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Agricultural policy and commodity price stabilisation in Ghana: The role of buffer stockholding operations

Emmanuel Abokyi*
Consultancy and Innovation Directorate, Ghana Institute of Management and Public Administration, Accra, Ghana. E-mail: eabokyi@gimpa.edu.gh

Kofi Fred Asiedu
KAAF University College, Accra, Ghana & Nobel International Business School, Accra, Ghana. E-mail: fkasiedu@yahoo.com

* Corresponding author

Abstract

This paper investigates the extent of price volatility of maize and rice in Ghana following the introduction of public buffer stockholding operations (PBSO) as a policy to stabilise farm output prices in the last decade. We analysed price volatility using the generalised autoregressive conditional heteroscedasticity (GARCH(1,1)) modelling technique. This econometric technique was applied to market-level time-series data from selected major markets in Ghana from 2006 to 2015. The results indicate that price volatility for maize and rice has declined in the long run and, in the short run, shows relatively slow volatility transmission. The findings show that the buffer stockholding operations policy in the selected markets has stabilised the prices of the two commodities, especially in the long run. The results suggest that buffer stockholding operation policy remains a viable alternative for curbing high price volatility if structured well to fit the country context. We also conclude that climate change resilience measures are needed to be integrated into the agriculture and food systems of the country if we want to address the persistent price volatility of maize and rice in Ghana sustainably.

Key words: agricultural commodity market; buffer stockholding policy; GARCH; price volatility; Ghana

1. Introduction

It is estimated that, globally, hunger and undernourishment affect over 960 million people, with a more significant proportion of these people living in Asia and Africa (Dessalegn 2018). The FAO *et al*. (2018) reports that the number of people facing chronic food deprivation has increased from 804 million to 821 million people from 2016 to 2017. While the undernourishment and food insecurity situation in most regions in Asia appears to be stable, it seems to be increasing in almost all regions in Africa. The prevalence of undernourishment in sub-Saharan Africa rose from 21% in 2010 to 23% in 2017, while it reduced from 13.6% to 11.4% in Asia over the same period. Today, a third of sub-Saharan Africans are food insecure and malnourished (FAO *et al*. 2018). Thus, without increased efforts, sub-Saharan Africa risks failing to achieve the Sustainable Development Goal (SDG) target of eradicating hunger by 2030. Food security in the region is under threat from high food price volatility resulting from failed markets and climate change variability (Wossen *et al*. 2018; Pincinato *et al*. 2020).

The African agricultural commodity market and the food markets of emerging economies continue to see rapid changes, including price volatility and volatility in the incomes of producers and other actors in the agricultural value chains. The changes in the price levels, for instance, affect the diets and nutritional status of households and the economy as a whole (FAO 2020). As a result, policymakers continue to design several interventions/tools to respond to these changing agricultural commodity market issues. When these market interventions are introduced, it is important to generate evidence that answers the question whether the interventions worked or not. The African agricultural commodity markets have not been studied much compared to non-agricultural commodity markets (Dahl *et al*. 2019; Boako *et al*. 2020). Consequently, this study investigates how an policy intervention to stabilise agricultural commodity prices using buffer stockholding has influenced cereal market and price volatility in a developing country context.

Farmers, especially smallholders – who account for about 90% of farmers in sub-Saharan Africa – cannot store their produce to postpone its sale for better prices due to a lack of storage facilities (Wiggins & Keats 2013). Most farmers sell their produce just after harvest and become food buyers later in the year. Agricultural production, especially of maize and rice, depends on rainfall, which means that most farmers harvest in about the same period. For instance, harvesting in Ghana is usually done between August and September each year, leading to gluts. As a result, the food system in sub-Saharan Africa is characterised by commodity price variations across seasons (Gilbert *et al*. 2017). This variation typically peaks before the harvest period and drops substantially during and after the harvesting of farm produce. There are always market actors who are beneficiaries/winners (gainers) and losers in the price volatility of agricultural commodities (Karabulut *et al*. 2020), and the losers include both producers and consumers. However, for low-income countries, high and uncontrolled fluctuations (volatility) in agricultural commodity prices continue to have devastating effects on the economy. For agricultural producers, especially smallholder maize and rice farmers, the stability of commodity prices is a positive outcome (Karabulut *et al*. 2020). Between 2009 and 2018, for example, farmers in Ghana had improved maize production – from 1.62 million tons to about 3.10 million tons (Ministry of Food and Agriculture [MoFA] 2019). Rice also saw a similar trend over the same period. While these farmers saw improvements in maize production, policies such as fertiliser subsidies and the supply of improved seeds, among others, meant that they continued to experience high instability in the prices of their outputs. As a result, farmers did not see an increase in income commensurate with the increase in production.

This means that policymakers in sub-Saharan Africa have adopted several price-stabilisation policy options to benefit farmers and stimulate economic growth. One agricultural policy, namely public buffer stockholding operations (PBSO), is a policy response tool adopted by governments in developing countries to reduce the effects of price volatility on consumers and farmers. Public buffer stockholding is a market intervention policy in which a government intervenes in a failed market to regulate the supply of an agricultural commodity by purchasing stocks (of the commodity) at a fixed price when the commodity is in abundance, mostly during harvest periods, and releasing the stocks when the commodity is in short supply, mostly during the lean season. The public stockholding programme holds stocks mainly in three forms, namely: a) buffer stocks, which are used mainly for trading purposes and regulating prices; b) emergency stocks for feeding people during times of disaster; and c) food safety net stocks, for feeding the most vulnerable populations (Beaujeu 2016). Thus, the focus of this paper is on the public holding of stocks as buffer stocks for trade in agricultural commodities.

Generally, policy relating to public stockholding as buffer stock aims to mitigate short-term price fluctuations, stabilise and eventually improve the income of producers, influence trade in commodities and, in the long term, to ensure agricultural growth and poverty alleviation (World Bank 2012). PBSOs are policies that function as stabilisers to smoothen price levels within a specific band. Within this price band, prices are often allowed to fluctuate in a particular market. PBSO involves using dual pricing mechanisms by setting up the ceiling (the upper end of the band) and floor prices (the lower end of the band), also known as the guarantee price, in a commodity market. Usually, when the community's price is outside of the price band, the government intervenes by purchasing the product to raise prices or selling old stockpiles to help depress prices and bring the price back to the band (Abokyi *et al*. 2018).

Governments in developing and low-income countries often use buffer stocks to stabilise the income of producers and ensure food security for the population (Cyrille 2015). These governments set up agencies and marketing boards to buy the produce when it is plentiful in the glut periods, and sell it when the produce is less in the lean periods. The buffer stockholding operations, if implemented efficiently, stabilise producer and consumer prices for the benefit of producers and consumers/ households (Fertő 1995). Countries such as India and China have implemented stabilisation programmes that involve buying and holding stocks, especially cereals, for the dual benefit of producers and consumers (Dorosh 2008; Gouel 2013b). Interventions to stabilise agricultural commodity/food markets form part of an age-old phenomenon that is widespread in developing and emerging countries.

To stabilise the prices of staple agriculture commodities (outputs) in Ghana, mainly of cereal food crops such as maize and rice, the government introduced a buffer stockholding programme. The buffer stockholding operations are implemented through the National Food Buffer Stock Company (NAFCO). The aim of the buffer stockholdings is to insulate farmers against income losses, provide them with access to the market, and help motivate then to invest in good agricultural farm practices that help improve their income and yields (Abokyi *et al*. 2018). The NAFCO programme purchases cereals from smallholder farmers and resells stocks during lean periods, when prices are high, to institutions such as schools, hospitals and poultry farmers. With farmers as the focus, the NAFCO programme is targeted at managing the annual glut (oversupply) of maize and rice. Also, the programme aims to stimulate investment in land and inputs to improve the production of these commodities by ensuring that farmers get good prices. Thus, NAFCO purchases cereals, maize and rice at a fixed (floor) price during the glut periods of the commodities and releases the stock during lean periods (Abokyi *et al*. 2020).

In the past, buffer stockholding policies have shown mixed results. While they have worked in some countries, they has often failed in others, as they have had little success in reducing the volatility of prices (World Bank 2012; Deuss 2015). Based on the mixed results globally, the Ghanaian policy was designed to fit the country context; first, by the government using licensed buying agents (LBCs), who are private entities, to purchase the farm produce instead of making the purchases directly (Abokyi *et al*. 2018). The purchase is made during the glut periods only, mainly to mop up excess or surplus produce. Over the years, farmers have complained about the low prices they receive during the glut period and the difficulties they go through to buy food at high prices during the off-season or in lean periods. The predicament of these farmers called for a sustainable and efficient price policy that would be likely to protect farmers and sustain the growth of cereal outputs throughout the year.

We therefore investigated the buffer stockholding operations in Ghana as a viable policy alternative to curb food price volatility. We provide critical information for answering whether the current buffer stockholding operations, which have been implemented in the country for a decade, have stabilised the price of maize. Our motivation for the study is that, after a decade of implementing the current buffer stockholding operations, a review of the policy is needed for its upscaling or for changes to its operations to serve farmers, as several other crop farmers are calling for similar interventions to stem seasonal fluctuations in prices. Non-cereal produce, such as vegetables and fruit, suffer the same fate as cereals during glut periods. Thus, this study seeks to provide empirical evidence that could form the basis for any potential policy review or reform. The contribution of this paper is to present a nexus or link between the current buffer stockholding policy in Ghana and commodity price stabilisation.

It also provides insights into the understudied African agricultural commodity markets and their price volatility. It seeks to analyse rice and maize price volatility in selected markets in Ghana by adopting autoregressive conditional heteroscedasticity (ARCH) and generalised autoregressive conditional heteroscedasticity (GARCH) modelling as approaches to evaluate the success or otherwise of NAFCO in stabilising cereal crops in the country.

The rest of the paper is structured as follows. Section 2 presents a brief overview of the literature on price volatility and buffer stock operations. In Section 3, we discuss the materials and methods used in the analysis, including the data and the econometric aspects of the ARCH/GARCH models. Section 4 presents the empirical results of the ARCH/GARCH modelling and the nullity and unitary tests of the ARCH/GARCH coefficients, while the final section draws together the conclusions and policy implications of the study.

2. Price volatility and buffer stock operations

Price volatility as an indicative measure of price uncertainty is a factor influencing income, food security, and food stocks (Pincinato *et al*. 2020). An increase in food price volatility makes it difficult for smallholder farmers to adjust their activities or make crucial decisions on production. For smallholder farmers, increasing or decreasing farm output levels in the short run in response to price volatility stemming from underlying production characteristics, such as climate change, affects output, thereby sending signals to the market (Pincinato *et al*. 2020). Therefore, in the case of cereals, environmental conditions due to climate change and variations in production are some of the key factors affecting prices.

However, it is not always the case that food price volatility is negative (Jayne 2012). It is essential to entertain some level of food price volatility to allow for the smooth running of the markets. For instance, some level of price volatility takes care of the storage cost of cereals until the lean season. These types of volatility are not harmful compared to the wide inter-annual variations in food prices, which often are not predictable. Volatility is also not harmful when food prices move along a smooth and well-established seasonal pattern. Variations in prices that do not reflect the commodity market fundamentals turn out to be problematic, as they are likely to lead to incorrect farm and household decisions (Balié & Demeke 2016). The volatility of farm produce becomes an issue for possible public policy responses when significant and unanticipated, and creates a level of uncertainty leading to risks for producers, traders and consumers (Kalkuhl *et al*. 2016). High volatility induces the risk-averse behaviour of these market actors and can lead to inefficient investment decisions, since it creates problems beyond their capacity to cope. It also poses a threat to the food and nutrition security of households, especially in low- and middle-income countries, and among poorer groups in high-income countries (Upton *et al*. 2016) because they lack the stable income to offset food price increases. With food forming a chunk of their expenditure, these households become vulnerable when price volatility persists.

The impact of food price volatility is very detrimental to developing countries, because it can cause food security challenges, and political and social unrest (see, for example, Jayne 2012; Gouel 2013a; Abokyi *et al*. 2018). With high food price instability, poor households are more likely to reduce their consumption or turn to less preferred foods, which affect their nutritional balance, especially in households with children. High food price volatility deters risk-averse smallholder farmers from making the necessary investments to increase productivity and yields. There is no incentive to adopt good agricultural practices such as fertiliser usage and improved seed application. The effects are poor nutrition and low-income levels for farmers.

Volatility affects the purchasing power of consumers and the overall food security of households and communities, and even economic growth at the national level through inflation (Timmer 2010).

According to Arezki and Brückner (2011), political institutions are likely to deteriorate in low-income countries during periods of increased food prices, giving rise to potential civil conflicts. High inflation, a critical consequence of food price instability that reduces farmers' and consumers' household income, can induce social unrest among the poor segment of the citizenry (Bellemare 2015). Therefore, it is necessary to stabilise food prices, even though it comes at a cost to the country. Revisiting commodity price volatility is vital because, while producers prefer high and stable food prices, consumers prefer low and steady prices. In Ghana, cereals, especially maize and rice, account for about 23% of households' food budget (Rahaman & Mohammed 2014). Therefore, changes in the price level of cereals (price volatility) have implications for household food consumption, especially for the poor, who have limited ability to insure themselves against adverse and unanticipated price shocks. Price volatility hurts poor households that are not self-sufficient and jeopardises their ability to eat (Gouel 2013a). Knowing the extent of the effect of the buffer stock policy on commodity price volatility and seasonality is critical for Ghana, for two major reasons. First, it provides the basis for policy review and reform. Second, it guides the drive for improving food security and protecting farmers against income loss. An empirical study to evaluate the effect of such policy after a decade of implementation is critical, given that other farm produce also experiences similar price volatility, and there therefore could be lessons for replication.

3. Materials and methods

3.1 Data

We analysed market-level data based on monthly wholesale price information from the Ministry of Food and Agriculture (MoFA) in three selected markets in Ghana. The markets include Techiman and Tamale markets, where the policy was implemented, and the Ho market, where no implementation was done. The data covers the period from January 2006 to April 2015,[1] giving us 112 data points. From January 2006 to December 2010 the markets did not have the buffer stockholding policy, whereas they had the policy in the period from January 2011 to April 2015. There are no missing observations for the period, and the choice of these three markets provides a fair reflection of the maize and rice marketing in the country, as these constitute essential centres for these crops. Market actors from communities near and far across the country travel to these selected market centres to purchase the two commodities and distribute them to other parts of the country.

Furthermore, the choice of these three markets is also because they constitute the traditional markets for maize and rice in terms of production and consumption. Hence, studying these markets presents a better understanding of maize and rice marketing and the price stabilisation of the two commodities in Ghana. Furthermore, the choice of these markets provides an opportunity to compare markets with and without such policy in place.

3.2 Econometric aspects

We employed the ARCH and GARCH models due to the time-dependent fluctuation of maize and rice prices. Our motivation for the ARCH and GARCH models is that models have become important tools for analysing time-series data, mainly when the goal is to analyse commodity price volatility and forecast price volatility for maize and rice, and the potential price offered to farmers, especially smallholders. The conventional assumption is that time-series models exhibit a constant standard and variance, something often encountered when studying price volatility. In other words, regular models assume that the variance in the error is constant over time, i.e. homogeneity of variance. However, this assumption has been proven to be invalid in many cases (Ilbeigi *et al*. 2017). Therefore, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model to deal with the

[1] To prevent an overlap with the Ghana Commodity Exchange (GCX), a programme was introduce in 2018 to also purchase cereals from farmers in Ghana; the time-series data ended prior to the introduction of the GCX.

situation by allowing for the conditional variance to vary over time. The ARCH model therefore is instrumental in measuring price volatility because it considers volatility to change over time, i.e. price volatility exhibits time-varying variance. ARCH models are zero mean and serially uncorrelated, with non-constant variance conditional on past or historical data (Srivastava 2008). The ARCH models are designed specifically to model and forecast the conditional variance of the dependent variables. The model thus reads as (Muthusamy *et al*. 2008):

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 P_{t-2} + \dots \dots .\beta_k P_{t-k} + e_t \quad (1)$$

$$\delta_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 \dots \dots \dots .\alpha_k e_{t-k}^2 + v_t, \quad (2)$$

where P_{t-k} is price lagged by k periods, $\beta_1, \beta_2, \dots \beta_k$ are parameters to be estimated (Equation (1)), δ_t^2 is conditional variance at time t, and e_{t-l}^2 are lagged squared errors. The $\alpha_{1..} \dots .\alpha_k$ in Equation (2) are parameters to be estimated, and e_t and v_t are the error terms of equations (1) and (2) respectively. The limitation of the ARCH model is that a relatively long lag in the conditional variance is often required to adequately measure the nature of the volatility (Michael *et al*. 2015). It therefore is difficult to decide how many lags to include in an ARCH model to produce a non-parsimonious model (Kumar *et al*. 2012). When the ARCH model does not include the right number of lags, the model could be over-parameterised, or the non-negativity constraint could fail (Onyeka-Ubaka *et al*. 2014). The non-negativity constraint implies that all the coefficients of the explanatory variables in the ARCH model must be positive; that is, α_0, α_1 and $\alpha_k > 0$.

As an alternative to the ARCH model, Bollerslev (1986) proposed the generalised autoregressive conditional heteroscedasticity (GARCH) model, which includes the lagged conditional variance. This model is an extension of the ARCH model. The GARCH (q, p) model reads as follows (Kumar *et al*. 2012):

$$\delta_t^2 = \alpha_0 + \alpha \sum_{i=1}^{q} e_{t-i}^2 + \beta \sum_{i=1}^{p} \delta_{t-i}^2, \quad (3)$$

with $\alpha_0 > 0$, $\alpha \geq$ and $\beta \geq 0$ as the sufficient conditions.

The GARCH model generally incorporates much of the information that a larger ARCH model usually contains. The general form of the GARCH model is presented as GARCH (p, q), where p is the number of autoregressive lags or ARCH terms in the equation, and q is the number of moving averages specified or the GARCH terms (Engle 2004). A GARCH (1,1) model is often sufficient to incorporate all that a large ARCH model contains (Matei 2009; Chipili 2014). The GARCH differs from the ARCH model in that it incorporates squared conditional variance terms as additional explanatory variables. This allows the conditional variance to follow an autoregressive moving average (ARMA) process (Michael *et al*. 2015).

In addition, the GARCH model transforms the ARCH model into an autoregressive moving average model (Jordaan *et al*. 2007). According to Engle (2004), the weights on past squared residuals are assumed to decline geometrically at a rate estimated from the data in the GARCH model. Engle (2004) further states that the GARCH forecast variance is a weighted average of three different variance forecasts. First, a constant variance corresponding to a long-run average; second, the variance in the forecast made in the previous period; and third, the new information that was not available when the previous forecast was made. How quickly the variance changes and gets back to its long-run mean depends on the weights of the three forecast components. The GARCH model recognises the difference between the unconditional and the conditional variances and allows the latter to change over time due to past errors (Bollerslev 1996). The benefit of the GARCH model is its simplicity, and it has three parameters – as shown in Equation (3). This allows an infinite number of squared roots to influence the conditional variance. As a result, GARCH models are more parsimonious than ARCH models (Michael *et al*. 2015). GARCH models are better for modelling time-series data when the data exhibits heteroskedasticity and volatility clustering (Ghorbel *et al*. 2014). Incorporating long memory in the data-generating process and the flexible lag structure is another reason why the GARCH model is more robust than other models (Amado & Teräsvirta 2008).

GARCH models are a popular method to analyse and predict volatility in stock prices, with GARCH (1,1) being considered the standard model specification (Naik *et al*. 2020). Some researchers regard the choice of GARCH (1,1) as arbitrary, as they think that an information criterion could be used to determine the higher-order specifications. However, the GARCH (1,1) continues to enjoy popularity because the first lag of the conditional variance can capture all the volatility clustering in the data; hence, further lags may not be necessary (Brooks & Burke 2003). The GARCH (1,1) is also popular because of its simplicity, yet it has not been proven inferior to higher GARCH models (Hansen & Lunde 2005). In addition, the available limited observation of data does not allow us to fit a higher level of GARCH (>1, >1).

GARCH models measure the persistence of volatility in two ways: in the short run, using recent data, and in the long run, using the sum of ARCH and GARCH (Samanta & Samanta 2007). In a GARCH (1,1) model, as demonstrated in Equation (3), the ARCH term, α, measures the extent to which current volatility feeds into the next period's volatility (Campbell *et al*. 1996). That is, it helps to predict future volatility in the market. The sum of the ARCH and GARCH terms ($\alpha + \beta$) measures the persistence of the price volatility in the long run, i.e. the rate at which the effect of the volatility decreases over time (see Morimune 2007). If $\alpha + \beta = 1$ is accepted, volatility has been persistent (Hammad *et al*. 2015). If $\alpha + \beta > 1$, the variance increases over time and signifies that the increase in volatility is exponential (explosive). Similarly, when the sum of the coefficients of the GARCH terms is less than 1, i.e. if $\alpha + \beta < 1$, it means that the variance decreases over time. Besides, if $\alpha + \beta = 0$, the volatility will likely die soon.

This study tested the nullity and unitary of the sum of the coefficients (ARCH/GARCH effects) based on the standard Wald score test (Francq & Zakoïan 2009). In addition, we used the Lagrange multiplier (LM) test proposed by Engle (1982) on our data to justify the use of the ARCH and GARCH models (Gel & Chen 2012).

4. Results and discussion

4.1 Preliminary results

As a preliminary analysis to the start of the primary analysis (GARCH), we present a visual description (graphs) of the raw data, a Chow test, and a coefficient of variation of the price series. The graphs provide a visual description of the raw data, showing the maize and rice price trends at the three markets across the months/years. The graphs also show how volatile the market prices are and whether there is a seasonal price trend. The Chow test is to help us identify if there is any structural break in the price volatility data, and the coefficient of variation (CV) is intended to help us check the level of stabilisation before and after introducing the buffer stockholding policy. Figures 1 to 3 present the visualisation of the raw data.

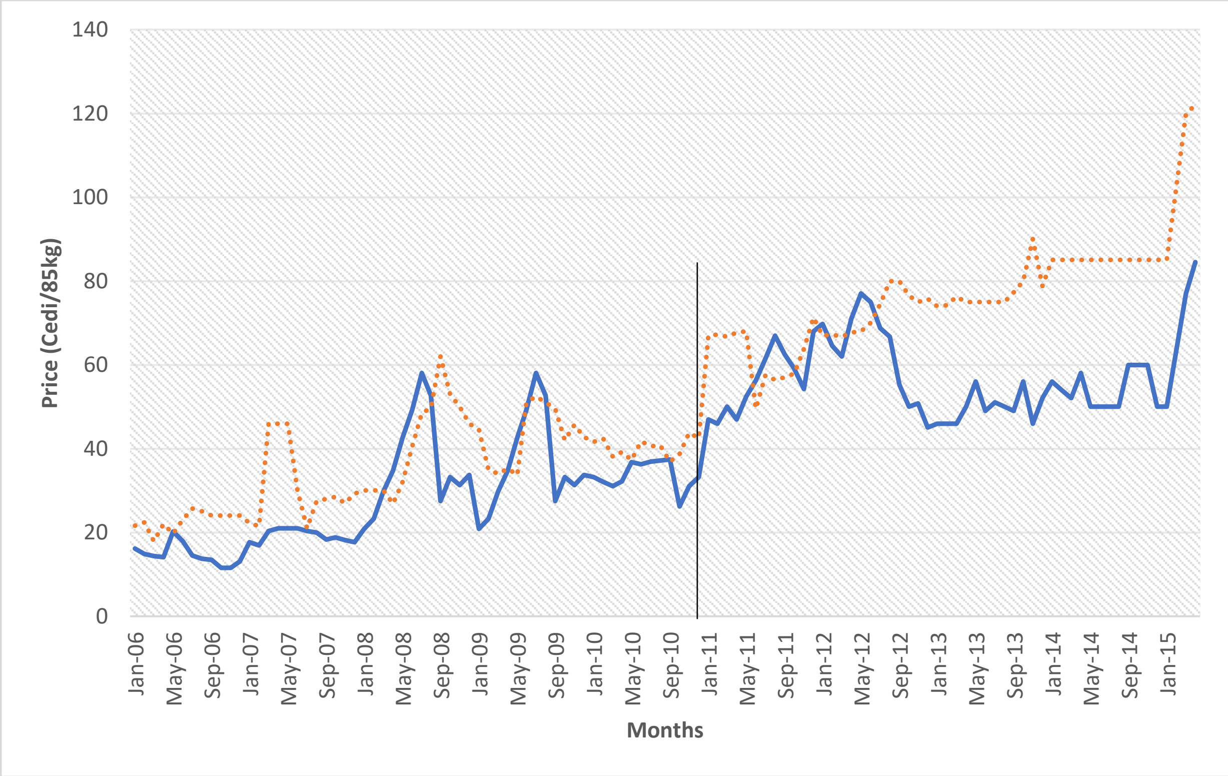

Figure 1: Price trends for maize and rice in Techiman market

Notes: The thick line is the maize price series, the dotted line is the rice price series, and the vertical line indicates the month when the buffer stockholding started in Ghana

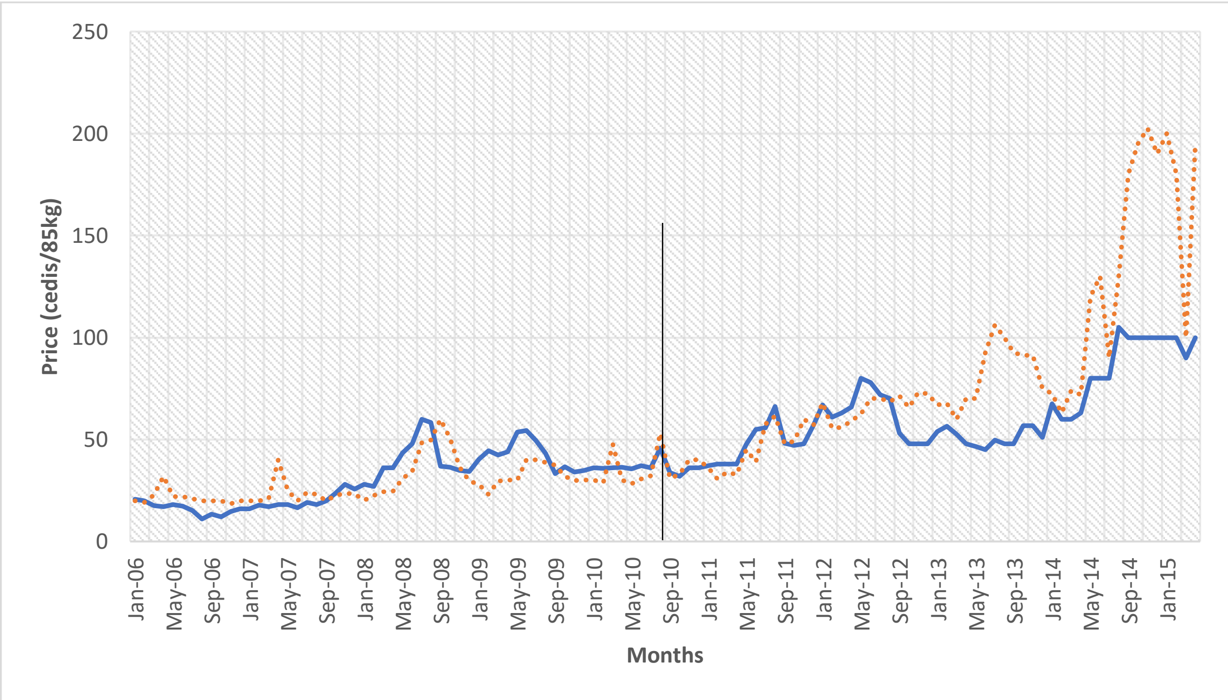

Figure 2: Price trends for maize and rice in Tamale market

Notes: The thick line is the maize price series, the dotted line is the rice price series, and the vertical line indicates the month when the buffer stockholding started in Ghana

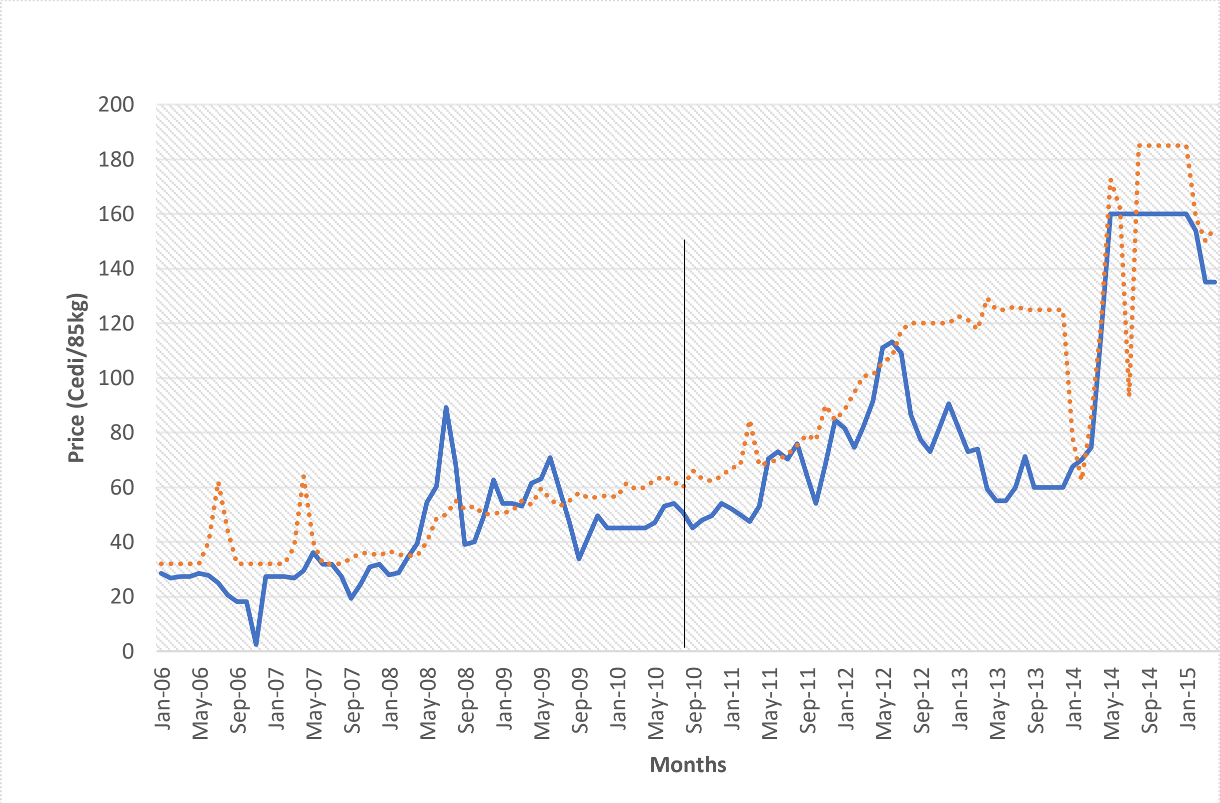

Figure 3: Price trends for maize and rice in Ho market

Notes: The thick line is the maize price series, the dotted line is the rice price series, and the vertical line indicates the month when the buffer stockholding started in Ghana

The graphs in Figures 1 to 3 show that the price volatility of the commodities increased over time, i.e. from 2005 to 2015. In addition, the variations in prices of the two commodities follow a similar pattern/trend in all the markets.

4.1.1 The Chow test

In addition to the data visualisation, we present a Chow test to identify any break in the data structure (the prices) before and after introducing the buffer stockholding policy. Table 1 summarises the results of the Chow test (for details on the Chow test, see Biu and Nwakuya 2022).

Table 1: Chow test for the price series

Market	Techiman		Tamale		Ho	
Commodity	**Maize**	**Rice**	**Maize**	**Rice**	**Maize**	**Rice**
F-statistics	78.51	239.71	114.44	207.55	39.69	126.96
P-value	0.00	0.00	0.00	0.00	0.00	0.00

The Chow test results presented in Table 1 show that, for the two periods (2006 to 2010 and 2011 to 2015), there is a structural break in the mean prices across the three markets. This can be seen in the fact that the p-value of the F-statistics of the Chow test for all the price series in all the markets for the two cereals is significant at 1%. This suggests that the introduction of the buffer stockholding policy resulted in a structural change in the price volatility of the cereals.

4.1.2 Coefficient of variation (CV)

Table 2 shows the coefficient of variation (CV) (ratio of standard deviation to mean) for the price series (see details of calculation of CV in Abokyi *et al*. 2018).

Table 2: Coefficient of variation for the prices within the markets across periods

Market	Techiman		Tamale		Ho	
Commodity	**Before**	**After**	**Before**	**After**	**Before**	**After**
Maize	0.45	0.21	0.42	0.33	0.41	0.44
Rice	0.31	0.22	0.33	0.57	0.25	0.34

The preliminary results of the coefficient of variation (CV) presented in Table 2 show that, for the markets where the policy is present, viz. Techiman and Tamale (except for maize in Tamale), the CV of the two commodities before the introduction of the buffer stockholding policy (2006 to 2010) is much better than the CV after the introduction of the policy (2010 to 2015). There is a reduction in the CV following the introduction of the buffer stockholding scheme. However, in the case of the Ho market, where the policy is absent, the CV for both crops after the policy is higher than before, indicating that the price volatility of the cereals is still increasing, despite the introduction of the policy. The downward trend of the CVs in Techiman and Tamale (policy-on markets) and upward in Ho (policy-off markets) suggest a possible stabilisation of the prices of maize and rice due to the policy. Following these preliminary suggestions of possible prices stabilisation, we now follow with the main analysis.

4.2 Results of the stationarity tests

To begin the main analysis of volatility, we need to ensure that the series under analysis are stationary. We applied the Phillips-Perron (PP) test to test for unit root instead of the Augmented Dickey-Fuller (ADF) test, because the PP test is more robust and more reliable because it checks errors of the data series to ensure homogeneity (Shiller & Perron 1985; Kim & Schmidt 1993; Sukati 2016). The PP test corrects any serial correlation and any heteroskedasticity in the errors. The test modifies the Dickey-Fuller test statistics and makes them more robust to serial correlation using the Newey–West (Newey & West 1987) heteroskedasticity and autocorrelation-consistent covariance matrix estimator. The PP tests for unit root are performed for all the series across all markets. The results are presented in Table 3. The results show that, at the 5% critical level, most of the series is not stationary. However, after the first lagged difference, the series does become stationary.

Table 3: Results of Phillips-Perron unit root tests

Market	Price series	Parameter	Test statistics	Data at level Critical values			Test statistics	Data at first difference Critical values		
				1%	5%	10%		1%	5%	10%
Techiman	Maize	Z(rho)	-21.304	-27.473	-20.744	-17.537	-98.172	-27.467	-20.74	-17.533
		Z(t)	-3.224	-4.036	-3.449	-3.149	-10.336	-4.037	-3.449	-3.149
	Rice	Z(rho)	-28.705	-27.473	-20.744	-17.537	-119.759	-27.467	-20.74	-17.533
		Z(t)	-3.509	-4.036	-3.449	-3.149	-11.519	-4.037	-3.449	-3.149
Tamale	Maize	Z(rho)	-15.41	-27.473	-20.744	-17.537	-122.513	-27.467	-20.74	-17.533
		Z(t)	-2.72	-4.036	-3.449	-3.149	-11.159	-4.037	-3.449	-3.149
	Rice	Z(rho)	-15.042	-27.473	-20.744	-17.537	-110.588	-27.467	-20.74	-17.533
		Z(t)	-2.455	-4.036	-3.449	-3.149	-10.452	-4.037	-3.449	-3.149
Ho	Maize	Z(rho)	-14.355	-27.473	-20.744	-17.537	-107.352	-27.467	-20.74	-17.533
		Z(t)	-2.706	-4.036	-3.449	-3.149	-13.237	-4.037	-3.449	-3.149
	Rice	Z(rho)	-32.047	-27.473	-20.744	-17.537	-120.116	-27.467	-20.74	-17.533
		Z(t)	-4.359	-4.036	-3.449	-3.149	-11.908	-4.037	-3.449	-3.149

Note: The p-values for Z(t) are more than 0.5 for the data at levels and are less than 0.05 for the series at first difference

4.3 The results of the Lagrange Multiplier (LM) test

After confirming stationarity, we needed to establish the presence of the ARCH effect to warrant the use of GARCH modelling. Therefore, to start with the GARCH modelling, we present the results of the test for the ARCH effect using the Lagrange Multiplier (LM) test in Table 4.

Table 4: LM test for autoregressive conditional heteroskedasticity (ARCH effect)

Market	Price series (2006-2015)	Chi^2	p-value
Techiman	Maize	72.050***	0.000
	Rice	86.150***	0.000
Tamale	Maize	80.709***	0.000
	Rice	75.161***	0.000
Ho	Maize	83.509***	0.000
	Rice	73.404***	0.000

Source: Authors' calculations. Note: *** = significant at the 1% level

The LM test results in Table 4 show that, for all the price series, the chi^2 values have a p-value of less than 0.05. Therefore, we reject the null hypothesis of no ARCH (1) effects. The results in Table 4 mean that the price volatility of maize and rice vary over time, thus making it possible to apply the ARCH/GARCH approach. The confirmation of the ARCH effect in the price series allows us to use the GARCH approach in modelling the volatility of the price series.

4.4 The ARCH/GARCH effects

We used the GARCH (1,1) modelling, and the summary of the fitted model is presented in Table 5. The nullity and unitary tests of the coefficients of the ARCH/GARCH terms are shown in Table 6.

In Table 5, the ARCH/GARCH model results for the Techiman market generated log-likelihood values of 46.37 and 106.30 for maize and rice respectively. The results for the Tamale market showed a likelihood of 70.46 for maize and 61.81 for rice. Compared to the Tamale and Techiman markets, the Ho market generated a log-likelihood of 35.02 for maize and -26.11 for rice respectively. Thus, the results show a better fit of the Techiman and Tamale market models than the Ho market model.

The results of the GARCH analysis presented in Table 5 indicate that, in all three markets, the volatility in the current period depends on volatility in the preceding period. This is evident from the significant ARCH effects for both crops. For example, the reported ARCH effect for maize – of 0.107 and 0.367 for the Techiman and Tamale markets respectively – are significant at 5%. In the case of the Ho market, the ARCH effect for maize is 0.897. It is significant at 1%, showing that, in the current period, volatility depended on the variations of the previous period in both markets. The results corroborate similar findings for a pulse in India, where Bisht and Kumar (2019) reported that the volatility of the current period depended on the volatility pf the preceding period. The ARCH effects for maize are smaller for the Techiman and Tamale markets, where the buffer stock operation is being implemented, compared to the Ho market, where the policy is absent. Similar results of ARCH effects are reported for rice in these markets.

Table 5: The results of the ARCH/GARCH model

Crop	Parameters	Coefficient	Std. error	Z stats	P-value	Log-likelihood
	Techiman market					
Maize	ARCH	0.107**	0.054	1.980	0.047	47.169
	GARCH	0.853***	0.055	15.620	0.000	
	Constant	0.001	0.001	1.350	0.176	
Rice	ARCH	0.406**	0.182	2.230	0.026	106.294
	GARCH	0.150	0.180	0.830	0.406	
	Constant	0.005***	0.001	3.730	0,000	
	Tamale market					
Maize	ARCH	0.367**	0.167	2.190	0.029	70.457
	GARCH	0.073	0.283	0.330	0.744	
	Constant	0.010*	0.006	1.830	0.067	
Rice	ARCH	0.184*	0.110	1.670	0.094	61.807
	GARCH	0.614**	0.251	2.450	0.014	
	Constant	0.004	0.004	1.090	0.274	
	Ho Market					
Maize	ARCH	0.897***	0.326	2.750	0.006	35.017
	GARCH	0.481***	0.099	4.870	0.000	
	Constant	0.004	0.003	1.080	0.279	
Rice	ARCH	0.285*	0.162	1.770	0.077	-26.108
	GARCH	0.660***	0.127	5.190	0.000	
	Constant	0.016**	0.007	2.380	0.017	

Source: Author's calculations. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively

In Table 6, the results show that the sum of the α and β coefficients (the ARCH and GARCH terms) are 0.556 for rice and 0.459 for maize. These results are significantly different from 1, at 5% for rice and 10% for maize respectively (i.e. $\alpha + \beta > 1$ for both crops). The results indicate that the price volatilities of maize and rice have generally been declining over the years (from the data we see from January 2006 to April 2015) in the Tamale and Techiman markets. Although the GARCH effect is insignificant for maize in Tamale (see Table 5), it is relatively smaller than the ARCH effect. The positive GARCH effects in the models suggest the relatedness of vitality to previous price changes (Kuwornu *et al*. 2011). The results show that maize price volatility has declined in the long run and demonstrate the relatively slow transmission of volatility in the short run. These results further imply that the volatility of maize prices has not been persistent over the period, further demonstrating the stabilisation of maize prices to some extent.

Table 6: Unity and nullity tests of the sum of the ARCH and GARCH coefficients

Market	Crop	ARCH	GARCH	Sum (α + β)	Unity test	
					Chi²	p-value
Techiman	Maize	0.107	0.853	0.960	1.190	0.276
	Rice	0.406	0.150	0.556	5.090**	0.024
Tamale	Maize	0.367	0.073	0.459	2.830*	0.093
	Rice	0.184	0.614	0.798	1.050	0.304
Ho	Maize	0.897	0.481	1.378	1.930	0.165
	Rice	0.285	0.660	0.945	0.270	0.261

Source: Authors' calculations. ** and *** indicate significance at the 5% and 1% levels respectively

In the case of maize in the Techiman market and rice in the Tamale market, the results indicate that the sum of α and β (α + β) does not differ statistically from 1 (0.960 for maize in Techiman and 0.798 for rice in Tamale). These results indicate that price volatility has been persistent in these markets. Even though the sum of the ARCH and GARCH effects (α + β) is not statistically different from 1, our results indicate a marginal decline in volatility for rice in Tamale in the long run, corroborating the findings of Abokyi *et al*. (2018). These authors report a decline in volatility in the prices of the two crops in these markets compared to the findings of Kuwornu *et al*. (2011) who report increasing volatility of rice prices throughout the period from 1970 to 2006 – a period without the buffer stocking operations. The results of Abokyi *et al*. (2018) and Kuwornu *et al*. (2011), along with the findings from the present study, lead to the conclusion that the buffer stock operations have affected the price volatility of these two crops: maize and rice.

By contrast, the results presented in Tables 5 and 6 reveal that price volatility has been persistent in the Ho market, where the policy is absent. The ARCH and GARCH terms for maize in the Ho market sum to 1.378. The ARCH/GARCH sum has a chi^2 of 1.930 and a p-value of 0.165, as shown in Table 6, indicating that the ARCH/GARCH effect is statistically equivalent to 1, and thereby demonstrating the presence of persistent volatility over the period. For the rice price, the ARCH and GARCH sum to 0.92, with the ARCH being significant at 10% and the GARCH term significant at 1%. The results indicate that the ARCH/GARCH effect for rice (0.92) is statistically equivalent to 1, with a chi^2 of 0.261 and a p-value of 3.74. All these values show persistent volatility over the period. The only reason could be the absence of the buffer stock policy in the Ho market.

Overall, the results presented in both Table 5 and Table 6 show that price volatilities of maize and rice have generally been declining over the years (January 2006 to April 2015) in the Techiman and Tamale markets, where the buffer stockholding policy is present, with the reverse persisting in the Ho market, where the policy is absent. One could safely say that the results from the three markets demonstrate the effect of the buffer stockholding operations policy in stabilising the prices of maize and rice, at least to some extent in the areas where the policy is operational. These findings corroborate new evidence from research (see, for example, Abokyi *et al*. 2018), which reports that the buffer stockholdings in Ghana have successfully met one of the objectives of price stabilisation in the operational area.

The results of this study support, in part, the findings reported by Sukati (2016) using the GARCH method to model the volatility of maize prices in Swaziland. Sukati concluded that maize price volatility has been increasing over the years in the country without any policy from the government. Comparing the study to the Ghanaian situation illustrates the critical role of specific agriculture policy in regulating maize prices in the Swazi economy (Sukati 2016), where the production, supply and price of maize have been characterised by fluctuations in worsening climatic conditions, affecting supply levels and the pricing mechanisms in the economy. However, in Ghana, implementing the buffer stockholding operations policy, which targets cereals, has seen maize and rice price volatilities in these markets being managed well.

While the results show modest achievement by the buffer stockholding operations in stabilising the prices of maize and rice, previous studies on climate change variability indicate that the phenomenon continues to pose a threat to buffer stockholding operations (Diffenbaugh *et al*. 2012; Thompson *et al*. 2018; Wossen *et al*. 2018). Thompson *et al*. (2018) observe that climate change variability has critically important consequences for farmers' crop yields and land use, especially that of smallholders. In Ghana, research shows that climate variability affects the supply of agricultural output/food and causes price variability in what is described as "climate-induced food price variability" (see Wossen *et al*. 2018). Wossen *et al*. (2018) report that climate variability continues to have an adverse effect on price volatility in Ghana. Thus, climate change effects can derail the modest gains made by the buffer stockholding operations initiative.

Sub-Saharan nations are vulnerable to climate change, as climate variability is expected to make more lands dryer and result in more drought, leading to a fall in crop yields, especially that of cereals (Wood *et al*. 2021). This is because cereal production in Ghana is rainfed, without any irrigation being used. Atiah *et al*. (2021), for instance, report that climate change variables constitute about 75% of the variations in maize yields in Ghana. Therefore, any negative climate change is likely to reduce maize yields and could significantly effect supply, leading to increased price volatility of the cereals, despite buffer stockholding activities.

5. Conclusions

This paper has presented an analysis of the price volatility of maize and rice in selected markets in Ghana following the implementation of buffer stockholding operations policy in the country over the past decade. We analysed whether the policy has stabilised maize and rice price volatilities over time by using the ARCH/GARCH methods with market-level price series data spanning from January 2006 to April 2015. We used the unitary test to determine if the GARCH effect and the ARCH effect are unitary so as to decide on the long-run and short-run price volatilities. The results indicate that maize and rice price volatility has declined in the long run and shown relatively slow transmission of volatility in the short run in the markets with interventions. The results of the analysis further show that, in the markets without policy intervention, maize and rice prices have been volatile over the years due to the absence of any specific market policy to regulate price changes. Overall, the results indicate that the buffer stock operation has helped stabilise the volatility of maize and rice prices over the years. Note that, even though we did not expect any integration between the markets with and without intervention due to different geographical locations, this study did not distil any possible spillover effect from a possible market integration between these markets.

Based on our results, the modest success of the current buffer stock initiative indicates that tailoring public buffer stockholding policy to fit the country context is critical for its success. The current buffer stockholding in Ghana is focused on buying maize from farmers, especially smallholders, and selling it to institutions (such as schools, hospitals, prison services and poultry farmers), who buy in bulk during the lean period at predetermined prices. The practice minimises price fluctuation in the market, and household consumers, including farmers, benefit from this practice by getting these cereals at reasonable prices during the lean periods. The results serve as an incentive to increase investment in the buffer stockholding operations in the country and possibly to upscale it nationally. The results of our analysis have implications for farm investment as, with a buffer stock policy, farmers are assured of stable prices for their farm produce, as price risks and uncertainty in income are reduced.

Our results show that such interventions could possibly help farmers make decisions to invest in productivity-enhancing technologies and adopt improved agricultural practices to increase farm outputs. However, climate change variability, as evident in erratic rainfall patterns and drought in the producing areas, threatens the sustainability of price stability gains obtained from the buffer stockholding operations. Therefore, climate resilience adaptation measures, such as irrigation systems, are needed to be integrated into the agricultural and food systems in the country.

Although our results show improvement in price stabilisation through the buffer stock policy, it would also be interesting to assess if there is any market price co-integration between (among) the markets, and also if there is any change in the level of integration before and after buffer stock policy interventions.

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