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# Climate Factors and Maize Price Volatility in Developing Countries: Evidence from Benin

Changes in climate conditions are expected to significantly alter food production patterns and increase food price volatility, leading to challenges for food and nutrition security. Thus, this paper aims to investigate the extent to which climate factors contribute to the volatility of maize price in Benin, using monthly data from 7 markets. To this end, an autoregressive conditional heteroskedasticity in mean (ARCH-M) model is estimated. Mean and variance equations of monthly maize price are specified as functions of temperature, rainfall of the growing season and a set of control variables including a policy variable and the international price of maize with an ARCH(1) term in the variance equation. The findings from the mean equation suggest that rainfall has a negative effect on maize prices. Moreover, the estimation results from the variance equation indicate that rainfall and temperature are negatively associated with price volatility. Therefore, the findings indicate that climate change will affect maize price volatility.

**Keywords:** ARCH model; price volatility; rainfall; temperature; maize; climate change

**JEL classifications:** D40, O55, Q54

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Received: 2 January 2022; Revised: 19 February 2022; Accepted: 22 February 2022.

## Introduction

A change in climate factors constitutes one the causes of food price volatility and variability; affecting productivity, production, and transaction costs (IFPRI, 2015; Springmann *et al.*, 2016; Chen and Villoria, 2019). Indeed, recent spikes in world food prices have often occurred owing to extreme weather events in major producing countries, and they are likely to become recurrent due to climate change (Lobell *et al.*, 2011). Oxfam (2012) reports that climate change somehow affects the occurrence of extreme events (e.g. droughts, floods and hurricanes), leading to an increase in the prices of agricultural commodities. Thus, markets will be destabilised, and there will be more food price spikes due to the increase in the occurrence of extreme weather events (Oxfam, 2012). Nevertheless, Headey and Fan (2008) argue that although climatic factors undoubtedly play a role, they are not in themselves convincing causes of the price spikes of 2007-2008 and the resulting food crises. Other factors such as economic reforms, market conditions, and deforestation may affect agricultural commodity price volatility (Shively, 1996; Barrett, 1997; Kilima *et al.*, 2008; Lundberg and Abman, 2021). In addition, epidemics and pandemics can lead to huge food price volatility and food crises. Historically, agricultural commodities prices dynamics are assumed to be driven by real shocks (based on rational expectations framework), and to stem from forecasting errors (based on the coordination issues caused by price instability) (Gouel, 2012). Moreover, studies including Nelson et al. (2010) and Baldos and Hertel (2014) argue that price variations give only a very partial indication of the socio-economic impact of climate change. Baldos and Hertel (2014) find that due to climate change, the malnourished population will increase by 27 million in 2050 compared to a baseline scenario without climate change.

Food price spikes can intensify and contribute to broader social risks in terms of food and nutrition security, human development, and political stability. For instance, the Intergovernmental Panel on Climate Change (IPCC, 2007) earlier reported that climate change has amplified the effects of droughts, floods and storms and exposes many people to food poverty resulting from the high volatility of agricultural commodities prices. The decrease in food availability due to climate change leads to an increase in food prices, *ceteris paribus*. As illustration, Nelson *et al.* (2010) find that climate change will lead to an increase in malnutrition in 2050 of between 20 and 25 million for children under 5. These results are partly due to a more unfavourable scenario of yield change than that adopted by studies such as Baldos and Hertel (2014). Without climate change, world prices are expected to increase during the period 2000-2050 for the main agricultural commodities (rice, wheat, corn, and soybeans) due to the increase in population and demand for biofuels; this highlights the competition between food crops and biofuels in terms of land use (Nelson *et al.*, 2010). Consequently, even without climate change, the price of rice would increase by 62%, that of corn by 63%, that of soybeans by 72% and that of wheat by 39%. However, climate change could induce additional price increases; overall from 32% to 37% for rice, from 52% to 55% for maize, from 94% to 111% for wheat and from 11% to 14% for soybeans. Thus, the maize price would be more affected by climate change compared to crops such as rice, wheat and soybeans.

It should be noted that, in both rural and urban areas, poor populations will be the most affected, given that they devote a much larger share of their income to food consumption. Moreover, smallholder family farmers will also suffer, as most of them are net food buyers (Zezza *et al.*, 2008; IPCC, 2014). Although conceptually higher prices may lead to an increase in the area under cultivation on less fertile land, and therefore a reduction in yield, several empirical studies have shown that the positive effect outweighs the negative one (Haile *et al.*, 2016; Miao *et al.*, 2016). It is worth noting that the volatility of crop prices discourages agricultural production because it introduces a producer price risk. Moreover, price risk has negative consequences for producers' resource allocation and investment decisions (Sandmo, 1971; Moschini and Hennessy, 2001). Actually, it is hard for poor farmers to take advantage of rapid price increases due to many factors such as lack of access to credit, land and other necessary inputs to expand production (Oxfam, 2012). This is the case for agricultural producers in low- and middle-income countries, due to poor risk management (Binswanger and Rosenzweig, 1986) and these producers are not well protected from the consequences of price volatility (Miranda and Helmberger, 1988). It should also be noted that episodes of food crises trigger concerns about the peculiarities of agriculture and the need for public intervention in agricultural markets (Gouel, 2012).

Maize is the most consumed cereal in Benin and is produced all over the country. In terms of food insecurity, in 2017, 45.5% of the population are food insecure, with food insecurity more pronounced in rural areas (République du Benin, 2017). This low-middle income country ranks among those developing nations that are acknowledged as having a low capacity to adapt to climate change. Thus, it is of paramount importance to investigate the relationship between climate factors and food price volatility. This study aims to analyse the extent to which climate factors affect the volatility of maize prices in Benin. To this end, an autoregressive conditional heteroskedasticity in mean (ARCH-M) model is estimated. The study contributes to the literature by analysing how climate factors and in time, climate change could result in food price volatility in developing countries. The findings can guide policymakers in designing appropriate economic policies to mitigate the effects of climate factor on the welfare of both producers and consumers. It is also worth noting that beside climate factors, the extent to which the food price stabilisation policy implemented in the country starting from July 2008, which consists of assembling grain stocks after harvests and selling them during periods of scarcity, influences maize price volatility.

The remainder of the study is proceeds as follows. Section 2 present a synthesis of the literature on the drivers of agricultural commodity price volatility. The methodology (analytical tools and data) is presented in Section 3. Section 4 presents the empirical findings and the discussion. Finally, there are the conclusion and policy implications.

# Drivers of agricultural commodity price volatility: a synthesis of the literature

Many factors are identified in the literature as having the potential to drive agricultural commodity price volatility, These include market fundamentals like yields and stock levels, weather and changing weather patterns with their related impacts, cycles in key markets, policy driven developments including large purchases by the governments, developments outside the agricultural sector (e.g. exchange rate and oil price movements), trade policies and their transmission, and lastly, investments in agricultural production (Tothova, 2011). According to Tothova (2011), the following factors contribute to greater volatility: i) low levels of stocks; ii) climate change and weather-related events; iii) policies; iv) strong co-movements with energy and other agricultural prices.

As market fundamentals driving agricultural commodity price volatility, there are supply, demand, storage with their relative shocks including weather, technological progress, and population growth (Williams and Wright, 1991; Piot-Lepetit and M'Barek, 2011; Karali and Power, 2013; Algieri, 2014; Ott, 2014). For Piot-Lepetit and M'Barek (2011), the shocks are caused by other structural factors that simultaneously influence different crops at the same time (e.g. energy and fertiliser prices, exchange rates, interest rates). Policies are also found to affect the volatility of food prices (Piot-Lepetit and M'Barek, 2011). For instance, market price volatility depends to a large extent on trade policies designed to isolate domestic markets from international markets (Tigchelaar *et al.*, 2018). Studies such as Diffenbaugh *et al.* (2012); Schaub and Finger (2020) and Putra *et al.* (2021) identify climate change and extreme events such as droughts as driving factors of price volatility. They report that the volatility of US corn prices is more sensitive to short-term changes in climate conditions. The impact of climate change is mainly due to the intensification of severe heat conditions in the cultivation of primary corn in the United States, which has led to a sharp increase in the volatility of corn prices. For these authors, there is a closer integration between agriculture, energy, and markets. They underline the crucial importance of the interactions between energy policies, the links between energy and agriculture and climate change. In addition, agronomic factors as well as the historically low levels of world cereal stocks are found to drive food price volatility (Ngare *et al.*, 2014). It should be noted that Chen and Villoria (2019) highlight the effects of food imports on the variability of domestic maize prices in 27 net-importing countries. Meanwhile, Lundberg and Abman (2022) find strong empirical evidence showing that there is negative association between maize price volatility and forest loss, using data from 26 countries in Sub-Saharan Africa.

# Material and Methods

## Modelling maize price volatility accounting for climate factors

This study estimates mean and variance equations of monthly maize prices as functions of climate factors (rainfall and temperature), a policy variable, seasonal and regional variables with the ARCH term in the variance equation following studies such as Engle *et al.* (1987) and Kilima *et al.* (2008). This modelling approach is choosing drawing on Kilima *et al.* (2008) who state that theoretically storable commodity prices have an ARCH process, and distinct from standard time-series models, conditional volatility can directly influence the conditional mean in an ARCH in mean (ARCH-M) model. Note that there are other methods of volatility analysis such as the standard generalized autoregressive conditional heteroskedasticity (GARCH) model and its variants like the Spline-GARCH model – that can decompose daily price volatility into high- and low frequency components with the latter plausibly being driven by slowly-changing common and commodity-specific macroeconomic factors (Engle and Rangel, 2008), and the regime switching GARCH-MIDAS model (Pan *et al.,* 2017). Thus, the specification of the empirical model is as follows:

$$\begin{aligned} LnPrices_{it} &= \beta_0 + \beta_1 LnPrices_{it-1} + \beta_2 Trend_t + \\ &+ \beta_3 LnR_{it} + \beta_4 LnT_{it} + \beta_5 Policy_t + \\ &+ \beta_6 Price\_International_t + \sum_m 0_m \times M_{tm} + \sum_k \gamma_k A_{ik} + \\ &+ \delta h_{it}^{1/2} + \epsilon_{it}, \epsilon_{it} \mid \varphi_{t-1} \sim i.i.d\ N(0, h_{it}) \end{aligned} \quad (1)$$

$$\begin{aligned} h_{it} &= \alpha_0 + \alpha_1 \epsilon_{it-1}^2 + a_2 LnPrices_{it} + \alpha_3 Trend_t + \\ &+ \alpha_4 LnR_{it} + \alpha_5 LnT_{it} + \alpha_6 Policy_t + \\ &+ \alpha_7 Price\_International_t + \sum_m \rho_m \times M_{tm} + \sum_k \tau_k A_{ik} \end{aligned} \quad (2)$$

where $LnPrices_{it}$ and $LnPrices_{it-1}$ are current and one-month lagged of the natural logarithm of the real maize prices in market *i*, respectively, *Trend*, *R*, *T*, *Policy*, *Price_International*, *M* and *A* refer to monthly trends, rainfall, temperature, a dummy variable capturing the policy implemented in the country starting from July 2008 consisting of assembling grain stocks after harvests that are to be sold during period of scarcity (food price stabilisation policy), the international maize price, monthly dummies, and regional dummies, respectively. The error term $\epsilon$ is assumed to be independently, identically, and normally distributed, conditional on the information set $\varphi_{t-1}$ with mean zero and variance *h*. It should be noted that monthly rainfall and temperature are not used directly in the model. Rather, seasonal values are computed; April-July and September-November average temperature and total rainfall are calculated. April-July values are assigned to August, September, October, and November, and September-November ones to January, February, March, April, May, June, and July. Using these climate variables instead of monthly data helps to capture data for the growing period.

In this modelling framework, the short-term trend of price volatility is represented by $\alpha_3$ and the short-term difference in price volatility before and after the grain stock policy is represented by $\alpha_6$ in the variance equation. One can obtain the long-term effects as follows:

$$\omega_{LT}^{1} = \frac{\alpha_3}{1 - \left(\alpha_2 / Prices_{it-1}\right)} \quad (3)$$

$$\omega_{LT}^{2} = \frac{\alpha_6}{1 - \left(\alpha_2 / Prices_{it-1}\right)} \quad (4)$$

From the ARCH-M risk term, $\delta$, which is the observed price attributable to risk premium, one can estimate the short-term relative risk premium defined as:

$$RRP = \frac{\delta h_t^{1/2}}{Price_t} \quad (5)$$

The long-term relative risk premium is obtained by dividing the short-term relative risk premium (based on equation 5) by $(1-\beta_1)$.

The data are pooled into a panel data structure to enable an estimation of the aggregate effects of climate factors and the policy variable included, as well as to ascertain the extent to which maize price volatility is due to the specified regional factors in the variance equation. Prior to the estimations, the variables must be tested for stationarity. Indeed, the order of integration of the variables is of paramount importance for the modelling. Moreover, prior to run the unit root tests, it is of paramount importance to test for cross-sectional dependence for the continuous variables except for the international maize price as it does not vary across markets included in the analysis. In fact, cross-sectional dependence can be due to the presence of common shocks and unobserved components in the series (de Hoyos and Sarafidis, 2006) and panel unit root tests are sensible to that. The selection of the appropriate panel unit root test should be motivated by the results of the cross-sectional dependence test; either first-generation or second-generation panel unit root tests should be adopted. Second-generation panel unit root tests should be used when the hypothesis of cross-sectional dependence is not rejected instead of using first-generation panel unit root tests (Pesaran, 2007). This paper makes use of the Pesaran cross-sectional dependence test (Pesaran, 2004) to test for cross-sectional dependence in the series. Although, the paper relies on an ARCH-M modelling approach, the Engle's Lagrange multiplier test for ARCH effects has been conducted for the individual markets to test for the presence of ARCH effects.

## Data and summary statistics

The data used in this paper are monthly maize prices and are from the Ministry of Agriculture of Benin. The dataset covers the period from August 1998 to December 2016 and are relative to several principal markets of the country. These are consumer prices and are measured in local currency per kg (F CFA, in 2016 1 US$=593.01 CFA F). The markets included in the paper are Banikoara, Bohicon, Dassa, Djougou, Malanville, Parakou, and Savalou. These markets capture the regional distribution of the country and are chosen due to data availability. Cotonou is not included as it is not concerned by maize production; it is the main city of the country. Consumer Price Index (CPI) of agricultural products collected from the Food and Agriculture Organization of the United Nation (FAO) is used to deflate the monthly maize prices. Monthly international maize prices are from the Economic Research Division of the Federal Reserve Bank of St. Louis and are in US$ per metric ton. Monthly rainfall and temperature data are from the Meteorological service of Benin.

Table 1 reports summary statistics for deflated maize prices in the eight markets included in the analyses. One can notice that means prices and standard deviations differ across markets. As a result, there are differences in the coefficients of variation; the highest is from Djougou and the lowest in Parakou. It should be noted that Djougou is located in the North-West of the country, and that maize is more consumed in the South compared to the North. Parakou is the main city of the northern part of the country. These differences in the coefficients of variation, suggest the heterogeneities of the

**Table 1:** Summary of deflated monthly maize prices in the markets included in the analyses.

| Markets | Mean | Standard Deviation | CV | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Banikoara | 331.023 | 187.997 | 0.568 | 0.503 | 1.921 |
| Bohicon | 330.860 | 176.096 | 0.532 | 0.558 | 2.005 |
| Dassa | 350.007 | 188.016 | 0.537 | 0.585 | 1.968 |
| Djougou | 363.267 | 444.903 | 1.225 | 11.457 | 157.778 |
| Malanville | 357.146 | 196.604 | 0.550 | 0.569 | 1.926 |
| Parakou | 331.654 | 173.403 | 0.523 | 0.436 | 1.809 |
| Savalou | 354.462 | 189.049 | 0.533 | 0.521 | 1.907 |

Source: Own composition

markets in terms of price volatilities. In fact, the volatility of commodities prices affects the population, compromising food security and nutritional status.

## Results and Discussion

As previously indicated, cross-sectional dependence tests results are important to guide the choice of the appropriate unit root test. The results of cross-sectional dependence (Table 2) indicate the presence of cross-sectional dependency in the series, and so suggest the use of second-generation panel unit root tests to the detriment of first-generation panel unit root tests. Consequently, a Pesaran (2007) panel unit root test has been used. It should be noted that it is the Im-Pasaran-Shin unit root test which is used for the international maize price. The panel unit root test results (Table 3) show that the three variables are stationary at level; at level the null hypothesis of a unit root can be rejected (the variables are thus integrated of order zero). The Engle's Lagrange multiplier test for ARCH effects conducted for the individual markets suggest the presence of ARCH effects. Thus ARCH(1) is estimated.

The estimation results are reported in Table 4. The findings from the mean equation suggest that rainfall has a negative effect on maize prices. However, the effect of temperature on maize prices is not significant. These findings suggest that maize price will be sensible to climate change and are in line with those of previous studies such as Diffenbaugh *et al.* (2012); Schaub and Finger (2020) and Putra *et al.* (2021). So,

**Table 2:** Pesaran cross-section dependence test for the series.

| Variables | CD-test | P-value | Average joint T | Mean ρ | Mean abs(ρ) |
|---|---|---|---|---|---|
| Ln(maize price) | 65.887*** | 0.000 | 221.00 | 0.95 | 0.95 |
| Ln(Precipitation) | 36.878*** | 0.000 | 221.00 | 0.54 | 0.54 |
| Ln(Temperature) | 46.896*** | 0.000 | 221.00 | 0.69 | 0.69 |

*** Significant at the 1% level of significance.
Source: Own composition

**Table 3:** Panel unit root test results.

| Variables | Intercept | Intercept and Trend |
|---|---|---|
| Ln(maize price) | -6.149*** | -6.345*** |
| Precipitation | -5.978*** | -6.141*** |
| Temperature | -5.157*** | -5.898*** |
| Ln(world maize price) | -1.959* | -2.877*** |

*** Significant at the 1% level of significance.
Source: Own composition

**Table 4:** ARCH-M estimation results.

| Variable | Mean equation | Variance equation |
|---|---|---|
| Constant | 1.112 | 28.429** |
| | (0.875) | (10.573) |
| $LnPrice_{t-1}$ | 0.949*** | -0.448*** |
| | (0.009) | (0.099) |
| *LnRainfall* | -0.030** | -0.647*** |
| | (0.014) | (0.162) |
| *LnTemperature* | -0.229 | -8.363** |
| | (0.256) | (3.178) |
| *LnWorld maize price* | 0.036** | 0.914*** |
| | (0.016) | (0.195) |
| *Policy* | -0.021 | 0.191 |
| | (0.017) | (0.233) |
| $h^{1/2}$ | -0.662** | |
| | (0.284) | |
| $\beta_1$, ARCH(1) term | | 0.092*** |
| | | (0.0264) |
| Market dummies (Reference = Bohicon) | | |
| Banikoara | -0.019 | -0.288* |
| | (0.013) | (0.171) |
| Dassa | -0.006 | -0.212 |
| | (0.012) | (0.151) |
| Djougou | 0.007 | 0.435** |
| | (0.015) | (0.177) |
| Malanville | -0.011 | -0.181 |
| | (0.013) | (0.165) |
| Parakou | -0.014 | -0.451** |
| | (0.012) | (0.167) |
| Savalou | -0.008 | -0.190 |
| | (0.012) | (0.154) |
| Monthly dummies (Reference = January) | | |
| February | -0.120*** | -1.264*** |
| | (0.025) | (0.186) |
| March | -0.035** | -2.726*** |
| | (0.014) | (0.211) |
| April | -0.058*** | -2.773*** |
| | (0.014) | (0.201) |
| May | -0.031** | -2.693*** |
| | (0.014) | (0.196) |
| June | 0.002 | -2.548*** |
| | (0.014) | (0.201) |
| July | 0.004 | -1.831*** |
| | (0.018) | (0.231) |
| August | 0.023 | -2.258*** |
| | (0.017) | (0.238) |
| September | 0.012 | -2.207*** |
| | (0.017) | (0.233) |
| October | 0.128*** | -1.275*** |
| | (0.030) | (0.274) |
| November | -0.037** | -2.771*** |
| | (0.016) | (0.260) |
| December | | -2.814*** |
| | | (0.196) |
| Trend | -3.61e-05 | -0.006*** |
| | (1.239e-04) | (0.001) |
| Observations | 1,547 | |
| Wald chi2(16) | 25,561.92 | |
| Prob > chi2 | 0.000 | |

Notes: Standard errors are in parentheses. ***P<0.01, **P<0.05, *P<0.1.
Source: Own composition

adaptation policies are necessary to limit food price spikes attributable to climate change. Maize prices differ in some extent across months as shown by the significant coefficients associated with several monthly dummies. This suggests that some months are abundance periods, while others are scarcity periods. Thus, maize prices decrease in abundance periods, and increase in scarcity periods. As with normal goods, an increase in supply should lead to a decrease in prices, *ceteris paribus*. In addition, the findings indicate that the policy implemented to assemble grain stocks after harvesting does not have any significant effect on maize prices.

The estimation results from the variance equation indicate that rainfall and temperature have a negative effect on price volatility. Price volatility decreases with rainfall and temperature. Therefore, maize price variance depends also on climate factors and by extension, climate change. This indicates that climate change will somehow affect maize price variance. It can be concluded that the decrease in seasonal rainfall associated with the increase in seasonal temperature could lead to increase in volatility in maize prices with implications for food and nutrition security, and this is consistent with the findings of previous studies such as Diffenbaugh *et al.* (2012); Schaub and Finger (2020) and Putra *et al.* (2021). These findings suggest that maize price volatility will increase or decrease depending on the changes in rainfall and temperature. However, an increase in rainfall, *ceteris paribus*, will lead to a decrease in maize price volatility. Price volatility decreases in all other months compared with January: it can be observed that maize prices are more volatile in January relative to the remaining months of the year. The findings also reveal that the grain stock policy does not affect significantly maize price volatility. This indicates that this policy does not contribute to stabilising prices. This may be because certain persons may buy maize from the shops where public authorities sell the commodity during scarcity periods to sell it back. Price volatility is significantly higher in Djougou, and significantly lower in Banikoara and Parakou relatively to Bohicon. These findings confirm the heterogeneities of the markets in terms of price volatilities. As production decision is somehow linked to prices, high price volatilities may affect the level of production. The short-term trend of price volatility is equal to 6 and the short-term difference in price volatility before and after the grain stock policy is equal to  in the variance equation. One can obtain the long-term effects using the equations (3) and (4) that are  and , respectively. These figures indicate that both short-term and long-term price volatility have been decreasing and there is no difference between these two effects. In addition, the grain stock policy has contributed to an increase in maize price volatility but the effect is not significant, indicating that this policy has not had the expected effect on price volatility.

Moreover, the value of short-term and long-term relative risk premia are estimated as -0.004 and -0.073, respectively. These negative relative risk premia are consistent with previous findings such as those of Barrett (1997) and Kilima *et al.* (2008). It should be noted that for Barrett (1997), negative risk premia in staple food pricing could indicate consumers' dedication to keep diet and food preparation habits around staple foods. Moreover, Domiwitz and Hakkio (1985) argue that a negative risk premium could mean that price risk widens the marketing cost wedge between wholesale and retail maize prices. Higher costs for traders resulting from price risk might lead to upward pressure on retail prices and lower wholesale and producer prices (Domiwitz and Hakkio, 1985). Price fluctuations have always been viewed as unfavourable to the expectations of economic agents. They exacerbate the vulnerability of both producers and consumers that depend on the commodities whose prices are volatile. High food prices lead to a reduction in food consumption (Zezza *et al.*, 2008; Springmann *et al.*, 2016), thereby exacerbating food and nutrition insecurity. One of the means to reduce vulnerability and poverty in rural areas as well as in urban and peri-urban areas is to guarantee stable prices. In addition, food price volatility undermines growth prospects and poverty reduction in low-income countries. Thus, stabilisation policies have the role of ensuring the stability of agricultural commodities for the population, especially for the poor. Commodity price volatility affects people, compromising their food security and nutrition status.

## Conclusion and policy implications

Climate change is expected to significantly alter food production patterns and increase food price volatility, leading to challenges for food security and poverty. The objective of this paper was to investigate the extent to which climate factors contribute to increase the volatility of maize price in Benin. To achieve the objective, an ARCH-M model has been estimated. Mean and variance equations of monthly maize price are specified as functions of temperature, rainfall of the growing season and a set of control variables including a policy variable and the international maize price with an ARCH(1) term in the variance equation. The findings from the mean equation suggest that rainfall has a negative effect on maize prices. The findings indicate also that the policy implemented to assemble grain stocks after harvest does not significantly affect the price of maize. Moreover, the estimation results from the variance equation indicate that rainfall and temperature are negatively associated with price volatility, so the net effect of climate factors will depend on the direction of the changes in those factors. The findings also reveal that the grain stock policy does not significantly affect price volatility. Furthermore, the short-term and long-term relative risk premia are negative. From the findings the following policy implications can be drawn: (i) Policymakers should design policies that aim to control for maize price volatility based on their goals (targeting either producers or consumers), but also need to have a clear understanding of the situation of farm households (whether they are net buyers or net sellers of maize); (ii) As food security is more pronounced in rural settings, public policies could target producers (farm households) in terms of maize price stabilization related to climate factors; (iii) Adaptation policies could also be designed to increase maize production and limit price volatility. This research does not assess volatility transmission across markets; future research could focus on this aspect.

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