Exchange Rate, Crude Oil Price, and Volatility Transmission between International and Domestic Beef and Mutton Prices in Ghana: What Could Be Done?

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Abstract

In the last two and a half decades, the volatility of agricultural commodity prices has become a significant concern for governments, policymakers, farmers, traders, and consumers. This issue gained prominence particularly during the episodic rises in prices from 2007 to 2011, and has been exacerbated by the Covid-19 pandemic and the Russia-Ukraine war. In this volatile global economy, Ghana has relied on imports of livestock and meat products, such as beef and mutton, to supplement its domestic supply. This dependence on foreign imports implies a trade flow between Ghana's domestic meat markets and foreign markets, with the potential for volatility transmission across these markets. To investigate this issue, we employed multivariate GARCH models (DCC & CCC) to assess the nature of volatility transmission between foreign meat markets and domestic meat markets in Ghana. Additionally, we examined the influence of macroeconomic indicators such as crude oil price returns and exchange rates on the volatility of meat returns. Our study utilized monthly data from five countries that traded beef and mutton with Ghana from 2016 to 2020. The findings indicate that the domestic and foreign meat markets are interdependent, particularly in the beef markets, where volatility in foreign markets is transmitted to Ghana's domestic market. The study further reveals that, the instability of key macroeconomic variables, specifically crude oil price returns and exchange rates, significantly impacts the volatility transmission of meat price returns in Ghana. Based on these findings, we recommend that the government of Ghana adopt a coordinated approach to market regulation in the meat sector to help stabilize prices and reduce volatility. This could involve setting standards for quality, hygiene, and pricing among meat importers and traders, as well as monitoring imports to ensure that only certified and licensed traders are involved in the import and trade of foreign meat products. Such measures would help prevent market distortions and contribute to a more stable meat market in Ghana.

Keywords: *COVID-19, Russian–Ukraine War, Multivariate GARCH, Meat Price Volatility, Exchange Rate, and Crude Oil Prices*

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1 Introduction

In the bustling markets of Accra, where vendors negotiate prices and consumers stretch their cedis to make ends meet, the fluctuating costs of essential goods like beef and mutton significantly impact daily life. Imagine a family suddenly forced to alter their dietary habits or reduce their

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protein intake due to abrupt spikes in meat prices, triggered by global events or exchange rate instability. This scenario is not merely a localized issue but reflects a broader economic challenge faced by many developing countries, where food price volatility can undermine food security, disrupt livelihoods, and exacerbate poverty.

In fact, over the past two and a half decades, agricultural commodity price volatility has become a pressing concern for various stakeholders, including governments, policymakers, farmers, traders, and consumers (Gilbert & Morgan, 2011; Sumpsi, 2013; von Braun & Tadesse, 2012). This concern is especially pronounced in developing, food-deficit countries, where a significant majority of households allocate between 70% and 75% of their income to food expenditures (Global Panel, 2016).

Volatility in this context refers to situations where market prices or quantities of a commodity deviate significantly from their normal, seasonally-variable thresholds (FAO et al., 2011; Kalkuhl et al., 2016; Tothova, 2011). This variability can be attributed to three main categories of shocks: policy shocks, market shocks, and social stability shocks (Kalkuhl et al., 2016; Pieters & Swinnen, 2016; Gilbert & Morgan, 2011). Policy shocks affect domestic production and consumption, including the impact of exchange rate and crude oil price fluctuations on domestic prices (Miranda-Agrippino & Ricco, 2017). Market shocks arise from actual production and consumption, influenced by weather and input price changes (Antonakakis et al., n.d.; Kilian, 2006). Social stability shocks, such as conflicts and disease outbreaks like the Russia–Ukraine conflict and the COVID-19 pandemic, further compound these issues (Adam, 2011; Rigolini et al., 2023; Steensland, 2022).

Globalization has strengthened the linkages among food, energy, and financial markets, making shocks in one sector more likely to affect others (Prasad et al., 2007; Wilkinson, 2019). This interconnectedness raises the critical question of how food markets are adapting to these shocks, especially as climate change increases the likelihood of significant weather-related disruptions in agriculture (Amare et al., 2018).

The global food crisis of 2007-2008 exemplifies the volatility of food prices, including those of meat, as a significant economic challenge for governments and stakeholders worldwide (Brobakk & Almås, 2011; Charnavoki & Dolado, 2013; Kidane et al., 2011). Although food price hikes moderated in 2009, recent factors such as rising crude oil prices (Fernández & Bs, 2014; Obadi & Korček, 2014), exchange rate fluctuations (López & Nguyen, 2015), and ongoing global challenges like the COVID-19 pandemic and the Russia-Ukraine conflict have driven food prices and their volatility upward (Hassen & Bilali, 2022; Desalegn & Tangl, 2022; Paudel et al., 2023).

For many Sub-Saharan African (SSA) economies, which are food-deficit and reliant on imports, food price volatility is a recurring issue with significant economic, policy, and governance implications (Arment & Arment, 2019; Kidane et al., 2011; Rajaonarison, 2016). In SSA, the volatility in meat prices is particularly notable due to the region's growing middle class (Abdallah et al., 2020; Balanay, 2013). Price volatility affects both food producers, who are also net food buyers, and urban consumers. Therefore, analyzing meat price volatility and understanding the cross-border transmission of these effects is crucial in the sub-region. The impact of price volatility on the availability, accessibility, and stability of meat and meat products underscores the importance of this research (Abdallah et al., 2020; Balanay, 2013; FAO, 2019).

The recent surge in price inflation, coupled with various risks and uncertainties, has exacerbated food price volatility. The disequilibrium created by supply and demand gaps during episodic price rises, such as those witnessed in 2007-2008, and the current challenges resulting from the COVID-19 pandemic and the Russia-Ukraine war contribute to this volatility (Urak et al., 2023; Abdallah et al., 2020). Given that international meat price fluctuations are likely to transmit volatility to the domestic markets of importing countries, it becomes essential to analyze these dynamics, particularly in the context of Ghana (Destiarni et al., 2021; Mittal et al., 2017; Rapsomanikis & Sarris, 2008; Tiwari et al., 2019). This is due to the fact that, the ongoing global economic crisis has intensified volatility in food commodity markets across Africa. Macro-economic variables like crude oil prices and exchange rate fluctuations further destabilize food prices, including meat (Dadzie et al., 2023; Damba et al., 2019; Du et al., 2011). In response, several African countries, including Ghana, have implemented fiscal policy changes, such as tax increases on essential goods, exacerbating price rises (Mkalama, 2022; Dadzie et al., 2023). Recent evidence indicates that the COVID-19 pandemic's lockdowns and policy restrictions affected demand and supply dynamics, leading to price shifts in major food staples (see Adeeth et al., 2022; Mohiuddin, 2023; Rossouw

& Greyling, 2022).

In the face of these challenges, analyzing food price volatility becomes imperative for developing effective coping strategies and maximizing benefits (Kuwornu & Mensah-Bonsu, 2011). However, while most studies focus on domestic market transmission, few delve into cross-border price volatility and its transmission in Ghana, especially concerning the effects of crude oil and exchange rates (Oyewumi & Sarker, 2010; Baidoo, 2014; Phan & Roques, 2015; Annan-Phan & Roques, 2018; Guo & Tanaka, 2022). This gap highlights the need for a nuanced understanding of cross-border food price volatility and its contributing factors.

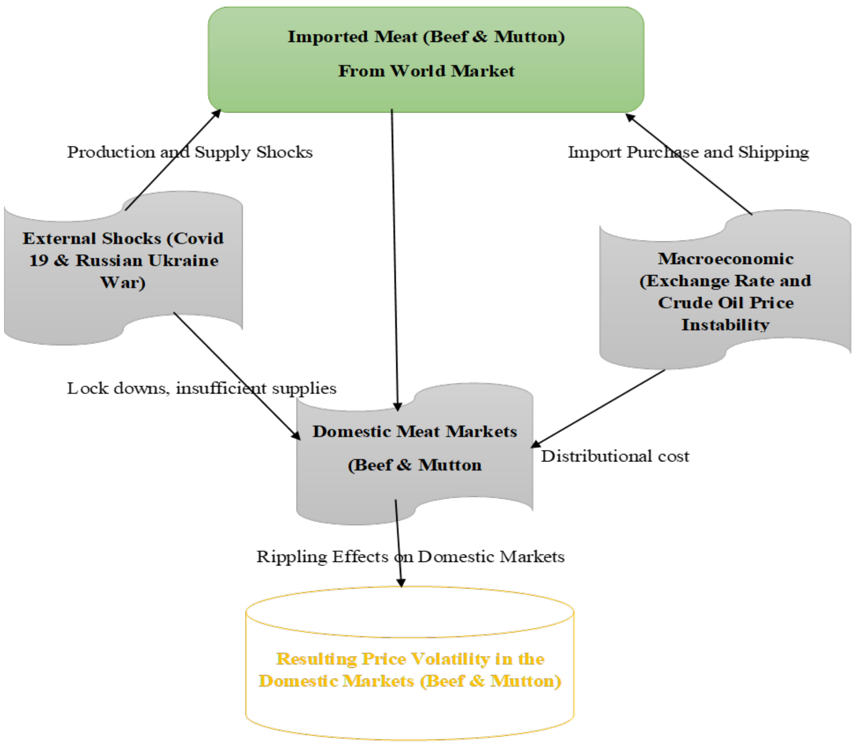
This study therefore seeks to fill this gap by exploring volatility transmission across borders and examining how crude oil prices and exchange rates interact with the volatility of Ghana's beef and mutton markets. Given Ghana's reliance on imported meat products, increases in international prices could lead to domestic price hikes, posing significant challenges to food security (Onumah et al., 2019). By addressing these issues, this research aims to guide policymakers in regulating the meat market and provide valuable insights for market participants. Additionally, it offers a foundation for future research on food price volatility, particularly in the context of meat.

Looking ahead, this study not only sheds light on the challenges posed by price volatility but also points toward potential adaptive strategies for stakeholders in Ghana. By implementing targeted policies and market interventions, Ghana could enhance its resilience to external shocks, thereby contributing to greater food security and economic stability in the region

1.1 Conceptual Framework of the Interplay of Factors Influencing Meat Price Volatility

The conceptual framework presented in Figure 1 illustrates the key factors contributing to meat price volatility in Ghana, emphasizing the complex interplay between global production and supply shocks, exchange rate fluctuations, and crude oil price changes. The flowchart in Figure 1 visually depicts the pathways through which external shocks and global events propagate volatility in domestic meat prices, highlighting how these factors interact and amplify their effects on local markets.

Figure 1: Flowchart of the Interplay of Factors Influencing Meat Price Volatility in Ghana



Source: Conceptualized by Authors, 2022

Volatility in global meat markets, particularly for beef and mutton, significantly impacts domestic markets in developing countries like Ghana. This framework examines how international price volatility transmits to domestic markets, considering the multifaceted interactions between these contributing factors. For example, the COVID-19 pandemic caused severe disruptions in global supply chains, leading to increased volatility in meat prices (Hassen & El Bilali, 2022; Erokhin, 2020; Urak et al., 2023). Similarly, the ongoing Russian-Ukraine War has further constrained the availability of essential commodities, thereby inflicting challenges in global meat markets (Urak et al., 2023; Abdallah et al., 2020).

Exchange rate fluctuations directly impact the cost of meat imports. When the local currency, such as the Ghanaian cedi, depreciates, the cost of importing meat rises, leading to higher prices in the domestic market (Dadzie et al., 2023; Damba et al., 2019; Du et al., 2011). Additionally, fluctuations in crude oil prices play a critical role in determining transportation costs. Increases in oil prices drive up the cost of shipping imported meat and distributing it within the country, further contributing to price volatility in domestic markets (Fernández & Bs, 2014; Obadi & Korček, 2014).

This framework provides a comprehensive understanding of the factors influencing meat price volatility in Ghana, offering insights into how global events and local economic conditions converge to affect domestic markets.

1.2 Price Volatility in Ghana

The interplay of various macroeconomic factors, including inflation, reliance on crude oil, and exchange rate fluctuations, has collectively exacerbated agricultural price volatility in Ghana, particularly in the wake of global crises such as the COVID-19 pandemic and the geopolitical conflict between Russia and Ukraine. These events have triggered severe economic challenges, prompting Ghana to seek financial assistance from the International Monetary Fund (IMF) in response to the downturn. The ripple effects of these global disruptions have permeated the Ghanaian economy, driving inflation to unprecedented levels and destabilizing key welfare indicators, thereby posing a significant threat to food security.

Inflation, which had been steadily rising in Ghana, escalated dramatically during the pandemic and the Russia-Ukraine war, marking a historic peak in the country's economic records. This surge in inflation has had a pronounced impact on the volatility of agricultural product prices, including staples like beef and mutton. For example, the year-on-year inflation rate in January 2023 was 53.6%, following a peak of 54.1% in December 2022. Food price inflation during this period also rose sharply to 61%, up from 59.7% in December 2022 (GSS, 2023). The consumer price index (CPI), another key cost of living indicator, averaged 51.66% from 1997 to 2023, a significant increase from the record low of 4.47% in October 1997 (GSS, 2022). These factors, combined with elevated international food and meat prices, are identified as major drivers of food price volatility in Ghana (Kuwornu & Mensah-Bonsu, 2011), posing challenges to the country's efforts to reduce malnutrition, end hunger, and achieve food security by 2030.

The reliance on crude oil further compounds food price volatility in Ghana. With approximately 28% of the country's energy consumption derived from oil (Energy Commission of Ghana, 2015; Zankawah & Stewart, 2020), fluctuations in oil prices have a direct impact on the cost of shipping and distributing food commodities. This dependence on oil means that any volatility in crude oil prices is likely to be mirrored in food prices, adding another layer of instability to the agricultural market.

Exchange rate fluctuation is another critical factor contributing to the volatility of agriculture and food prices in Ghana, particularly for imported commodities like foreign meat. The depreciation of the cedi has been dramatic, with the currency losing 54.2% of its value in just 11 months of 2022, compared to an average depreciation of 31.2% at the end of 2014 (Najimu & Mahama, 2022). Such exchange rate dynamics can significantly influence the market performance of importing countries, thereby affecting the price volatility of goods purchased in foreign currencies (Bollerslev, 1990; GSS, 2021; Nortey et al., 2015). Given that Ghana produces only about 30% of its animal protein requirements and relies heavily on imports to meet domestic demand for meat, the country is particularly vulnerable to these macroeconomic shifts. Approximately 50% of Ghana's total livestock consumption demand is met through imports, including frozen meat products from various countries and live animals from the Sahel region (Abdou Salla, 2017; Taylor, 2023; Timpong-Jones et al., 2014). The importation and distribution of meat products, influenced by exchange rates and crude oil prices, therefore play a significant role in meat price volatility transmission between Ghana and its trading partners.

To address these challenges and stabilize food prices, it is imperative for Ghana to strengthen domestic production, reduce its reliance on imports, and consider revising taxes on crude oil. By doing so, the country could create a more resilient agricultural sector, better equipped to withstand the pressures of global economic fluctuations.

2 Literature Review

2.1 Concept of Volatility

Volatility, defined as the variation of economic variables over time, becomes problematic when large price fluctuations create uncertainty and risks (Gilbert and Morgan, 2011; Haliam, 2011; Díaz-Bonilla, 2019). This uncertainty can lead to sub-optimal decisions by producers, traders, consumers, and governments (FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, 2011). Technically, variability measures the change in price from period t-1 to time t, making volatility a crucial policy consideration globally (Chiriac & Voev, 2011; Gardebroek et al., 2016; Piot-lepetit & Barek, 2011). This importance has prompted numerous studies influencing agricultural market policies worldwide, particularly on commodity price volatility. Some of these studies are explored in the next section.

2.2 Empirical Studies on Food Price Volatility

In examining the impact of macroeconomic variables like crude oil on food prices, various studies have explored different aspects of this relationship. Dadzie et al. (2023) analyzed the correlation between petroleum energy volatility and commodity prices in Ghana, while Damba et al. (2019) investigated how volatility in crude oil prices and exchange rates influenced agricultural product prices in both Ghana and Turkey. Similarly, in the United States, Siami-Namini (2019) found a positive correlation between U.S. agricultural commodity returns and crude oil price volatility, particularly around the 2007–2008 financial crisis. Mutuc, Pan, and Hudson (2011) also highlighted how exchange rate instability affected U.S. food commodity prices, noting that the depreciation of the U.S. dollar contributed to increased agricultural exports to China.

Focusing on specific commodities, Onumah et al. (2022) studied price volatility transmission in the rice market in Ghana, emphasizing its implications for food security. Kuwornu and Mensah-Bonsu (2011) similarly explored maize price volatility in Ghana, and Abokyi, Folmer, and Asiedu (2018) examined the effects of buffer stock implementation on the price volatility of maize and rice in Ghana. In southern Africa, Oyewumi and Sarker (2010) investigated the sheep market in Namibia and South Africa, revealing significant volatility spillovers and asymmetric effects. Balanay (2013) conducted a study in the Philippines, analyzing the price volatility of chicken, chicken eggs, pork, and beef.

These studies collectively provide valuable evidence on the volatility of food commodity prices and the significant influence of macroeconomic variables, including crude oil prices and exchange rates. For instance, several studies have identified that crude oil or energy shocks contribute to rising agricultural commodity prices (e.g Damba et al., 2019; Siami-Namini, 2019; Dadzie et al., 2023). The strong correlation between these macroeconomic variables and the returns on agricultural and food commodities such as energy grains, meat, cooking oil, maize, soybeans, and rice underscores their role in driving food price volatility (Mutuc et al., 2011; Damba et al., 2019; Siami-Namini, 2019; Dadzie et al., 2023). Additionally, exchange rates have been shown to significantly influence price volatility in agricultural and food commodities (Mutuc et al., 2011; Damba et al., 2019). The literature on specific commodities reveals varying degrees of price fluctuations, including the markets for sheep, chicken, chicken eggs, pork, beef, maize, and rice (Abokyi, Folmer, & Asiedu, 2018; Kuwornu & Mensah-Bonsu, 2011; Oyewumi & Sarker, 2010; Balanay, 2013).

These findings support the argument for implementing policies to mitigate the impact of macroeconomic variables on food price volatility, especially in the aftermath of the COVID-19 pandemic and the ongoing Russia-Ukraine war. The consistent evidence of crude oil price and exchange rate effects on food price volatility poses significant challenges to achieving the sustainable development goals related to food security.

The studies reviewed employed a variety of methodological approaches, ranging from simple measures like the coefficient of variation and corrected coefficient of variation (Abokyi et al., 2018) to more complex models like the univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Oyewumi & Sarker, 2010; Kuwornu & Mensah-Bonsu, 2011; Balanay, 2013; Onumah et al., 2022), multivariate GARCH models (Mutuc et al., 2011; Siami-Namini, 2019; Damba et al., 2019), and Granger causality, co-integration, vector autoregressive, and vector error correction models (Dadzie et al., 2023). This diversity of methods highlights the range of tools available for studying agricultural and food price volatility, though each has its strengths and weaknesses. For example, while the corrected coefficient of variation (CCV) and standard coefficient of variation (CV) provide a more accurate representation of volatility in cases where sample size may influence results (Gómez-Puig & Sosvilla-Rivero, 2015), these measures may not be widely accepted in food price volatility literature due to their limited applicability in comparative studies (Zivot & Wang, 2006). Univariate ARCH and GARCH models are powerful for analyzing food price volatility due to their ability to capture time-varying volatility (Bollerslev, 1986) and clustering effects (Engle, 1982; Bollerslev, 1986), but they also have limitations, such as failing to account for structural breaks, multivariate interactions (Bauwens, Laurent, & Rombouts, 2006), and potential asymmetries in the data (Glosten, Jagannathan, & Runkle, 1993). The limitations of univariate GARCH models have led to the broader adoption of MGARCH models in food price volatility analysis. Despite the complexity, data requirements, and model specification challenges, these models offer significant strengths in capturing and analyzing the dynamic relationships and volatility in food prices (Engle, 2002; Bauwens, Laurent, & Rombouts, 2006; Tsay, 2010; Wang & Wu, 2012).

This current study critically examines the shortcomings of these models and adopts the MGARCH models of DCC and CCC, which collectively address the weaknesses of the models reviewed in this section, to provide more accurate estimates of meat price volatility.

The findings from the various studies consistently suggest that food price volatility is becoming a persistent global issue, necessitating urgent policy interventions to prevent further escalation, particularly in the pursuit of sustainable development goals related to food security. The inclusion of exogenous macroeconomic variables such as crude oil prices and exchange rates in the reviewed studies highlights how these factors exacerbate the already volatile food prices. In developing countries, where a large share of household income is spent on food, maintaining price stability is crucial to ensuring proper nutrition and reducing malnutrition. Therefore, governments in these countries must focus on policies that mitigate these impacts.

In conclusion, the existing literature on agricultural and food price volatility reflects a high level of research interest due to its significant implications for livelihoods and socio-economic policies. However, there is still a gap in cross-border volatility analysis, particularly concerning meat markets and the integration of exchange rates and crude oil prices as exogenous factors in volatility transmission across borders. Further research is necessary, especially in light of the global economic turmoil caused by the COVID-19 pandemic and the Russia-Ukraine war. This study aims to utilize advanced econometric techniques such as the MVGARCH DCC and CCC models to examine price volatility transmission in Ghana's meat markets, influenced by foreign meat imports and macroeconomic variables. The subsequent section of the paper provides a detailed description of the analytical framework used in these models.

3 Data and Methodology

3.1 Data Source, Collection and Processing

This study utilizes secondary data to analyze meat price volatility. We focused on average monthly retail prices of beef and mutton from five countries. In Ghana, the national average prices for beef and mutton were sourced from the Statistics, Research, and Information Directorate (SRID) of the Ministry of Food and Agriculture (MoFA). These prices were initially reported in Ghanaian cedis per kilogram and were converted to dollars per kilogram for consistency.

For Argentina and South Africa, average monthly beef prices were obtained from the Food and Agricultural Organization (FAO) FPMA tool website, which provides the average dollar value per kilogram of beef in retail markets. The monthly average price of sheep meat in Belgium was retrieved from EU market prices for representative products. Similarly, mutton prices in New Zealand were downloaded from the FAO's Food Price Monitoring and Analysis (FPMA) tool website.

Data on exchange rates and crude oil prices for Ghana were acquired from Bank of Ghana Data/Statista and FAOSTATS. Consumer price indices (CPI) for each country were also downloaded from FAOSTATS. These indices were used to adjust all prices to real terms using the following formula:

$$Realprice = \frac{price}{CPI} \times 100 \tag{1}$$

To account for potential unit roots in the data, real prices were transformed into returns using the formula provided by Hassan and Malik (2007).

$$Returns = 100 \times ln(\frac{p_t}{p_{t-1}}) \tag{2}$$

whereby; P_t is either real price levels or closing levels and P_{t1} represents the lag values of P_t. All return series were logged and transformed to facilitate the subsequent volatility analysis and interpretation of results.

3.2 Theoretical Framework of the Multivariate GARCH Models

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model, incorporates past conditional variances into the model (Daly, 2008). This extension provides a more parsimonious representation of higher-order ARCH processes. A GARCH(p, q) model is typically specified as:

$$\vartheta_t^2 = \varphi + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \tag{3}$$

Where ϑ_t^2 is representing the lags of $u_t^2, \alpha_i, I = 1, p$, and β_i are all nonnegative constants. This model accounts for high-frequency effects through the first lag (squared residuals) and long-term impacts through the second lag (lagged variance) (Daly, 2008). In this study, two types of multivariate GARCH models; Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) were employed to analyze the persistence of volatility and interdependencies among meat price returns in Ghana and other macroeconomic variables.

Conditional Correlation MGARCH Models

There are three main variants of the conditional correlation models: Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC), and Variable Conditional Correlation (VCC). These models use a nonlinear approach to measure volatility by combining univariate GARCH models to capture the conditional co-variances. The parameters of these models help to explain how errors in the equations are correlated (Neifar, 2020).

In this study, we employed the CCC and DCC variants of the multivariate GARCH (MGARCH) models. The CCC model assumes that correlations between variables remain constant over time, simplifying the analysis of volatility persistence and interdependencies. The DCC model, on the other hand, allows for time-varying correlations, providing a more dynamic view of how volatility in meat prices across importing countries, including Ghana, interacts with other macroeconomic variables. Both models were used to explore how shocks to these variables might affect meat prices in Ghana. The detailed mathematical specifications of these models are provided below.

Specification of the constant conditional correlation (CCC) Model

This model is a special case of MGARCH model proposed by Bollerslev (1990) where the number of volatility equations are reduced when the correlation coefficient $\rho_{ij,t} = \rho_{ij}$ becomes constant with time and $\rho_{ij} < 1$ (Neifar, 2020). This makes ρ_{ij} a constant parameter under this assumption with k equations for;

$$\phi *_t = (\sigma_{1,t}^2, \cdots\cdots\cdots \sigma_{k,t}^2) \tag{4}$$

For a GARCH (1,1) model, $\phi *_t$ takes the form of;

$$\phi *_t = (\alpha_0 + \alpha_1 \epsilon_h^2 + \beta_1 \phi *_h) \tag{5}$$

Whereby, $(\epsilon_{t-1}^2 = \epsilon_{1,t-1}^2, \epsilon_{2,t-1}^2, \ldots\ldots\ldots\ldots, \epsilon_{k,t-1}^2), a_0$ represents a k-dimensional positive vector, α_1 and β_1 denotes a kxk non-negative definite matrices.

In the conditional correlation specification of the model, exogenous variables can be incorporated into the variance equation with the option of using common coefficients across different equations (Neifar, 2020). When common coefficients are employed, it is assumed that the exogenous variables share a single, uniform slope, λ for all equations (Neifar, 2020). Alternatively, if individual coefficients are used, each exogenous variable, δ_i can have a different effect in each equation, allowing for variability in how these variables influence the model.

$$\psi_{it} = \delta X_{1it} + \lambda_i X_{2it} \tag{6}$$

$$\varphi_{it}^2 = \alpha_{ii,0} + \alpha_{ii,1}\epsilon_{i,t-1}^2 + \beta_{ii,1}\sigma_{i,t-1}^2 + \delta_i Z_{1it} + \lambda_i Z_{2it} \tag{7}$$

where; δ_i and λ_i are coefficients of X1 and X2 which in this study represent exchange rate and crude oil prices respectively. Due to this, the constant conditional correlation (CCC) MGARCH model imposes restriction to Λ_t to have constant matrix in order to ensure reduction of the parameters in a simplified estimation though it may be deemed too restrictive in some cases (Neifar, 2020).

3.3 Specification of the Dynamic conditional correlation (DCC) model

Dynamic conditional correlation (DCC) model is proposed by Engle (2002) to follow a GARCH (1,1) order with the conditional quasicorrelations, $\forall_t$, in the form of a model,

$$\forall_t = \delta_t Q_t \alpha_{tt} \tag{8}$$

whereby, $Q_t = q_{i,j,t}$ denotes a kxk positive definite matrix, $\delta_t = diag(q_{11,t}^{-1/2}, \ldots\ldots\ldots, q_t^{-1/2})$ and $Q_t = (1-\varphi_1-\varphi_2)Q + \varphi_1\alpha_{t-1}\alpha_{t-1}' + \varphi_2 Q_{t-1}$; with α_t representing unconditional standardized innovation vector that has the elements $\alpha_{it} = \frac{\epsilon_{it}}{\sqrt{\sigma_{it}^2}})$, Q also denotes the unconditional covariance matrix of the parameters, $\alpha_t, \alpha_{it}, \varphi_1$ and φ_2 which are all non-negative scalars that satisfies $0 > \varphi_1 + \varphi_1 < 1$, and δ_t is a normalized matrix to provide guarantee for $\forall_t$ to be a correlation matrix (Nortey et al., 2015).

By employing these GARCH models, this study aims to capture the complex dynamics of food price volatility and its interplay with macroeconomic factors in Ghana. A combination of data analysis software including Microsoft Excel and Regression Analysis of Time Series (RATS) are the main statistical software used for the data analysis in this paper. The results of the analysis are presented and discussed in the next section (Section 4).

4 Results and Discussion

4.1 Descriptive Statistic of Meat prices and Macroeconomic variables

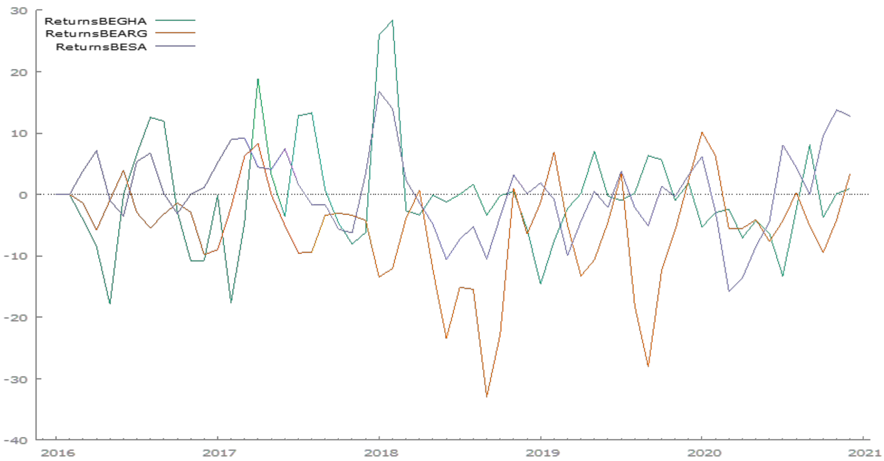
The descriptive statistics of the return series used in this study are summarized in Table 1. The average price returns for beef from 2016 to 2020 are -0.406307 for Ghana, -5.556958 for Argentina, and 0.566550 for South Africa. Similarly, the average returns for mutton are -0.745499 for Ghana, -0.383062 for Belgium, and 1.206885 for New Zealand. These figures reflect the fluctuations in meat price returns across these countries. Notably, the t-values for most price series were not statistically significant, with the exception of Ghana. Here, the return price of beef was statistically significant and negative, highlighting the impact of the weakened Ghanaian currency when purchasing beef imports. Conversely, the t-values for Ghana's exchange rate and crude oil price returns were positive and statistically different from zero.

Analyzing the distribution of the return series, the smaller yet significant skewness values compared to kurtosis suggest that most of the price returns among these countries are not normally distributed. The data series showed an equal distribution between positive and negative skewness. Specifically, positive skewness was observed in the beef prices of Ghana and South Africa, mutton prices of Belgium, and Ghana's exchange rate. In contrast, negative skewness was noted in the beef prices of Argentina, mutton prices of Ghana and New Zealand, and Ghana's crude oil prices.

The abnormal distribution of meat price returns across these countries suggests the potential for extreme positive and negative return values. In particular, the higher standard deviation of beef returns in Ghana, coupled with its elevated skewness and kurtosis, indicates greater volatility in beef prices in Ghana compared to its trading partners. This is further corroborated by the highly significant Jarque-Bera statistics (P<0.01) for Ghanaian beef prices, suggesting the presence of outliers that deviate from a normal distribution. On the other hand, the standard deviation of mutton returns in Ghana is smaller, with insignificant skewness, kurtosis, and Jarque-Bera statistics, indicating lower volatility in mutton returns in Ghana compared to Belgium and New Zealand.

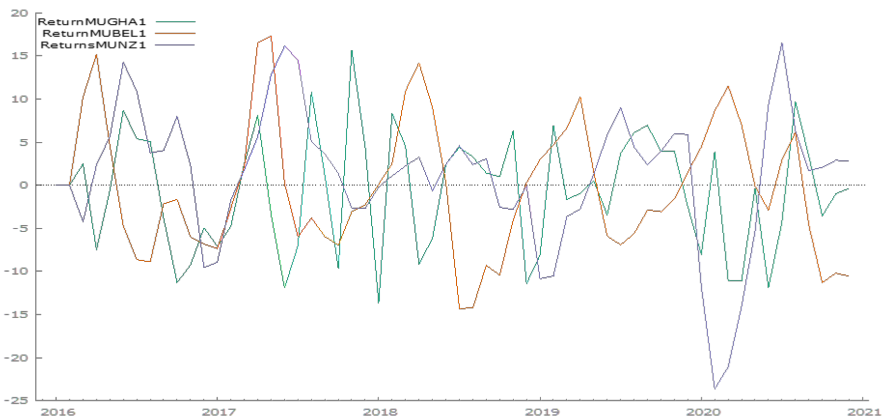
Table 1 also presents the bivariate unconditional correlation coefficients between the price returns and selected macroeconomic indicators in Ghana. The results show that beef prices in Ghana are correlated with those in Argentina and South Africa, as well as with crude oil price returns. Similarly, the return on mutton prices in Ghana is highly correlated with those in New Zealand, along with Ghana's crude oil price returns and exchange rates. These findings suggest that meat price returns exhibit significant volatility transmission from foreign trading partners and Ghana's macroeconomic variables (crude oil and exchange rate). The predominance of positive correlation coefficients indicates that the volatility in returns across these markets is interdependent in a positive manner.

Figure 2: Beef price returns of the three countries



Source: Analysed from data, 2022

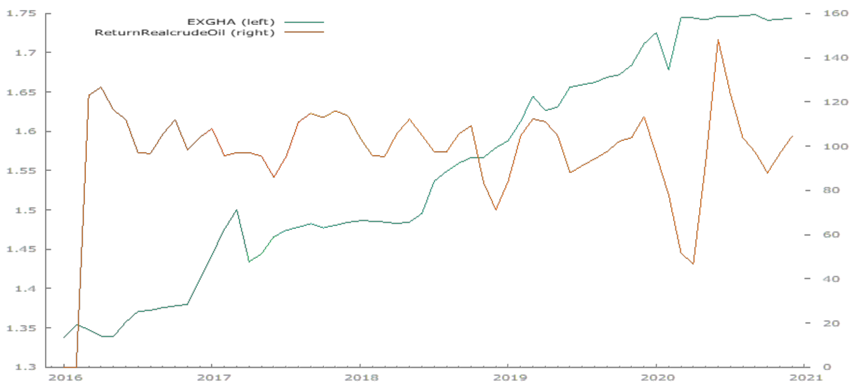
Figure 3: Mutton price returns of the three countries



Source: Analysed from data, 2022

The Ljung-Box statistic presented in Table 1 indicates significant autocorrelation in the univariate analysis of meat prices and macroeconomic variables. Similarly, the multivariate Q test for the beef and mutton market pairings reveals autocorrelation between the meat price returns

Figure 4: Crude price return and Exchange rate trend in Ghana



Source: Analysed from data, 2022

across the three markets involved in this study. In line with Neifar (2020), both individual and multivariate ARCH effects were tested for in the return series of meat prices, using individual and multivariate LM tests.

The results in Table 1 show strong evidence of individual ARCH effects across the return series, with the null hypothesis being strongly rejected at conventional significance levels. Additionally, the multivariate LM test confirms the presence of multivariate ARCH effects, as the test statistic significantly rejects the null hypothesis of zero mean, absence of serial correlation, and constant covariance matrix.

Figures 2 and 3 further illustrate the volatility of beef and mutton price returns over time. Figure 2 demonstrates that beef price returns in Ghana fluctuate more rapidly than in its trading partners, Argentina and South Africa, suggesting higher beef price volatility in Ghana. In contrast, the mutton return series in Ghana fluctuates more moderately compared to Belgium and New Zealand, as depicted in Figure 3.

To identify the data generation process (DGP), we applied commonly used time series stationarity tests, such as the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests, with the Akaike Information Criterion (AIC) employed to select the appropriate lags. The real prices of meat were transformed into returns, making them inherently stationary. Consequently, the ADF and KPSS test results, as shown in Table 1, confirm that the return series of meat prices and crude oil prices were stationary at levels, denoted as I(0). However, the exchange rate of Ghana required transformation and was differenced at the first difference to achieve stationarity for further analysis. The results are presented in Table 1.

Table 1: Descriptive Statistic of Meat prices and Macroeconomic variables

	Beef GHA	Beef ARG	Beef SA	Mutton GHA	Mutton BEL	Mutton NZ	CRUDE OIL	EXGHA
Mean	-0.406	-5.557	0.567	-0.745	-0.383	1.207	97.495	1.549
Std. Dev.	8.752	8.350	6.683	6.784	7.638	7.850	24.050	0.136
t-values	-0.360	-5.155***	0.657	-0.851	-0.388	1.191	31.401***	88.246***
(mean = 0)	(0.720)		(0.514)	(0.398)	(0.699)	(0.238)	(0.000)	(0.000)
Skewness	1.036***	-0.988***	0.041	-0.053	0.472	-0.812**	-2.359***	0.0768
	(0.001)	(0.002)	(0.900)	(0.870)	(0.145)	(0.012)	(0.000)	(0.813)
Kurtosis	2.362***	1.728***	0.194	-0.684	-0.300	1.712**	8.150***	-1.295*
	(0.000)	(0.010)	(0.773)	(0.308)	(0.655)	(0.012)	(0.000)	(0.054)
Jarque-Bera	20.931***	14.813***	0.032	1.347	2.468	11.700***	189.372***	4.203
	(0.000)	(0.001)	(0.984)	(0.510)	(0.291)	(0.003)	(0.000)	(0.122)
LB-Q (10)	13.548*	13.580*	9.935	33.809***	69.064***	171.827***	11.238	370.754***
HM-Q (10)		703.236***			756.236***			
		(0.000)			(0.000)			
LM-test (2)	5.827*	6.078**	11.259***	4.818*	12.621***	27.542***	27.218***	52.375***
	(0.05428)	(0.04789)	(0.004)	(0.0899)	(0.0018)	(0.000)	(0.000)	(0.000)
MLM-test (3)		1029.50***			1628.91***			
		(0.000)			(0.000)			
ADF	-6.124**	3.071*	-4.506**	-3.515*	-5.571**	-4.960**	-27.406**	-0.701
	(Lags = 1)	(Lag = 2)	(Lags = 1)	(Lags = 2)	(Lags = 1)	(Lags = 1)	(Lags = 1)	(Lags = 0)
KPSS	0.103	0.184	0.154	0.050	0.041	0.161	0.277	1.272**
Unconditional Correlation Matrix								
Beef GHA	1	-0.256**	0 .474***	0.550***	0 .054			
Beef ARG		1	0.162	0.185	-0.959***			
Beef SA			1	0 .666***	-0.239**			
Crude Oil				1	-0.368***			
EXGHA					1			
Mutton GHA	1	0.103	-0.327***	0 .222**	-0.613***			
Mutton BEL		1	-0.431***	-0.133	-0.403***			
Mutton NZ			1	0.523***	0 .429***			
Crude Oil				1	-0.368***			
EXGHA						1		

. *, **, *** Denotes significance at the10%, 5% and 1% level respectively. Values in brackets are p-values.

LB and HM-Q denote Ljung-Box and the Hosking multivariate Q-statistic for serial autocorrelation tests in residuals while LM and MLM denote Lagrange and multivariate Lagrange tests for ARCH effects, respectively. The null under MLM test is that the series are mean zero, not serially correlated and with a constant covariance matrix. ADF stands for Augmented Dick-Fuller test with constant and trend assumptions. The critical values vary with lags selected; KPSS denotes Kwiatkowski-Phillips-Schmidt-Shin. (Source: Authors' Computation, 2022)

4.2 Econometric results and diagnoses

4.2.1 Models Diagnoses

The results of the Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) models, along with their associated diagnostic tests, are presented in Table 2. The return series of each meat market were analyzed separately, incorporating exogenous variables into the two meat markets. The analysis began by assessing the diagnostic tests, which evaluated the significance of the model parameters and their collective ability to explain volatility. Additionally, the tests examined the role of crude oil prices and the exchange rate of Ghana in the volatility transmission process. The diagnostic tests also compared the relative fitness of the CCC and DCC models in analyzing meat price return volatility.

The Wald test statistics value of 405,349.62 ($P<0.001$) for the CCC model and 10,850.21 ($P<0.001$) for the DCC model indicate that the parameters in both models are statistically significant in explaining the volatility between the beef markets of the selected countries. Further, the Wald tests for the inclusion of crude oil prices and the exchange rate in the volatility modeling were reported. The results show that these variables in both the CCC and DCC models have a significant impact on the volatility of beef price returns in Ghana. The null hypothesis of zero impact for these two variables was rejected at the 1% level of significance in both models.

Similarly, the Wald tests for both the CCC and DCC models of mutton price return volatility also strongly rejected the null hypothesis of zero impact of the model parameters and the exogenous

variables, again at the 1% level of significance in the two models.
Overall, the results reveal a level of interdependence among the markets, where the average returns of meat prices in one market affect the others. This indicates volatility transmission across meat price returns, as well as between the selected macroeconomic variables

4.3 Econometric results of Volatility of Selected Meat Products

4.3.1 Volatility of Beef Returns

Table 2 presents the results of the multivariate Dynamic Conditional Correlation (DCC) and Constant Conditional Correlation (CCC) GARCH models used to analyze beef price volatility. Each model has its own limitations, so employing both allows for a more comprehensive analysis through complementarity and comparison.
The CCC model within the multivariate GARCH framework separately specifies the individual conditional variances and the conditional correlation matrix for each of the meat return series, assuming constant conditional correlations (Bauwens et al., 2006). This model identifies the degree and size of interdependence between the markets studied. In contrast, the DCC model captures both the dynamic conditional correlation matrix and the persistence that may occur between variances and covariances, with the imposition of common persistence across the covariance matrix (Neifar, 2020).
The results from the CCC model indicate a significant interrelationship between individual meat markets trading in beef, as evidenced by the significant conditional correlation coefficients. Notably, the negative correlation coefficients between the beef returns of Argentina and Ghana (ρ_BEARG_BEGHA) and between South Africa and Ghana (ρ_BESA_BEGHA) suggest that beef return volatility in Ghana is inversely related to volatility in these foreign markets. This means that an increase in volatility in Argentina or South Africa leads to a decrease in volatility in Ghana's beef market, holding other factors constant. This finding implies that these markets are interconnected, with meat price volatility co-varying across them. These results align with previous studies on agricultural price instability (Balanay, 2013; Kuwornu & Mensah-Bonsu, 2011; Mutuc, Pan, & Hudson, 2011; Damba, Bilgic, Yavuz, & Bilgin, 2019). However, the CCC model primarily reveals market interactions and the extent of interdependence, without pinpointing the source of volatility transmission.
The DCC model results, which account for non-constant changes in market interdependence, are also detailed in Table 2. The highly significant estimates of DCCα and DCCβ confirm that volatility across these markets is time-variant, justifying the use of a multivariate GARCH-DCC model for analyzing volatility between the beef markets. The persistence of volatility, calculated as the sum of DCCα and DCCβ, is below one, indicating an infinite unconditional variance in these markets. The model's ARCH and GARCH parameters reveal a relatively small ARCH effect (-0.0500) and a large GARCH effect (0.34465), signifying a high degree of volatility persistence. This indicates that the volatility correlation among the three beef markets is dynamic over time. Additionally, the ARCH (α) and GARCH (β) processes in the MVGARCH models are statistically significant across both DCC and CCC specifications, suggesting that current beef price volatility is influenced by past price volatilities. The presence of volatility clustering and the persistence of price return volatility are further supported by the highly significant (1%) coefficients. Similar findings on volatility persistence in agricultural markets have been reported in other studies (Oyewumi & Sarker, 2010; Damba et al., 2019).
To gain a deeper understanding of the drivers behind beef return volatility in Ghana, macroeconomic indicators such as the exchange rate and crude oil prices, factors likely to impact import transactions and distribution costs within Ghana were incorporated into the volatility models as exogenous variables. The results for these variables, specifically concerning Ghana's beef returns, are presented in Table 2. The Wald test rejects the null hypothesis that the two exogenous variables have no joint impact on beef return volatility, with significance at the 1% level in both the DCC and CCC models. This implies that the instability or volatility of the exchange rate and crude oil prices significantly affects beef price volatility in Ghana. The negative coefficients of these variables suggest that increased volatility in exchange rates and crude oil prices, all else being equal, will reduce the volatility of beef prices. This finding is consistent with the significant role these variables play in price fluctuations in both foreign and domestic markets, corroborating similar observations in previous studies (Mutuc et al., 2011; Damba et al., 2019; Siami-Namini, 2019).

The comprehensive results of the multivariate GARCH DCC and CCC models are summarized in Table 2.

4.3.2 Volatility of Mutton Returns

The analysis of mutton price return volatility, α across three markets, as presented in Table 2, reveals significant findings regarding the interdependence of price volatility. Both the Dynamic Conditional Correlation (DCC) and Constant Conditional Correlation (CCC) models indicate that there is interdependence in price volatility across the three markets. The univariate volatility process is strongly evident in each of the individual markets, with the ARCH (α) and GARCH (β) parameters being highly significant at conventional levels, especially in the CCC specifications. This signifies that the current volatility in mutton prices is influenced by the lagged volatilities of the same series, as indicated by the values, and by the persistence of this volatility, as represented by the β values.

Regarding the instability relationships between the markets, the CCC model in Table 2 shows that the conditional correlations are not statistically significant, suggesting that the mutton markets are not strongly interdependent in terms of volatility transmission. While there is some evidence of minor interdependence, the overall conclusion is that volatility in one mutton market does not significantly influence volatility in the other markets. This implies that volatility in foreign mutton markets may not necessarily affect the domestic mutton market.

The Multivariate GARCH DCC model also indicates an insignificant point estimate for DCCαin terms of volatility transmission between the three markets. However, the coefficient for DCCβ is highly significant (at the 1% level), and the sum of DCCα and DCCβ still indicates the presence of joint volatility persistence across the markets. The DCCα value of -0.00410 is less than the significant DCCβ value of 1.0141, suggesting that volatility in these markets may be persistent and take a long time to subside, delaying the return to market equilibrium. This persistence could be attributed to inefficient market intelligence, leading to overall market inefficiency (Oyewumi & Sarker, 2010; Damba et al., 2019).

Furthermore, the inclusion of exogenous variables, such as exchange rate and crude oil prices, into the volatility model provides additional insights. As presented in Table 2, crude oil price returns are statistically significant (at the 1% level) in both the CCC and DCC model specifications. The impact of these variables on the volatility of mutton price returns in Ghana is evident, as the Wald test rejects the null hypothesis of zero impact at the 1% significance level in both models. The positive coefficient for crude oil returns suggests that an increase in crude oil price volatility leads to increased volatility in mutton price returns in Ghana. On the other hand, the exchange rate has an insignificant negative impact on mutton price volatility, which contrasts with previous findings by Damba et al. (2019), where the exchange rate significantly influenced agricultural commodity prices.

The influence of crude oil on various aspects of agricultural markets, including transportation, distribution, and input manufacturing, explains its strong impact on mutton price volatility. This significant effect of crude oil price returns on agricultural market volatility is consistent with findings from other studies (e.g., Mutuc et al., 2011). The results of the Multivariate GARCH DCC and CCC models for mutton price volatility underscore the critical role of these factors in understanding market dynamics in Ghana and influencing policies to stabilize prices. The results of the MGARCH DCC and CCC models are presented in Table 2.

Table 2: CCC and DCC results for of volatility of meat price returns and the effect of exogenous variables on volatility

Prices	Beef Prices		Mutton Prices	
Parameters	CCC MGARCH	DCC MGARCH	CCC MGARCH	DCC MGARCH
α_1	-0.0692***	-0.08331***	-0.1200***	-0.10657
	(0.008605)	(0.000367)	(0.0894)	(0.06668)
β_1	0.4836***	0.503224***	0.3776***	0.365418***
	(0.03325)	(0.007872)	(0.1205)	(0.10542)
$\alpha_{1,0}$	0.12419***	0.230056***	0.0692***	0.070644***
	(0.01441)	(0.004101)	(0.0174)	(0.015714)
α_2	0.30159***	0.09815****	0.7299***	0.49945**
	(0.00419)	(0.033009)	(0.00345)	(0.06880)
β_2	-0.30123***	0.320755***	-0.1489***	-0.081573
	(0.000768)	(0.045971)	(0.00038)	(0.070924)
$\alpha_{2,0}$	0.03946***	0.038112***	0.120***	0.14621***
	(0.00111)	(0.004311)	(0.00034)	(0.020629)
α_3	0.500249***	0.116966	0.6524***	0.56034***
	(0.02686)	(0.077067)	(0.1098)	(0.0465)
β_3	-0.361324***	0.338855***	-0.2862*	-0.05569
	(0.02689)	(0.077361)	(0.1193)	(0.096537)
$\alpha_{3,0}$	0.083713***	0.10375***	0.0882***	0.07984***
	(0.01211)	(0.01741)	(0.0203)	(0.01585)
ρ_{12}	-0.22415***	DCCα =	0.1530	DCCα =
	(0.046688)	-0.0500***	(0.1362)	-0.00410
		(0.003739)		(0.003042)
ρ_{13}	-0.11275***	DCCβ =	0.1388	DCCβ =
	(0.03248)	0.34465***	(0.1161)	1.01410***
		(0.13347)		(0.085096)
ρ_{23}	0.376263***		0.0732	
	(0.012103)		(0.1123)	
Log likelihood	-54.0674	N/A	-83.8001	-79.2762
Wald Test (F-ratio)	405349.62***	10850.21***	17509.34***	54.769***
	[0.000]	[0.000]	[0.000]	[0.000]
Exogenous Variables and Beef and Mutton Price Volatility				
EXGHA	-0.03146***	-0.044967***	-0.0117	-0.00691
	(0.010030)	(0.003911)	(0.0115)	(0.0101)
CRUDOIL	0.041852***	0.004735	0.0335***	0.02870***
	(0.007502)	(0.00295)	(0.00934)	(0.00735)
Wald Test (F-ratio)	17.96****	212.017***	6.523***	7.645***
	[0.000]	[0.000]	[0.000]	[0.000]

*, **, *** Denotes significance at the10%, 5% and 1% level respectively; Values in parenthesis are standard errors; [] are p-values
Source: Authors' Computation (2022)

5 Summary, Conclusion and Policy Recommendations

5.1 Summary of Findings

Over the last two and a half decades, the volatility of agricultural commodity prices has posed a significant challenge for governments, policymakers, farmers, traders, and consumers, particularly in developing countries like Ghana. This volatility has become even more concerning in the wake of the COVID-19 pandemic and the ongoing Russia–Ukraine war, which have further destabilized global markets. In Ghana, where a substantial portion of household income is spent on food, the volatility of meat prices is especially troubling given the country's dependence on imported livestock and meat products, such as beef and mutton, to supplement inadequate domestic production.

This study utilized multivariate GARCH models, specifically the DCC and CCC models, to examine the transmission of price volatility between international and domestic meat markets in Ghana. The findings highlight a significant degree of interdependence between these markets, with a high persistence of volatility observed in almost all meat products. Notably, the study identified a negative transmission of shocks from the exchange rate to the volatility of beef and mutton prices. This likely reflects the increasing cost of converting domestic currency to purchase foreign commodities, exacerbating price instability in the domestic market.

Conversely, the study found a direct and positive relationship between crude oil price shocks and the volatility of meat prices in Ghana. This suggests that fluctuations in oil prices, likely through increased shipment and distribution costs, contribute to higher volatility in meat prices across retail markets in the country.

These findings have important implications for food security in Ghana, particularly concerning diets and nutrition. The volatility in meat prices, driven by external factors such as exchange rates and crude oil prices, can lead to increased uncertainty and instability in food access, potentially worsening the nutritional quality of diets for many Ghanaians. Given the critical role that meat plays in providing essential nutrients, the study underscores the need for policy interventions to mitigate the impact of external shocks on food prices. Strengthening the resilience of domestic food systems against global market fluctuations is crucial to ensuring stable and affordable access to nutritious food for all Ghanaians.

5.2 Conclusion

In conclusion, the domestic and international meat markets are closely interconnected, with volatility in one market being transmitted to the domestic meat market. Fluctuations in key external factors, such as oil prices and exchange rates, play a significant role in influencing both the pricing and the volatility of meat prices within the country. These findings highlight the sensitivity of domestic meat prices to global market dynamics, emphasizing the need for careful monitoring and management of external economic variables to stabilize meat prices domestically.

5.3 Policy Recommendations (The Way Forward for Ghana)

Based on the findings of this study, it is evident that Ghana has significant work ahead to address the issue of food price volatility, including meat products such as beef and mutton. To manage the impacts of external shocks such as COVID-19 and geopolitical events like the Russian-Ukraine War and to handle exchange rate and crude oil price instability, a comprehensive approach involving both domestic production and market regulation is essential.

Firstly, Ghana should enhance its domestic production of beef and mutton by leveraging existing policies or introducing specific livestock policies tailored for meat production. Strengthening initiatives such as the Rearing for Food and Jobs (RFJ) program, which supports local livestock farmers, is crucial. This program could offer incentives like tax waivers and logistical support to promote commercial livestock farming. The government should also consider implementing additional production-oriented policies to boost the domestic supply of beef and mutton. Subsidies for feed, veterinary care, and infrastructure development could enhance the efficiency and productivity of local livestock farmers. As part of the RFJ initiative, the Ministry of Food and Agriculture should identify and support commercial livestock farmers with resources, training, and market access. Such support would increase the availability of fresh beef and mutton domestically, reducing reliance on imports and creating employment opportunities within the meat sector. Although changes in government may affect the RFJ policy, collaborative efforts by all stakeholders could ensure its sustainability.

Secondly, a coordinated approach to market regulation is needed to stabilize meat prices and reduce volatility. This approach might include setting standards for quality, hygiene, and pricing, as well as monitoring imports to prevent market distortions. Encouraging domestic production through favorable policies and support mechanisms can reduce dependency on imported meat products, thereby mitigating the impact of exchange rate fluctuations on domestic prices. Successful examples of such policies are seen in Brazil, Thailand, India, and the European Union through the EU's Common Agricultural Policy (CAP).

Efforts should also be made to stabilize the exchange rate and crude oil prices. This could be achieved by implementing policies to reduce unnecessary imports, which would help stabilize the exchange rate by decreasing the demand for foreign currency. Collaboration between the Ministry of Trade and Industry (MoTI) and the Ministry of Food and Agriculture (MoFA) to promote domestic alternatives to imported goods, such as beef and mutton, could support this goal. Additionally, revising fiscal policies on crude oil, such as removing fuel taxes, could stabilize domestic fuel prices, which would subsequently impact transportation costs and, in the long run, meat prices. Successful examples of import restrictions and domestic production promotion can be observed in Nigeria's rice sector, as well as in South Korea and China, which have maintained stable food prices through the stabilization of their exchange rates and crude oil prices.

Finally, investing in infrastructure, improving data collection, and enhancing market information systems are vital for ensuring food price stability, including beef and mutton. Developing robust market information systems can provide stakeholders with timely data on supply, demand, and prices, facilitating better decision-making and risk management among traders and consumers. For instance, the Kenyan government has significantly invested in market information systems, such as the Kenya National Farmers Information Service (KNFIS), which offers real-time data on market prices and supply chain information. This initiative has improved transparency and decision-making for farmers and traders, contributing to the stabilization of food prices and reduced volatility.

By implementing these measures, Ghana can better manage food price volatility and ensure stability in the meat market.

5.4 Suggestion for Future Study

We recommend that future research explore how both positive and negative shocks in exchange rates and crude oil prices affect domestic beef and mutton prices differently. This investigation could employ asymmetric GARCH models to capture nonlinear relationships and differences in volatility transmission during periods of economic stress versus stability.

Additionally, the analysis could be expanded by incorporating other macroeconomic variables, such as inflation rates, interest rates, and GDP growth as well as some other imported food commodities, to provide a more comprehensive understanding of the factors influencing domestic food prices.

Another avenue for research could involve examining the impact of changes in trade policies, such as tariffs or export restrictions, on the relationship between international and domestic meat prices. This study could analyze how policy shifts affect price volatility and contribute to the understanding of trade policy's role in price dynamics.

Declarations

Competing Interests

The authors declare that no known competing financial interests or personal relationships could have appeared to influence the work reported in this paper

Authors contributions

Nanii Yenibehit: Conceptualization, Methodology, Software, Data Analysis, and Writing- Original draft preparation. **Joseph Amikuzuno:** Supervision and Writing- Reviewing and Editing. **Isaac Gershon Kwodo Ansah:** Co-Supervision and Writing- Reviewing and Editing. **Osman Tahidu Damba:** Software and Supervision of Data Analysis. **Razak Alhassan:** Writing- Reviewing and Editing.

Availability of Supporting Data

Data for this study are public data obtained from multiple sources. In Ghana, beef and mutton price data were obtained from the Research and Information Directorate (SRID) of MoFA. Data from other countries were obtained from the website of the FPMA tool of the Food and Agricultural Organization (FAO). The data on crude oil prices and exchange rates in Ghana were obtained from the websites of the Bank of Ghana, Statista, and FAOSTATS. These datasets are available on the websites of these sources. The transformed data for analysis is available upon request.

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