Global Food Price Volatility Spillover from International to Domestic Markets

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Abstract:

A substantial portion of household income in a developing country is spent on food consumption and thus a thorough understanding of global food price fluctuations in recent years convey crucial importance to bolster food and nutrition security in economically vulnerable nations. The main objective of this study is to determine the direction and magnitude of price and volatility transmission from international to domestic markets. We utilize Multivariate Generalized Autoregressive Conditional Heteroskedasticity framework on monthly price data spanning from January 2003 to November 2022 of major consumed agricultural commodities covering 42 developing countries in the world. Among the 75 sample markets, volatility spillover from the own markets is statistically significant for 71 tested markets; volatility spillover from international to domestic markets are statistically significant for 21 tested markets; and asymmetric effects are being statistically significant in 19 tested markets. The results of this research may provide a valuable insight for predicting agricultural commodity prices, enabling governments to support policy options that mitigate the impact of food grain price volatility and protect economic vulnerable groups from its adverse effects.

Keywords: food security; international food price; domestic markets; volatility transmission, food policy

Introduction:

For centuries, agriculture has been an essential industry for human sustenance, but it has undergone notable transformations in the last three decades mostly due to population growth, urbanization, scarcity of natural resources, reduction of labor supply in rural and suburban areas, and climate change (Conforti, 2011; Dawe et al., 2015). The demand for increasing supply of agricultural goods and the need for higher productivity has increased substantially to fight against hunger and malnutrition that may induced by higher food price in domestic market, especially in developing countries. The global food price surge is not a new phenomenon rather it happened multiple times from 2007 to 2011 due to production and inventory shock, market disorders, increase in energy and oil prices, panic orders from major importers, and global trade restrictions that dragged millions of people into food insecurity (Gilbert, 2010; Ceballos et al., 2017).

Moreover, the world economy is experiencing a dramatic shock in recent years due to global supply chain disturbance, macroeconomic policy changes, trade restrictions, and highly volatile commodity prices induced by worldwide lockdown conditions during the COVID-19 pandemic (Xue et al., 2021). The sudden shock in commodity demand and supply has major effects on the global food value chain. Food price fluctuation is inevitable to some extent throughout the world because of changes in consumers' tests and preferences, rapid changes in production technologies, innovation, macroeconomic indices, and changes in energy prices. However, the supply shortage and trade restrictions during the COVID-19 pandemic may have a substantial effect on the pattern and extent of spatial price transmission of agricultural products between international and domestic markets of developing countries.

Domestic food price is the primary factor that mainly influences poverty and welfare in developing countries as the price directly paid by the consumers and received by the producers (Dawe et al., 2015). Some previous studies indicated that food price in global market may not be a crucial important for economically vulnerable countries as the international price not likely to transmit into domestic prices due to imperfect information, transport costs, and government policies (Conforti, 2004; Dawe et al., 2010; Timmer, 1993; Minot, 2010). However, recent studies of Ceballos et al. (2017) and Hernandez et al. (2014) identified that international food price volatility has significant impact on domestic food price volatility in developing countries, especially for

grain markets. Hence, a better and clear understanding of food price fluctuations in international market can inform policy decisions and interventions to achieve the United Nations Sustainable Development Goal of zero hunger, by ensuring access to safe, nutritious, and affordable food for all considering the recent economic turmoil.

A clear understanding of the directional flow and intensity of food price transmission between global and domestic markets will have significant policy implications. If the price information flows from international to domestic markets, then policies should be taken by international organizations such as World Trade Organization (WTO) and other multilateral bodies to maintain food price stability in the global market. However, if there is no market integration and price transmission relationship between the global and domestic markets then more emphasis should be given to the regional level as countries are not dependent on importing food to fulfill domestic demand (Ceballos et al., 2017). In that case policies regarding improving transportation facilities, production systems, marketing infrastructure, storage facilities, and dissemination of market information will immensely help developing countries to stabilize food prices.

A significant portion of consumers' income in developing countries is spent on food consumption and therefore, the extent to which global food prices affect domestic prices has serious implications to ensure food security for economically vulnerable people. Food security is a major concern for developing countries due to the limited availability and accessibility of domestically produced food to people living below the poverty line. Most developing countries are heavily dependent on exporting high-valued food products and importing low-valued food items from the international market. Since the 1980s, numerous multilateral and bilateral free trade agreements were established to provide sustainable food supply and efficient allocation of resources to support citizens of developing regions (Luo & Tanaka, 2021). It is essential to have a lucid understanding of the price transmission and market integration relation between global and domestic markets for agricultural products to propose suitable trade policies that may bring food price stability and food security in developing regions.

There is a plethora of articles published focusing on price transmission of food products along the horizontal and vertical value chain nodes covering the globe while a majority targeted developing countries (Abdulai, 2000; Baulch, 1997, Lutz et al., 2006, Moser et al., 2009; Meyer & Von

Cramon-Taubadel, 2004). The articles that investigate the price transmission relationship between global and domestic markets mostly rely on the error correction model (Luo & Tanaka, 2021). The error correction model can capture the long-run and short-run price linkage but is unable to explain the extent and intensity of the price transmission relationship among the value chain nodes. Hence, it is essential to have a thorough understanding of spatial price and volatility transmission of agricultural products from global to domestic markets of developing countries using an improved econometric framework.

Our study contributes to existing literature both empirically and methodologically. First, we assess the food price volatility spillover effect over past two decades from international market to economic vulnerability countries in Asia, Africa, and Latin America, with a focus on time-varying correlations explaining recent price shocks till 2022. Second, we distinguished positive and negative shocks of the international market and its effect on domestic markets using asymmetric multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) framework. The rest of the article is organized as follows. Next, we provide a detailed description of the data source and econometric model to capture food price volatility transmission. Then we present the empirical results which is be followed by the discussion and policy recommendation section. At the end there is a concluding remark.

Data and Methodology:

Data

To investigate the spatial price transmission of agricultural products from global to domestic markets, we obtained publicly monthly domestic commodity price data from the Global Information and Early Warning System (GWIES) of the Food and Agriculture Organization (FAO) of four major agricultural consuming commodities: rice, maize, wheat, and sorghum starting from January 2003 to November 2022. We covered most of the developing countries from Asia, Africa, and South and Central America that are available on the GWIES except those counties with limited observations and consequently not sufficient to model long-term volatility effect. Since each county may have several different geographical markets in the database, we select either the price of capital market or national average to represent the domestic nominal price. We compiled a total

of 24 rice-importing countries, 16 wheat-importing countries, 11 sorghum-importing countries, and 24 maize-importing countries for this study.

In the meantime, we utilized the available monthly commodity prices from FAO International Commodity Prices databases (FAOSTAT) as the global export referenced market price. More specifically, the global rice market price is Thai A1 super rice price at Bangkok, Thailand; The global wheat market price is No.2 Hard Red Winter wheat price at US Gulf; The global sorghum market price is No.2 yellow sorghum at US Gulf. All the collected data are converted to the unit scale of U.S. dollars per tonne from the local currency. Appendix table A1 provides the detailed description for each price series used, including the type of commodity, the location of local market, the type of sales price (retail or wholesale), and the observed period.

Before conducting any econometric analysis, we need to make the time series data stationary to avoid any misleading interpretations. The most common way to covert time series data stationary is log returns: $r_t = log(P_t) - log(P_{t-1}) = log(P_t/P_{t-1})$, where P_t is the nominal price at time t and P_{t-1} is the nominal price at time t - 1, respectively. We use Augmented Dickey Fuller (ADF) (Dickey & Fuller, 1981), one of the most widely used tests to confirm the stationary property.

Methodology

Global food price and volatility transmission analysis in this article is based on a Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model using Baba-Engle-Kraft-Kroner (BEKK) framework (Engle and Kroner, 1995). The BEKK model is a statistical model used to estimate the conditional covariance matrix of multivariate time series and is widely used in the analysis of volatility and risk management, as well as in portfolio optimization and asset allocation. We implement two-stage bivariate VAR-BEKK GARCH model. We first compute the mean equation using vector autoregressive (VAR) model and subsequently use BEKK GARCH model to estimate the asymmetric price volatility spillover effect.

The VAR model is a generalization of the univariate autoregressive model and use for multivariate time series. The VAR model can be written as follows:

$$x_t = \alpha + \sum_{n=1}^{n} \phi_n x_{t-n} + \varepsilon_t \tag{1}$$

Where x_t is the 2-dimensional vector (domestic and international) of food grain price at time t, α is the constant term, ϕ_n are matrices of estimated coefficients and ε_t is the noise at time t assuming normally distributed with zero mean and variance σ^2. The optimum lag length n is selected based on Hannan-Quinn (HQ) information criterion.

The BEKK GARCH model is a multivariate extension of the standard GARCH model, used for modeling and forecasting the conditional covariance matrix of a set of variables. The model specifies the conditional variance-covariance matrix of a vector of returns as a function of lagged squared errors and lagged conditional variances, allowing to capture the time-varying volatility and cross-sectional correlations between different markets. Besides, to comprehend the positive and negative shocks of international market and its effects on regional market, we introduced an additional matrix that measuring the asymmetric effects in the BEKK framework (Kroner and Ng, 1998). The model parameterization can be written as following equations:

$$\varepsilon_{i,t} = \vartheta_{i,t} h_{i,t}, \qquad \vartheta_{i,t} \sim N(0,1) \tag{2}$$

$$h_{i,t} = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{3}$$

$$H_t = C^T C + A^T \varepsilon_{t-1} \varepsilon_{t-1}^T A + G^T H_{t-1} G + B^T z_{t-1} z_{t-1}^T B \tag{4}$$

Where $h_{i,t}$ is the conditional variance, H_t is conditional variance covariance matrix, C is the lower triangular matrix of coefficients that capture the static correlations between markets, A matrix contains the ARCH coefficients that captures temporary price shocks between markets, G matrix contains the GARCH coefficients that captures persistent price shocks between markets, B matrix is the additional matrix representing the asymmetric effects. We set $z_{t-1} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} \leq 0$, indicating bad news or negative shocks, otherwise $z_{t-1} = 0$. All the parameter matrices can be defined as follows:

$$H_t = \begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22t} \end{bmatrix} \quad C_t = \begin{bmatrix} C_{11,t} & C_{12,t} \\ C_{21,t} & C_{22,t} \end{bmatrix}$$

$$A_t = \begin{bmatrix} A_{11,t} & A_{12,t} \\ A_{21,t} & A_{22,t} \end{bmatrix} \quad G_t = \begin{bmatrix} G_{11,t} & G_{12,t} \\ G_{22,t} & G_{22,t} \end{bmatrix} \quad B_t = \begin{bmatrix} B_{11,t} & B_{12,t} \\ B_{21,t} & B_{22,t} \end{bmatrix}$$

Here, subscript 1 represents domestic market and subscript 2 represents international market; A_{11} measures domestic market's own price volatility clustering. A_{12} measures cross price volatility clustering from international to domestic market. G_{11} indicates the own GARCH effect (volatility persistence) of the domestic market. G_{12} indicates the volatility spillover effect from international

market and domestic market. B_{11} and B_{12} represents the asymmetric effect of international market and domestic market, respectively. The optimization of the BEKK parameters is based on the Berndt–Hall–Hall–Hausman (BHHH) algorithm (Berndt, et al., 1974).

We use analytical derivates and follow quasi Maximum Likelihood (QML) estimation to compute the log-likelihood function and reduce the possibility of misspecification of innovation distribution.

$$L(\theta) = \sum_{t=1}^{T} -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t\theta| - \frac{1}{2}\varepsilon_t^T H_t^{-1}(\theta)\varepsilon_t \tag{5}$$

Where T is the number of observations, N is the number of markets, $\ln|H_t\theta|$ is the log-determinant of the conditional covariance matrix and ε_t is the transpose of the vector of standardized residuals. The QML method is used because it is computationally efficient and provides consistent estimates under weak assumptions about the distribution of the residuals. The QML method involves maximizing the log-likelihood function with respect to the parameters of the BEKK GARCH model using a quasi-Newton algorithm (Hafner & Herwartz 2008).

Empirical Results:

Figure 1 represents the percentage of markets that have significant ARCH, GARCH, and asymmetric effect. We can see almost all the markets have significant GARCH coefficient (either own market, cross market, or both). 64 percent of markets experience significant price volality clustering while only 20 percent exhibits asymmetric effect. From figure 2 we can see most of the domestic markets are not experiencing significant short-run and long-run volatility transmission spillover effect from international markets. In case of rice for selected 24 developing countries, only 8 countries have significant cross market spillover effect where majority are African countries. The countries which experience significant cross market spillover effects for maize are also situated in Africa. Only Ethiopia, Brazil, Afghanistan, Kazakhstan, and Peru for wheat market and Somalia, El Salvador, and Mali for sorghum market have significant spillover effect from international market. The geographical scope of volatility spillover effect conveying from international market to regional markets in developing countries is limited and thus emphasis should be given to regional policies to maintain food price stability.

Tables 1-4 provide the estimated parameters of the BEKK GARCH model for the selected food grains market with the measure of their statistical significance. In general, regardless of food item, we find a significant ARCH and GARCH effect for own price (domestic markets) within the covered period. This indicates most of the developing countries' domestic markets have been influenced by their own short-term and long-run price shocks in the last 20 years. More specifically, 64% of selected domestic markets experienced temporary volatility effect, 93.3% of selected markets experienced persistence volatility effect, 20% of selected markets had asymmetric volatility effect. In terms of direction of volatility transmission, 33.3% of selected rice markets, 25% of selected maize markets, 31.3% of selected what markets, and 27.3% of selected sorghum markets have significant volatility spillover effect from global markets. The residual autocorrelation and ARCH tests as model diagnostics are also provided to avoid any unintended model misspecification. Appendix table A1 provides the conditional mean equation of VAR. Also, the summary statistics including testing basic time series properties such as stationarity test, normality test, autocorrelation test etc. are provided in appendix table A2 to table A4.

In terms of own price ARCH effect, more than half of the A_{11} values are statistically significant, indicating the evidence of strong own price volatility clustering effect for most of the developing countries. The significant A_{11} parameter widely varies among selected food grains that range from 0.049 for Rwanda maize market to 0.637 for Niger rice market. In case of own price GARCH effect (G_{11}), almost all the covered markets are statistically significant indicating previous period own price volatility significantly influence current period volatility in domestic markets, regardless of selected food grains. Also, we find the estimated G_{11} value for all markets is larger than the estimated A_{11} value suggesting the impact of past volatility shocks on current volatility is relatively stronger than the effect of past squared errors on the current variance. This indicates that food grains price volatility in developing countries is mainly driven by the persistence of past shocks in domestic markets rather than the magnitude of those shocks.

The asymmetric term of BEKK-GARCH model separates the impact of positive and negative shocks on the conditional covariance matrix. For rice market, only Colombia experience significant own market asymmetric effect (B_{11}) with positive coefficient. This indicates negative news in Colombia rice market increases the price volatility of its own rice market. In the case of maize market, there are 7 countries that experience significant own market or cross market (from

international to domestic) asymmetric effect. Ghana is the only country that has significant B_{11} and B_{12} coefficient. The negative B_{12} coefficient of Ghana maize market indicates bad news from international maize market decreases the price volatility of domestic markets in Ghana. Also, there are 5 countries for wheat market and 3 countries for sorghum market have significant own or cross market asymmetric effect.

The figures 3-6 in appendix show the time-varying conditional correlations of selected developing countries' domestic price with respect to international price of four major food grains. Overall, during the sample period, the conditional correlations of all four commodities exhibit significant time variability and are found to be largely dependent on the markets involved in the analysis. We find that the conditional correlation for the sample markets were predominantly positive throughout the entire sample period, indicating an increase in the volatility of the global price could result in an increase in the volatility of domestic food grain prices for almost all the developing countries.

The time varying conditional correlation diagrams also exhibit interesting patterns for the selected food grains. Before 2010, it is clearly observed that the correlations for most of the sample markets exhibited significant fluctuations and sharply peaking between 2008 to 2010. These pronounced fluctuations can be explained by the unprecedented global major food price brunt starting in 2007 due to production and inventory shock, energy, and oil price increase. During the year 2010-2019, it can be seen that overall trend moderately fluctuates around the mean correlations with some correlations reach extreme values in a very short time around 2013 to 2015, showing the huge different movements between global and local prices. The third stage can be considered as the period starting from March 2020, the outbreak time of the Covid-19 pandemic. COVID-19 has touched every aspect of people's lives and has had a profound impact on the world economy and agricultural sectors. The global food supply chain that has developed over the years experiences supply disruptions leading to driving up food prices (Das, et al., 2021). Interestingly, we find that more than half of sample markets experienced a sharp decrease in correlation right after March 2020.

When the outbreak occurred in early 2020, there were labor shortages and disruptions in production which caused a decline in the correlation between domestic and international markets.

Additionally, to respond to the pandemic, numerous countries enacted protectionist trade policies that aimed to safeguard their local industries and ensure food security. These policies, which included export restrictions, import tariffs, and subsidies for domestic production, reduced the level of interconnectedness between agricultural markets in developing nations and the global market, resulting in a reduction in the conditional correlation. However, as the world began to recover from the Covid-19 pandemic, supply chains began to stabilize, and global trade resumed leading to an increase in the correlation.

Discussion and Policy Recommendations:

Our results uncover the spatial price volatility transmission of major agricultural products from global to domestic markets in developing economies. Since the study is based on major food grain markets, the implications of our findings are applicable to promote suitable international and domestic policies to bolster food and nutritional security. Given the complex interlinkages and interactions between various actors and economic sectors, food prices are not determined solely by the farm supply and consumers demand, nor price volatility is solely a result of harvest and income shocks. For policy implicating, the goal is not to propose a detailed policy instrument, but rather to develop a portfolio of policies that effectively address the pertinent issues. Therefore, the primary objective for addressing stabilize price policies is to maintain domestic food security and to protect vulnerable groups by implementing domestic level policies.

Rice is one of the most important staple food grains consumed by almost half of the world's population. Domestic rice markets in developing countries can greatly influenced by supply and demand in the international market as well as some other regional drivers including the structure of rice production, marketing and consumption patterns (Timmer, 2009). Based on our results, Mali, Mexico, Nicaragua, Peru, Dominican Republic, Costa Rica, Togo, Cambodia, Ghana, Samoa, and Sri Lanka rice markets have significant volatility clustering and persistence effects from own markets. Around 33.3% of selected countries rice markets experience price volatility spillover from international market. Existing studies have emphasized several key factors that significantly influence rice price volatility in developing countries such as USD exchange rate (Hathurusingha, et al., 2019), crude oil price (Kong, et al., 2012), speculation in future commodity markets (Algieri, 2016), and regional stockpiling policies (Caballero-Anthony, et al., 2016).

Brazil is one of the largest rice importing, exporting, and producing nations in the world (Muthayya, et al., 2014) and may serves as a significant source of inspiration for the conceptual framework of food and nutritional security, in addition to its relevant context of associated public policy and programming. Notably, Brazil has recently enshrined the right to food as one of the social rights guaranteed by its constitution. Such accomplishments have been the outcome of a protracted process of public intervention and widespread social mobilization, which have brought together diverse stakeholders from the government and civil society (Chmielewska and Souza, 2011). To stabilize domestic rice markets in developing countries, implementing policies by supporting long-time investment to improve primitive marketing infrastructure, efficient transportation facilities, and better irrigation system may help immensely to bolster food security. Anticipating market behavior can also help policymakers and market participants prepare for potential price fluctuations and strengthen agricultural sectors confidence, including monitoring market trends, identifying supply and demand imbalances, and developing contingency plans. In some cases, flexible trade policies can promote competition and increase market efficiency, which may result in lower prices and reduce the adverse impact of higher price volatility on consumers. In addition, promoting regional integration through the free movement of goods may help create a more integrated and efficient market leading food grain price stability. Also, improving storage facilities in economically vulnerable countries through direct or indirect local government interventions can help ensure food security and prevent unexpected price spikes.

Wheat is considered one of the most strategic crops in the world. In 2021, with a production exceeding 776 million metric tons, wheat solidified its position as one of the most consumed grains worldwide, ranking just behind rice[1]. It also serves as the leading source of vegetable proteins in human food, having a relatively high protein content compared to other major cereals. According to the World Bank, the largest importers of wheat in 2021 are Indonesia, Turkey, Philippines, and Brazil. Our findings suggest that Ethiopia, Brazil, Afghanistan, Kazakhstan, and Peru wheat price volatility significantly influenced by international market. Given the situation the Russia-Ukraine's war has inevitably induced wheat market volatility since both countries are the important players in the global wheat markets. From policy perspective, other global scale studies of wheat

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[1] For more information, please visit https:// www.tradefinanceglobal.com.

market have indicated that reducing the foreign dependency on importing and higher self-sufficiency rate could effectively abate the conveyance of international market shocks to indigenous markets (Guo and Tanaka, 2019, Luo and Tanaka, 2021).

Countries highly dependent on international wheat market to fulfill domestic demand may implement policies facilitating improvise agricultural practices, diversifying importing sources, implementing strategic grain reserves, and encouraging regional cooperation to reduce international market dependency. It is worth noting that Kyrgyzstan is the only country with no significant wheat price volatility spillover effect from either own or international market. Wheat production in Kyrgyzstan is not always sufficient to meet domestic demand, which sometimes necessitates importing wheat or flour from neighboring countries like Kazakhstan and Russia (Yamano, et al., 2019). In the past decade, Kyrgyzstan government has implemented different programs and initiative to address food and nutrition security and sustainable development such as rehabilitation of infrastructure, enhancing agricultural public goods provision, implementation of tax incentives for agribusiness enterprises and individual farmers, improvement of market access to neighbor countries and providing affordable credit provision for farmers and agribusinesses (Mogilevskii, et al., 2017, Yamano, et al., 2019). Reducing international market dependency is a complex issue that requires sustained efforts over the long term, therefore those strategies will need to be tailored to specific country contexts based on local conditions and resources.

Turning to maize, the production has exceeded that of wheat and rice, making it a staple food in many regions across the world. According to the World Bank[2], Mozambique, Angola, and many African and Asian developing countries are the top maize importers in the world in recent years. In Africa, some small countries experience high levels of poverty, which exacerbate food insecurity particularly with the unpredictable rise of food prices. Moreover, with limited dietary diversity, households cannot offset the effects of maize price hikes by shifting to alternative staple foods (Sukati, 2017). Hence, many African (Ariga, et al., 2010, Govereh, et al., 2010, Morrison, et al., 2010, Temu, et al., 2010) and Asian (Gulati and Dixon, 2008) countries have implemented policy interventions in maize market to reduce the adverse impact of higher price fluctuations in domestic

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[2] For more information, please visit https://wits.worldbank.org.

market albeit some of them still not meeting their expectations. Based on our empirical results, own market GARCH effect is detected for all the selected maize markets while Niger, Central African Republic, and Dominican Republic experience cross-market GARCH effect.

Given the situation that Africa expects the highest population growth and already has the largest food insecurity problems in the world and Asia faces challenges in meeting the growing demand for food, water, and other resource for a growing population (Grote, et al., 2021), reducing price volatility in maize markets for developing countries can be challenging. But some potential strategies may be providing better results, such as compensating seeds and irrigation cost, providing farmers easy access to credit facilities, and encouraging farmers to grow a variety of crops that can help to reduce the reliance on maize and mitigate price spikes when they occur. To reduce the sensitivity of the price shocks from international markets, policymakers need to enhance market information and provide farmers and trades with timely and accurate market information to respond more effectively to price changes.

Sorghum is also an important cereal crop, ranking fifth globally after corn, rice, wheat, and barley. It is grown all over the world and serves as a vital food grain for more than 750 million people residing in Africa, Asia, and certain areas in Central and South America (Schnitzenbaumer and Arendt, 2014). All the selected countries for sorghum market experience long run price volatility persistence influence by own market while Somalia, El Salvador, and Mali show significant long run volatility spillover effect from international market. Previous research indicates that the most common influential factors for sorghum production are improved agricultural inputs, population and economic growth, and climate change (Mundia, et al., 2019). Also, most volatile sorghum markets are marked by inconsistent supply, high transaction expenses, distant access to superior markets and lack of an organized marketing infrastructure (Bhagavatula, et al., 2013). To reduce price volatility, possible measures could include increasing capacities and market functioning, improving infrastructure to reduce transportation costs, and introducing supply and price risk management schemes. More importantly, policymakers should prioritize interventions in areas that have less adaptive capacity to climate change, as these regions tend to experience greater volatility in sorghum production (Mundia, et al., 2019). Besides, as sorghum is a vital food source for many of the world's poorest communities, monitoring sorghum markets could serve as an early warning sign for potential food insecurity, prompting swift action to prevent malnutrition and famine.

Conclusion:

Food price fluctuation can have a significant impact on food security and access to food, particularly for low-income countries. We use bivariate asymmetric BEKK GARCH model to assess and evaluate the intensity of price and volatility transmission from international markets to domestic markets for five major agricultural commodities of total 80 sample markets covering the period from January 2003 to November 2022. Significant own price volatility is found for almost all the covered markets regardless of commodity type while significant cross-market volatility transmission that imply strong interaction between international and domestic market are found in 33% of rice sample markets, 25% of maize sample markets, 31.3% of what sample markets, and 27.3% of sorghum sample markets. The asymmetric effects indicating the advent of positive and negative news in international markets that significantly influence domestic markets are detected only in a few markets.

By comprehending the extent of volatility spillover between prices, the government can recognize price uncertainty and implement appropriate measures to safeguard both agricultural sectors and food industry. There are a range of policies and interventions that can help to mitigate the effects of price volatility in the agricultural sector. However, it is important to note that approaches must be customized for individual country situations, especially considering local conditions and available resources. Overall, the transmission of agricultural food prices and the volatility of those prices are important issues that have significant implications for producers, consumers, and policymakers. By understanding the underlying drivers of price changes and implementing effective policies and interventions, it may be possible to create a more stable and sustainable food system that meets the needs of all stakeholders.

References:

Abdulai, A. (2000). Spatial price transmission and asymmetry in the Ghanaian maize market. Journal of development economics, 63(2), 327-349.

Algieri, B. (2016). Conditional price volatility, speculation, and excessive speculation in commodity markets: sheep or shepherd behaviour? International Review of Applied Economics, 30(2), 210-237.

Ariga, J., & Jayne, T. S. (2010). Maize trade and marketing policy interventions in Kenya. Food security in Africa: Market and trade policy for staple foods in eastern and southern Africa, 221-251.

Baulch, B. (1997). Transfer costs, spatial arbitrage, and testing for food market integration. American Journal of Agricultural Economics, 79(2), 477-487.

Berndt, E. R., Hall, B. H., Hall, R. E., & Hausman, J. A. (1974). Estimation and inference in nonlinear structural models. In Annals of Economic and Social Measurement, Volume 3, number 4 (pp. 653-665). NBER.

Bhagavatula, S., Rao, P. P., Basavaraj, G., & Nagaraj, N. (2013). Sorghum and millet economies in Asia–Facts, Trends and outlook. International Crops Research Institute for the Semi-Arid Tropics.

Caballero-Anthony, M., Teng, P., Lassa, J., Nair, T., & Shrestha, M. (2016). Public stockpiling of rice in Asia Pacific.

Ceballos, F., Hernandez, M. A., Minot, N., & Robles, M. (2017). Grain price and volatility transmission from international to domestic markets in developing countries. *World Development*, 94, 305-320.

Chmielewska, D., & Souza, D. (2011). The food security policy context in Brazil (No. 22). Country Study.

Conforti, P. (2011). Looking ahead in world food and agriculture: perspectives to 2050. Food and Agriculture Organization of the United Nations (FAO).

Das, N. K., & Roy, A. (2022). COVID-19 and agri-food value chain: a systematic review and bibliometric mapping. Journal of Agribusiness in Developing and Emerging Economies, 12(3), 442-462.

Dawe, D., Morales-Opazo, C., Balie, J., & Pierre, G. (2015). How much have domestic food prices increased in the new era of higher food prices? Global Food Security, 5, 1-10.

Dawe, D., Block, S., Gulati, A., Huang, J., & Ito, S. (2010). Domestic rice price, trade, and marketing policies. Rice in the global economy: strategic research and policy issues for food security. Los Baños, Philippines, International Rice Research Institute. 477p.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica: journal of the Econometric Society, 1057-1072.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric theory, 11(1), 122-150.

Gilbert, C. L. (2010). How to understand high food prices. Journal of agricultural economics, 61(2), 398-425.

Govereh, J., Chapoto, A., & Jayne, T. S. (2010). Assessment of alternative maize trade and market policy interventions in Zambia. In Food Security in Africa. Edward Elgar Publishing.

Grote, U., Fasse, A., Nguyen, T. T., & Erenstein, O. (2021). Food security and the dynamics of wheat and maize value chains in Africa and Asia. Frontiers in Sustainable Food Systems, 4, 617009.

Guo, J., & Tanaka, T. (2019). Determinants of international price volatility transmissions: the role of self-sufficiency rates in wheat-importing countries. Palgrave Communications, 5(1), 1-13.

Hafner, C. M., & Herwartz, H. (2008). Analytical quasi maximum likelihood inference in multivariate volatility models. Metrika, 67, 219-239.

Hathurusingha, C., Abdelhamid, N., & Airehrour, D. (2019). Forecasting Models Based on Data Analytics for Predicting Rice Price Volatility: A Case Study of the Sri Lankan Rice Market. Journal of Information & Knowledge Management, 18(01), 1950006.

Hernandez, M. A., Ibarra, R., & Trupkin, D. R. (2014). How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets. European Review of Agricultural Economics, 41(2), 301-325.

Kong, M., Han, D. B., & Nayga Jr, R. M. (2012). Interrelationship and volatility transmission between grain and oil prices (No. 323-2016-11744, pp. 2-13).

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. The review of financial studies, 11(4), 817-844.

Luo, P., & Tanaka, T. (2021). Food import dependency and national food security: A price transmission analysis for the wheat sector. *Foods*, 10(8), 1715.

Lutz, C., Kuiper, W. E., & van Tilburg, A. (2007). Maize market liberalisation in Benin: a case of hysteresis. Journal of African Economies, 16(1), 102-133.

Meyer, J., & Von Cramon-Taubadel, S. (2004). Asymmetric price transmission: a survey. Journal of agricultural economics, 55(3), 581-611.

Minot, N. (2010). Transmission of world food price changes to markets in Sub-Saharan Africa. Washington: International Food Policy Research Institute.

Mogilevskii, R., Abdrazakova, N., Bolotbekova, A., Chalbasova, S., Dzhumaeva, S., & Tilekeyev, K. (2017). The outcomes of 25 years of agricultural reforms in Kyrgyzstan (No. 162). Discussion Paper.

Sarris, A. (Ed.). (2010). Food security in Africa: Market and trade policy for staple foods in Eastern and Southern Africa. Edward Elgar Publishing.

Schnitzenbaumer, B., & Arendt, E. K. (2014). Brewing with up to 40% unmalted oats (Avena sativa) and sorghum (Sorghum bicolor): A review. Journal of the Institute of Brewing, 120(4), 315-330.

Moser, C., Barrett, C., & Minten, B. (2009). Spatial integration at multiple scales: rice markets in Madagascar. Agricultural Economics, 40(3), 281-294.

Mundia, C. W., Secchi, S., Akamani, K., & Wang, G. (2019). A regional comparison of factors affecting global sorghum production: The case of North America, Asia and Africa's Sahel. Sustainability, 11(7), 2135.

Muthayya, S., Sugimoto, J. D., Montgomery, S., & Maberly, G. F. (2014). An overview of global rice production, supply, trade, and consumption. Annals of the new york Academy of Sciences, 1324(1), 7-14.

Sukati, M. (2017). Analysis of maize price volatility and price pass through in Swaziland: Implications for price stabilization policies. Journal of Economics and International Business Management, 5(1), 1-13.

Temu, A. E., Manyama, A., & Temu, A. A. (2010). 12. Maize trade and marketing policy interventions in Tanzania. Food security in Africa, 317.

Timmer, C. P. (2009). Rice price formation in the short run and the long run: The role of market structure in explaining volatility (pp. 1-46).

Timmer, C. P. (1993). Rural Bias in the East and South-East Asian rice economy: Indonesia in comparative perspective. The Journal of Development Studies, 29(4), 149-176.

Xue, H., Li, C., Wang, L., & Su, W. H. (2021). Spatial price transmission and price dynamics of global butter export market under economic shocks. *Sustainability*, 13(16), 9297.

Yamano, T., Hill, H., Ginting, E., & Samson, J. (Eds.). (2019). Kyrgyz Republic: improving growth potential. Asian Development Bank.

Table 1: Asymmetric BEKK-GARCH Conditional Variance Results for Rice

	Nepal	Chad	Mali	Mozambique	Uganda	Mexico	Nicaragua	Peru
C_{11}	0.014	0.010	0.003	0.016	0.019	0.015***	0.005	0.010***
	(1.067)	(0.793)	(0.701)	(0.932)	(1.452)	(3.349)	(0.786)	(4.760)
A_{11}	0.314	0.305	0.318***	0.065	0.199	0.271***	0.341*	0.308***
	(1.531)	(0.917)	(3.011)	(0.067)	(1.435)	(6.654)	(1.877)	(5.229)
A_{12}	0.004	0.016	0.167*	-0.073	0.065	0.182	-0.021	-0.196**
	(0.097)	(0.118)	(1.924)	(-0.165)	(0.656)	(0.953)	(-0.076)	(-2.434)
G_{11}	0.921***	0.905***	0.939***	0.886***	0.924***	0.884***	0.921***	0.912***
	(41.786)	(4.838)	(90.237)	(3.095)	(22.245)	(6.821)	(11.283)	(58.662)
G_{12}	-0.047	-0.021	-0.088	0.111	-0.063	-0.129	-0.039	0.124***
	(-0.504)	(-0.388)	(-1.186)	(0.395)	(-1.532)	(-0.400)	(-0.218)	(3.860)
B_{11}	0.000	0.000	0.121	0.345	0.269	0.044	0.000	0.000
	(0.000)	(0.000)	(0.491)	(0.860)	(0.798)	(0.217)	(0.000)	(0.000)
B_{12}	0.065	0.085	-0.188	0.037	0.021	-0.119	-0.210	-0.150
	(1.511)	(0.663)	(1.454)	(0.307)	(0.123)	(-1.348)	(-0.681)	(-1.079)
LL	633.9815	693.716	731.656	717.760	603.745	729.4865	836.677	725.086
AIC	-1240.963	-1360.431	-1436.313	-1408.520	-1180.490	-1431.973	-1646.353	-1423.171
BIC	-1240.098	-1359.566	-1435.448	-1407.671	-1179.625	-1431.108	-1645.504	-1422.306
JB test (6)	9.161	3.907	4.646	2.065	4.759	3.658	2.922	7.566
JB test (12)	16.828	11.740	9.225	9.978	6.478	13.883	5.959	12.092
ARCH-LM (6)	0.532	3.353	6.043	0.812	4.995	1.548	1.037	3.535
ARCH-LM (12)	5.388	6.129	13.375	1.287	9.887	3.914	6.121	12.149

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 1: Asymmetric BEKK-GARCH Conditional Variance Results for Rice (continued)

	Niger	Dominican Republic	Costa Rica	Togo	South Africa	Burkina Faso	Brazil	Colombia
C_{11}	0.027***	0.003	0.005**	0.022	0.017	0.014	0.015	0.013***
	(4.874)	(0.521)	(2.270)	(1.638)	(1.029)	(4.522)	(0.637)	(3.900)
A_{11}	0.637***	0.294***	0.255***	0.327***	0.348	0.353	0.157	0.257*
	(3.902)	(8.008)	(2.191)	(11.337)	(1.224)	(1.473)	(0.313)	(1.922)
A_{12}	-0.018	-0.002	0.000	-0.030	-0.013	-0.020	0.001	0.062
	(-0.039)	(-0.023)	(0.000)	(-0.369)	(-0.132)	(-0.138)	(0.032)	(0.690)
G_{11}	0.302	0.956***	0.953***	0.935***	0.858***	0.884***	0.932***	0.875***
	(1.251)	(29.642)	(24.357)	(39.394)	(3.563)	(9.577)	(8.743)	(23.985)
G_{12}	0.252	-0.067	-0.034	-0.041	-0.031**	-0.079	0.037	-0.026
	(0.412)	(-0.229)	(-0.295)	(-0.817)	(2.196)	(-1.405)	(0.182)	(-0.681)
B_{11}	0.001	0.000	0.000	0.090	0.445	0.000	0.335	0.414**
	(0.000)	(0.000)	(0.000)	(0.697)	(0.621)	(0.000)	(0.254)	(2.005)
B_{12}	-0.122	-0.129	-0.090	0.038	0.279	-0.014	0.124	0.111
	(-0.126)	(-0.989)	(-0.074)	(0.563)	(0.166)	(-0.334)	(0.263)	(0.894)
LL	763.853	814.542	787.223	520.131	665.424	680.645	650.639	725.511
AIC	-1500.706	-1602.083	-1547.446	-1013.263	-1303.850	-1334.29	-1274.277	-1424.022
BIC	-1499.841	-1601.218	-1546.627	-1012.398	-1302.985	-1333.441	-1273.427	-1423.172
JB test (6)	8.801	8.527	7.984	6.395	3.435	4.341	2.699	1.208
JB test (12)	16.611	13.875	13.736	12.302	11.61	11.849	7.692	7.889
ARCH-LM (6)	1.739	15.250	4.638	7.248	12.555*	5.226	2.876	2.946
ARCH-LM (12)	8.997	17.125	5.849	14.593	32.998***	6.521	5.910	9.115

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 1: Asymmetric BEKK-GARCH Conditional Variance Results for Rice (continued)

	Cambodia	Cameroon	Ghana	Samoa	Sri Lanka	Tunisia	Philippines	Guatemala
C_{11}	0.011***	0.011***	0.013***	0.009***	0.014	0.007	0.007	0.009
	(2.748)	(2.983)	(4.429)	(3.643)	(1.256)	(1.443)	(0.598)	(1.148)
A_{11}	0.132***	0.265***	0.298***	0.211***	0.327**	0.286	0.293	0.252
	(3.794)	(2.704)	(3.982)	(3.988)	(2.578)	(1.376)	(0.209)	(0.187)
A_{12}	0.144***	0.030	-0.021	-0.031	-0.030	0.004	-0.037	0.109
	(15.939)	(0.622)	(-1.021)	(0.299)	(-0.351)	(0.015)	(-0.024)	(0.035)
G_{11}	0.960***	0.916***	0.940***	0.934***	0.899***	0.922***	0.909*	0.847
	(23.091)	(26.762)	(126.070)	(94.165)	(7.732)	(47.579)	(1.794)	(0.292)
G_{12}	-0.076***	-0.121*	-0.045**	-0.120**	-0.002	-0.058	-0.044	-0.317
	(-3.277)	(-2.086)	(-2.427)	(-2.420)	(-0.011)	(-0.831)	(-0.060)	(-0.194)
B_{11}	-0.031	0.189*	0.000	0.095	0.000	0.000	0.000	0.000
	(-0.113)	(1.744)	(0.000)	(1.359)	(0.000)	(0.000)	(0.000)	(0.000)
B_{12}	-0.255	0.189	0.063	0.191	-0.046	-0.138	-0.043	0.166
	(-0.397)	(1.649)	(-0.508)	(1.428)	(-0.544)	(-0.359)	(-0.007)	(0.079)
LL	644.996	720.782	608.953	740.682	695.899	787.820	836.008	846.485
AIC	-1262.991	-1414.565	-1190.906	-1454.364	-1364.798	-1548.64	-1645.016	-1665.97
BIC	-1262.126	-1413.700	-1190.041	-1453.499	-1363.934	-1547.821	-1644.166	-1665.105
JB test (6)	3.477	2.293	8.120	6.631	18.505***	6.045	1.183	16.722**
JB test (12)	9.891	3.667	10.653	10.976	32.604***	13.248	7.467	20.657**
ARCH-LM (6)	0.458	2.193	25.023***	7.496	1.057	1.166	4.528	7.784
ARCH-LM(12)	1.117	5.555	28.235***	10.669	4.045	2.204	8.962	14.165

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 2: Asymmetric BEKK-GARCH Conditional Variance Results for Maize

	Chad	Ethiopia	Mozambique	Zambia	Philippines	Colombia	Guatemala	Honduras
C_{11}	0.020	0.027***	0.041***	0. 035	0.018***	0.015	0.034**	0.062***
	(0.347)	(4.575)	(6.979)	(0.945)	(6.824)	(1.202)	(2.365)	(7.752)
A_{11}	0.131*	0.195*	0.290	0.307	0.421**	0.176	0.341**	0.295***
	(2.042)	(2.040)	(1.531)	(0.679)	(2.100)	(1.262)	(2.472)	(2.776)
A_{12}	0.031	0. 045	0.001	-0.013	0.060	0.060	-0.015	0.069***
	(0.116)	(0.855)	(0.038)	(-0.108)	(0.207)	(0.273)	(-0.298)	(2.905)
G_{11}	0. 906**	0.910***	0.884***	0.844**	0.805***	0.955***	0.812***	0.640***
	(2.239)	(36.164)	(23.863)	(2.210)	(10.395)	(24.261)	(9.254)	(9.758)
G_{12}	-0.054	0. 007	-0.024	0.054	-0.097	-0.084	0.011	-0.051
	(-0.236)	(0.270)	(-1.269)	(0.330)	(-1.181)	(-1.115)	(0.191)	(-1.517)
B_{11}	0.359	0.311	0.038	0.051	0.000	0.085	0. 151	0. 219
	(0.173)	(0.783)	(0.834)	(0.081)	(0.000)	(1.157)	(0.366)	(0.416)
B_{12}	0.069	0. 056	-0.082**	-0.155	-0.058	0.087	0.021	0.038
	(0.495)	(0.764)	(-2.093)	(-0.999)	(-0.166)	(0.347)	(0.562)	(0.450)
LL	558.290	523.837	456.096	553.133	732.105	548.804	556.280	542.378
AIC	-1089.579	-1020.674	-885.192	-1079.267	-1437.212	-1070.608	-1085.560	-1057.755
BIC	-1088.331	-1019.425	-883.944	-1078.019	-1435.964	-1069.360	-1084.338	-1056.507
JB test (6)	3.065	8.443	9.296	13.758**	15.153**	9.022	5.815	5.491
JB test (12)	9.433	29.943***	69.388***	56.139***	33.180***	18.737*	34.512***	40.986***
ARCH-LM (6)	3.182	0.418	7.831	2.754	6.075	3.175	3.433	5.604
ARCH-LM(12)	10.197	2.442	16.831	13.426	7.774	6.992	5.341	11.367

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 2: Asymmetric BEKK-GARCH Conditional Variance Results for Maize (continued)

	Mexico	Nicaragua	Niger	Cameroon	Central African Republic	Costa Rica	Dominican Republic	El Salvador
C_{11}	0.025***	0.069	0.019	0.020*	0.084***	0. 022***	0.019***	0.019
	(6.562)	(1.10)	(1.586)	(1.780)	(7.190)	(4.706)	(3.809)	(0.622)
A_{11}	0.258**	0.066	0.346***	0.280*	0.242***	0.379***	0.538***	0.331
	(2.208)	(0.409)	(4.209)	(1.758)	(3.696)	(3.720)	(4.670)	(0.424)
A_{12}	-0.084	-0.046	0.161***	0.022	0.004	-0.025	-0.053	0. 094
	(-1.490)	(-0.964)	(10.738)	(0.215)	(0.276)	(-0.331)	(-0.915)	(0.202)
G_{11}	0.765***	0.779*	0. 885***	0.917***	0.874***	0. 830***	0.784***	0.883*
	(8.369)	(1.966)	(16.135)	(11.132)	(56.748)	(10.819)	(13.500)	(1.805)
G_{12}	0. 043	0.084	-0.080***	-0.021	-0.021**	0.009	0.093*	-0.077
	(0.170)	(0.405)	(-8.326)	(-0.290)	(-2.327)	(0.107)	(1.997)	(-0.157)
B_{11}	0.302	0. 074	0. 156	0.000	0.315	0.304	0.294	0.180
	(0.809)	(0.478)	(1.051)	(0.000)	(1.039)	(0.721)	(1.570)	(0.417)
B_{12}	-0.005	0. 055**	-0.011	0.090	0.017	0.073***	-0.181	-0.058
	(-0.067)	(2.067)	(-0.714)	(1.611)	(0.614)	(3.163)	(-0.976)	(-0.375)
LL	699.384	464.398	627.364	514.413	245.540	561.518	554.710	562.917
AIC	-1371.769	-901.797	-1227.729	-1001.825	-464.080	-1096.037	-1082.419	-1098.834
BIC	-1370.521	-900.562	-1226.481	-1000.915	-463.170	-1095.128	-1081.509	-1097.924
JB test (6)	3.364	5.394	5.362	8.260	9.3366	12.216	3.389	2.505
JB test (12)	7.975	19.838*	9.518	18.733*	17.46	16.997	9.063	3.815
ARCH-LM (6)	3.079	0.620	2.249	1.256	2.024	12.392	0.891	3.210
ARCH-LM (12)	6.987	3.604	3.127	9.421	3.824	19.313*	3.475	8.746

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 2: Asymmetric BEKK-GARCH Conditional Variance Results for Maize (continued)

	Ghana	Panama	Paraguay	Peru	Rwanda	Togo	Uganda	Zimbabwe
C_{11}	0. 026	0.009**	0.042	0.020***	0.018**	0.021	0.039***	0.043***
	(1.315)	(2.377)	(0.464)	(4.682)	(2.202)	(0.800)	(10.572)	(3.200)
A_{11}	0.302	0.317*	0.370	0.213***	0.049	0.230***	0.180	0.418***
	(0.940)	(1.963)	(0.295)	(2.850)	(1.162)	(7.633)	(1.566)	(2.795)
A_{12}	-0.006	-0.028	-0.038	-0.132***	0.011	0.046	0.052	0.024
	(-0.086)	(-0.116)	(-0.261)	(-2.975)	(0.156)	(0.583)	(0.829)	(0.541)
G_{11}	0.897***	0.925***	0.820***	0.857***	0.961***	0.959***	0.925***	0.890***
	(25.369)	(27.164)	(4.914)	(16.856)	(47.536)	(14.171)	(36.790)	(23.684)
G_{12}	-0.014	0.003	0.010	-0.032	-0.044	-0.015	-0.035**	-0.003
	(-1.018)	(-0.169)	(0.130)	(-0.785)	(-1.568)	(-0.552)	(-2.484)	(-0.143)
B_{11}	0.254*	0. 366	0.336	0.453**	0.410**	0.000	0.175	0.177
	(1.719)	(0.443)	(0.273)	(2.609)	(2.002)	(0.000)	(1.168)	(0.775)
B_{12}	-0.115**	-0.211	-0.004	-0.026	0.026	0.071	-0.033	-0.047*
	(-2.300)	(-0.189)	(-0.014)	(-0.289)	(0.081)	(0.709)	(-0.415)	(-1.702)
LL	437.315	680.440	398.612	627.343	443.793	441.058	337.953	318.328
AIC	-847.632	-1333.88	-770.225	-1227.685	-860.586	-855.117	-648.906	-609.657
BIC	-846.722	-1332.97	-769.315	-1226.775	-859.676	-854.207	-647.997	-608.747
JB test (6)	8.653	10.614	11.242*	8.601	6.669	4.772	10.731	6.675
JB test (12)	19.791*	17.614	19.376*	26.649***	10.664	15.582	18.645	13.130
ARCH-LM (6)	2.232	14.203**	2.468	2.344	0.838	1.416	3.331	0.771
ARCH-LM (12)	4.793	19.856*	4.541	6.670	1.940	11.608	9.241	2.416

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 3: Asymmetric BEKK-GARCH Conditional Variance Results for Wheat

	Ethiopia	Nepal	Brazil	Colombia	Afghanistan	Azerbaijan	Tajikistan	Sudan
C_{11}	0.002	0.025***	0.008***	0.018***	0.013***	0.021***	0.012**	0.025
	(0.460)	(4.151)	(3.127)	(3.175)	(4.091)	(3.163)	(2.039)	(0.484)
A_{11}	0.210***	0.543***	0.095*	0.225**	0.107**	0.189	0.181	0.255***
	(3.874)	(4.722)	(1.747)	(2.575)	(2.435)	(0.385)	(1.449)	(3.014)
A_{12}	-0.247***	0.000	0.063	0.175	-0.296***	-0.053	-0.142	-0.002
	(-6.048)	(0.000)	(0.800)	(0.613)	(-2.938)	(-0.263)	(-1.073)	(-0.036)
G_{11}	0.938***	0.761***	0.896***	0.884***	0.922***	0.806***	0.928***	0.938***
	(29.078)	(22.131)	(45.924)	(8.747)	(43.992)	(3.546)	(15.130)	(8.842)
G_{12}	-0.055**	-0.114	-0.097***	-0.126	0.195***	0.038	-0.033	0.078
	(-2.127)	(-1.330)	(-3.104)	(-0.254)	(4.039)	(0.079)	(-0.326)	(0.553)
B_{11}	0.318*	0.233	0.494***	0.000	0.643***	0.393	0.589	0.071
	(1.733)	(0.446)	(3.701)	(0.000)	(2.797)	(0.879)	(1.424)	(0.384)
B_{12}	0.114	0.331	-0.080	-0.380	0.113	0.054	0.703	0.012
	(0.857)	(1.481)	(-0.649)	(-0.507)	(0.254)	(0.098)	(1.190)	(0.425)
LL	617.380	605.566	629.509	645.492	573.009	638.720	630.592	412.292
AIC	-1207.762	-1184.133	-1232.020	-1263.985	-1119.017	-1250.441	-1234.185	-797.585
BIC	-1206.678	-1183.049	-1230.936	-1262.929	-1118.122	-1249.546	-1233.29	-796.690
JB test (6)	1.556	4.342	4.789	3.500	2.900	1.496	9.439	2.254
JB test (12)	14.826	10.084	7.833	11.058	15.338	11.131	15.519	8.646
ARCH-LM (6)	0.604	2.172	13.205**	3.830	5.656	8.456	1.182	2.397
ARCH-LM (12)	6.988	4.245	17.185	9.876	13.488	40.163***	2.557	6.319

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 3: Asymmetric BEKK-GARCH Conditional Variance Results for Wheat (continued)

	Cameroon	El Salvador	Georgia	Kazakhstan	Kyrgyzstan	Peru	South Africa	Sri Lanka
C_{11}	0.009**	0.008	0.011	0.017***	0.013***	0.008***	0.018	0.013
	(2.279)	(0.767)	(0.822)	(3.256)	(4.066)	(2.623)	(1.415)	(1.094)
A_{11}	0.268**	0.355***	0.277	0.272**	0.222	0. 301***	0. 435**	0. 361***
	(2.232)	(2.925)	(0.462)	(2.061)	(0.270)	(2.876)	(2.434)	(3.891)
A_{12}	0.134	-0.055	0.015	-0.105	0.016	0. 019	0.016	-0.005
	(0.247)	(-1.030)	(0.010)	(-0.936)	(0.010)	(0.037)	(0.334)	(-0.038)
G_{11}	0.930***	0.901***	0.909***	0.750***	0.632	0. 905***	0.809***	0.880***
	(58.326)	(19.624)	(4.801)	(7.982)	(1.428)	(16.155)	(3.877)	(7.994)
G_{12}	0.004	-0.003	-0.049	-0.269***	-0.346	-0.075***	-0.089	-0.163
	(0.045)	(-0.029)	(-0.198)	(-10.559)	(-0.147)	(-3.889)	(-1.335)	(-1.135)
B_{11}	0.484	0.378	0.000	0.193*	0.000	0.000	0.000	0.000
	(1.140)	(0.737)	(0.000)	(1.876)	(0.000)	(0.000)	(0.000)	(0.000)
B_{12}	-0.520	0.351	0.019	0.172*	0.819	-0.206	0.201*	-0.473
	(-0.485)	(0.809)	(0.008)	(1.704)	(0.147)	(-0.055)	(1.928)	(-0.514)
LL	646.435	667.177	640.202	660.996	666.216	724.526	619.373	631.696
AIC	-1265.870	-1307.353	-1253.404	-1294.991	-1305.432	-1422.053	-1211.747	-1236.394
BIC	-1264.960	-1306.443	-1252.509	-1294.081	-1304.522	-1421.158	-1210.837	-1235.559
JB test (6)	4.627	2.585	6.639	3.414	3.373	5.406	5.622	5.624
JB test (12)	18.519	10.054	9.339	5.232	7.106	8.733	9.249	10.211
ARCH-LM (6)	3.645	1.299	6.691	9.055	11.426**	4.622	12.561*	5.092
ARCH-LM (12)	13.390	3.187	10.013	10.783	13.559	8.711	16.817	14.668

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 4: Asymmetric BEKK-GARCH Conditional Variance Results for Sorghum

	Chad	Nicaragua	Niger	Somalia	Sudan	Ghana	Haiti	Togo
C_{11}	0.038	0.041*	0.014	0.060	0.042	0.012*	0.069***	0.029
	(0.058)	(1.740)	(1.542)	(1.565)	(0.207)	(1.834)	(3.065)	(0.747)
A_{11}	0.317	0.307	0.314***	0.296**	0.252	0.295*	0.492***	0.307***
	(0.027)	(1.584)	(4.039)	(2.353)	(0.120)	(1.783)	(3.166)	(3.768)
A_{12}	0.000	0.017	-0.060	0. 002	-0.015	-0.061	-0.010	0.036
	(0.000)	(0.664)	(-0.429)	(0.010)	(-0.029)	(-0.595)	(-0.577)	(1.224)
G_{11}	0.882	0. 854***	0. 917***	0. 857***	0.897	0. 931***	0.719***	0.897***
	(0.187)	(11.911)	(14.294)	(22.247)	(1.388)	(24.612)	(5.973)	(6.844)
G_{12}	0.019	-0.021	0.031	-0.021***	0.006	0.009	-0.018	-0.025
	(0.025)	(-0.409)	(0.505)	(-7.824)	(0.039)	(0.159)	(-1.099)	(-0.925)
B_{11}	0.396	0. 346	0.000	0.326	0.387	0.000	0.000	0.258
	(0.025)	(1.368)	(0.000)	(0. 479)	(0.013)	(0.000)	(0.000)	(1.209)
B_{12}	0.057	-0.009	-0.071	0.015	-0.035	-0.073	0.057	0.008
	(0.026)	(-0.093)	(-0.165)	(0.129)	(-0.027)	(-0.086)	(0.816)	(0.167)
LL	459.339	459.031	620.978	339.096	406.476	502.597	323.772	404.832
AIC	-891.679	-891.061	-1214.956	-651.192	-785.953	-978.193	-620.544	-782.664
BIC	-890.4575	-889.840	-1213.734	-649.971	-784.731	-977.499	-619.851	-781.970
JB test (6)	1.792	16.382**	2.245	7.203	2.376	6.147	2.251	7.991
JB test (12)	11.924	28.526***	4.009	14.876	4.887	9.634	4.979	14.868
ARCH-LM (6)	2.046	1.307	7.123	1.089	1.265	4.345	0.600	2.223
ARCH-LM (12)	15.184	2.909	11.627	2.662	2.243	8.492	1.082	12.117

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.

Table 4: Asymmetric BEKK-GARCH Conditional Variance Results for Sorghum (continued)

	Burkina Faso	El Salvador	Mali
C_{11}	0.034***	0.019***	0.015***
	(3.385)	(2.297)	(2.931)
A_{11}	0.192	0.330***	0.159***
	(1.603)	(3.317)	(3.000)
A_{12}	0.040	0.025	0.074
	(1.603)	(0.771)	(1.078)
G_{11}	0.909***	0.895***	0.964***
	(9.898)	(55.484)	(77.690)
G_{12}	0.103	-0.046**	-0.041***
	(-0.325)	(-2.273)	(-2.928)
B_{11}	0.435*	0. 347***	0.000
	(2.021)	(2.677)	(0.000)
B_{12}	-0.095	-0.157**	0.124*
	(-1.492)	(-2.291)	(1.671)
LL	452.110	478.667	419.427
AIC	-877.220	-930.334	-811.856
BIC	-876.527	-929.641	-811.162
JB test (6)	11.193*	10.435	3.7005
JB test (12)	16.733	17,823	11.378
ARCH-LM (6)	5.227	8.453	2.863
ARCH-LM (12)	6.560	11.605	4.207

Notes: t-statistics value inside the parenthesis. ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Ljung-Box (JB) Portmanteau test and ARCH-LM test is performed to detect autocorrelation and ARCH effect of residuals at lag 6 and 12.
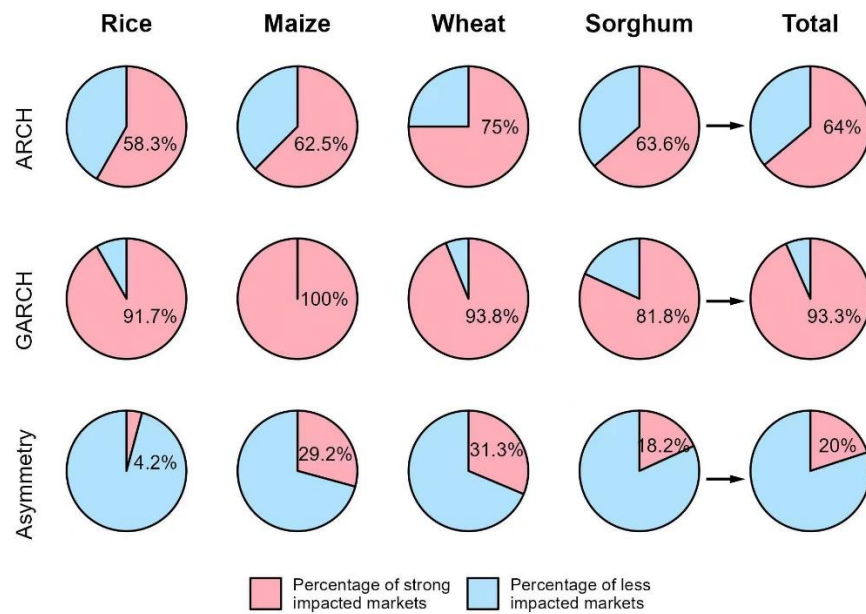
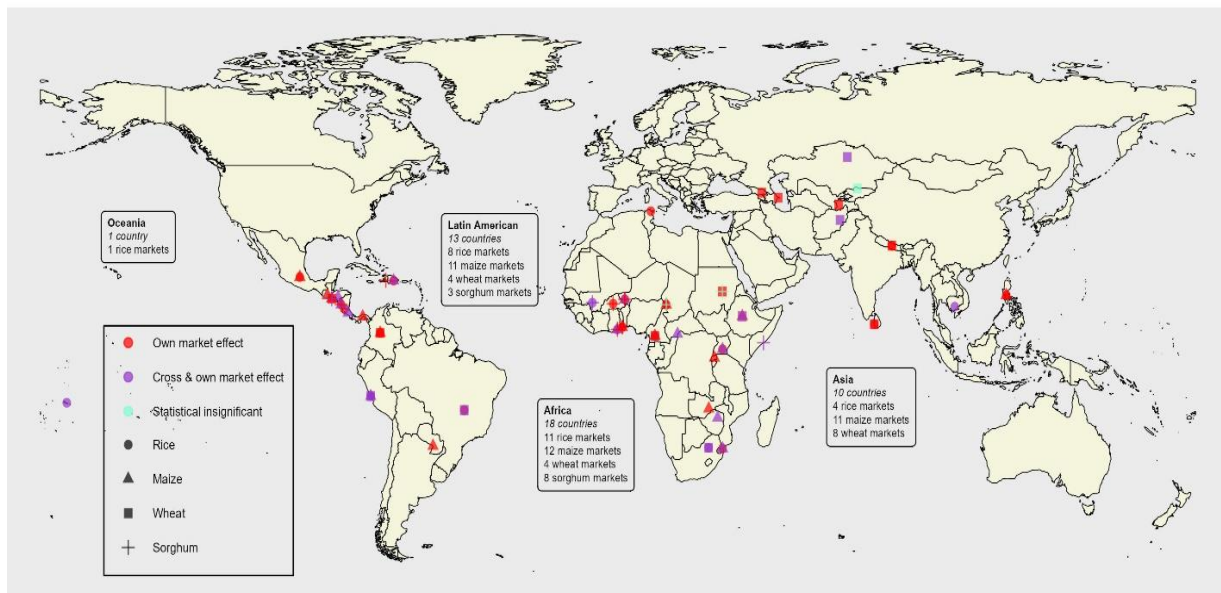Figure 1. Percentage of impacted markets

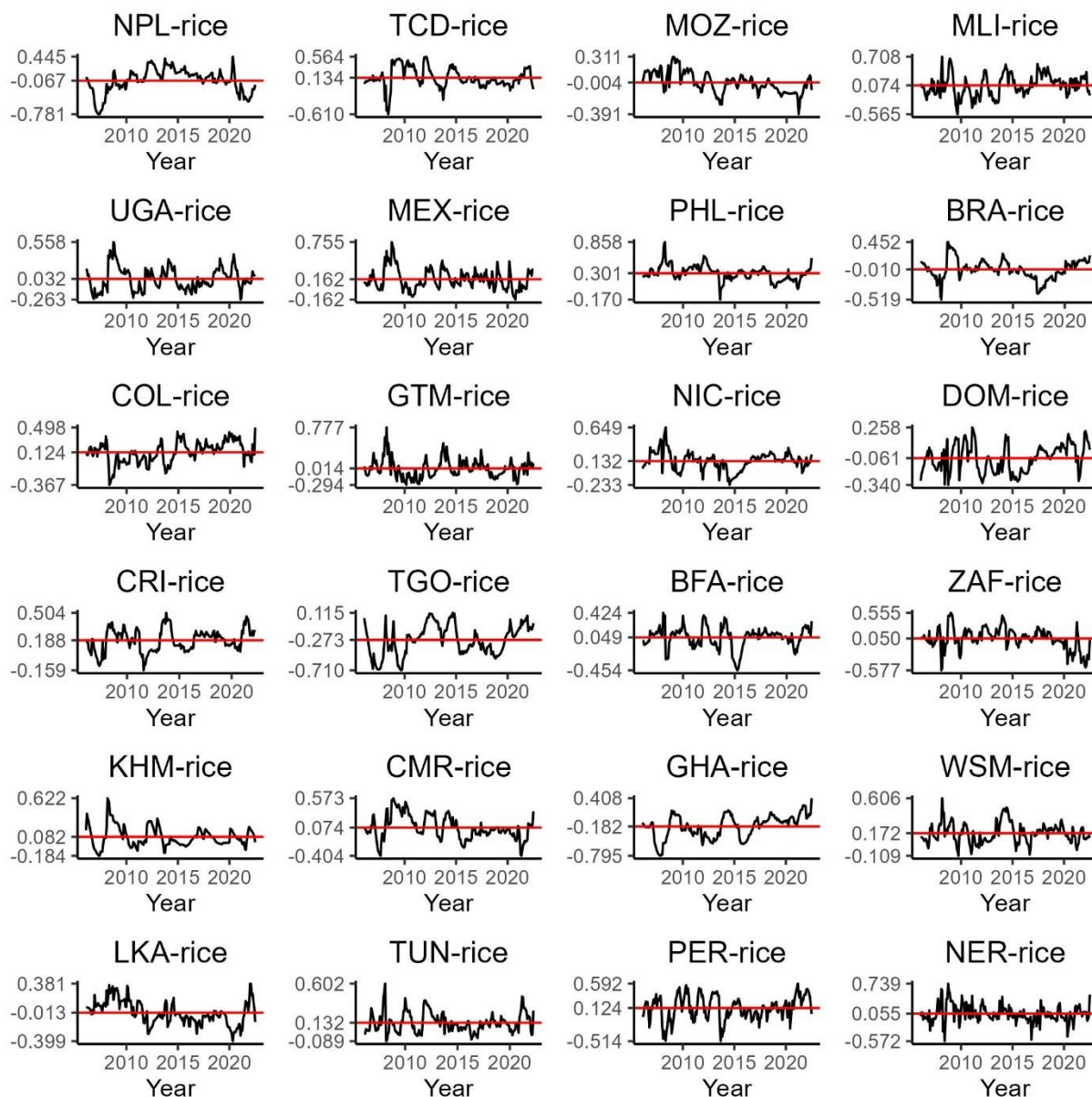Figure 2. Geographical distribution of covered markets

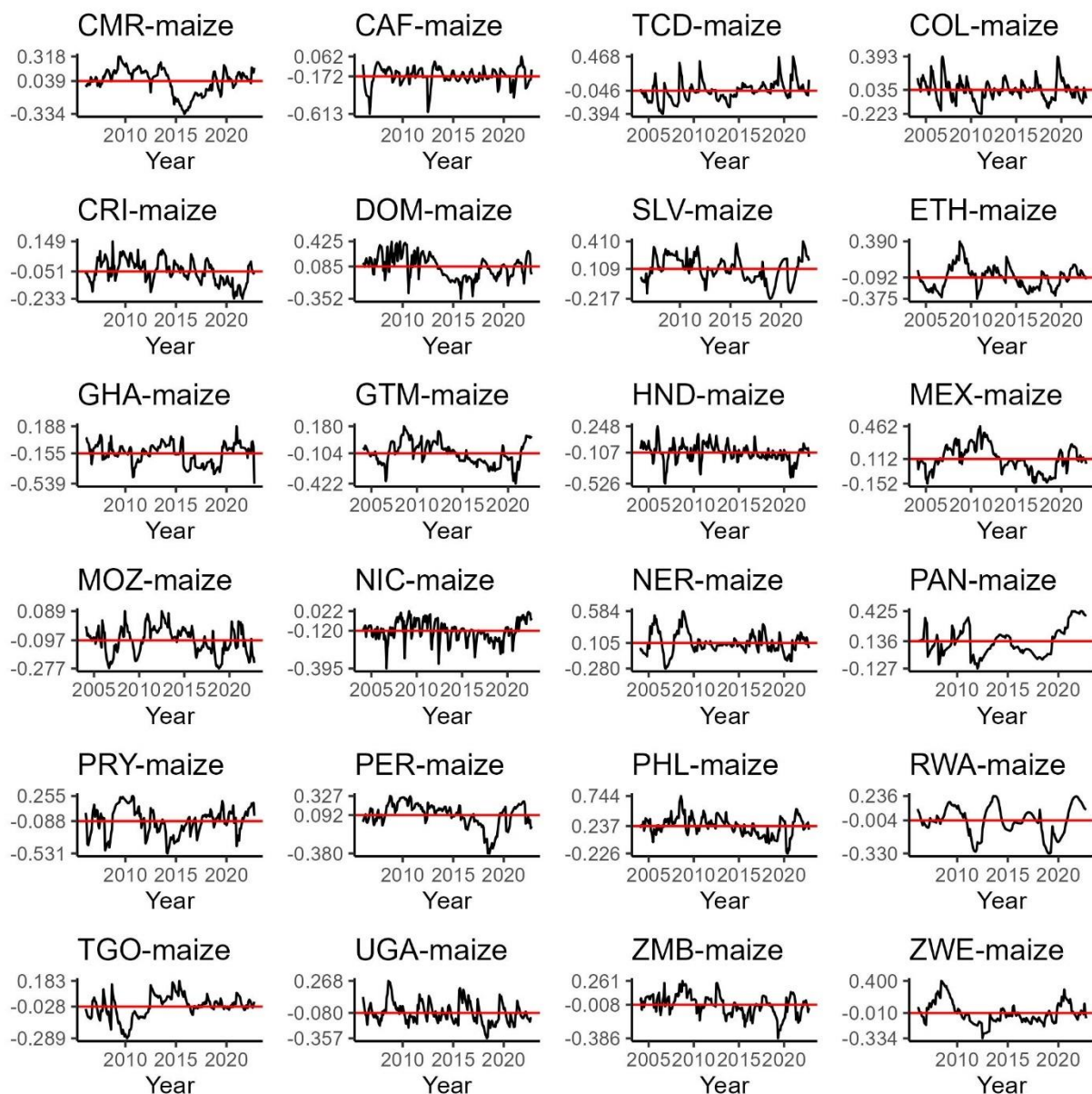Figure 3. Correlation plots for covered rice markets

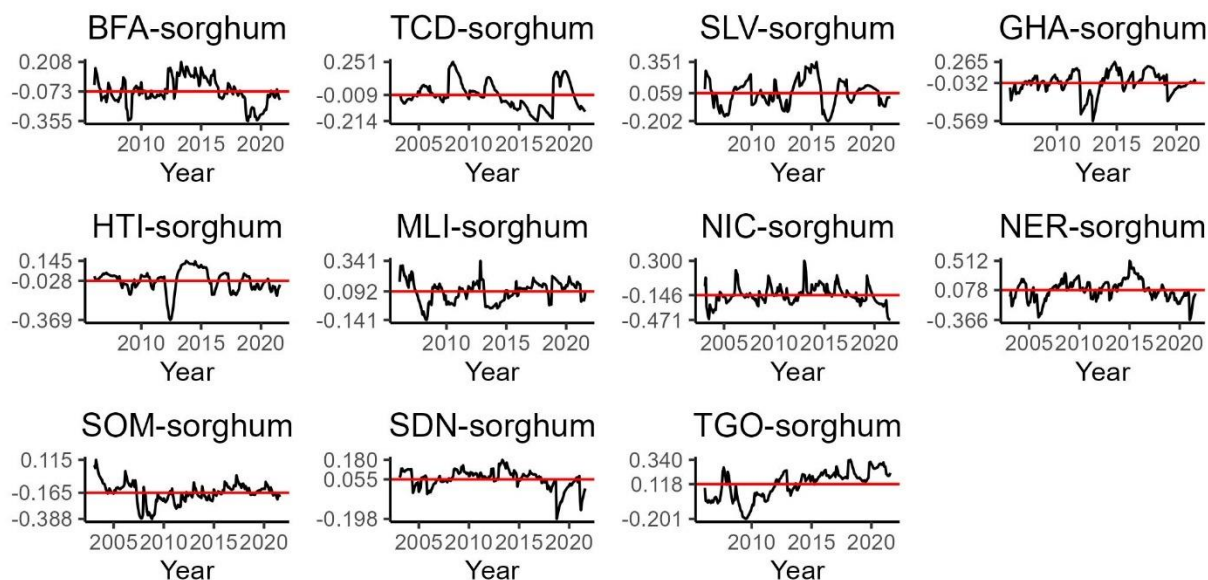Figure 4. Correlation plots for covered maize markets

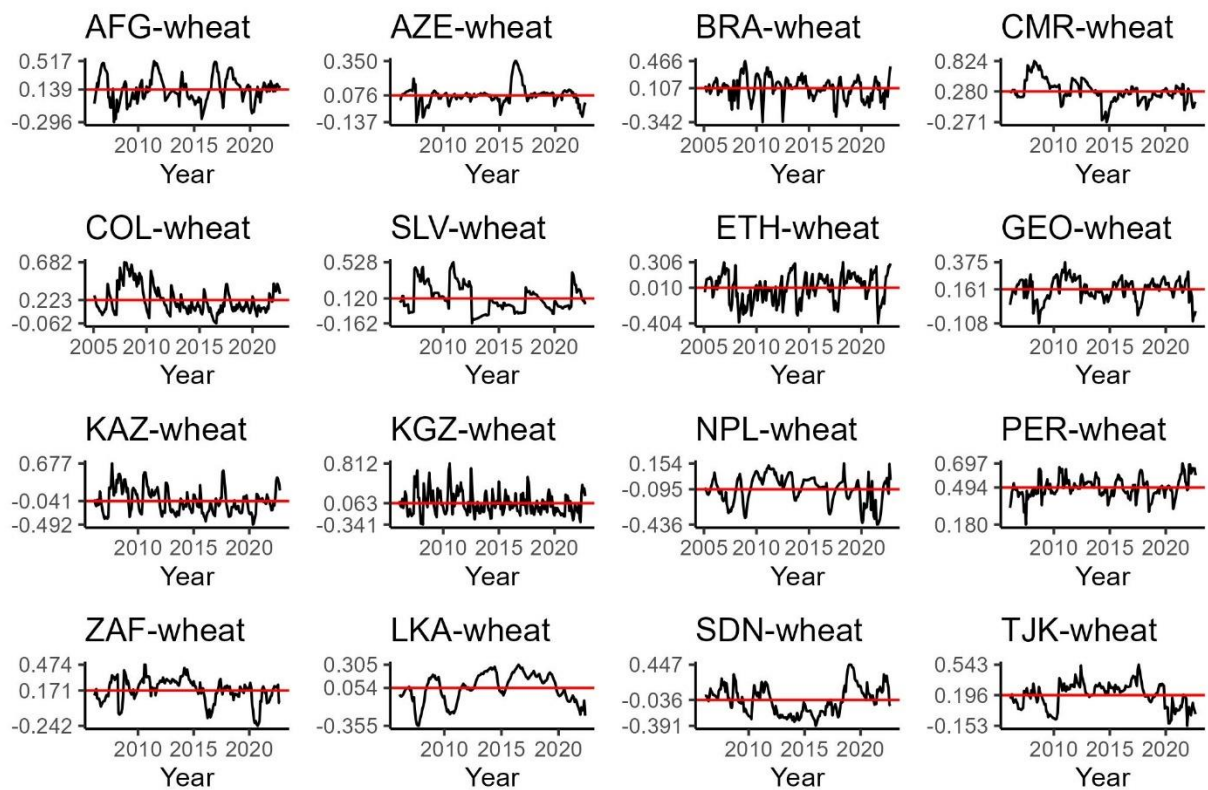Figure 5. Correlation plots for covered sorghum markets

Figure 6. Correlation plots for covered wheat markets

Appendix

Appendix table A1: Conditional Mean Equation results from VAR

Country	Lag	α_0	α_{11}	α_{12}
Rice				
Nepal	1	0.002	0.039	-0.077
Chad	1	0.000	-0.007	0.173**
Mali	1	0.000	-0.116	0.134**
Mozambique	2	0.002	0.004	0.211***
Uganda	1	0.001	0.155**	0.187**
Philippines	2	0.001	-0.063	0.056
Brazil	2	0.000	-0.009	0.233***
Colombia	2	0.001	-0.290***	0.236***
Guatemala	1	0.002	0.290***	0.154***
Mexico	1	0.001	0.371***	0.075
Nicaragua	2	0.002	0.001	0.124***
Peru	1	0.001	0.236***	0.187***
Niger	1	0.000	0.038	0.046
Dominican Republic	1	0.001	0.153**	0.026
Costa Rica	4	0.003	-0.061	0.241***
Togo	1	0.004	-0.354***	0.056
South Africa	1	0.002	0.075	-0.021
Burkina Faso	2	0.001	-0.023	0.247***
Cambodia	1	0.005	-0.174**	0.244***
Cameroon	1	0.003	0.064	-0.023
Ghana	1	-0.001	-0.100	0.245**
Samoa	1	0.003	0.010	-0.132***
Sri Lanka	1	0.002	0.300***	0.051
Tunisia	4	-0.002	-0.001	0.209***
Maize				
Chad	1	0.000	0.011	0.011
Ethiopia	1	0.000	-0.073	-0.006
Mozambique	1	0.000	0.044	0.013
Zambia	1	-0.001	0.056	-0.021
Philippines	1	-0.001	0.012	-0.012
Colombia	1	0.000	0.019	-0.024
Guatemala	1	0.000	-0.026	-0.024
Honduras	1	0.000	-0.013	-0.095
Mexico	1	0.000	-0.031	-0.025
Nicaragua	1	-0.001	-0.001	-0.030
Niger	1	0.000	-0.014	-0.029
Cameroon	1	0.000	-0.010	-0.008
Central African Republic	1	0.001	-0.031	-0.138

Costa Rica	1	0.000	-0.061	-0.029
Dominican Republic	1	0.000	0.006	-0.007
El Salvador	1	0.000	-0.001	-0.004
Ghana	1	-0.001	0.007	-0.037
Panama	1	0.003	-0.141**	-0.025
Paraguay	1	-0.001	0.008	0.118
Peru	1	0.000	-0.014	-0.012
Rwanda	1	0.000	0.013	0.003
Togo	1	-0.001	-0.014	0.014
Uganda	1	-0.001	0.014	0.010
Zimbabwe	1	0.001	-0.014	-0.028
Wheat				
Ethiopia	1	0.000	-0.032	0.010
Nepal	1	0.000	-0.012	-0.005
Brazil	1	0.000	0.008	0.000
Colombia	1	0.000	-0.017	0.004
Afghanistan	1	0.000	0.004	0.000
Azerbaijan	1	0.000	-0.006	0.013
Cameroon	1	0.000	0.003	0.002
El Salvador	1	0.000	-0.048	0.000
Georgia	1	0.000	-0.030	0.018
Kazakhstan	1	0.000	-0.021	0.017
Kyrgyzstan	1	0.000	-0.039	-0.001
Peru	1	0.000	-0.037	0.009
South Africa	1	0.000	0.024	0.001
Sri Lanka	1	0.000	0.028	0.021
Sudan	1	0.000	0.015	0.014
Tajikistan	1	0.000	-0.064	0.024
Sorghum				
Chad	1	0.000	-0.009	-0.015
Nicaragua	1	0.001	0.106	-0.013
Niger	1	0.000	0.003	0.018
Somalia	1	0.001	-0.016	0.001
Sudan	1	0.000	0.034	0.001
Ghana	1	0.000	0.010	0.001
Haiti	1	0.000	-0.050	0.047
Togo	1	0.000	-0.040	0.004
Burkina Faso	1	0.000	-0.006	-0.015
El Salvador	1	-0.001	0.009	-0.009
Mali	1	-0.001	0.010	-0.010

Notes: ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% significant level, respectively. Subscripts 1 and 2 represent own market (domestic) and cross market (international), respectively.

Table A2: Statistical summary for logarithm of domestic price

	Rice	Maize	Wheat	Sorghum	Total
# of domestic price series	24	24	16	11	75
Average log returns (%)	0.21	0.33	0.34	0.24	0.28
% of series rejecting ADF test's H0 at lag 6	100	100	100	100	100
% of series with skewness between -1 and 1	75.0	87.5	62.5	81.8	77.3
% of series with kurtosis >3	66.7	50	75	81.8	65.3
% of series rejecting ARCH-LM test's H0 at lag 6	8.3	4.2	18.8	0	8.0
% of series rejecting ARCH-LM test's H0 at lag 12	12.5	8.3	6.3	0	8.0
% of series rejecting Ljung–Box test's H0 at lag 6	8.3	12.5	0	18.2	9.3
% of series rejecting Ljung–Box test's H0 at lag 12	8.3	50	0	9.1	22.7

Table A3: Statistical summary for logarithm of international price

	Rice	Maize	Wheat	Sorghum
Average log returns (%)	0.31	0.45	0.46	-0.26
ADF test at lag 6	-5.94***	-5.60***	-4.87***	-5.97***
skewness	0.39	-0.09	0.28	0.34
kurtosis	8.23	1.41	2.30	1.97
ARCH-LM test at lag 6	91.10***	0.60	8.32	2.62
ARCH-LM test at lag 12	107.46***	6.99	13.75	16.554
Ljung–Box test at lag 6	88.12***	1.56	18.12***	7.81
Ljung–Box test at lag 12	100.37***	14.63	25.03**	17.40

Table A4: Data descriptions

Commodity	Country (Market)	Price Type	Time
Rice (Thai A1 Super)	**Thailand (Bangkok)**	**International**	**Jan 2006 – Nov 2022**
Rice (coarse)	Nepal (Kathmandu)	Retail	Jan 2006 – Nov 2022
Rice (imported)	Chad (N'Djamena)	Retail	Oct 2006 – Nov 2022
Rice (imported)	Mali (Bamako)	Wholesale	Jan 2006 – Nov 2022
Rice (imported)	Mozambique (NA)	Retail	Jan 2006 – Nov 2022
Rice	Uganda (Kampala)	Wholesale	Jan 2006 – Nov 2022
Rice (regular milled)	Philippines (NA)	Wholesale	Jan 2006 – Nov 2022
Rice	Brazil (Sao Paulo)	Retail	Jan 2006 – Nov 2022

Rice (first quality)	Colombia (NA)	Retail	Jan 2006 – Nov 2022
Rice (first quality)	Guatemala (Guatemala City)	Wholesale	Jan 2006 – Nov 2022
Rice (morelos)	Mexico (Mexico City)	Wholesale	Jan 2006 – Nov 2022
Rice (first quality)	Nicaragua (Managua)	Wholesale	Oct 2006 – Nov 2022
Rice (milled)	Peru (Lima)	Wholesale	Jan 2006 – Nov 2022
Rice (imported)	Niger (Niamey)	Retail	Jan 2006 – Nov 2022
Rice (first quality)	Dominican Republic (Santo Domingo)	Wholesale	Jan 2006 – Nov 2022
Rice (first quality)	Costa Rica (NA)	Retail	Jan 2006 – Nov 2022
Rice (imported)	Togo (Lomé)	Retail	Jan 2006 – Nov 2022
Rice	South Africa (NA)	Retail	Jan 2006 – Nov 2022
Rice (imported)	Burkina Faso (Ouagadougou)	Wholesale	Jan 2006 – Nov 2022
Rice (Mix)	Cambodia (Phnom Penh)	Wholesale	Jan 2006 – Nov 2022
Rice	Cameroon (Yaoundé)	Retail	Jan 2006 – Nov 2022
Rice	Central African Republic (Bangui)	Retail	Jan 2006 – Nov 2022
Rice	Ghana (Accra)	Wholesale	Jan 2006 – Nov 2022
Rice	Samoa (NA)	Retail	Jan 2006 – Nov 2022
Rice (white)	Sri Lanka (Colombo)	Retail	Jan 2006 – Nov 2022
Rice	Tunisia (NA)	Retail	Jan 2006 – Nov 2022
Wheat (No 2 Hard Red Winter)	**US (Gulf)**	**International**	**Jan 2005 – Nov 2022**
Wheat (white)	Ethiopia (Addis Ababa)	Wholesale	Jan 2005 – Nov 2022
Wheat (flour)	Nepal (Kathmandu)	Retail	Jan 2005 – Nov 2022
Wheat (flour)	Brazil (Sau Paulo)	Retail	Jan 2005 – Nov 2022
Wheat (flour)	Colombia (Bogota)	Wholesale	Jan 2005 – Nov 2022
Wheat (flour)	El Salvador (San Salvador)	Retail	Jan 2006 – Nov 2022
Wheat	Afghanistan (Kabul)	Retail	Jan 2006 – Nov 2022
Wheat (flour, local)	Azerbaijan (NA)	Retail	Jan 2006 – Nov 2022
Wheat (flour)	Cameroon (Yaoundé)	Retail	Jan 2006 – Nov 2022
Wheat (flour)	Georgia (NA)	Retail	Jan 2006 – Nov 2022
Wheat	India (New Delhi)	Retail	Jan 2006 – Nov 2022
Wheat (flour, first grade)	Kazakhstan (NA)	Retail	Jan 2006 – Nov 2022
Wheat (flour, first grade)	Kyrgyzstan (NA)	Retail	Jan 2006 – Nov 2022
Wheat (flour)	Peru (Lima)	Wholesale	Jan 2006 – Nov 2022
Wheat (flour)	South Africa (NA)	Retail	Jan 2006 – Nov 2022
Wheat (white)	Sri Lanka (Colombo)	Retail	Jan 2006 – Nov 2022
Wheat	Sudan (Khartoum)	Wholesale	Jan 2006 – Nov 2022
Wheat (flour, first grade)	Tajikistan (NA)	Retail	Jan 2006 – Nov 2022

Sorghum (No 2 Yellow)	US (Gulf)	International	Jan 2003 – Nov 2022
Sorghum	Chad (N'Djamena)	Retail	Oct 2003 – Nov 2022
Sorghum	Ghana (Accra)	Wholesale	Jan 2006 – Nov 2022
Sorghum	Haiti (Port-au-Prince)	Retail	Jan 2006 – Nov 2022
Sorghum	Togo (Lomé)		Jan 2006 – Nov 2022
Sorghum (white)	Nicaragua (Managua)	Wholesale	Jan 2003 – Nov 2022
Sorghum	Niger (Niamey)	Retail	Jan 2003 – Nov 2022
Sorghum (red)	Somalia (Mogadishu)	Retail	Jan 2003 – Nov 2022
Sorghum (feterita)	Sudan (NA)	Wholesale	Jan 2003 – Nov 2022
Sorghum (local)	Burkina Faso (Ouagadougou)	Wholesale	Jan 2006 – Nov 2022
Sorghum (Maicillo)	El Salvador (San Salvador)	Retail	Jan 2006 – Nov 2022
Sorghum (local)	Mali (Bamako)	Wholesale	Jan 2006 – Nov 2022
Maize (No 2 Yellow)	**US (Gulf)**	**International**	**Jan 2004 – Nov 2022**
Maize	Chad (N''Djamena)	Retail	Oct 2004 – Nov 2022
Maize	Ethiopia (Addis Ababa)	Wholesale	Jan 2004 – Nov 2022
Maize (white)	Mozambique (NA)	Retail	Jan 2004 – Nov 2022
Maize (white)	Zambia (NA)	Retail	Jan 2004 – Nov 2022
Maize (white)	Philippines (NA)	Retail	Jan 2004 – Nov 2022
Maize (white)	Colombia (Medellin)	Wholesale	Jan 2004 – Nov 2022
Maize (white)	Guatemala (NA)	Wholesale	Jan 2004 – Nov 2022
Maize (white)	Honduras (NA)	Wholesale	Jan 2004 – Nov 2022
Maize (white)	Mexico (Mexico City)	Wholesale	Jan 2004 – Nov 2022
Maize (white)	Nicaragua (Managua)	Wholesale	Oct 2004 – Nov 2022
Maize	Niger (Niamey)	Retail	Jan 2004 – Nov 2022
Maize	Cameroon (Yaoundé)	Retail	Jan 2006 – Nov 2022
Maize	Central African Republic (Bangui)	Retail	Jan 2006 – Nov 2022
Maize (white)	Costa Rica (NA)	Wholesale	Jan 2006 – Nov 2022
Maize (yellow)	Dominican Republic (Santo Domingo,)	Retail	Jan 2006 – Nov 2022
Maize (white)	El Salvador (San Salvador)	Retail	Jan 2006 – Nov 2022
Maize	Ghana (Accra)	Wholesale	Jan 2006 – Nov 2022
Maize	Panama (Panama City)	Retail	Jan 2006 – Nov 2022
Maize (white)	Paraguay (Asunción)	Wholesale	Jan 2006 – Nov 2022
Maize (yellow)	Peru (Lima)	Wholesale	Jan 2006 – Nov 2022
Maize	Rwanda (Kigali)	Wholesale	Jan 2006 – Nov 2022
Maize (white)	Togo (Lomé)	Retail	Jan 2006 – Nov 2022
Maize	Uganda (Kampala)	Wholesale	Jan 2006 – Nov 2022
Maize (white)	Zimbabwe (Harare)	Retail	Jan 2006 – Nov 2022

Note: NA represents National Average.