlin (2012) Granger causality model to determine the source of trade disruption at the international level. The reason for using two different Granger causality models is that, while the national model used time series data, the international model is a panel data model.

First, the study tested for unit root to ensure that the panel and time series data variables were stationary. This ensures that the variables' mean and variance remain constant over time. Table 4.4 shows the unit root results for the variables in the panel data and the time series data. The results in Table 4.4 indicated that most of the variables in the time series data became stationary after first differencing using the Dickey-Fuller test at a 5% significant level. However, beginning stock for soybean was stationary without differencing at a 1% significant level. Finally, export and feed consumption for corn were stationary without differencing at 1% significance.

Table 4.4: Unit Root Test for Time Series and Panel Data

Variables	Without differencing		First differencing	
	Corn	Soybean	Corn	Soybean
Export	0.0001	0.9083.		0.0000
Beginning stock	0.0659	0.0020.	0.0000	0.0000
Crush		0.7592		0.0000
Domestic consumption	0.7313	0.8911	0.0000.	0.0000
Feed waste/ consumption	0.0036	0.0127.		0.0000
Industrial consumption	0.9731	0.9783	0.0045	0.0000
Production	0.0879	0.6932.	0.0000	0.0000
Tariffs	0.1580	0.1975	0.0000	0.0000
War	0.9304	0.9304	0.0000	0.0000
Covid-19	0.9369	0.9369	0.0000	0.0000
Exchange rate	1.1710	1.1710	0.0001	0.0000
Supply	0.1437	0.6932	0.0000	0.0000
	Unit root for Panel Data			
Variable	Without differencing		First Differencing	
	Corn	*Soybean*	*Corn*	*soybean*
Export	0.9888	0.7379	0.0000	0.0000
Crush		0.9353		0.0000
Domestic Consumption	0.9943	0.9866	0.0000	0.0000
Feed waste/ consumption	0.9995	0.5529	0.0000	0.0000
Industrial Use	0.9198	0.9157	0.0000	0.0000
Production	0.9486	0.9347	0.0000	0.0000
Tariffs	0.9404	0.0031	0.0000	
War	0.9930	0.9930	0.0000	0.0000
Covid-19	0.9933	0.9933	0.0000	0.0000
Exchange Rate	0.9574	0.9574	0.0000	0.0000

The unit root result from the panel data also indicated that most of the variables were stationary after first differencing at a 1% significant level. However, soybean tariffs were stationary without differencing.

Table 4.5 first shows the causal effect of how aggregate demand factors affect aggregate supply. While column one used the full panel data sample for the analysis. Column 2 used the time series data of only the USA for the analysis. The initial estimates used the Granger causality for only the observed variables. These variables were production, industrial use of soybean and corn, domestic consumption, feed waste/ consumption, crush, and export.

The findings from Table 4.5 indicated that, internationally, the soybean supply is influenced or caused by export, crush, feed waste, domestic consumption, and production at a statistical significance of 5%. The result suggests that international changes in the export of soybeans influence the supply of soybeans. This result corresponds to the USDA Soybean Export Highlights (2021). This indicates that an increase in soybean exports influences soybean supply. Furthermore, column 1 in Table 4.5 indicated that soybean crush influenced soybean supply at a 1% significant level. This result confirms the USDA *Oilseeds world Market and Trade(2023*) assertion that an increase in soybean crush domestically or internationally increases soybean supply. Domestic consumption and production also influenced the supply of soybeans. However, industrial consumption did not influence soybean supply, but soybean supply somewhat influenced industrial consumption.

Additionally, export, feed consumption, domestic consumption, industrial use of corn and corn production granger caused soybean supply globally. This means that global corn supply is influenced by corn export, feed consumption, domestic consumption, industrial use of corn and corn production. The result suggests that changes in these variables affect the global corn supply. The result corresponds with USDA 2023 corn market outlook.

Column 2 in Table 4.5 indicates that soybean export, crush, domestic consumption, and production influence the USA soybean supply. The results in column 2 of Table 4.5 implied that USA soybean supply is correctly predicted by export, domestic consumption, soybean crush, and soybean production. The result confirms the USDA (2023). On export, the USDA reported an increase in soybean supply in 2021 due to an increase in soybean export (USDA, 2021).

However, industrial use does not influence USA soybean supply; somewhat, changes in soybean supply influence soybean industrial use at a significant level of 1%. The probable explanation is that changes in soybean production lead to a change in the industrial use of soybeans.

Furthermore, it was indicated that feed waste, industrial use, and production influence the US corn supply at 1% significant level. Also, Table 4.5 revealed that corn export and domestic corn consumption influence corn supply at 10% significant level.

Table 4.5: Structural Equation Model (Granger Causality between Soybean and Corn Supply and Observed Variable)

Variables	1. World P-Value		2. USA P-Value	
	Corn	Soybean	Corn	Soybean
Export Granger cause Supply	0.000	0.0031	0.065	0.005
Crush Granger cause Supply		0.0143		0.059
Domestic consumption Granger caused Supply	0.000	0.0015	0.059	0.025
Feed waste Granger caused Supply	0.000	0.0387	0.000	0.257
Industrial Use Granger cause Supply	0.000	0.223	0.000	0.255
Supply Granger Cause industrial use		0.034		0.000
Production Granger causes supply	0.000	0.000	0.035	0.011

The study then analyzed how the trade disruption influenced supply through export. The trade disruptors were the Russian War, Tariffs, Covid-19, and the exchange rate. This is presented in Table 4.6. Globally, Table 4.6 indicated that Russian wars, Covid-19, exchange rate, and tariffs influenced Global soybean export. The findings in column 1 indicate that war from Russia influences global soybean export. The result confirmed the assertion made by Paulson et al. (2022) that the tension between Russia and Ukraine will affect global soybean export.

Furthermore, in column 1, tariffs significantly influenced the global soybean export at a 1% level. This report confirms Grant et al. (2021) analysis that tariffs influence soybean export. Finally, the finding revealed that covid-19 and exchange rate volatility influenced the global soybean export. Kroner and Lastrapes (1993) revealed that although exchange rate volatility does not directly affect the quantity of goods and services exported, it affects the price of the good, making it more expensive in the international market. Kandilov (2008) also confirmed that exchange rates influence agricultural trade internationally.

Table 4.6: Granger Causality Between Export and Trade Disruptors

Variables	1. World P-Value		2. USA P-Value	
	Soybean	Corn	Soybean	Corn
War Granger caused Export	0.0001	0.0000	0.015	0.780
Covid-19 Granger caused Export	0.0002	0.0000	0.913	0.707
Exchange rate Granger caused export	0.0000	0.0035	0.165	0.012
Tariffs Granger caused export	0.0002	0.381	0.044	0.001

Additionally, the results from column 2, in Table 4.6, indicated that Russian Wars and tariffs affect USA soybean export at a significant level of 1%and 5%, respectively. This means that wars in Russia can potentially hurt the US soybean export directly or indirectly through increasing input prices or geopolitics among their allied countries. Finally, it has been proven that tariffs on soybean export from the USA have influenced the quantity of soybean exported (Fedoseeva & Zeidan, 2022).

Additionally, Table 4.6 indicated that global corn export is influenced by news from the Russian war, Covid-19 and the exchange rate at 1% significant level. Elleby et al. (2020) suggested that Covid-19 affected corn export. Furthermore, Table 4.6 indicates that corn exports are influenced by the exchange rate globally. This finding is consistent with Babula et al. (1995).

To determine the direction of influence that trade disruptors had on the USA corn and soybean export, the study used a vector autocorrelation regression model. The reason for using the VAR is that it makes it possible to determine the impulse response, and it helps to determine whether there is a long-run relation among the variables. First, the study tested for cointegration using the Johansen test to achieve this. The Johansen test for soybean and corn revealed cointegration among the variables at lag 1 and lag 3, respectively. This is because, at those lags, the trace statistics were smaller than the critical value. The results of the cointegration test are presented in Table 4.7. The presence of cointegration suggests that using the VAR model for the analysis is appropriate.

Table 4.7: Results from the Johansen Test for Soybean and Corn

Maximum rank	Eigenvalue	Trace statistics	Critical Value
0	-	77.3328	68.52
1	0.6581	31.1865	47.21
2	0.37490	10.9832	29.68
3	0.17820	2.5441	15.41
4	0.0574	0.0023	3.76
5	0.0000	0.0023	3.76
Johansen Test for corn			
0	-	78.4461	6852
1	0.48966	50.8662	47.21
2	0.40312	29.7083	29.68
3	0.36347	11.1875*	15.41
4	0.19566	2.2602	3.76

Furthermore, to identify the number of lag-order selections. The study used the vector ranking regression model for this purpose. The study used the vector ranking regression model because it makes it easy to select the lag order using the measure of model fit. The study used the AIC measure to select the lagged order. It provides the best predictive accuracy of the model fit and asymptotic efficiency (Aho et al., 2014; Akaike, 1978).

Furthermore, Bai et al.(2018) identified that it is easy to use and interpret the AIC compared to the other measure of model fit. The vector ranking regression model result indicated that the lag-order selection was lag-order four using the AIC. The result of the lag-order selection model is in 4.8.

Table 4.8: Lag-order Selection

Lag	AIC	HQIC	SBIC
0	4.730207	4.82338	4.98284*
1	3.65956	4.29878*	4.41494
2	4.27192	5.45902	7.53188
3	4.19032	5.834	8.70412
4	3.10741*	5.20767	8.87504

The result from the vector autoregression, as shown in Table 4.9, indicated that tariffs, the Russian war, and exchange rates negatively affect USA soybean export at 5% significant levels and 1% significant levels, respectively. Table 4.9 indicates that a percent tariff increase would lead to a 2% decrease in USA soybean exports. This result is consistent with the findings of Grant et al. (2021). Also, it confirms Martin et al. (2008) on the effect tariffs have on exports. Furthermore, the result indicated that a 5% increase in the news concerning the Russian war would lead to a 3% decrease in USA soybean exports. This is true because the Farm and Ranch Guide(2022), in their report, realized that wars from Russia had a negative but indirect influence on soybeans. Finally, with exchange rate volatility, it was revealed that a percentage increase in exchange rate volatility would reduce US exports drastically.

Additionally, Table 4.9 indicated that tariffs negatively influenced USA corn exports. This means that increasing tariffs from China will reduce US corn exports. This result was consistent with the USDA report (2021). Furthermore, the result is consistent with Cheng et al.(2023).

The study runs a model fit test on the VAR model. The result from the model revealed a minimum mean of $3.02e^{-10}$, which is close to zero. Furthermore, the autocorrelation test showed no autocorrelation in the model.

Table 4.9: Vector Autoregression Result of the Direction of Influence Trade Disruption on USA Soybean and Corn Export

Variables	Soybean Coefficient	Corn Coefficient
War	-0.0306**	-0.0184
Covid-19	0.1400	-0.0829
Exchange rate	-0.4300***	.9097**
Tariffs	-0.0202**	-00861***
R^2	0.9437	0.9561
Log-likelihood	38.66873	146.9359
AIC	-1.379941	-1.9467

***, **,* means 1%, 5% and 10% significant respectively

4.6.2. Impulse Response

The results from the impulse response are shown in Figure 4.12. Figure 4.12 indicates that COVID-19 shock had a short-term impact on US soybean exports. This result makes sense because, during COVID-19 in 2020, the USA recorded an increase in soybean exports to China (USDA report). Furthermore, Figure 4.12 indicates that reports on war from Russia have a lasting effect on the US soybean exports. It revealed that from the first period to the fourth, although stable, news of war from Russia had a negative impact on US soybean exports. In addition, from the fourth to the eighth period, the impact of war on Russia is still negative. Furthermore, the impulse response function graph indicated that the early stage of tariff imposition on US soybean export has a negative impact on US soybean export and becomes stable in the long run, although negative, but stabilizes.

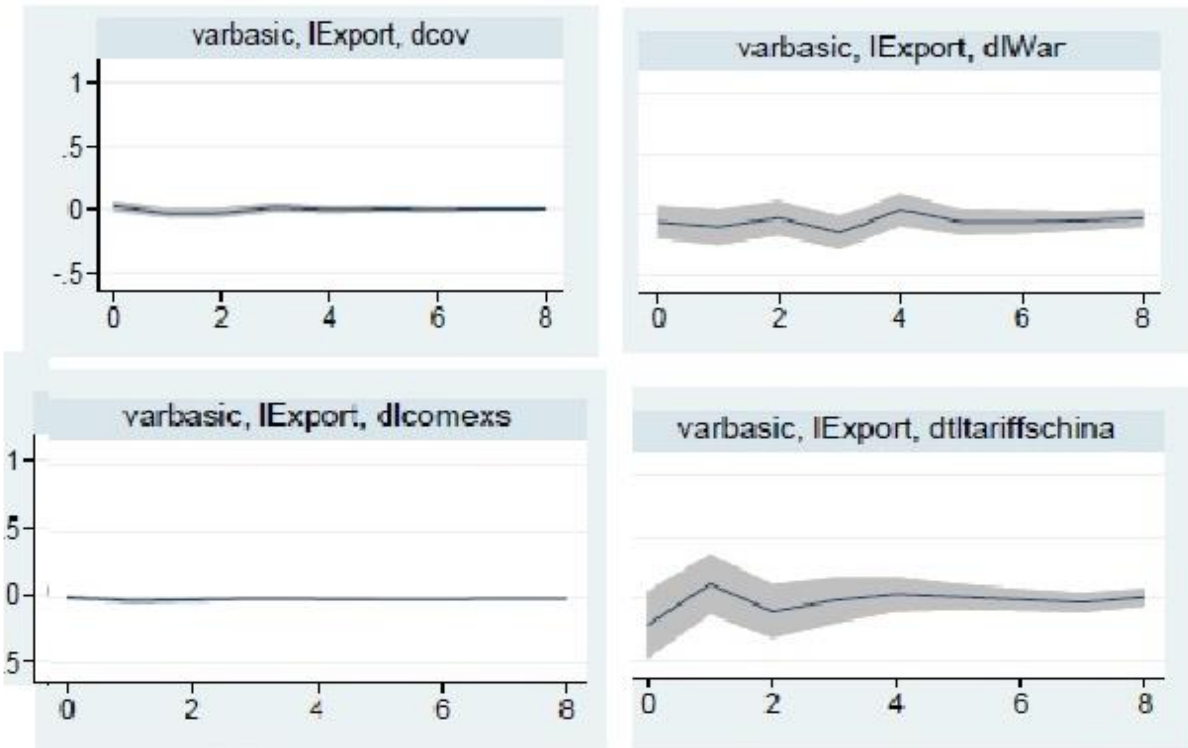

Figure 4.12: Impulse Response Graph

4.6.3. Estimating the Intensity of Trade Disruptions on Soybean and Corn Export

In estimating the intensity of trade disruption on soybean export, the study used a Panel GARCH Model. The reason is that trade disruption makes exports volatile. As a result, the study used the panel GARCH model to capture export volatility. First, the study estimated an OLS model. This pooling model allowed the estimation of time dynamics and individual specifics of the variables simultaneously. After which, we assume the existence of a fixed effect using a robust fixed effect. The study then tested for homogeneity in the variance using the Bruech-Pagan test. The null hypothesis suggests the presence of homogeneity in the variance, while the alternative hypothesis suggests the existence of heteroscedasticity. The result from the Bruech-Pagan test suggested the presence of heteroscedasticity at a 1% significant level.

Furthermore, the study tested for autocorrelation using the Wooldridge test based on the LM statistics. The Wooldridge test assumes a null hypothesis of no serial autocorrelation and an alternative hypothesis of the existence of serial autocorrelation. The test revealed the presence of serial autocorrelation in the fixed effect. Finally, we tested for the arch effect in the model. The result from the model revealed the presence of arch disturbance. This suggests that it is appropriate to use the Arch model.

The study estimated the AR (1) specification for the conditional mean equation to begin estimating the arch model. Then, from the AR (1) equation, Ljung-Box Q-statistics, and partial autocorrelation were computed for the residual. The result indicated the presence of serial autocorrelation at lag 1, which supports the application of the GARCH (1, 1) model.

Table 4.10 and Table 4.11 show the results of the various panel model specifications for soybean and corn exports. For comparison, the study showed the fixed effect and OLS results in columns A and B, while the ML panel GARCH model with the variance equation in column C. The information criteria value of the models was also estimated. From Tables 4.10 and 4.11, the Akaike information criteria for the GARCH effect was smaller than that of the fixed effect and the pooled OLS, which indicates that the GARCH model was a better model for the analysis.

Table 4.10: Panel GARCH Estimation Result Global Model for Soybean

Variable	Column A (OLS)	Column B Fixed effect	Column C Panel GARCH
Lagged Export			0.9882862***
News on War	0.2662627	.2488509**	-0.0207416***
Exchange rate	1.07889	-.1082459	0.1039016***
Tariff	0.0206192	.0619502	-0.0269389*
Supply	-0.2498284	.0077069	0.3491474***
Covid-19	1.250497	1.215713**	-0.1682421***
Arch (1)			0.8134569***
Garch (1)			0.1388569 ***
AIC	1671.762	1205.938	409.7716

***, **,* means 1%, 5% and 10% significant respectively

Table 4.11: Panel GARCH Estimation Result Global Model for Corn

Variable	Column A(OLS)	Column B Fixed Effect	Column C Panel GARCH
Lagged Export			0.833***
News on War	0.001***	0.0009***	0.0007
Exchange Rate	0.024**	0.039***	0.011***
Tariffs	0.001	-0.008	-0.004
Supply	0.205***	0.205	0.105***
Covid 19	0.265	0.428	-0.1593***
Arch(1)			0.276***
Garch(1)			0.680***
AIC	1270.55	1031.169	596.255

***, **,* means 1%, 5% and 10% significant respectively

The result from the mean equation of the GARCH model in Table 4.10 indicated that lagged exports significantly influence global soybean export, news from the Russian war, covid-19, exchange rate volatility, and production at a 1% significance level. With lagged export it was revealed that the lagged export positively affected future exports. This suggests current exports will have a positive trend on future exports, all other things being equal. Also, news on the Russian war negatively affects global soybean exports. This suggests that in the long run, if the war should continue, it will have a negative influence on the soybean supply. The result is in conjunction with Paulson et al. (2022) assertion that if the war is not curtailed, it will have a lasting effect on soybean export in the long run. The exchange rate and production were revealed to impact soybean export positively. The result from production was in line with the a-prior expectation of the study.

However, the tariff was not significant. Therefore, the implication is that tariffs will not affect soybean exports in the long run. This confirms Kee et al. (2013) assertion that, in the long run, exporters adjust to the trade environment through changes in production patterns and trade partners.

Additionally, the conditional variance model of the GARCH model revealed that the Arch(1) was significant at a 1% significance level, and it was positive. This implies that the magnitude of the error term increases over time and indicates the volatility of soybean exports. Furthermore, the GARCH(1) in the model in the conditional variance equation was positive and significant. The implication is that there is persistent volatility in the error term in the model. This implies that past shocks to volatility have a lasting effect on current volatility. This also implies that any large changes in the series will significantly change future volatility. Therefore, the positive sign of the GARCH (1) indicates high future volatility in global exports. Finally, the stability condition of the model suggested that the GARCH model fits the analysis.

Furthermore, the panel Garch model for corn in Table 4.11 indicated a conditional variance with a positive Arch(1) significant at 1%. This implies that the error term's magnitude increases over time and indicates that corn exports is volatile. Also, the GARCH (1) was positive and significant at 1%. The implication is that there is persistent volatility in corn exports. The mean equation suggested that lagged corn export, corn supply, exchange rate, and covid-19 significantly influenced corn export at 1% significant level. Covid-19 influence on corn export was negative. This result is consistent with Mallory (2021) finding.

4.6.4. Risk Trade Disruptors have on Export

The study estimated the trade disruptors' risk on soybean export. First, the study used the estimates of the panel GARCH model in Tables 4.10 and 4.11 to estimate the risk these trade disruptors have on exports. Then, from the GARCH-Value at Risk estimates, as shown in Table 4.8, the study calculated the magnitude of the risk trade disruption will have on export at 90%, 95%, and 99% confidence intervals.

The result from the value at risk indicates the maximum potential loss that exporters can incur over a period. Table 4.12 indicates that the value at risk for a 90% confidence interval was -1.0861 for soybean and -2.602 for corn. This indicates that the maximum loss to soybean and corn exporters at a 90% confidence interval is 1.08% and 2.602% in a given year. Furthermore, at a 95% confidence interval, the result from the value at risk was -1.3941 and -3.3406 for corn and soybean, respectively. This means that the maximum loss soybean and corn exporters will incur at a 95% confidence interval is 1.39% and 3.3406% in a given year. Finally, at a 99% confidence interval, the value at risk was -1.9717 and -4.7246, indicating that the maximum loss of soybean export to exporters is 1.97% and 4.7246% over the given horizon.

Table 4.12: Results from GARCH-VaR for Global Export

Confidence interval	90%	95%	99%
Soybean value	-1.0861%	-1.3941%	-1.9717%
Corn Value	-2.6027	-3.3106	-4.7246

***, **,* means 1%, 5% and 10% significant respectively

4.6.5. Impact of PLC (Price Loss Coverage) in Mitigating Trade Disruption Risk

The study estimated the risk these trade disruptors had on the US soybean export. The study used the GARCH-VaR model to estimate the risk. To achieve this, the study analyzed the risk from the trade disrupters assuming PLC had not been introduced and later analyzed the risk when it was introduced. The estimates for the GARCH-VaR were estimated at 90%, 95%, and 99% confidence intervals. Table 4.13 presents the VaR estimates for corn and soybean exports with or without the PLC. From the analysis, the VaR estimate for soybean export without PLC in Table 4.9 at 90%, 95%, and 99% confidence interval was -0.5629, -0.7225, and -1.0218, respectively. Given the trade disruptors, this indicates that the maximum loss the USA soybean export will incur is 0.56%, 0.72%, and 1.02% at 90%, 95%, and 99% confidence intervals, respectively. Furthermore, Table 4.9 shows a VaR estimate for soybean export with PLC at

90%,95%, and 99% confidence intervals of -0.3950, -0.5070, and -0.7171, respectively. This means that the maximum loss of the US soybean export after introducing the PLC was approximately 0.4%, 0.5%, and 0.7% at a confidence interval of 90%, 95%, and 99%, respectively.

Additionally, the VaR estimates for corn export without the PLC in Table 4.13 are 0.144, 0.185, and 0.261 at 90%, 95%, and 99% confidence intervals, respectively. This means that the maximum loss of the US corn export without introducing the PLC was approximately 0.14%, 0.19%, and 0.26% at 90%, 95%, and 99% confidence intervals, respectively. Also, Table 4.13 indicates that the VaR estimate when the PLC was introduced is 0.127, 0.164, and 0.232 at 90, 95 and 99 confidence intervals. This means that the maximum loss of the US corn export after introducing the PLC was approximately 0.13%, 0.16% and 0.23%, respectively. This suggests that although the PLC was not formulated as a policy to reduce risk from the international market, it has the potential to reduce trade disruption risk as indicated in table 4.9.

Table 4.13: Results from the Impact of PLC Mitigating the Risk from Trade Disruption Using GARCH-VaR

Row/Confidence Intervals	90	95	99
Soybean			
without PLC	0.56%	0.72%	1.02%
with PLC	0.395%	0.51%	0.7%
Corn			
Without PLC	0.144%	0.185%	0.261%
with PLC	0.127%	0.164%	0.232%

The analysis revealed that introducing PLC reduced the loss in soybean and corn exports compared to when it was not introduced. Although this does not directly affect export, the PLC affects export indirectly through production and has a positive relationship with production (Swanson et al., 2019). This also suggests that the PLC does not only help farmers to mitigate price risk but also helps to reduce risk from trade disruptions. Furthermore, it also suggests that increasing PLC payments will help further reduce the risk farmers encounter from this trade disruption.

CHAPTER FIVE: SUMMARY, CONCLUSION, AND SUGGESTIONS

5.1. Summary of Results

Trade disruptions have been an intriguing issue recently, considering the bottleneck it creates in international trade. This study examines how commodity-program payments mitigate risk from trade disruption. The study considered soybean and corn as the significant US crop for this purpose. Relevant tests were conducted to ensure the validity of the result for inference. First, the study tested for stationarity, heteroscedasticity, autocorrelation, cointegration, and Arch disturbance. The study collected Data from the PS&D database.

The specific objectives to achieve the study's goal were i) to examine the source of trade disruption at the Global and National level using the structural Equation Model, ii). To analyze the intensity of Trade disruption using a GARCH model (Panel Garch), iii). Analyze the magnitude of trade disruption risk on soybean and corn farmers using value at risk, iv). Evaluate the impact of relevant farm policies (Price Loss Coverage) in mitigating the shocks from trade disruption. The study collected country data on soybean production, beginning stock, industrial use, domestic consumption, industrial consumption, crush, and feed-waste from PS&D. Furthermore, data on the exchange rate, news on war, covid-19, and tariffs from China were collected from the FED, NEWSBank Inc and World Integrated Trade Solution.

5.1.1. Identify the Effects of Trade Disruptors on Soybean and Corn Export

In identifying the effects of trade disruption at the global and national levels, the first set of analyses confirms the stationarity of the data. Then, having validated the absence of unit root, the study used Granger causality to determine the path diagram. First, the panel data used the Dumitrescu and Hurlin Granger causality model. Second is the time series Granger causality.

From the Dumitrescu and Hurlin Granger causality model results, export, crush, domestic consumption, feed waste, and production were the variables found to affect soybean supply globally and significantly. Furthermore, News from the Russian War, Covid-19, exchange rate volatility, and Tariffs from China significantly influenced soybean exports. This was consistent with Paulson et al. (2022), Grant et al. (2021), and Kroner and Lastrapes (1993).

Also, the study revealed that export, feed consumption, domestic consumption, industrial use, and production influenced corn supply globally. Furthermore, News from the Russian War, the Covid-19 Exchange rate, and tariffs affected global corn export. This was consistent with Grant et al. (2021), and Kroner and Lastrapes (1993)

The study used the US data for the time series Granger causality model. The study discovered that export, crush, domestic consumption, and production influenced soybean supply. The result confirmed the USDA soybean export report in 2021 and the USDA Oilseeds world market and trade report. On trade disruption, the study discovered that news from War and Tariffs from China influenced US soybean export. The results confirm Fedoseeva and Zeidan (2022) assertion that tariffs on soybean export influenced the quantity of soybeans exported.

However, the corn model revealed that export, domestic consumption, feed consumption, industrial use, and production affected the US corn supply. Also, the study discovered that exchange rates and tariffs were the trade disruptors that affected corn exports.

The study used a VAR model to determine the direction of influence and the impulse response. After testing for cointegration and agreeing that it is necessary to use the VAR model, the VAR result revealed that News from war and tariffs from China negatively influence USA soybean exports. This confirms the Farm and Ranch (2022) report that the war from Russia hurt the US soybean export, although it is indirect. The impulse and response analysis showed that war has a long-term effect on soybean exports, while tariffs had a short-term effect. On the other hand, the VAR analysis revealed that exchange rates and tariffs influenced USA corn exports. While tariffs had a negative influence on the US corn export. However, the exchange rate had a positive influence on US corn exports.

5.1.2. Estimating the Intensity of Trade Disruption on Soybean and Corn Export

In estimating the intensity of trade disruption on soybean and corn exports, the study used a panel GARCH model. This was first achieved after running a pooled OLS and a fixed effect model (robust fixed effect). Next, the study used the Bruech-Pagan and Wooldridge test for autocorrelation and heteroscedasticity. The result revealed the presence of heteroscedasticity and autocorrelation. Finally, the ARCH effect and AR (1) specification were tested. The result revealed the presence of ARCH disturbance and serial autocorrelation at lag 1, confirming using the panel GARCH model.

The result from the mean equation from the panel GARCH model revealed that export was significantly influenced by lag-export, news from the Russian war, Covid-19, exchange rate volatility, and soybean supply. The direction of effect indicated that news from Russian War negatively affects global soybean export whiles soybean supply positively influences Global soybean export. Also, the result indicated that lag export, exchange rate, covid-19, and corn supply influenced corn export globally. The direction of effect indicated that tariffs negatively influenced corn exports while exchange rates and corn supply positively influenced global corn exports. The GARCH and ARCH in the conditional variance equation were significant and positive. This indicates that the volatility of exports is not constant but clustered. It also implies persistent export volatility, and changes in the series will lead to significant changes in future volatility in exports.

5.1.3. Risk of Trade Disruptions on Export

The study used GARCH-Value at Risk to calculate the magnitude risk of trade disruption on soybean and corn export. The reason is that it is easier to estimate and provides an accurate result. This is because it provides the risk based on the volatility of exports due to these trade disruptors. The risk was estimated for the global and national levels at 90%, 95%, and 99% confidence intervals. At the global level, it was indicated that the trade disruption risks on soybean export were -1.0861, -1.3941, and -1.971 at 90%, 95%, and 99% confidence intervals, respectively. This indicates that the maximum potential loss of soybean export due to these disruptors was 1.08%, 1.39%, and 1.97% globally. For corn export, the estimated risk was 2.60%, 3.34%, and 4.72% at 90%, 95%, and 99% confidence intervals, respectively. The result of the USA soybean export revealed a 0.56% ($192.5million), 0.72 %($247.6million), and 1.02% ($350.8million) loss of export at 90%, 95%, and 99% confidence intervals, respectively. Finally, the US corn export result indicated 0.14% ($ 26.05 million), 0.19% ($ 35.3 million), and 0.26% ($ 48.3 million) at 90%, 95%, and 99% confidence intervals, respectively.

5.1.4. Impact of PLC on Mitigating the Risk

The study achieved this aim by using Value at Risk to estimate the magnitude of risk trade disruptors had of soybean and corn export when the PLC was initiated. The result revealed a reduction in the risk at 90%, 95%, and 99% confidence intervals, respectively. This suggests that the introduction of the PLC reduced the risk these trade disruptors had on soybean exports. The value-at-risk values for soybean export were 0.395%, 0.51%, and 0.7% compared to 0.56%, 0.72%, and 1.02% loss of export at 90%, 95%, and 99% confidence intervals, respectively. Also, the value at risk values for corn export were 0.127%, 0.164%, and 0.232% at 90, 95 and 99 confidence intervals. This confirms Swanson et al. (2019) assertion that although the PLC does not directly influence export, the policy's influence on production reduces risk from export and is now becoming an essential policy for farmers.

5.2. Conclusion

Understanding the source of trade disruption and its risk to farmers is important to the economy. Research has proven that these disruptors destroy the fruitful relationship countries enjoy from trade. Hence, it is crucial to have a framework that holistically analyses these disruptors and estimates the risk they pose to farmers. Furthermore, it is also essential to examine how the risk can be mitigated using existing commodity program payments. Two crops considered by the study were (soybean and corn) due to their share in export and production. The reason is that soybean and corn contribute about $72 billion and $49.2 billion of the cash receipts. Also, the USA is the world's biggest corn producer and the second soybean producer after Brazil. Therefore, the main concern is that any corn and soybean supply and export risk could harm the US economy. For example, the US-China trade war negatively affected US soybean and corn export in 2018, affecting several US producers.

The result of the study will add new insight to studying trade disruption and its effects on farmers. Furthermore, the study is timely, considering recent happenings in the world. For example, the Russian-Ukraine war, Covid-19, exchange rate volatility, and the recent USA-China trade war.

5.2.1. The Structural Equation Model

Using the path diagram, the result from the structural equation model revealed that covid-19, exchange rate volatility, tariffs from China, and news on the Russian war influenced global corn and soybean exports. On the supply side, the study revealed that globally, export, crush, domestic consumption, feed waste, and production affect global soybean supply. Also, the study revealed that corn export, feed consumption, domestic consumption, industrial use, and production influenced corn supply.

Furthermore, the structural equation model at the national level showed that export, crush, domestic consumption, and production influenced soybean supply. Also, it showed that tariffs from China and news from the Russian war influenced US soybean exports. Furthermore, the study discovered that corn export, feed consumption, domestic consumption, industrial consumption, and corn production influenced the US corn supply. Also, the study revealed that tariffs from China and the exchange rate influenced the US corn export.

First, it can be concluded that global events (the Russia-Ukraine war), tariffs from China, pandemics, and exchange rate volatility affect global soybean exports. This result validates World Bank Commodity Markets Outlook (2022) reports that the Russia-Ukraine war affects agriculture commodity trade. Also, it can be concluded that global events (the Russia-Ukraine war), pandemics, and exchange rate volatility affect global corn exports.

Secondly, it can be concluded that US soybean export is influenced by war from Russia. This confirms the report from the Farm and Ranch (2022). Furthermore, it can also be concluded that maintaining a peaceful trade relationship with China will be an advantage to the USA. This is because tariffs from China also affected the US soybean and corn exports. This conclusion confirms the USDA trends on soybean and corn exports.

5.2.2. The Impact of Trade Disruption on Global and The US Soybean and Corn Export

In examining the impact of trade disruption on global soybean export, it was concluded that war and covid-19 influenced soybean export negatively. This conclusion affirms the world bank’s assertion that the pandemic and the war led to commodity supply shocks that sparked prices (World Bank Commodity Markets Outlook 2022). Therefore, the study can conclude that the absence of war will increase the US trade flow. However, we can conclude that tariffs have a sort-run effect on trade because countries adjust to the trading environment in the long run, as posited by Kee et al. (2013). Furthermore, we can also conclude that the pandemic negatively affects corn exports.

5.2.3. Mitigating the Risk Trade Disruptions Have on Farmers

Finally, the model presents an easy and reliable approach to measuring risk and how existing policies help mitigate it. It was concluded that soybean export is somewhat volatile because of these disruptors. Furthermore, it was concluded that the risk these disruptors pose on soybean and corn exports was significant. No wonder the World Bank Commodity Markets Outlook (2022) reported a disruptive trade system from 2020 to 2022. The study revealed the importance of implementing policies that absorb shocks in the agriculture system. From the result, we can conclude that implementing the price loss average has significantly reduced the risk from these trade disruptors.

5.3. Suggestions

The results from the effects of trade disruption on US soybean export and corn present a holistic way to detect the source of trade disruption. Although this is challenging, it is recommended that researchers consider the importance of latent variables when dealing with trade disruptions. This is because these variables are not directly observed but are inferred from the observed variables. These variables are rare events (pandemics and wars), tariffs, and exchange rate volatility.

Finally, the impact of government program policies to mitigate soybean and corn export suggests that policy makers should use an efficient policy design with accurate and holistic model, as used in this stud

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APPENDIX

Table A1: Unit Root Test

Variables	Without differencing (p-value)	First Differencing
Export	0.9083.	0.0000
Beginningstock	0.0020.	
Crush	0.7592	0.0000.
Domesticconsumption	0.8911	0.0000.
Feedwaste	0.0127.	0.0000.
Industrialconsumption	0.9783	0.0000
Production	0.6932.	0.0000
ChinaDomesticconsumption	0.9991.	0.0000.
ChinaProduction	0.0005	
Argentina Export	0.0303	
Brazilexport	0.9986	0.0000.
EUDomesticconsumption	0.5710.	0.0000.
EUProduction	0.8898	0.0000.
Brazilproduction	0.9983	0.0000.
UkraineExport	0.7490.	0.0000.
RussiaExport	0.9682.	0.0000.
population	0.0001	

Table A2: Regression Analysis for top Soybean Export Countries

	Brazil		Argentina	
Variables	Coefficient	P value	Coefficients	P-value
Constant	-5879.07218	0.370313	-586.443	0.88689
Beginning stock	0.680700995	5.42E-05	0.545427	2.14E-06
Crush	7.25402851	4.57E-05	2.570331	0.725977
Domestic consumption	-7.8130051	5.7E-05	-3.23828	0.657533
Feed waste	6.150237465	0.202435	2.142876	0.770492
Industrial consumption	7.568717532	1E-05	0.231097	0.643732
Production	0.510555434	3.44E-08	0.527093	1.23E-12
population	5.18201E-05	0.466368	4.69E-05	0.750839
GDP	-4.5715E-09	0.002358	-2.6E-09	0.36051
Multiple R	0.996028525			0.970919
R Square	0.992072824			0.942684
Adjusted R Square	0.990358839			0.930292
Standard Error	2751.950039			909.1109
Observations	46			46

Table A3: Regression Analysis of the USA Soybean Exports

	USA	
Variables	Coefficients	pValue
Beginning stock	0.228536	0.164867
Crush	-79.21	0.816451
Domestic consumption	79.48907	0.815899
Feed waste	-81.804	0.810703
Industrial consumption	-4.19891	0.006718
Production	0.375477	0.00493
ChinaDomesticconsumption	0.704352	0.000184
ChinaProduction	-0.264	0.327738
Argentina Export	-0.64829	0.00465
Brazilexport	-0.31422	0.041535
EUDomesticconsumption	0.052035	0.817899
EUProduction	1.953549	0.43693
Brazilproduction	0.073423	0.531619
UkraineExport	-3.83878	0.012684
RussiaExport	-2.35154	0.543491
population	-0.00025	0.042196
Multiple R	0.991119	
R Square	0.982318	
Adjusted R Square	0.972562	
Standard Error	2285.011	
Observations	46	

Table A4: Johanssen Test

Rank	Parameters	Eigen value	Trace stat	Critical stats
0	30	….	77.3328	68.52
1	39	31.1865*	47.21	58.99
2	46	0.37490	10.9832	29.68
3	51	0.17820	2.5441	15.41
4	54	0.05740	0.00023	2.76
5	55	0.0005		

Table A5: Lag-order Selection

Lag	AIC	HQIC	SBIC
0	4.730207	4.82338	4.98284*
1	3.65956	4.29878*	4.41494
2	4.27192	5.45902	7.53188
3	4.19032	5.834	8.70412
4	3.10741*	5.20767	8.87504

Table A6: Fixed Effect Regression and OLS Regression of Export

	Fixed effect			OLS
Variable	Coefficient	P-value	Coefficient	P-value
Lnwar	0.288	0.000	0.266	0.000
tltariffschina	0.062	0.587	0.0206	0.930
dlcomex	-0.108	0.545	1.079	0.001
dcov	1.215	0.056	1.250	0.341
lnSUproduction	0.008	0.959	-0.249	0.423
cons	3.16	0.000	2.753	0.000

TableA7: Heteroscedasticity and Serial Correlation Test

	Fixed effect	OLS
Test	p-value	P-Value
Heteroscedasticity	0.0000	0.000
Serial correlation	0.0003	0.000

Table A8: GARCH Model for Global and USA Soybean Export

	Global			USA With Plc	Without Plc
Variable	Coefficient	P-Value	Variable	Coefficient	P-value
Lag export	0.9882	0.000			
Inwar	-0.021	0.002	Lnwar	0.056***	0.057***
dIcomex	0.104	0.000			
Intariffchina	-0.027	0.093	Lntariffch	-0.025***	-0.23**
lnsupply	0.349	0.000	lnsupply	0.690***	
Cov	0.168	0.016	Cov	0.066	0.293
Constant	-0.1363	0.001		9.469***	9.465***
Arch L1	0.813	0.000		1.639**	1.289**
Garch L1	0.139	0.000		-0.407	-0.290
constant	0.002	0.389		0.002	0.004

TableA9: Unit Root for The USA Corn Data

Variable	Without differencing	First differencing
Export	0.0001	
Beginning stock	0.0659	0.0000
Domestic Consumption	0.7913	0.0000.
Feed Domestic Consumption	0.0036.	
FSI Consumption	0.9731.	0.0045
Production	0.0879.	0.0000
Supply	0.1437	0.0000

Table A10: Unit Root for the Global Corn Data

Variable	Without differencing	First differencing
Export	0.9888	0.0000
Beginning stock	0.0060	
Domestic Consumption	0.9943	0.0000
Feed Domestic Consumption	0.9995	0.0000
FSI Consumption	0.9198	0.0000
Production	0.9486	0.0000
WAR	0.8390	0.0000
Tariffs	0.9047	0.0000.
Exchange rate	0.9622	0.0000
Covid-19	0.9369	0.0000
Supply	0.1437	0.0000

Table A11: GARCH Model for Global and USA Corn Export

	Global			USA With Plc	Without Plc
Variable	Coefficient	P-Value	Variable	Coefficient	P-value
Lag export	0.8330	0.000			
Inwar	-0.0007	0.569	Lnwar	-0.022***	-0.0240***
dIcomex	0.011	0.000		-0.0015	-0.352
Intariffchina	-0.003	0.95	Lntariffch	-0.0065	-0.006
lnsupply	0.1045	0.000	lnsupply	0.0543	0.0796
Cov	0.159	0.016	Cov	0.1208**	0.293
Constant	0.508	0.001		9.8260	12.318
Arch L1	0.0286	0.000		0.930**	0.867***
Garch L1	0.9677	0.000		-1.2585	-1.208***
constant	0.008	0.389		0.002	0.004