Modeling Volatility Spillover between Carbon Emissions Prices and Agricultural Commodity Prices in European Union Market

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Abstract:**Global warming is one of the greatest challenges facing the environment today. Recent studies have shown tremendous impact of global warming on climate which is majorly caused by human activities, specifically emission of greenhouse gases. Carbon trading was introduced in order to help curb this menace by encouraging firms to adopt environmental friendly technologies. The pricing and policies for Carbon Emissions therefore influence the "right to pollute" the environment by firms. Agriculture is highly affected by adverse climatic and weather conditions and hence poor production that affects agricultural commodity prices. This study investigated volatility spillover between Carbon Emissions prices and Agricultural commodity prices, with interest in Wheat prices, in the European Union market for the period between May, 2008 and April, 2018. Variable fluctuations over a long period of time are a sign of the volatility of such a variable, whose deviation from the expected value describes that volatility. ARMA-GARCH models were used to model the volatility of each variable that is Carbon Emissions and Wheat. ARMA(0,1)-GARCH(1,1) was the optimal model fitted for Carbon Emissions, whereas ARMA(0,0)-GARCH(1,1) was fitted for Wheat. Both models used student-t distribution as the data portrayed presence of heavy tails. VAR(3) model revealed significant unidirectional Granger causality from Carbon Emissions to Wheat. The study used VARMA-GARCH and VARMA-AGARCHto investigate cross-market volatility spillovers between Carbon Emissions prices and Wheat prices. There were spillover effects from Carbon Emissions market to Wheat market. VARMA-AGARCH is preferred to VARMA-GARCH in modeling volatility spillovers between these two markets.**

Keywords: **Volatility Spillover, VARMA, Granger Causality**

I. INTRODUCTION

One of the greatest challenges facing the environment today is the aspect of global warming. This has been a key interest due to adverse climate and weather changes around the globe. Recent studies have shown tremendous impact of global warming on climate which is majorly caused by human activities. [1], observed that one of the major contributors to global warming are the greenhouse gases (GHGs). The GHGs include the carbon dioxide, chlorofluorocarbons and nitrous oxide among others. Carbon Emissions account for over 80% of all GHGs emissions [1]. It is therefore a key interest in studies pertaining to climate and weather conditions.

Carbon trading was established to help reduce the emissions into the atmosphere from industries and other sectors of the economy. In carbon trading, countries are allowed to buy allowances equivalent to the emissions they want to release into the atmosphere. This implies that, there is a specified level for the environmental cleanup which can be attained at total cost that is lower to the society. It also means that, we can achieve lower total pollution levels more resourcefully than would be projected if cleanup cost were higher [2]. Therefore, in this case, technology improvements can be of great help to the environment and for the good of the firm as well while fulfilling its mandate towards the environment.

Agriculture as a sector is one of the areas highly dependent on climate and weather conditions. Adverse climatic and weather conditions imply poor production by farmers due to inconsistencies of seasons of farming especially as a result of rainfall unpredictability. This causes fluctuations of prices of different commodities in the market over a long period of time. Wheat is one of the major crops in Europe which is grown on large scale for both local and international use. It is also among the crops highly affected by adverse climatic changes thus affecting its market prices, both internally and externally.

Variable fluctuations over a long period of time are a sign of the volatility of such variable, whose deviation from the expected value describes that volatility. The measure of that variation of prices of financial instruments over time is referred to as financial volatility. There are a number of considerable factors that cause financial volatility, among them, increase in inflationary expectations, interest rates' ceilings removal and restrictive monetary policies. One country's financial market volatility may be affected or caused by volatility of financial market of another country. Also, within country, the changes in prices of a commodity in one sector may affect the price changes of a commodity in a different sector. This scenario is referred to as volatility spillover[3]. These transmission effects of financial volatilities have been key areas of interest for the policymakers and investors.

[4], noted that in order to describe fully the transmission in mean, it is necessary to take into account the transmission in volatility. Also, transmissions in volatility are likely to be

affected by transmission in mean which have been left out without being filtered out before, as shown by[5]. Therefore, to increase reliability of the transmissions' inferences and making it more powerful, it is necessary to do a combined modeling of both conditional mean and their conditional variance processes. Analysis of information pertaining to causal relationships between time series is also important in that, it gives in-depth understanding of the structures and integration of the financial markets. The presence of Granger causal relations in the conditional variances during volatility modeling also help in volatility forecasting involving option pricing, Value at Risk estimation and portfolio selection. The implications of this kind of study are to help in assessment of global risk, international diversification of portfolios, and on working towards global markets' integration.

This study therefore sought to identify existence and extent of volatility spillover between carbon emissions prices and agricultural products prices. Carbon Emission allowances are traded on the energy sector. The aim of the carbon allowances is to make countries engage in technologies that discourage emissions of carbon and other GHGs into the atmosphere. This will enhance clean environment and low level degradation of the ozone layer and hence lower the rate of global warming. Low impact of global warming means better climatic and weather conditions, that eventually makes farming and other agricultural activities less susceptible and hence high production.

The other parts of the paper are as follows; part 2 gives the literature review of past studies, part 3 outlines the methodology, part 4 gives the data and results of analysis, part 5 gives a conclusion and the last part outlines the references.

II. LITERATURE REVIEW

[1], noted that global warming has become one of the most important but difficult challenge to the environment which is facing the international community today.[6], pointed out that human activities are key motivators of unwanted changes in the climate which result from the release of GHGs emissions into the atmosphere. [7], pointed out that there is a broad agreement that ice and snow are melting, climate is warming, ocean temperatures and air are higher and the sea levels are rising. They observed that emissions of GHGs from human activities have increased between 1970 and 2004 by 70%. [8], observed that technology failure and delay in participation are two major factors that make GHGs emissions control difficult in this 21st century. Recently, a considerable attraction of attention from scientists and policy makers has been due to low feasibility of limiting concentrations of GHGs and associated 2 degrees Celsius of global mean temperature increase above preindustrial levels.[9], examined that the GHGs and more specifically the CO_2, are the main components in the atmosphere that are enhancing a focus on Certified Emissions Reduction (CER) in international market. The GHGs emissions, CO_2 in particular, have increased international concern due to consequent climate change potential worldwide. The accounting of CER does not only touch chemical and manufacturing, but also has widespread impact on agricultural sector.

[10], affirmed that country's rights to emissions would be allocated in accordance to emissions per purchasing power adjusted Gross Domestic Product (GDP) index. They reiterated the rights could be used to aid channel the flows of capital for development in the programme of global emissions trading thus steering economic activities. One of the most significant challenges facing governments, businesses and societies is the issue of climate change[11]. They covered opportunities, risks and preparedness relating to climate change and financial sector association. In climate change response, financial sector is critical due to its task as a capital provider and advices' provider that influences both the consumers and overall business. Through the climate change, business performance as well as asset value and the risk associated with the businesses are also affected. The regulatory amendments relating to environmental laws also impact the financial sector.

[12], summarized reasons for transmission mechanism, one, as a market efficiency indicator. The presence of spillovers in return series enable exploitation of strategy profits that are against the criteria of market efficiency. Secondly, the availability of information on effects of return spillover is helpful in the construction of portfolios and allocation of resources. Thirdly, the knowledge concerning volatility spillovers is very essential when dealing with areas of financial applications that require conditional volatility estimation such as pricing of derivatives and estimation of the value at risk (VaR).

Autoregressive integrated moving average (ARIMA) models together with autoregressive conditional heteroskedastic (ARCH) developed by[13] and the generalized ARCH (GARCH) model developed by[14] have been extensively used as methods for modeling the mean and the volatility of various commodity prices across markets in the globe. Subsequent application of GARCH models has led to families of univariate and multivariate GARCH models. [13], showed that an adequate model is that which is in a position to show varied financial returns' behaviors, including persistence of volatility and clustering, time-varying volatility, Autoregressive Conditional Heteroskedasticity (ARCH) effects and the asymmetric effects of negative and positive innovations of equal magnitude. Famous volatility models extensively used include ARCH and its extensions, that is, Generalized ARCH (GARCH), Threshold GARCH, Power GARCH and Exponential GARCH.

Vector Autoregressive (VAR) model has been used as multivariate method to address various questions by empirical macroeconomists involving several variables.[15], used VAR to model economic indicators in Nigeria. The model aimed at providing a quantitative analysis of dynamics on exchange rate, gross domestic product, currency in circulation, price deflator, money supply and external reserve. The empirical results yielded a sustainable and stable economic model for all the six variables studied. VAR modeling approach is better compared to a structural one as it is straight forward, and does not require one to give a dynamic theory to specify the relationship among jointly determined variables. It considers several endogenous variables as it resemble a modeling of simultaneous equation. VAR model is used in Causality analysis, impulse response analysis, structural estimation and specification, forecasting, and forecast error variance decomposition.

Several studies involving volatility spillovers have been done across different markets and especially in stock markets.[16], developed some theoretical results to achieve a multivariate simultaneous GARCH model, referred to as BEKK model.[17], used the BEKK model of [18] to examine presence of volatility spillovers between the stock markets of India and the Hong Kong, Singapore, Korea, Japan, and US markets. The results indicated positive spillover effects between the Indian and other markets, but between US, Pakistan and India markets the spillover was negative. It was observed that, volatilities of particular indices were mostly affected by those markets found to have opened earlier before them implying that the difference in times of opening of the stocks is key in analyzing volatility spillover between markets.

On energy markets,[19], examined volatility spillover outcomes between the International Petroleum Exchange (IPE) and the New York Mercantile Exchange (NYMEX) contracts of crude oil in both concurrent and the non-overlapping trading hours. Their results showed that effective spillover exists when both markets are trading simultaneously.[20], investigated volatility transmission between natural gas and oil markets using data on daily returns and found that volatility changes in one market may have spillover effects to the other market.[21], investigated multivariate conditional correlation and conditional volatility models of futures, spot and forward returns from three markets of crude oil, namely West Texas Intermediate (WTI), Brent and Dubai, and gave evidence of significant asymmetric effects and volatility spillovers in conditional volatilities across returns for each market. On energy and agricultural markets, [22], investigated dynamic returns and volatility spillovers across cereal commodity and energy markets. They made use of VAR with BEKK-GARCH and VAR with DCC-GARCH which showed significant linkages between gasoline, heating oil, Europe Brent oil, wheat, sorghum, barley and corn.

[23], used BEKK model to study volatility spillover across different sectors of the international stocks' markets. Their focus was on volatility spillover between similar sectors but across several stocks' markets, that is, Banking, Industrial, Financial Service, Oil and Real Estate. The findings showed significant volatility spillover among Real Estate, Banking and Oil sectors. The findings appear to support the hypothesis that the level of integration of a stock market among countries, between the given three sectors is comparatively higher in comparison to that of the industrial and the financial services' sectors. However, according to [24], the BEKK and VECH model suffer a dimensionality problem as when to compared with VARMA-GARCH or VARMA-AGARCH that assume constant conditional correlations and which possess statistical and regularity properties.

The multivariate GARCH models stipulate risk for assets as depending dynamically on their own past and also on the past of any other given asset(s). [24], explored the multivariate VARMA-GARCH model of [25]and the vector ARMA-asymmetric GARCH model (VARMA-AGARCH) of [24]and realized that the two were more powerful to the univariate GARCH model [14]and the GJR model [26]. There exist few studies on the use of VARMA-AGARCH to model spillovers and asymmetry. Also, literatures on the linkage between carbon emissions and agriculture commodities are lacking. This study therefore explores the possibility and extent of volatility spillovers between carbon and agriculture commodity markets.[27], used VARMA-GARCH which showed significant volatility spillovers between different sectors in the Nairobi Stocks Exchange (NSE) in Kenya. There was volatility spillover from commercial and financial sectors as most of the other sectors are highly dependent on these two. They also observed significant spillover effects from the agricultural and industrial sectors to the financial sector, then to services and commercial, with agriculture having a greater effect, an indication of more attention required henceforth.

III. METHODOLOGY

3.1 Univariate GARCH Models

ARCH model provides a systematic framework for modeling of volatility in time series data [13]. The basic idea is that (i) the asset return consists of a shock a_t that is serially uncorrelated, but that is dependent, and (ii) dependence of this shock a_t can be explained by a simple quadratic operation of its lagged values [28]. Conditional heteroscedasticity implies that the dependence of scattering or the variance not being constant over time for a given variable and that these changes cannot be attributed to specific events. Non constant variances imply non constant volatility of the return series. The term autoregression imply that current variance is affected by those preceding it. The ARCH model is used to describe such volatile variances. It is used where the series has experienced periods of decreased or increased variance.

The ARCH(m) model is given by,

$$a_t = \sigma_t e_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2$$

where $\{e_t\}$ is a sequence of iid random variables, assumed to follow standard normal distribution, generalized error or a standardized Student-t distribution. That is, has zero mean and variance 1. $\alpha_t > 0$, and $\alpha_i \neq 0$ for i>0. The structure of the model shows that large past squared shocks $\{a_{t-i}\}_{i-1}^{m}$ means a large variance for the innovation, which as a result tends to take a large value. This therefore implies that, under ARCH framework, large shocks in the series tend to be followed by another large shock [28]. Let $a_t = r_t - \mu_t$ be the residuals of the mean equation. To check for conditional heteroscedasticity, we use squared series a_t^2. We apply the Ljung-Box Q(m) test statistic to the a_t^2 series [29]to test for the presence of serial correlations. ARCH model is simple but for adequacy purposes, many parameters must be included for it to give proper description of the process of volatility of an asset return as observed by[14]. Bollerslev proposed a generalized ARCH (GARCH) model to enable deal with the issue of parameterization.

We have $a_t = r_t - \mu_t$ and $a_t = \sigma_t e_t$, then a_t follows GARCH(m,s) model if

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

With regularity conditions; $\alpha_0 > 0$ and $\alpha_i \neq 0$, $\beta_j \neq 0$, and $\sum_{i,j=1}^{\max(m,s)} \left(\alpha_i + \beta_j\right) < 1$. The constraint on $\alpha_i + \beta_j$ means that the unconditional variance of a_t is finite, whereas the conditional variance σ_t^2 is seen to evolve over time. Their non-negativity also guarantees the positiveness of σ_t^2 [14].

3.2 Granger Causality

In testing for Granger causality, our aim was to explore possible linear relationships between the Carbon Emissions prices and the Wheat prices. If we have two variables, say $r_{c,t}$ and $r_{w,t}$, then a variable $r_{c,t}$ is said to Granger cause $r_{w,t}$ if the past values of $r_{c,t}$ have an explanatory power on present values of $r_{w,t}$. $r_{w,t}$ can also Granger cause $r_{c,t}$ [30]. But this does not simply mean either of the two causes the other, it implies an economic relationship. In this study, we consider a simple Granger causality test under the VAR framework. The empirical analysis of the prices mean return causation assume that the conditional mean of carbon emissions price returns and that of Wheat can be expressed as a Vector Autoregressive (VAR) model. Now, under the two-variable model, we have the VAR(p) model given as;

$$r_{c,t} = \alpha_c + \sum_{i=1}^{p} \beta_{ci} r_{c,t-i} + \sum_{i=1}^{p} \beta_{wi} r_{w,t-i} + \varepsilon_{c,t}$$

$$r_{w,t} = \alpha_w + \sum_{j=1}^{p} \beta_{wj} r_{w,t-j} + \sum_{j=1}^{p} \beta_{cj} r_{c,t-j} + \varepsilon_{w,t}$$

where $r_{c,t}$ and $r_{w,t}$ are the logarithmic returns of the Carbon Emissions and Wheat price return series, respectively. The residuals $\varepsilon_{c,t}$ and $\varepsilon_{w,t}$ are assumed to be serially uncorrelated, but the covariance does not have to be zero. The parameter coefficients, β_{ci} and β_{wj}, $i, j = 1,\ldots,p$, provide measure of own spillovers on mean price return. The other parameter coefficients measure cross-mean spillovers between the Carbon Emissions prices and the Wheat prices. $r_{c,t}$ is said to Granger cause $r_{w,t}$ if the hypothesis that coefficient β_{cj} is zero is rejected as well as $r_{w,t}$ is said to Granger cause $r_{c,t}$ if the hypothesis that coefficient β_{wi} is zero is rejected. A bidirectional Granger causality is where both β_{wi} and β_{cj} are not zeros, whereas independence between the two commodities is evident if both coefficients, β_{wi} and β_{cj}, are zeros.

The lag length of an optimal VAR model is determined using various information criteria, including Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and Hannan-Quinn (HQ). To check for the model adequacy, there are several methods that can be used. Different methods apply depending on the inferences to be made about the model. That is, testing conformity of the estimated residuals to white noise assumption, autocorrelation, conditional heteroscedasticity and non-normality assumptions. This study uses analysis of residual autocorrelation using the multivariate Portmanteau test in testing the adequacy of the VAR model. The null hypothesis is that the residual autocovariances are zero. $H_0 : E(\varepsilon_t \varepsilon_{t-i}^{'}) = 0$, for $i = 1,2,3,\ldots$

3.3 Volatility Spillover Models

In this study for the volatility spillover, we use a multivariate GARCH model of vector autoregressive moving average with generalized autoregressive conditional heteroscedasticity, VARMA-GARCH model, developed by [25].[31], attested that VARMA-GARCH enables the examination of the conditional volatility and the cross effects of correlation with significant estimated parameters and less complications during computation in comparison to other methods, say BEKK model. A general VARMA-GARCH model for time varying variances and covariances is given by

$$R_{it} = E(R_{it} \mid F_{t-1}) + \varepsilon_t$$

$$\Phi(L)(R_{t-\varepsilon}) = \Psi(L)\varepsilon_t$$

$$\varepsilon_t = D_t \eta_t$$

$$H_t = W_t + \sum_{i=1}^{r} A_i \overrightarrow{\varepsilon_{t-i}} + \sum_{j=1}^{s} B_j H_{t-j}$$

where R_{it} is the return for the variable series i at time t, F_{t-1} gives the past information that is available at time t, $\Phi(L) = l_m - \Phi_{1m}L - ... - \Phi_p L^p$, $\Psi(L) = l_m - \Psi_1 L - ... - \Psi_q L^q$, $H_t = (h_{1t},...,h_{mt})'$, $W_t = (\omega_{1t},...,\omega_{mt})'$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$, $\overrightarrow{\varepsilon_t} = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)'$, $D_t = diag(h_t^{\frac{1}{2}})$, and m are the returns to be analyzed. A_i and B_j are mxm matrices with typical elements α_{ij} and β_{ij} for $i, j = 1,...,m$ which represent ARCH and GARCH effects respectively. The spillover effects of conditional variance between carbon price returns and the London wheat price returns are given in conditional volatility for each of the market in the portfolio.

VARMA-GARCH model is capable of presenting numerical estimates for the variance equation, mean equation and the constant conditional correlations for the selected sectors. The variance equations, for each of the commodities, can be described as a function of the past volatilities of the commodity itself as well as that of other commodities in the market. Here, the 'Meteor shower' hypothesis of cross-spillover states that the market's present volatility is a function of both its past volatility and the past volatility from other markets, that is, volatility transmissions. In this case, we want to observe the presence of volatility transmission between Carbon Emissions market and Wheat market. We observe that, if m=1, then the VARMA-GARCH model will reduce to a univariate GARCH model of [14].

VARMA-Asymmetric GARCH (VARMA-AGARCH) model was proposed by [24] to accommodate multivariate asymmetric effects of the negative and positive innovations and also describe asymmetric spillover impacts from each of the other returns. It has well established statistical and structural properties to capture spillovers, accommodates asymmetries, can have variable weights for forecasting, and satisfies Basel Accord thresholds. The specification of the conditional variance for the VARMA-AGARCH model is given by

$$H_t = W_t + \sum_{i=1}^{r} A_i \varepsilon_{t-i} + \sum_{i=1}^{r} C_i (I_{t-i}) \overrightarrow{\varepsilon_{t-i}} + \sum_{j=1}^{s} B_j H_{t-j}$$

Where $\varepsilon_{it} = \eta h_{it}^{\frac{1}{2}}$ for all i and t, A_i and B_j are mxm matriceswith typical α_{ij} and β_{ij} respectively. C_i is an indicator mxm matrix and I_{it} is an indicator function, such that $I_{it} = \begin{cases} 0, \varepsilon_{it} > 0 \\ 1, \varepsilon_{it} \le 0 \end{cases}$

Now, if we take $C_i = 0$ for all i, then the VARMA-AGARCH will reduce to a VARMA-GARCH model. If $C_i = 0$ with A_i and B_j which are diagonal matrices for all i and j, then the VARMA-AGARCH will reduce to a Constant Conditional Correlation (CCC) model [32]. But, the CCC model does not have asymmetric impact of negative and positive innovations on conditional volatility and the volatility spillovers effects across various financial assets. Asymmetry in time series is mostly influenced by news. Integrated markets get affected by events and news emanating from each other's economic, socio-political, trade, environment, commerce, legal, and market innovation scenarios. VARMA-AGARCH captures the asymmetries concerning the impacts associated to unconditional negative and positive shocks to the market.

3.4 Parameter Estimation

Here, we apply the method of maximum likelihood estimator (MLE) to estimate the parameters using joint normal density given as,

$$\hat{Q} = \arg\min \frac{1}{2} \sum_{t=1}^{n} (\log | Q_t | + u_t^1 Q_t^{-1} u_t)$$

Where $\hat{Q}$ is a vector of the parameters to be estimated by the conditional log likelihood function. $| Q_t |$ is the determinant of Q_t, which is the conditional covariance matrix, when η_t does not follow joint multivariate normal distribution. [33], observed that Quasi-maximum likelihood estimator (QMLE) model derives the appropriate estimators. In the presence of fat tails, leptokurtic, we use an adjusted QMLE to a non-Gaussian QMLE.

IV. RESULTS AND DISCUSSION

4.1 Data

The data set covers daily CO_2 allowance prices from May 1, 2008 to April 30, 2018. The starting point of the data set is explained by the fact that, between 2005 when the EU ETS market was established and 2007, which was the end of the first phase, this phase operated as a pilot period for the market. April 30, every year, marks the end of the financial year as each country is required to submit the allowances they have emitted in the past one year. We also obtained daily wheat prices for the period between May 1, 2008 and April 30, 2018. This is necessary as it helps in the analysis of spillover effects, as it is more effective when markets are trading simultaneously [19].

To study volatility, stationarity is a key aspect. A time series r_t is said to be stationary if both the mean and the covariance of r_t are time-invariant. That is, they are constant over time. The price series of an asset is not stationary since the prices are not fixed over time. In this case, the price series is said to exhibit unit-root non-stationarity. Hence, to get the log returns;

$$r_t = \log\left(\frac{p_t}{p_{t-1}}\right)$$

Where r_t the log returns for the given commodity, p_t is the commodity price at time t.

4.2 Descriptive Statistics

Figure 4.1 shows the time series plot of Carbon Emission prices. There is a sharp decline in prices at the end of the year 2008 through 2009. This can be explained by the global financial crisis of 2007-2008, where housing and banking fallout across United States, Europe and Asia, involving lending banks, among them, the Lehman Brothers and the Wall Street investment bankers where the lending bubble of sub-prime did burst necessitating lack of confidence by investors, and the homeowners were unable to repay their mortgages. The increase in prices around the year 2011 is attributed to the high demand of carbon allowances by many countries that were joining the EU ETS at the time it was registering a success towards the end of the second phase. The decline again from the year 2012 is attributed to the surplus of the allowances as governments could trade amongst themselves through Joint Implementation (JI). Again, figure 4.2 shows the wheat prices were low during the period between 2008 and early 2010. This can also be attributed to the global financial crisis of 2007-2008 and its aftermath in the commodity markets. The sharp increase is attributed to the stability in the market and high demand for wheat in the EU market.

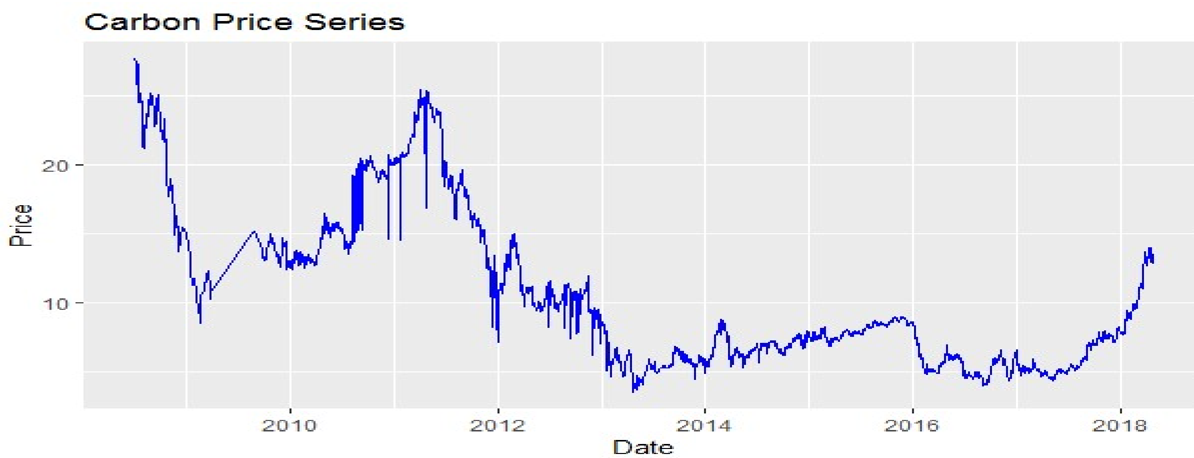

Figure 4.1 Time series plot for Carbon Emissions

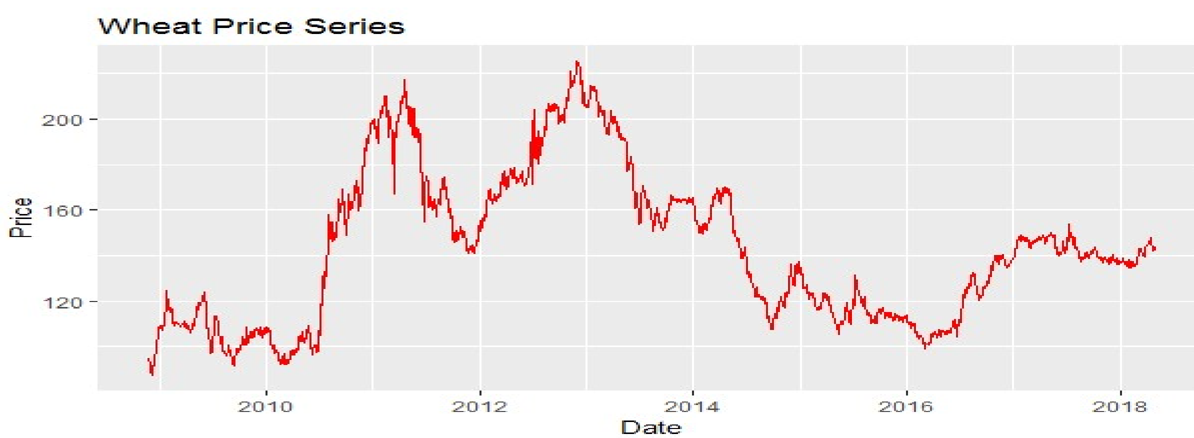

Figure 4.2 Time series plot for Wheat

The basic summary statistics for the returns of the two time series are shown in the table 4.1. The basic statistics for Carbon emissions returns indicate a mean return of 0.000296, a variance of 0.002896, a skewness of 0.291225 and kurtosis of 26.738601. This kurtosis is greater than 3, which implies that this data exhibit a heavy tail, hence leptokurtic as compared to a normal distribution. A normality test was carried out using Jarque-Bera test to confirm this output whereby a null hypothesis of normality was rejected at 5% significance level when compared to the resulting p-value.

The basic statistics for Wheat returns indicate a mean return of -0.000171, a variance of 0.000184, a kurtosis of 13.384829 and a skewness of 1.074964. Again, this kurtosis of the Wheat returns is greater than 3, implying heavy tails, hence data is leptokurtic compared to a normal distribution. On carrying out a normality test using Jarque-Bera test, the null hypothesis of normality was rejected at 5% significance level compared to the resulting p-value.

Table 4.1 :Summary Statistics for Returns

Statistics	Carbon Emissions	Wheat
Minimum	-0.425799	-0.138646
Mean	0.000296	-0.000171
Maximum	0.495584	0.098989
Variance	0.002896	0.000184
Skewness	0.291225	-1.074964
Kurtosis	26.738601	13.384829
Jarque-Bera (JB)	71721.5281	18430.0706
JB p-value	<2.2e-16	<2.2e-16

The figures 4.3 and 4.4 show plots of the log returns for Carbon emissions and Wheat. As shown in the plots, there are periods of high volatility and that of volatility clustering, where large spikes follow other large spikes and small spikes follow other small spikes. The plots also shows the returns data are stationary. To confirm this, a test was carried out using Augmented Dickey-Fuller (ADF) test of Said and Dickey (1984), where the null hypothesis states that there is a unit root in the series being tested. The ADF test for each of the returns series gives a p-value= 0.01 which is less than 5% significance level, hence we reject the null hypothesis thus the series are stationary.

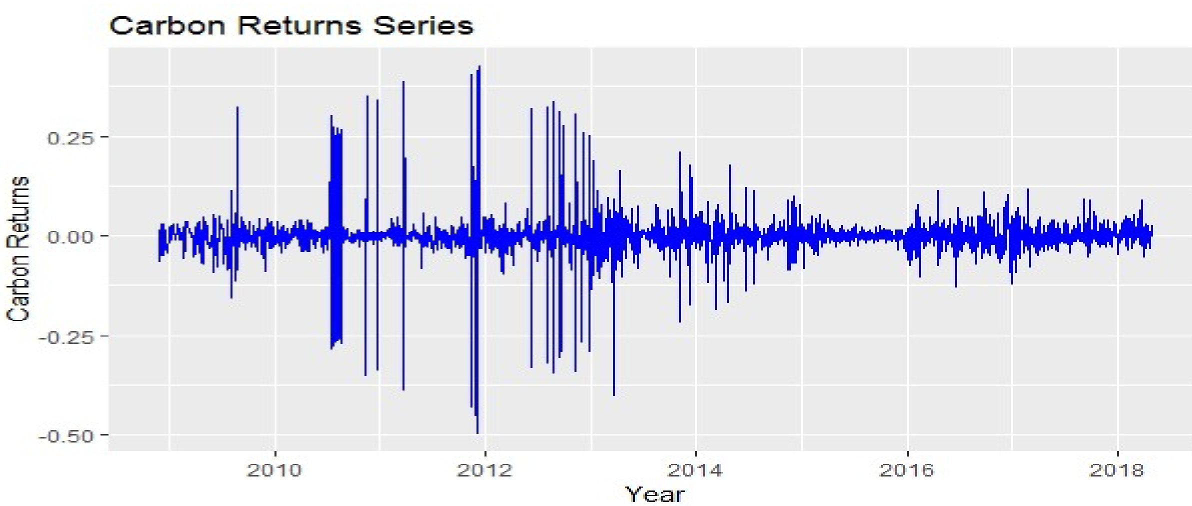

Figure 4.3 Carbon Returns Series

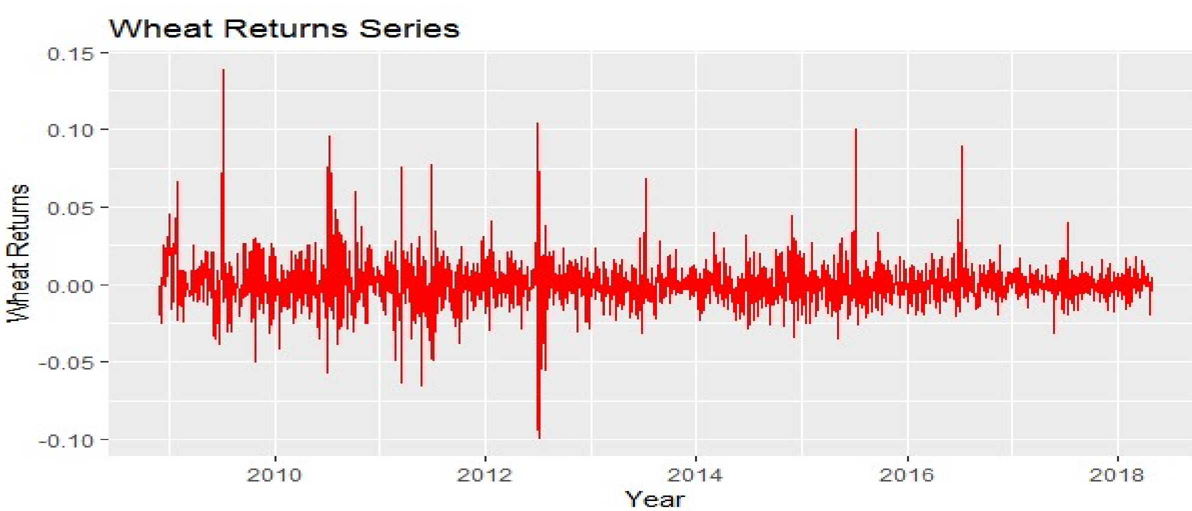

Figure 4.4 Wheat Returns series

4.3 Heteroscedastic Modeling- Univariate GARCH

The presence of ARCH effects necessitates heteroscedastic modeling of the time series. The Box-Ljung test has that; H_0 : No ARCH effects vs H_1 : There are Arch effects.

The p-values obtained from the statistics are less than 0.05 indicating presence of ARCH effects in both the Carbon Emissions and Wheat series; hence we reject the null hypothesis of no ARCH effects at 5% significance level.The optimal GARCH models, GARCH(1,1) for both variables using student-t distribution were fitted. This is because both series exhibited heavy tails, thus rejecting the assumption of normality. The optimal model for Carbon Emissions is an ARMA(0,1)-GARCH(1,1), whereas for Wheat is ARMA(0,0)-GARCH(1,1).

4.4 Granger Causality

VAR model fits well with stationary data. This helps to avoid spurious regression issues as well as inconsistencies in the estimation. An ADF test was carried out to determine the stationarity of the time series for the two variables, Carbon Emissions and Wheat. Since the time series were not stationary in their raw form, first difference was conducted to make them stationary.

4.4.1 Selecting VAR order

Three methods were used to evaluate the optimal lag length of the two-variable VAR model, that is, AIC, BIC and HQ methods. In this case, the BIC had the smallest value at length p=3, hence a VAR(3) is fitted to the data. The results for the VAR order selection are shown in the table below.

Table 4.2 Order Selection Statistics for VAR model

p	AIC	BIC	HQ	p-value
0	-14.4399	-14.4399	-14.4399	0.0000
1	-14.5469	-14.5372	-14.5434	0.0000
2	-14.5704	-14.5512	-14.5634	0.0000
3	-14.5815	**-14.5526**	-14.5710	**0.0000**
4	-14.5802	-14.5416	-14.5661	0.3240
5	-14.5808	-14.5326	-14.5633	0.0519
6	-14.5926	-14.5348	-14.5715	0.0000
7	-14.5941	-14.5266	-14.5695	0.0220
8	-14.5924	-14.5153	-14.5643	0.4249
9	-14.5894	-14.5027	-14.5579	0.9193
10	-14.5889	-14.4926	-14.5539	0.1496

4.4.2 Model Adequacy and Stability

To confirm the adequacy of the model, a diagnostic test was done on the residuals extracted from the fitted model, shown in table 4.3. [28], states that a model is said to be significant at given level of probability when the model residuals fail to show any form of significant cross-correlations and when the residuals are not in violation of the distribution assumption. In our study, the model was tested using a Multivariate Ljung-Box (Portmanteau) test statistic to see whether it removes the serial cross-correlations in VAR(3) residuals. As illustrated in the table below, the reduced VAR(3) model removed serial dependencies (p-values>0.05 probability level). The model is stable as all the eigen values in the companion matrix have a value less than a unit, thus lie inside a unit circle: 0.493526, 0.493526, 0.471839, 0.286338, 0.286338, 0.285183, are all less than 1.

Table 4.3 VAR(3) Residuals Diagnostic Test Results

M	Q(m)	df	p-value
1.0000	0.0576	4.0000	1.00
2.0000	0.2437	8.0000	1.00
3.0000	0.6488	12.0000	1.00
4.0000	3.9971	16.0000	1.00
5.0000	9.9831	20.0000	0.97
6.0000	47.4635	24.0000	0.00
7.0000	62.9170	28.0000	0.00
8.0000	66.3158	32.0000	0.00
9.0000	66.7275	36.0000	0.00
10.0000	71.7411	40.0000	0.00

4.4.3 Testing for Granger Causality

The VAR(3) model above was used to test for Granger Causality between Carbon Emissions and Wheat prices at 5% level of significance. The null hypothesis that Carbon Emissions prices fail to Granger Cause Wheat prices is rejected as the F-statistics value (3.067) is significant with p-value less than 0.05. The null hypothesis that Wheat prices fail to Granger cause Carbon Emissions prices is not rejected as the F-statistic value (1.0341) is not significant with p-value greater than 0.05 level of significance. The table below gives the results of this test indicating that, when past observations of Carbon Emissions prices are added to the information set with which we would want to forecast the Wheat prices, the added observations improves such a forecast [30]. However, the past observations of the Wheat prices (when added to the information set of Carbon Emissions prices) do not improve the forecast of Carbon Emissions prices. Hence, this results to a unidirectional Granger Causality.

Table 4.4 Granger Causality Test Results

Null Hypothesis	F-Statistics	p-value
Carbon Emissions /⟶Wheat	3.067	0.02693
Wheat /⟶Carbon Emissions	1.0341	0.3763

H_0: A /⟶B implying "A does not Granger Cause B"

4.5Volatility Spillover- Multivariate GARCH

Table 4.5 and 4.6 presents the parameter estimation results for VARMA-GARCH and VARMA-AGARCH models respectively. Looking at the mean equations in table 4.5, the coefficient for Carbon Emissions show negative but statistically significant effects of individual/own spillover. The coefficient for Wheat mean equation is positive and statistically significant, thus own spillover effects are evident. Short-term predictability for both commodity price changes is also evident from these findings over time.

The variance equations are such that, the A matrix elements are the estimated coefficients in ARCH volatility measuring persistence in the short-run volatility. The own conditional effects of ARCH A(1,1) and A(2,2) are all positive and statistically significant at the 5% level of significance, thus indicating short-term persistence. In addition to these, the condition variances are seen to be a function of own lagged covariance and the lagged cross product of the innovations. A(1,2) coefficient is negative and statistically significant indicating that a shock of Carbon Emissions volatility spills over to Wheat price market. The coefficient of A(2,1) is negative but not statistically significant, indicating Wheat volatility does not spill over to Carbon Emissions price market. This shows that VARMA-GARCH is in a position to model the short term volatility spillover.

Again, in the variance equation, the own conditional GARCH effects B(i,j), the B matrix elements are the coefficients estimated for GARCH volatility measuring long-term persistence.

Table 4.5 Parameter Estimates for VARMA-GARCH

Variable	Coefficient	T-Statistics	Significance
Mean(Carbon Emissions)	-0.000006578	-7.94855	0.00000000
Mean(Wheat)	0.000303712	143.71919	0.00000000
C(1)	0.000647358	7.91428	0.00000000
C(2)	0.000087172	17.05840	0.00000000
A(1,1)	0.152078825	6.21988	0.00000000
A(1,2)	-0.032345359	-5.35059	0.00000009
A(2,1)	-0.000331246	-1.48409	0.13778470
A(2,2)	0.101070372	7.26708	0.00000000
B(1,1)	0.283882433	16.14822	0.00000000
B(1,2)	0.111103291	0.50296	0.01499156
B(2,1)	-0.000462521	-0.43505	0.66352533
B(2,2)	0.506256819	28.10422	0.00000000
DCC(A)	-0.007756858	-19846.56162	0.00000000
DCC(B)	0.738732495	99452.67104	0.00000000
Shape(t degrees)	3.282940318	19.94004	0.00000000
ARCH-LM	0.50023		
Q-Statistics	64.82795***		

The GARCH effects B(1,1) and B(2,2) are both positive and statistically significant at 5% level, indicating a considerable evidence of own long term persistence in volatility. In addition to these own past shocks, there is evidence of the conditional variance in the given market being affected by the innovations arising from the other market. There are positive and statistically significant volatility spillovers from Carbon Emission market to the Wheat market, B(1,2). However, the coefficient for conditional variance equation, B(2,1), is not statistically significant indicating that there is no substantial evidence of volatility spillovers from Wheat market to the Carbon Emissions market, The findings of A(2,1) and B(2,1) conquers with the Granger causality test that earlier showed no evidence of Wheat Granger-causing Carbon Emissions.

The estimates for the DCC parameters are such that, DCC(A) is negative and statistically significant at 5% level indicating a joint significance in the ARCH effects for short term persistence. The DCC(B) is positive and statistically significant revealing a joint significance of the GARCH effects for long term volatility spillovers across the markets. These DCC estimated coefficients have values summing to less than one, which is a proof that the dynamic conditional correlations portray mean reverting aspect and are significant hence the assumption of constant conditional correlations cannot apply.

Now, the two-variable asymmetric M-GARCH model is presented in table 4.6. Again, the mean equation for Carbon Emissions has negative coefficient which is slightly statistically insignificant at 5% level. This shows that the current returns do not depend on own past returns. Thus, accounting for asymmetric effects therefore explains this phenomenon where the returns are likely to be influenced by other factors in the market, say changes in prices of energy prices such as oil, gas, electricity, among others. However, the coefficient for Wheat mean equation is positive and statistically significant.

The conditional variance equations are such that, the conditional volatility of the variables are determined by own conditional ARCH effects A(i,j), measuring short-run persistence, and own conditional GARCH effects B(i,j), measuring long-run persistence. The conditional variance equations also show significant cross-market shock and volatility effects from Carbon Emissions market to Wheat market. Again, the coefficient for conditional variance equation B(2,1) is not statistically significant, hence no spillover effects from Wheat market to Carbon Emissions market. VARMA-AGARCH reveals statistically significant estimates of the asymmetric effects D(1) and D(2), which have been left out in VARMA-GARCH.

Table 4.6 Parameter Estimates for VARMA-AGARCH			
Variable	Coefficients	T-Statistics	Significance
Mean(Carbon Emissions)	-0.000021712	-0.01774	0.05001600
Mean(Wheat)	0.000205941	60.34441	0.00000000
C(1)	0.000862395	14.32331	0.00000000
C(2)	0.000094137	28.33868	0.00000000
A(1,1)	0.072597904	5.71912	0.00000001
A(1,2)	-0.003924164	-0.42283	0.02241878
A(2,1)	-0.000307129	-1.39702	0.16240875
A(2,2)	0.029245566	3.53427	0.00040890
B(1,1)	0.299254388	16.26107	0.00000000
B(1,2)	-1.188786446	-4.95396	0.00000073
B(2,1)	-0.000250728	-0.23240	0.81622349
B(2,2)	0.468999979	27.96335	0.00000000
D(1)	0.059276352	3.74526	0.00018020
D(2)	0.013293591	2.30520	0.02115534
DCC(A)	-0.007781635	-30.70587	0.00000000
DCC(B)	0.730711550	12.10515	0.00000000
Shape(t degrees)	3.348541511	27.88226	0.00000000
ARCH-LM	0.65508		
Q-Statistics	67.76442***		

V. CONCLUSION

Previous studies about energy markets indicate high volatility and interrelations between the commodities in these markets. Analysis of volatility spillovers between energy markets and other markets, other than among the commodities in energy markets, is important for traders, investors and government agencies dealing with policy making in across markets. This therefore necessitates this study of interrelationships between Carbon Emissions in energy market and Wheat in agricultural market. This study used VAR(3) model to test Granger causality between Carbon Emissions prices and Wheat prices, and revealed a unidirectional/one-way Granger causality from Carbon Emissions to Wheat. VARMA-GARCH [25] and VARMA-AGARCH [24] models were used to investigate presence volatility spillovers between Carbon Emissions and agricultural commodities, herein using Wheat. The empirical results revealed that both models capture dynamic structures of interaction in returns and volatility spillover effects, which were evident from Carbon Emissions to Wheat, both under short-run and long-run persistence impacts. The level of significance at which VARMA-AGARCH model eliminates ARCH effects makes it more preferable in modeling volatility spillovers between these two commodity markets as compared to VARMA-GARCH model.

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