Full Research Article

The welfare cost of maize price volatility in Malawi

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Abstract. This paper investigates conditional and unconditional maize price volatility in Malawi at the country and local-economy market levels and related welfare costs. The empirical analysis applies an ARCH/GARCH approach that uses monthly data from January 1991 to March 2013, and the welfare cost is estimated via the Lucas formula. The study findings underline the importance of the domestic factors in explaining maize price volatility and of seasonality in affecting the unconditional variance and welfare cost.

Keywords. Maize price volatility, welfare cost, local-economy market, malawi

JEL Code. Q11, Q12, Q13

1. Introduction

Using an ARCH/GARCH approach, this paper investigates maize price volatility in Malawi at the country level and with reference to nine local-economy markets using monthly data over the time period of January 1991 to March 2013. This information is collected to estimate related welfare costs via the Lucas formula.

Approximately 80 percent of the Malawian population relies on maize production for income and food consumption. Dominating the country's maize sector, 96 percent of the total cropland is occupied by smallholder and resource-poor farmers who practice rain-fed methods in typically harsh climates (Feed the Future, 2013). Maize is cultivated for subsistence needs, and only 20 percent of the total production is marketed by one-third of the country's smallholder farmers (Fuentes, 2013). However, the main harvest of the year does not provide an adequate food supply over several seasons, particularly during the lean season. For this reason, a large proportion of the population depends on the local economy or national market food purchases when stocks are depleted. Moreover, market dependence on maize has increased over time with pressure from populations whose growth is exceeding the pace of household production (Elis and Manda, 2012; Sahley *et al.* 2005).

Thus, the analysis of maize price volatility provided in this paper can support informed policy strategies aimed at addressing the negative effects that these processes

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have on welfare trends for a significant portion of the Malawian population that lives in chronic poverty and food insecurity.

In a recent paper, Minot (2014), analysing the trends of food price volatility in Africa, noted that, in the wake of the global food crisis of 2007-2008, there was an unprecedented interest by international organisations and governments in high and volatile prices in the international cereal markets and very few empirical investigations addressed this issue with reference to the African context. Explanations for developing countries were based on the ideal maximum pass-through assumption, an hypothesis that tends to divert attention away from domestic factors, such as production and consumption shocks, which are often more influential in affecting local market volatility (Rapsomanikis, 2009). The possible influence of these factors may, for instance, be reflected in the fact that reported staple food price volatility levels in the global market are lower than those of African countries (Minot, 2011). Moreover, the existing literature shows that the maximum pass-through hypothesis is not valid for all cases (Conforti, 2004; Quiroz and Soto, 1995). The global price corresponds to the futures market price, which is not equivalent to the price at which the majority of households and farmers buy and sell cereals in Africa. Rather, households and farmers trade based on local market prices that are denominated in local currencies that reflect local market conditions (Gilbert, 2011). It is also important to note that transportation costs, stabilisation policies, and the variety of cereals traded on international and African markets may limit or even fully protect local markets from the world market price pass-through mechanism.

For these reasons, studies on international cereal markets must include investigations of volatility at the national and local market levels. Such examinations are necessary for constructing responsive policies aimed at mitigating the negative effects of cereal price volatility and its consequent reduction in welfare losses in particular (Aizeman and Pinto, 2005; Deaton, 1999). An extensive body of literature indicates that unforeseen price variations following endogenous or exogenous shocks in world cereal markets can lead to sudden and major social and economic consequences for individuals, households, and farmers while also impacting economic growth, inequality, and balance-of-trade trends in developing countries (see, for example, Prakash, 2011). Recent studies also show that these negative impacts are not typically offset by good economic times, and as a consequence, negative effects are likely to have a permanent effect (Aizeman and Pinto, 2005). This impact is exacerbated by the fact that numerous developing countries are not currently implementing adequate mechanisms designed for reducing or managing risks for producers and consumers (Balcome, 2011).

The aforementioned study by Minot (2014) includes Malawi in its sample of analysed African countries and investigates maize price volatility. However, the study does not consider three critical aspects that are relevant to developing accurate conceptualisations of volatility.

First, the adopted measures of price volatility do not control for seasonality and trends. Second, the issue of data quality is not discussed. Third, the study's focus on aggregate average volatility, standard deviation and unconditional variance, does not account for intra-year and inter-month variability in the data series.

These aspects must be considered to develop an adequate understanding of maize price volatility in Malawi, and the present study will incorporate these aspects using the approach outlined below.

In this paper, volatility is measured from unpredictable components of price variability. For this reason, the maize price series has been de-trended and seasonally adjusted. The control for seasonality is especially important as it acts as a predictable indicator of cereal prices. In Malawi, a major maize price increase occurs during the lean season before the maize harvest from January to March, whereas a major reduction in prices occurs after the harvest from April to June, when most households sell their maize yields (Sassi, 2012; 2014).

The quality of maize price data for Malawi should also be adequately discussed. For example, the number of local-economy markets utilised for the computation of average prices at the country level has improved over time, leading to possible bias in long-term price investigations. This limitation justifies our decision to integrate our analysis at the country level with the investigation of the nine local-economy markets. Moreover, following suggestions from the study by Minot (2014), we examine a longer study period to produce more robust results.

Finally, our analysis is based on the conditional and unconditional variance value that is estimated using the ARCH/GARCH approach. The existing literature generally focuses on aggregate average values of volatility while providing very few indications regarding whether distributions are leptokurtic, i.e. on the possible "heavy" nature of the distribution tails and, hence, the amount of variability in the data they capture. This study overcomes this limitation focusing on monthly dynamics of volatility and allowing a deeper understanding of the effect of domestic factors on the unpredictable variability of maize price. To this end, our analysis begins with an investigation of the pass-through mechanism through examinations of integration between the Malawian maize market and international and South African markets. The South African market is included because 60 to 70 percent of cereal imports into Malawi originate either formally or informally from southern African countries, namely Mozambique, Zimbabwe, Zambia and Tanzania (Zant, 2005). Moreover, the existing literature focusing on the recent food price spike excludes short-term effects, focusing only on long-term relationships with South African maize prices. We have accounted for this aspect by considering a longer time period, and we provide a more robust analysis of the influence of domestic, regional, and international factors that affect maize price volatility in Malawi. The study also compares volatility in international and Malawian maize prices for this same reason.

The paper is structured as follows. Section 2 addresses the issue of data quality. Section 3 illustrates the adopted empirical strategy, which is outlined in three steps. First, we present the approach selected for determining maize price transmission. We then discuss the procedure followed to compute the unpredictable component of maize price. Finally, we describe the ARCH/GARCH approach adopted to estimate unconditional and conditional volatility as well as the Lucas formula, which is used to calculate the welfare cost of volatility. This same structure is applied for the presentation and discussion of results provided in Section 4. Section 5 presents the conclusions.

2. Data

Our empirical investigation on volatility in Malawi is based on the price of maize in Malawi as well as in international and South African markets.

For the study of Malawian maize prices, we consulted the monthly retail white maize prices in Kwacha (MWK) per kilogram provided by the Famine Early Warning System Network (FEWSNet) National Representative in Malawi as well as the Malawian Ministry of Agriculture and Food Security. Our definition of white maize includes local, composite, and hybrid varieties.

In Malawi, there are three maize markets, the local-economy, farm-level, and national markets. In our empirical investigation, we consider the local-economy market. As illustrated by Mapila *et al.* (2013), a local-economy market is defined as a trading centre for a specific rural area that consists of villages and communities. At this market level, maize is sold by producers directly to consumers, or by large traders stationed at the reference central market, and by roving traders who buy from producers and sell to large traders at the same reference trading centre. The local-economy market does not account for maize traded in villages or communities, i.e., in the farm-level market, where prices are discussed in terms of the farm-gate price. This market also excludes maize sold to the Malawian Agricultural Development Marketing Corporation (ADMARC) at national market prices established by this government-controlled institution.

The quality of our dataset reflects the evolution of the methodology adopted by the Ministry of Agriculture and Food Security for the collection of food crop prices at the local-economy market scale. The current agricultural price data system was established in 1988 as an Agricultural Marketing and Estate Development initiatives and funded by the World Bank until 1995, when responsibility for the system was transferred to the Agro-Economic Survey of the Ministry of Agriculture and Food Security with the financial participation of various donors. Over time, data collection procedures were improved with the support of the Initiative for Development and Equity in African Agriculture (IDEA Malawi, 2005). In 2005, efforts to refine this system were accelerated in response to unusual variations in prices between markets and time and with the discovery of missing information in the official data. The retail price survey for crops currently covers 80 local-economy markets of its original 30, 72 of which are used to calculate monthly data (Government of Malawi, 2003). Data are collected on a weekly basis at the local-economy market level and aggregated according to the simple monthly average at the market and national levels. Over the time period analysed in this paper, the number of local-economy markets with at least one maize price observation per year used for country-level, average-price calculations by the Ministry of Agriculture and Food Security has increased from an average of 17 from 1991 to 1995 to an average of 67 from 2009 to 2013 (Figure 1).

This fact represents a weakness in our long-term price investigation as it may lead to biased conclusions. Malawi is characterised by poor maize market integration across livelihood zones and regions (World Food Programme, 2010; Mapila *et al.*, 2013). In fact, maize price levels and their degree of variability are affected by numerous factors such as harvest conditions, climatic circumstances, transportation costs, commercial openness, and household welfare, all of which vary, often significantly, across the country (Malawi Vulnerability Assessment Committee, 2005). In this circumstance, data cannot be comparable over time.

The price series also exhibit a number of missing monthly values that have largely been collected in the field, with the support of local key informants, and remaining values have been estimated using the classic method of mean substitution.
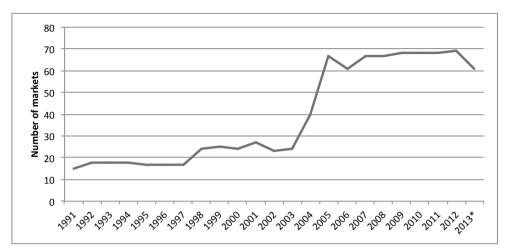
Figure 1. Number of maize markets with at least one observation made each year (1991-2013).

* Data are for the period of January to March

For the local-economy market-level analysis, we selected market datasets that had missing values for no more than two consecutive months per year, and missing values were treated as previously described. As a consequence, only nine local-economy markets were considered. However, these markets account for various districts and regions, as illustrated in Table 1.

Table 1. Local-economy markets analysed by district and region.

Local-economy market	District	Region
CHITIPA	Chitipa	
KARONGA	Karonga	
RUMPHI	Rumphi	Northern
MZUZU	Mzimba	
NKHOTAKOTA	Nkhotakota	
MITUNDU	Lilongwe	
CHIMBIYA	Dedza	Central
LIZULU	Ntcheu	
NCHALO	Chikwawa	Southern

For the analysis of the pass-through mechanism, we used the international price in US dollars (US$) for US No. 2 yellow maize, F.O.B. Gulf of Mexico provided by the World Bank and the White Maize Spot Price of South African Future Exchange (SAFEX) in South African Rand (ZAR), F.O.B. Johannesburg.

For the purposes of our investigation, we also used the Consumer Price Index (CPI) provided by the IMF for the US and South Africa in addition to the same index variable provided by the Malawian National Statistical Office and Reserve Bank of Malawi for Malawi. Finally, the exchange rates for MWK to US$ and ZAR were provided by the Reserve Bank of Malawi.

3. Empirical strategy

3.1 Approach to maize price transmission

Following Baffes and Gardner (2003), Gilbert (2011), and Minot (2011), we adopted a Vector Error Correction (VEC) model to analyse the transmission of maize price changes from the international and South African markets to the Malawian market. This approach allowed us to examine the nature of this relationship over time and, as a consequence, to examine the extent of the pass-through (Listorti, Esposti, 2012). More precisely, we examined the long-run equilibrium between the international and South African maize price and the Malawian maize price, the short-run dynamics and adjustment to the log-run price relationship, and the flow of price information from international and South African maize markets to the Malawian maize market (Rapsomanikis, 2009).

The VEC model was adopted because our variables were non-stationary, I(1), and cointegrated (Engle and Granger, 1987).

First, we tested the international, South African, and Malawian maize price series for the presence of a unit-root using the Augmented Dickey-Fuller (ADF) with the number of lagged variables used to determine the residuals of serial correlation based on the Schwarz Information Criterion (SBIC) with 15 maximum lags. The results of the ADF test were compared with those of the Phillips-Perron (1988) non-parametric unit-root test (see, for example, Moledina *et al.*, 2004), which is supported by asymptotic theory and which therefore performs better for large samples (Mahadeva and Robinson, 2004). Moreover, this test has two main advantages over the ADF test. The test is robust for general forms of heteroskedasticity in the error term and does not require any lag length specification for the test regression.

We then detected whether linear combinations of international or South African and Malawian maize prices were stationary by conducting the Johansen (1991, 1995) test.

As previously mentioned, due to the presence of I(1) and cointegrated series, we estimated a VEC model specified as follows:

$$\Delta p_t^m = \alpha + \theta\left(p_{t-1}^m - \beta p_{t-1}^w\right) + \delta \Delta p_{t-1}^w + \rho \Delta p_{t-1}^m + \varepsilon_t \qquad w = International, \ South \ African \qquad (1)$$

where Δ is the difference operator; p^m is the natural logarithm of the real maize price in Malawi expressed in MWK and converted to US$ and ZAR according to the specification of w; p^w is the natural logarithm of the real market maize price in US$ for the international price and in ZAR for the South African price; α is a constant; θ is the error correction coefficient; β is the cointegration factor expressing the long-run elasticity of domestic prices with respect to international prices; δ is the short-run elasticity of the domestic maize price relative to the global or South African maize price; ρ is the autoregressive term; and ε_t is the error term.

As suggested by Minot (2011), the nominal Malawian maize price in US$ and the international price of maize in US$ were converted to real terms using the US consumer price index. The same procedure was adopted for testing pass-through values from the South African to Malawian maize market. In this case, we used the South African consumer price index to compute the real price series.

3.2 Unpredictable components of price variability

Following Moledina *et al.* (2004), we focused on the stochastic component of the price process as an appropriate measure of volatility. For this reason, the Malawian and global maize price time series were seasonally adjusted and de-trended.

We applied this procedure to both nominal and real prices, with the latter obtained by deflating the nominal price by the consumer price index. The results are compared based on these two price typologies due to concerns raised in the literature (see, for example, Peterson and Tomek, 2000) that problems of biased estimates can occur when series are deflated. Such biases include potential changes to the time series process and the generation of spurious cycles that do not reflect original data. As the results for the variables for real and nominal prices were virtually identical, following what suggested by the literature (see, for example, Sarris, 2000; Moledina *et al.*, 2004; Huchet-Bourdon, 2011), this paper only presents empirical findings based on deflated prices.

As was previously underlined, predictable and seasonal movements around the trend are of peculiar importance to the analysis of cereal prices and, more specifically, to the analysis of maize prices in Malawi. For this reason, the time series were seasonally adjusted using an X-12-ARIMA procedure (Findley *et al.*, 1998) based on multiplicative adjustments. In other words, the price time series is a multiplicative function of the trend-cycle, seasonal and random components. According to the statistical tests, such as the Akaike's Information Criterion (AIC), this decomposition method provided a better fit to the additive model, showing that seasonal effects fluctuate proportionately with the trend. This result is confirmed by empirical literature that makes reference to the same methodology for calculating the composition of Malawian maize prices (Cornia *et al.*, 2012; Sassi, 2012, 2014)

The Hodrick-Prescot (1997) filter was adopted to extract the long-term trend component from the price series. This method minimises series variance in the smoothed area of the series. The smoothness of the trend estimate depends on a penalty parameter. The higher is the value of this parameter, the smoother the resulting trend will be. In our analysis, the value of the penalty parameter was assumed to be equal to 14,400, following the original Hodrick-Prescot value for monthly data (Quantitative Micro Software, 2007).

The natural logarithm for the seasonally adjusted price series divided by the trend component represents the price time series used to analyse maize price volatility, i.e. the deviation of the observed maize price from its trend.

A de-trended time series was adopted because the Global Bai-Perron L Breaks vs. None stability test (Bai and Perron, 2003) for the regression coefficients of the seasonally adjusted series over its trend, highlighted the existence of multiple structural breaks in all considered price series. As suggested by Sarris (2000), by de-trending the time series we avoided misrepresenting structural breaks in the trend as increases in series variance.

3.3. Measuring price volatility and its welfare cost

This paper estimates conditional volatility as a measure of price volatility using an ARCH/GARCH approach.

This particular model typology requires the use of a stationary time series. For this reason, we first tested our seasonally adjusted and de-trended price series in natural logarithm to determine the presence of a unit-root.

According to the existing literature, when the unit-root-hypothesis is rejected, i.e., the mean and autocovariance are not time-dependent, the series remains in levels. On the contrary, the first-difference series must be adopted.

However, the unit root test has low power in the presence of a small sample and structural breaks in the series (Sarris, 2000). For this reason, we tested the existence of structural breaks by performing the Global Bai-Perron L Breaks vs. None stability test, which confirmed multiple structural breaks in the series. Thus, following Sarris (2000) and Dhen (2000), we decided to use the first-difference series as a measure of price volatility.

As the second step of our investigation, we tested for serial correlation using the following model:

$$\Delta y_t = \alpha_t + \varepsilon_t \tag{3}$$

where y is the natural logarithm of the de-trended and seasonally adjusted price. All variables are in natural logarithm.

We investigated the possibility that the residuals from our regression may be correlated with their own lagged values using the Breusch-Godfrey test. When a serial correlation was found, we determined the order of the autoregressive integrated moving average (ARIMA) process and adjusted equation (3) by including autoregressive (AR(p)= $\sum_p \theta_p \, y_{t-p}$ and moving average (MA(q)= $\sum_q \rho_q \, \varepsilon_{t-q}$ terms as follows:

$$\Delta y_t = \alpha_t + \sum_p \theta_p \, y_{t-p} + \sum_q \rho_q \, \varepsilon_{t-q} + \varepsilon_t \tag{4}$$

Model (3) is the "null hypothesis model" which is tested against the complete and alternative model (4) which includes also AR and MA parts.

The abovementioned Breusch-Godfrey test, combined with the AIC and Schwarz Criterion (SBIC), informed the selection of AR(p) and MA(q) terms.

After correcting for serial correlation, we tested for ARCH terms, i.e., autoregressive conditional heteroskedasticity in the residuals, by performing the ARCH Lagrange multiplier (LM) test.

Because all of the time series presented an ARCH term, we estimated an ARCH-type model for all of the series. More precisely, we initially made reference to a GARCH(1,1) model because previous studies, specifically those focusing on the analysis of financial time series, have favoured its performance over that of other models (Hansen and Lunde, 2011).

In our GARCH(1,1) model, equation (4) was used as the mean equation, whereas the equation for the conditional variance (σ^2) was

$$\sigma^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad\qquad\qquad (4.a)$$

where ω is a constant α and β are parameters, ε_{t-1}^2 is the previous month's residual volatility (the ARCH term given by the square residual lag of equation 4), and σ_{t-1}^2 denotes the last month forecast variance—the so-called GARCH term.

Four types of error distribution have been verified: the normal Gaussian distribution, the Student's t-distribution, the generalised error distribution, and the generalised error distribution with a fixed parameter.

To determine the most appropriate model, we performed three tests: the Q-statistics test for detecting the absence of serial correlations in the mean equation; the Jarque-Brera test for verifying normal distributions among the residuals; and the ARCH LM test for proving the absence of residual ARCH effects. When the results of the abovementioned tests indicated the GARCH(1,1) model as not appropriate to describe the investigated phenomena we estimated other variance models (ARCH, TARCH, EGARCH, and PARCH) selecting the appropriate according to the aforementioned tests. The model estimated in each case is indicated in the tables presenting results in Section 4.

As previously indicated, the trend was not included as an exogenous variable in the estimated ARCH-type models contrary to what has generally been done in empirical investigations reported in the literature on volatility (see, for example, Sarris, 2000). In fact, we decided to de-trend the time series. To detect possible efficiency losses in our two-step approach for the definition of the de-trended and seasonally adjusted price time series, we tested our GARCH models using: a seasonally adjusted price time series and including the Hodrick-Prescot filter and a linear trend as regressor alternatively; and the original price time series with the Hodrick-Prescot filter or linear trend and a seasonal factor as regressors. The AIC and SBIC tests indicated that our choice did not compromise the efficiency of our estimate.

We monitored the conditional variance process using the estimated variance of returns. Moreover, as equation (4.a) satisfied the non-negative constraints ($0 \leq \alpha$ and $0 \leq \beta$) and stationarity condition ($\alpha + \beta < 1$) which ensures that the process has finite variance (Hamilton, 1994), we calculated the unconditional variance of ε as follows:

$$\sigma^2 = \frac{\omega}{1 - \alpha - \beta} \qquad\qquad\qquad (5)$$

The conditional and unconditional variance of maize price in Malawi at the country and local-economy market levels were both adopted to assess the volatility welfare cost according to the Lucas formula (Lucas, 1987).

Lucas constructed an agent model in which the utility function (U) of a single consumer over an infinite horizon in the case of absence of volatility is

$$U^v = \sum_{t=0}^{\infty} \beta^t \frac{\left(Ae^{g_t}\right)^{1-\gamma}}{1-\gamma} \qquad\qquad\qquad (6)$$

where A is the mean level of consumption at time t, g is its rate of growth, γ is the degree of risk aversion, and β is the discount factor.

In the presence of volatility, consumption in each period includes a stochastic stream such that equation (6) becomes

$$U^v = \sum_{t=0}^{\infty} \beta^t \frac{\left(A e^{g_t} e^{-0.5\sigma^2} \varepsilon_t \right)^{1-\gamma}}{1-\gamma} \tag{7}$$

where σ^2 the natural logarithm of consumption variance, describes the amount of risk present and ε is a random variable whose natural logarithm is normally distributed with a mean of zero and a variance of σ^2.

The welfare cost of volatility (λ) is represented by the level of utility calculated via (6) and (7), where λ is chosen such that the consumer is indifferent to the deterministic stream and risk stream adjusted by compensation (Lucas, 2003, p.4).

The result, when solving for λ is the Lucas formula, which follows the mathematical notation

$$\lambda \cong 0.5 \ \gamma\sigma^2 \tag{8}$$

According to Lucas (2003), the compensation parameter depends, naturally enough, on the amount of risk present (σ^2) i.e. the conditional and unconditional variance estimated by our GARCH models, and the consumer's aversion to the determined risk(γ). Concerning this latter parameter, we referred to varying degrees of risk aversion that are commonly observed in the literature, over a range of one to four in magnitude, and thereby adopted the highest value (Prakash, 2011).

4. Results and discussion

4.1. Market integration

The results for price transmission are illustrated in Table 2.

These results confirm that from January 1991 to March 2013, maize prices in Malawi only show a statistically significant, long-term relationship with the SAFEX maize price and are consistent with the results reported in the literature, such as the findings of Rapsomanikis (2009) for the 1998-2008 period. As maize is an imported commodity, β, the cointegration factor, is positive and less than one. According to the estimated parameter, approximately 70 percent of the proportional change in South African maize prices is transferred to the Malawian price in the long-run, with an error correction coefficient of nearly 12 percent.

Short-term effects between international or SAFEX maize prices and maize prices in Malawi are found to be statistically insignificant over the time period investigated. Thus, in Malawi, the short-run maize price movements are primarily affected by domestic market conditions. Moreover, the statistically significant autoregressive term indicates that past shocks in the domestic market play an important role in determining future maize price trajectories.

Table 2. Maize price pass-through mechanism (January 1991-March 2013).

$$\Delta p_t^m = \begin{array}{cc} 0.0017 & - & 0.0283 \\ (0.0081) & & (0.0124) \end{array} \left(p_{t-1}^m - \begin{array}{c} 1.3826 \\ (0.6354) \end{array} p_{t-1}^w \right) - \begin{array}{c} 0.05936\Delta \\ (0.1375) \end{array} p_{t-1}^w + \begin{array}{c} 0.4560 \\ (0.05589) \end{array} \Delta p_{t-1}^m + \varepsilon_t \qquad \begin{array}{l} m = Malawi \\ w = International \end{array}$$

Standard OLS regression statistics

Adj. R-squared 0.1951	Sum sq. resids 4.4961	S.E. equation 0.1312
F-statistic 22.3285	Log likelihood 164.1200	AIC -1.2084
SBIC -1.1544	Mean dependent 0.0024	S.D. dependent 0.1462

Summary statistics for the VAR system

Determinant resid. covariance 5.39E-05	Determinant resid covariance 5.23E-05	Log likelihood 554.1317
AIC -4.1067	SBIC -3.9715	

$$\Delta p_t^m = \begin{array}{cc} -0.0012 & - & 0.1156 \\ (0.0112) & & (0.0279) \end{array} \left(p_{t-1}^m - \begin{array}{c} 0.6953 \\ (0.0279) \end{array} p_{t-1}^w \right) - \begin{array}{c} 0.0519 \\ (0.1276) \end{array} \Delta p_{t-1}^w + \begin{array}{c} 0.4765 \\ (0.0754) \end{array} \Delta p_{t-1}^m + \varepsilon_t \qquad \begin{array}{l} m = Malawi \\ w = SAFEX \end{array}$$

Standard OLS regression statistics

Adj. R-squared 0.2829	Sum sq. Resids 2.1300	S.E. equation 0.1284
F-statistic 18.3648	Log likelihood 86.2061	AIC -1.2361
SBIC -1.1492	Mean dependent -0.0036	S.D. dependent 0.1517

Summary statistics for the VAR system

Determinant resid. covariance 0.0001	Determinant resid covariance 0.0001	Log likelihood 223.9019
AIC -3.2165	SBIC -2.9992	

(...) p-value

The studies that focus on Malawi attribute this result to government price interventions and active government involvement in the maize market operations. As underlined by Jayne *et al.* (2006, 2008, 2010), the ADMARC, which is controlled by the government, can purchase and sell maize, set private sector price bands, and control imports and exports with licenses and duties. This board operates not only in response to economic conditions but often acts according to political circumstances. Moreover, Malawi possesses a strategic grain reserve that is operated by a state agency, the National Food Reserve Agency (NFRA). Ellis and Manda (2012), focusing on the 2000s, provide a detailed discussion of the failure of the Malawian government to stabilise maize markets, of the role of the ADMARC and NFRA in exacerbating maize price variability levels, and of variability trends resulting from seasonal and climatic shocks in particular.

The effect of government presence on volatility is first demonstrated by the fact that our analysis finds that unconditional variance for the unpredictable maize price component of Malawi is greater than that of international maize price volatility (Table 3).

In both the analysed cases, the estimated constant term (ω) and GARCH parameters (α and β) are strongly statistically significant. Moreover, the GARCH process is mean-reverting ($\alpha+\beta<1$).

Table 3. GARCH estimate of maize price volatility for the international and Malawian markets (January 1991-March 2013).

	International market	Malawian market
ω	0.0012	0.0029
	[0.0067]	[0.0177]
α (ARCH term)	0.4332	0.2425
	[0.0004]	[0.0307]
β (GARCH term)	0.2917	0.4209
	[0.0224]	[0.0423]
ARIMA process	(2,2)	(0,1)
GARCH	(1,1)	(1,1)
GARCH distribution	Normal	Normal
Unconditional variance	0.0041	0.0094

[...] p-value

Our empirical findings also show that the unpredictable component of the international maize price is more sensitive to external shocks during the volatility phase: the ARCH parameter is found to be greater than the GARCH value. Conversely, in Malawi, the higher estimated GARCH parameter found with respect to the ARCH value indicates that volatility during the previous period has a stronger effect on the development of volatility.

4.2 The GARCH process

The limited effectiveness of policy interventions to respond to volatility-inducing crisis events (Sahley *et al.*, 2005) becomes increasingly apparent through an analysis of the conditional variance of the unpredictable component of Malawian maize prices (Figure 2).

According to our findings, the distribution of this variable is leptokurtic, with the highest values coinciding with crisis episodes related to climatic events, namely in 1992, 1994, 2002-2003, 2005-2006, and 2012. This result is fairly predictable. Rain-fed agriculture is the dominant farming system applied in Malawi, and thus, maize production is highly vulnerable to climatic shocks, which have resulted in acute food shortages and food insecurity over the last two decades (Sahley *et al.*, 2005). With maize being the chief dietary staple and with very limited alternative sources of dietary energy available, the elasticity of maize demand is low, and thus, any variation in the volume of maize production significantly affects price fluctuations (Manda, 2010). Hence, increases in maize prices resulting from a production shortage generate higher levels of volatility. However, during the 2000s in particular, the impact of these events was largely fuelled by strategic grain reserve mismanagement, the ADMARC interventions based on poor crop estimates, and more recent failures in fertiliser policy (Chirwa, 2009; Jayne *et al.* 2010). With constraints limiting both supply and demand, the introduced market restrictions appear to have further accentuated fluctuations in price volatility.

Considering the yearly average conditional volatility by month over the investigated time period, it can be argued that maize price volatility is also driven by factors other than weather events and government policies.
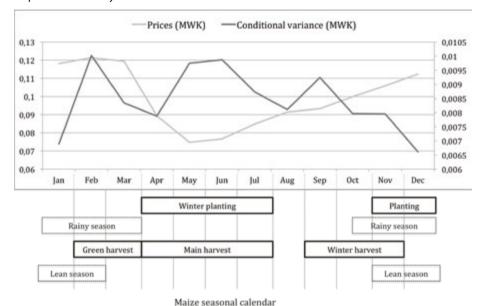
Figure 2. Conditional variance of the unpredictable component of maize price in Malawi by month (January 1991-March 2013).

Figure 3 shows that, on average, the conditional variance of the unpredictable component of maize price reaches its highest levels in February, May, June, and September in relation to variations in maize stocks.

This seasonal component of volatility further limits food access for poor households.

Our findings show that in February, maize prices reached a peak. This period marks the end of the lean season when the majority of poor households have depleted maize grain stocks produced in the previous season and when most farmers have already sold their maize yields (Cornia *et al.*, 2012; Sassi, 2012; 2014). These abnormally high maize prices during a time of intensified population dependence on the local-economy market for maize demand is an incentive for large-scale wholesalers to release maize stocks accumulated throughout the year (Jayne *et al.*, 2010). In February, market activity intensifies, resulting in relatively higher levels of volatility.

At the start of the main harvest period, which lasts from April to July, maize is readily available, and the majority of poor farmers sell their maize production early on in the marketing season, often in a desperate effort to repay debts incurred during the previous farming season and to meet short-term cash needs (Jayne *et al.*, 2010). As a consequence of this excess supply, maize prices decline, reaching their lowest and most volatile levels in March. During this period, distressed sellers become price takers, and because the ADMARC is active only in the latter part of the season (June), there is no floor price. Moreover, wholesalers and traders compete to acquire as much maize as possible before the ADCMRC sets the floor price (Jayne *et al.* 2010, Manda, 2010). As illustrated by Mapila *et al.* (2013), private traders start to buy maize at the beginning of the har-

Figure 3. Yearly average maize price and conditional variance of the unpredictable component of maize price in Malawi by month and the maize seasonal calendar.

Maize seasonal calendar

vest period, whereas the ADMARC typically does this at a later date, primarily because the organisation first waits until the official selling and purchasing price are announced. For this reason, to secure income, poor smallholder farmers often prefer or are forced to sell their maize yields to private traders at lower prices than those established by the ADMARC. Under the pressures induced by these dynamics, the maize market becomes more volatile. As was reported by Jayne *et al.* (2010), when the ADMARC enters the market, the parastatal agency competes with private traders to acquire maize. As a consequence, maize prices tend to rise rapidly. However, volatility reduced because the ADMARC price band limits the floor and ceiling of price fluctuations, and by this time, traders have already purchased the majority of maize supplies needed.

As a result, the majority of poor households begin to run out of food stocks from their own production by September (Sassi, 2012). Maize demand intensifies and there is an expansion in maize sales with the approach of the next farming season. During this period, maize prices and maize price volatility increase.

4.3 The welfare cost of volatility

The high level of maize price volatility estimated through our empirical investigation corresponds with a relevant welfare cost for smallholder farmers that increase during specific periods of the year due to the estimated seasonal component of the maize price volatility. Assuming the highest level of consumer's price risk aversion ($\gamma=4$) as suggested by the literature for poor smallholder farmers in Malawi (Mac Brey Msusa, 2007), over the

analysed time period, the Lucas formula indicates that the welfare cost of the estimated maize price volatility constitutes an average of 1.7 percent of 1 percent of average monthly consumption, with a maximum value of 6.3 percent of 1 percent of average monthly consumption. Because the assumption of complete markets of the Lucas formula cannot be confirmed in the case of Malawi, the estimated welfare cost of volatility is likely to be higher. Following Lucas (2003), this cost should be considered negligible for a mature economy in light of the implementation cost of policies aimed at eliminating fluctuations. However, on this point it must be reminded that the welfare cost measured by this paper is not related to aggregate consumption as in Lucas, but to the consumption of a subsistence staple food. Thus, its burden on the food security of poor households in Malawi may be relevant, particularly for distressed sellers. The increase in maize price volatility during the high-price period further compromises the ability of poor households to purchase food. In addition, poor households must endure the consequences of high maize price volatility during the low-price period when they are forced to sell maize with reductions in expected real incomes, which act as disincentives to investment in farming activity.

The maize price volatility dynamics estimated through our study also accentuate the low-income and food-insecure status of poor households because the most common method for coping with shocks in the country involves limiting food portion sizes and the frequency of meals (World Food Programme, 2010). The poorest households may also suffer from irreversible impacts on human capital and future production and income flows because another typical response strategy to shocks involves selling livestock and assets at low prices, seeking employment in the informal market, and migrating to urban centres (Malawi Vulnerability Assessment Committee, 2005).

Furthermore, surplus maize producers, that do not have stock capacities, suffer due to the seasonal component of volatility.

4.4 Volatility in local-economy markets

The aforementioned considerations become even more critical at the local-economy market level, in which the unconditional volatility of the stationary GARCH process, with the estimated parameters being statistically significant (Table 4), is considerably higher than the value at the country level (Figure 4).

In addition, over the analysed time period, the intensity of volatility varies across the local-economy markets of the same region (Figure 5).

Mapila *et al.* (2013) emphasise the key role of the ADMARC price in maize price formation at the local market level in combination with the minor effects of spatially varying factors. In contrast, our analysis suggests that volatility appears to be more heavily influenced by factors that reflect specific conditions of local-economy markets (Figure 6 and 7).

Such factors include maize supply and demand features such as the existence of maize imports from bordering countries, food aid provisions, the development of the informal market, diversification, road networks and transportation costs, weather conditions, wealth levels, soil quality, and population density.

For example, local informants suggested that maize price volatility in Rumphi is attributable to frequent droughts. This possibility is consistent with the results of the estimated GARCH(1,0) model, in which the ARCH term is found to strongly affect volatil-

Table 4. GARCH estimate of maize price volatility in Malawian local-economy markets (January 1991-March 2013).

Deflated	ω	α (ARCH term)	β (GARCH term)	ARIMA process	GARCH	GARCH distribution
CHITIPA	0.0077 [0.0029]	0.3354 [0.0031]	0.3666 [0.0133]	(1,1)	(1,1)	Normal
KARONGA	0.0030 [0.0050]	0.1706 [0.0008]	0.7324 [0.0000]	(1,1)	(1,1)	Normal
RUMPHI	0.0089 [0.0000]	0.8320 [0.0000]		(1,1)	(1,0)	Normal
MZUZU	0.0059 [0.0026]	0.1546 [0.0034]	0.5545 [0.0000]	(1,2)	(1,1)	Normal
NKHOTAKOTA	0.0080 [0.0096]	0.2515 [0.0114]	0.3929 [0.0321]	(2,2)	(1,1)	Student's t
MITUNDU	0.0262 [0.0000]	0.1654 [0.0300]		(1,1)	(1,0)	Normal
CHIMBIYA	0.0160 [0.0000]	0.2032 [0.0455]		(0,1)	(1,0)	Normal
LIZULU	0.0059 [0.0016]	0.3549 [0.0005]	0.4379 [0.0001]	(1,1)	(1,1)	Normal
NCHALO	0.0111 [0.0001]	0.6245 [0.0000]	0.2006 [0.0434]	(1,1)	(1,1)	Normal

[...] p-value

Figure 4. Unconditional variance of the unpredictable component of maize price for the Malawian local-economy markets and country-average value (January 1991-March 2013).
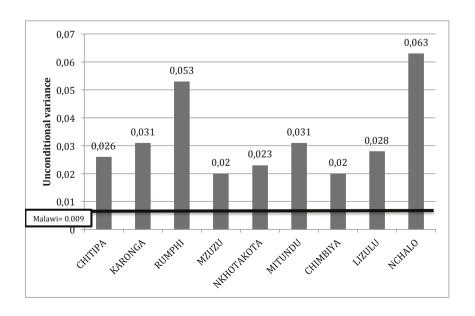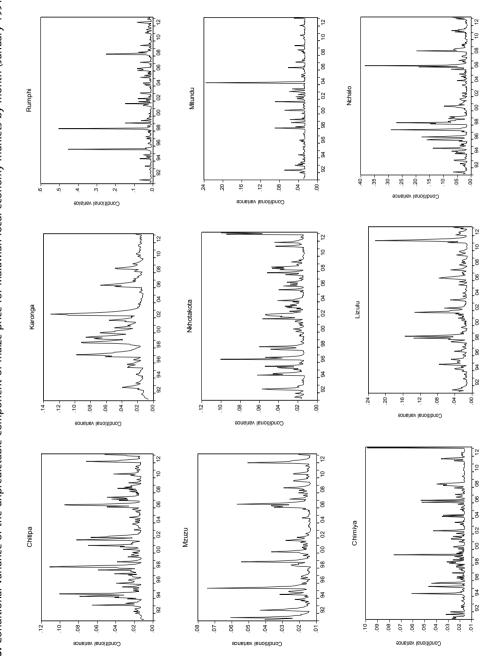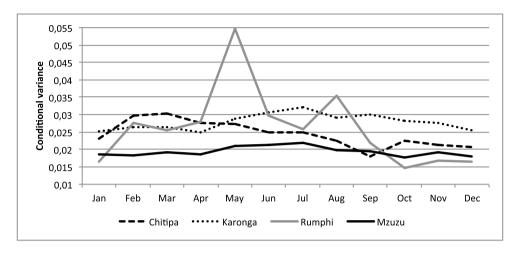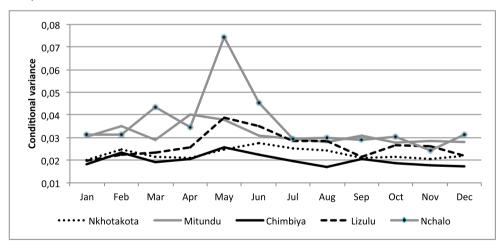
Figure 5. Conditional variance of the unpredictable component of maize price for Malawian local-economy markets by month (January 1991-March 2013).

Figure 6. Yearly average conditional variance of the unpredictable component of maize price in the local-economy markets of northern Malawian region by month (January 1991-March 2013).

Figure 7. Yearly average conditional variance of the unpredictable component of maize price in the local-economy markets of northern and southern Malawian regions by month (January 1991-March 2013).

ity dynamics. This aspect may also partly explain why the highest levels of volatility were reached in the months of May and August, when the dramatic need to sell a poor a short maize production increased the price response of the market, resulting in an intensification of volatility.

In the local-economy market of Chitipa the monthly average maize price volatility is relatively low during the lean season, likely due to the region's location adjacent to the

major maize surplus area of Tanzania (Minot, 2011), which in turn causes the area to be affected by cross-border trade: imports can mitigate the price market response to domestic factors.

According to our results, the highest level of unconditional volatility found in the local-economy market of Nchalo, which is located in southern Malawi, seems to be dependent on shocks: the ARCH term in the GARCH(1,1) model is higher than the GARCH term. This local-economy market is located in a densely populated area that is prone to flooding and in a region where the dominant farming system is characterised by households with the smallest plots of land in the country.

Our analysis indicates that not only the level but also the time dynamics of maize price volatility varies across the local-economy markets. As discussed by Jayne *et al.* (2010), this latter aspect may be determined by the fact that market activity varies seasonally and regionally. Maize is marketed at earlier periods in areas dominated by poor smallholder farmers who specialise in maize production or who wish to purchase chemical fertilisers. These farmers effectively wish to use income from other activities or livelihood strategies during the lean season. A different strategy is adopted by poor smallholder farmers who combine tobacco production with maize production. These farmers sell tobacco first while selling maize later in the season to capitalise on higher prices. In turn, maize markets in these areas are activated later on in the marketing season.

As a consequence of the estimated intensity of conditional maize price volatility, the welfare costs calculated at the local economy-market level are found to be dramatically higher than those at the country level (Table 5).

Table 5. Summary of the welfare cost of conditional price volatility by local-economy market (January 1991-March 2013).

Local-economy market	Mean	Minimum	Maximum	Std. Dev.	No. observations
CHITIPA	0.0487	0.0195	0.2223	0.0327	265
KARONGA	0.0558	0.0125	0.2617	0.0397	265
RUMPHI	0.0521	0.0177	1.0097	0.0945	265
MZUZU	0.0387	0.0269	0.1490	0.0163	265
NKHOTAKOTA	0.0456	0.0266	0.2011	0.0271	264
MITUNDU	0.0627	0.0523	0.4727	0.0320	265
CHIMBIYA	0.0401	0.0320	0.1974	0.0175	266
LIZULU	0.0528	0.0219	0.4485	0.0484	265
NCHALO	0.0725	0.0279	0.7705	0.0841	265

Moreover, as demonstrated in Figures 6 and 7, the seasonal component of maize price volatility is also confirmed at the local-economy market level. Despite single-market specificities, maize price volatility and thus welfare cost reach a peak when the majority of poor households depend on markets as buyers only, net buyers, or distressed sellers.

5. Conclusions

Several interesting findings emerge from our empirical investigation.

First, the study confirms the findings of the existing literature focusing on more restricted time periods that argue that maize price volatility in Malawi is primarily dependent on domestic factors rather than on international market shocks. The Malawian maize market is integrated with the South African market but only with respect to long-run trends. As a consequence, to reduce maize price volatility levels, which in Malawi are higher than those of the international market, a primary focus on domestic policies is needed.

One of the most relevant findings of the country-level analysis relates to the effect of seasonality on unconditional volatility: maize price volatility levels are higher during certain periods of the year. This trend is confirmed at the local-economy market level despite varying spatial factors that determine different volatility dynamics. These findings underline the need to improve or establish an effective storage, marketing, and trade structure for inter-seasonal and spatial arbitrage. Moreover, this finding partly confirms the storage model. According to the model's prescriptions, increases in price and volatility are positively correlated: price increases tend to deplete stocks and increase volatility (Williams and Wright 1991). In our study, maize price volatility levels also rise when the price of this staple food declines due to the poor stock capacity of poor smallholder farmers and their often desperate need to sell produce.

Moreover, the seasonal dynamics of maize price volatility reflects the complex maize marketing system established in Malawi and the composite production and consumption strategies put in place by poor smallholder farmers and their households in a poor and highly food-insecure country.

In fact, the analysis suggests that the conditions in farm-level and national maize markets affect price volatility at the local-economy market level. Poor households depend on the local-economy market for purchasing and selling maize when the farm-level market cannot satisfy their food and income needs. The farm-level market remains undiversified on both the demand and supply side in addition to being heavily exposed and vulnerable to climatic shocks due to the presence of a rain-fed-dominated farming system. Trade business remains poorly developed and, due to high transportation costs, operative over short distances (Zant, 2005). Due to the existence of a single major harvest and poor stock capacity, the majority of poor households, assuming their combined role of consumers and producers, depend on the local-economy market during the same periods of the year (Jayne *et al.* 2010). According to our analysis, maize price volatility levels increase with the intensification of negotiations between poor smallholder farmers and private traders and declines when the ADMARC activates the national market. This finding suggests the importance of enhancing poor farmer productivity and marketing knowledge in an effort to limit maize price volatility.

Minot (2014) presents a number of possible explanations for his findings regarding the fact that African countries with large state agencies attempting to stabilise food prices generally show higher volatility levels than those with little or no stabilisation efforts. Our empirical investigation of the conditional variance allows us to better address this issue. Our results suggest that maize price volatility on the maize local-economy market in Malawi intensifies with an increase in competition among private actors before the ADMARC

enters the market. In particular, private traders during the post-harvest period strengthen their activity to avoid price band limitations and competition from this state agency.

It should also be noted that volatility is partly affected by competition within the private sector in the local-economy market, which is severely constrained by government trade controls and, more generally, by a dysfunctional policy environment (Sahely *et al.*, 2005). Moreover, due to the presence of a diet composition and agricultural production structure that are both dominated by maize, maize demand and supply dynamics are not affected by the price of substitutes and complements. For this reason, the recent discussion on clarifying the role of the ADMARC in private-sector participation (Jayne *et al.*, 2010) should be enlarged and be also focused on the need to diversify the maize economy as a means for poor households to manage risks of maize price volatility.

With respect to the seasonal aspect of volatility, according to our results, volatility intensity reaches its highest levels during the adverse price conditions for poor households when they are sellers and buyers hurting their food security because a more limited food access. In contrast to the conclusions of certain authors (Waug, 1994; Oi, 1961; Massel 1969), such households only suffer from the welfare costs of volatility. For this reason, our findings support the body of literature (see, for example, Pallage and Robe, 2003) that perceives smoothing price volatility gains as being significantly high particularly during maize price volatility seasonal peaks in this land-locked country, which exhibits widespread food insecurity and poverty and a lack of major natural resources other than Lake Malawi, thus making populations dependent on maize production for household welfare, economic growth, and employment.

According to our analysis, a new food price problem faces policymakers in Malawi. The classical policy dilemma examines strategies for keeping prices low enough to ensure low-income consumers' access to food while also keeping prices high enough to incentivise farm production (Jayne *et al.*, 2010). A new consideration involves devising strategies for reducing volatility levels when maize prices reach their peak and lowest values. This problem, which is related to the classical dilemma, is of specific importance for the improvement of food security in Malawi. Features of the seasonal component of maize price volatility underlined by our empirical investigation damage the consumption capability of the vast majority of Malawians represented by buyers only, net buyers, and distressed sellers of this dominant staple food.

Acknowledgements

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