"Asymmetric effects of rainfall on food crop prices: evidence from Rwanda"

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Asymmetric effects of rainfall on food crop prices: evidence from Rwanda

Abstract

This study examined the effects of the likely change in rainfall on food crop prices in Rwanda, a landlocked country where agriculture is mainly rain-fed. The empirical investigation is based on nonlinear autoregressive distributed lag cointegration framework, which incorporates an error correction mechanism and allows estimation of asymmetric long-run and short-run dynamic coefficients. The results suggest that food crop prices are vulnerable to rainfall shocks and that the effect is asymmetric in both the short and long run. Moreover, there was evidence of seasonal differences, with prices falling during harvest season and rising thereafter. Considering the ongoing threat of global climate change, and in order to cope with rainfall shortage and uncertainty, increase food affordability and ultimately ensure food security throughout the year, there is a need to develop and distribute food crop varieties and crop technologies that reduce the vulnerability of farming to rainfall shocks.

Keywords: asymmetric ARDL, climate change, food crop prices, rainfall.
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Introduction

Despite attempts to sustainably maintain a steady food supply, agriculture remains heavily dependent on seasonal weather, especially in developing countries, where greenhouse farming is yet to be developed. The economics of food production and price dynamics clearly predict that food price spikes emerge as the natural consequences of demand growth consistently outpacing supply expansion and importantly the unseen forces of climate change (Barrett, 2013; Deaton & Laroque, 1992). The latter is regarded as major threat to global food production and is potentially expected to exacerbate food insecurity in many parts of the world (Burke, Hsiang, & Miguel, 2015). The impacts will be particularly great in sub-Saharan Africa – the food crisis epicentre of the world – where poor smallholders depend heavily on agriculture and have limited livelihood alternatives (Scholes & Biggs, 2004; Watson, Zinyowera, & Moss, 1998). Furthermore, it has been found that climate events played an important role in the surge in global food price in 2008 (Ericksen, Ingram, & Liverman, 2009). The consequences of climate changes such as flooding, higher temperatures and unexpected frequent and extreme weather events negatively affected food production, leading to a decrease in food supply and ultimately in higher prices. It has beenargued that climate change is linked to poverty traps in developing regions (Enfors & Gordon, 2008)[1]. Moreover, extreme climate events are expected to increase in frequency and severity as the global climate changes (Field, 2012). Jones and Thornton (2003) simulated the effects of possible future climate change on rain-fed smallholder maize production and found an estimated overall reduction of 10% in maize production by 2055 in Africa and Latin America, which is equivalent to losses of $2 billion per year. They also found that the future effects of climate change will be severe in developing countries, where the majority of farmers are still heavily dependent on subsistence agriculture.

Moreover, the global economic crisis between 2005 and 2007 and the subsequent food price spikes on the international market in late 2008 until early 2011 have raised concerns among the policymakers on issue of food shortage and unpredictability of climate change. For instance, wheat prices went up by 70% and rice prices by 20%, while the price of powder milk and maize was 90% and 70% higher, respectively (Dillon & Barrett, 2015; Ivanic & Martin, 2008).

The use of rainfall[2] as a proxy for climate change is justified, especially in developing countries, where

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[1] Enfors, E. I., and Gordon, L. J. (2008) report that in dryland parts of Tanzania, farmers frequently deplete their asset holdings during droughts, which perpetuates climate-related poverty traps.

[2] Besides rainfall, another strand of literature highlights a significant negative effects of increasing temperatures on crop yields. See, e.g., articles by FUNK, C.C., and Brown, M. E. (2009) and Gourdji, S. M. et al. (2013).

irrigation systems and agricultural mechanization are yet to be developed. Blanc (2012) showed that the unexpected variability of temperature and rainfall in Sub-Saharan Africa have had substantial adverse effects on maize, millet, sorghum and cassava production in the region. Baez, Lucchetti, Genoni, and Salazar (2015) investigated the effects of rainfall shocks on household welfare in Guatemala and found a substantial negative impact of shocks in precipitation, with the effect being particularly high among urban households. They also found that rainfall shocks increase poverty by 18% and reduce household food consumption by 10%. Similarly, in a study by Sassi and Cardaci (2013) investigating the consequences of different rainfall scenarios on Sudan's food availability, a strong relationship was found between climate change and variability, poverty and food shortage. They also uncovered a direct correlation between unpredicted precipitation change and sorghum, millet and wheat yield.

Moreover, the effects of climate change are likely to fall disproportionately on developing nations and on poorer, agrarian households within those nations (Jarvis et al., 2011; Schmidhuber & Tubiello, 2007; Jarvis et al., 2011; Schmidhuber & Tubiello, 2007; Wood, Jina, Jain, Kristjanson, & DeFries, 2014).

As in most parts of East Africa that are essentially dependent on rainfall, agriculture in Rwanda faces adverse effects from climate change (De la Paix, Anming, Lanhai, Ge, & Habiyaremye, 2011; Kseniia Mikova, Enock Makupa, & Kayumba, 2015; Poulton, Kydd, Wiggins, & Dorward, 2006). Volatile precipitation patterns increase the risk of short-run crop failure and long-run production declines. The latter, together with excessive urbanisation, population increase and income growth, leads to high food price inflation (World Bank, 2015). Nelson et al. (2009) argue that the overall effects of climate change on agriculture are likely to be severe, threatening food security in developing countries. In Rwanda, agriculture sector remains a considerable engine of economic growth.

The sector has been growing at 4-5% over the past decade, contributing 33% to overall annual national income. The agriculture sector employs approximately 80% of the total labor force, while generating more than 43% of Rwanda's export revenues (World Bank, 2011).

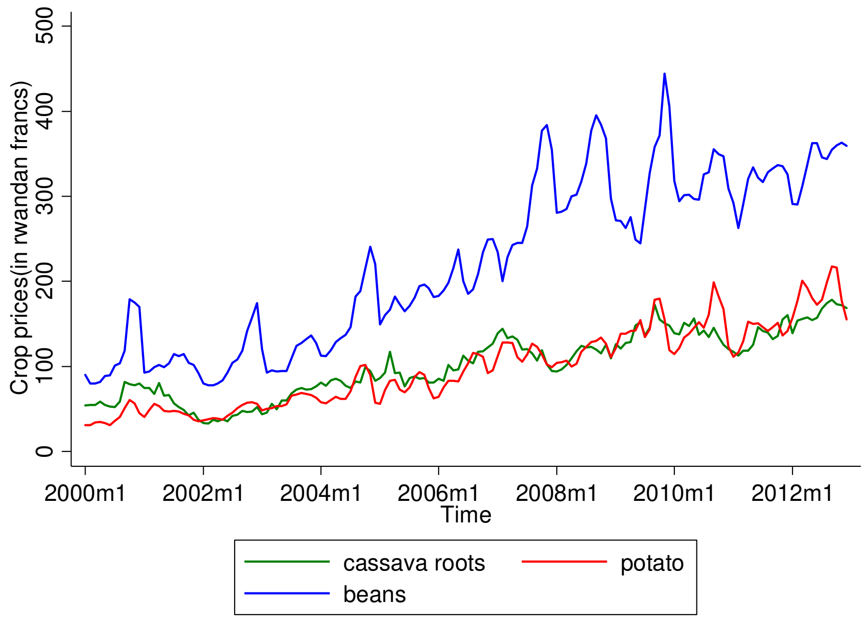

Fig. 1. Monthly average nominal price of the staple crops cassava roots, beans and potatoes in Rwanda, 2000–2015

Source: authors' calculations based on data from the National Institute of Statistics of Rwanda (NISR) (2016).

In this study, we focus on dynamic asymmetric changes of three food crops prices, namely cassava roots, beans and potatoes[3] and overall, the prices of these crops have exhibited significant variability and an upward trend in the past decade (Figure 1).

Rwanda has recognized the necessity of agricultural development. The National Agricultural Policy (NAP) was devised in 2004 with the aim of transforming the sector, increasing rural income and improving food security and the nutritional

[3] According to Rwandan Integrated Living Conditions Survey (EICV4, 2013/14), the consumption rate of dry beans, cooking cassava and Irish potatoes in Rwanda is 89.5%, 59% and 61% respectively. This indicates the weight of the three crops in terms of food demand in the country.

status of the population (World Bank, 2015). However, the supply side faces imminent challenges – farmers depend heavily on rain-fed farming systems[4], where agricultural mechanization and irrigation systems are yet to be implemented at advanced stage and consequently crop yields are affected by rainfall changes. The effect of this eventually emerges in the form of higher food prices at local markets. Figure 2 depicts the distribution of average monthly precipitation in Rwanda during the period 2000–2012. As can be seen, there is excess rainfall from September until the end of May, a period that corresponds to two agricultural seasons. Thereafter, rainfall decreases from early June until late August, the harvest season.

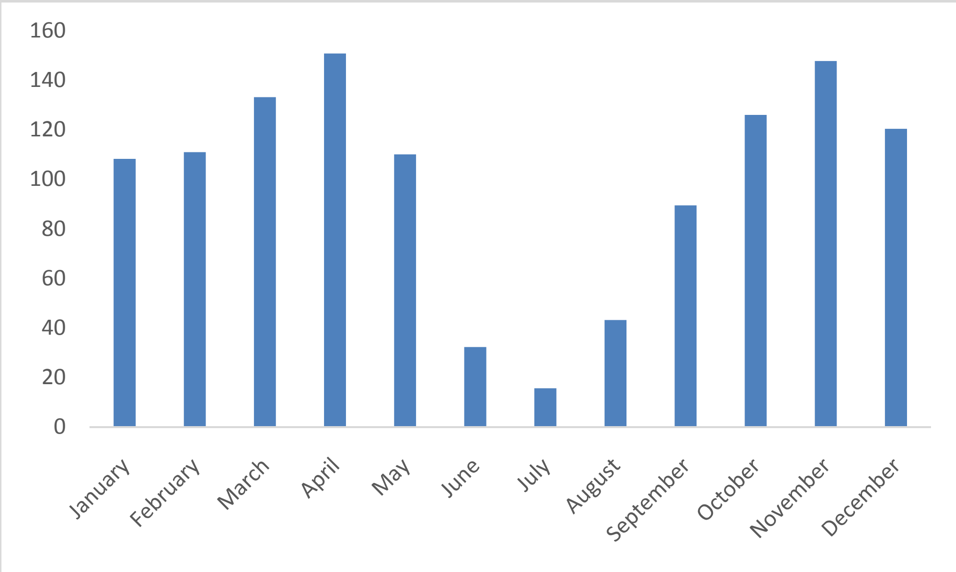

Fig. 2. Distribution of mean monthly rainfall (mm) in Rwanda, 2000–2012

Source: authors' calculations based on data from the World Bank's climate change portal, 2016.

Considering the ongoing threat of climate change and the evidence that its relative effect is greater in low-income countries (Tol, 2010), a clear understanding of the significance and magnitude of the effect of rainfall on food prices is of utmost importance for policy making. However, there is a lack of empirical evidence in this regard. This leads to an important research question: How do food prices respond to precipitation changes?

A number of previous studies have analyяed asymmetries in the transmission of information between stages of the food chain (Santeramo & von Cramon-Taubadel, 2016; Von Cramon-Taubadel, 1998), while other studies have considered spatial and transportation costs and market price cointegration (Kouyate, von Cramon-Taubadel, & Fofana, 2016). However, less is known on the symmetric effect of rainfall on food crop prices, which is essential information, especially in a developing country context, where a high proportion of household income is spent on food and where crop production heavily depends on rain-fed farming.

The aim of this study is to complement the existing literature in investigating the driving forces and the vulnerability of food prices to weather shocks in developing countries (Baulch & Hoddinott, 2000; Bellemare, Barrett, & Just, 2013; Dillon & Barrett, 2015; Hill & Porter, 2017; Kassie et al., 2017; Mawejje, 2016). Although some studies consider non-linear effects of rainfall on food prices (Dillon & Barrett, 2015; Mitra, 2014), the majority of the existing studies assume a linear relationship. The present study advanced this strand of literature by considering possible non-linear and asymmetric effects. To this end, we applied the recently developed asymmetric non-linear autoregressive distributed lag (NARDL) cointegration framework proposed by Shin Shin, Yu, and Greenwood-Nimmo (2014).

The remainder of this paper is organized as follows: section 1 describes the theoretical model and estimation techniques. Section 2 presents the data and descriptive statistics, while section 3 presents and discusses the empirical findings. Final section lists some conclusion and recommendations.

[4] Rwanda experiences three main agricultural seasons A, B and C. Season A runs from September to January and season B from February until the end of May. A and B are rainy seasons. The quantity of rain during these seasons has a direct effect on crop production, and hence on market food prices. Season C runs between June and September, and is the dry season, during which harvest of large crops takes place, especially cereals such as rice, maize and wheat and starchy foods such as cassava and potatoes, among others.

1. Econometric methods

A great number of studies have applied cointegration to study asymmetric price transmission (APT) in food crop markets (Tifaoui & von Cramon-Taubadel, 2017; Von Cramon-Taubadel, 1998; von Cramon-Taubadel, 2017). The present study did not investigate APT in the supply chain, but rather examined the transmission of rainfall changes to food crop prices. In a related strand of literature, several studies have questioned the assumption that weather-related variables affect crop yield in a linear way (Burke & Emerick, 2012; Dell, Jones, & Olken, 2014; Deressa, Hassan, & Poonyth, 2005; Lobell, Schlenker, & Costa-Roberts, 2011; Ma & Maystadt, 2017). Nonlinearities and asymmetries in the effect of rainfall on food crop prices can be quite often expected.Nonlinearity comes from the fact that insufficient rainfall is expected to reduce crop yield and eventually lead to an increase in food prices, but so does excess rainfall, which is sometimes associated with floods (see, e.g.,Wang et al. (2009) for the effect of a rise in precipitation on agriculture in Northern China). We wanted to investigate whether there is an asymmetric knock-on effect of rainfall on food prices. For this task, we employed the NARDL framework, which is a generalization of the ARDL bounds testing approach of M. H. Pesaran Shin, and Smith (2001) that incorporates an error correction mechanism and allows estimation of asymmetric long-run and short-run dynamic coefficients in a cointegration framework.

The starting point is the standard linear Autoregressive Distributed Lag (ARDL) model of order p and q proposed by H. Pesaran and Shin (1999) and M. H. Pesaran et al. (2001). The relationship between two series p_t (food crop price) and r_t (rainfall) can be expressed in a cointegration model as follows:

$$\Delta p_t = a_0 + \rho p_{t-1} + \theta r_{t-1} + \sum_{j=1}^{p-1} a_j \Delta p_{t-j} + \sum_{j=0}^{q-1} \gamma_j \Delta r_{t-j} + \phi z_t + \varepsilon_t , \tag{1}$$

where Z_t is a vector of three agricultural seasons A, B and C that we control for; ε_t is an *iid* process. Under the null hypothesis of no cointegration, $\rho = \theta = 0$. The ARDL framework has several advantages. One advantage that deserves mention is that it can be applied even when the series are integrated of different order. The series can be either I(0), I(1) or a mixture of the two (M. H. Pesaran et al., 2001).

Following Shin et al. (2014), we extended the linear ARDL and decomposed rainfall into positive and negative partial sum $\mathrm{r}_t^+$and r_t^- to account for asymmetries, such that:

$$\mathrm{r}_t^+ = \sum_{j=1}^{t} \Delta \mathrm{r}_j^+ = \sum_{j=1}^{t} \max\left(\Delta \mathrm{r}_{j,} 0\right) \text{ and } \mathrm{r}_t^- = \sum_{j=1}^{t} \Delta \mathrm{r}_j^- = \sum_{j=1}^{t} \min\left(\Delta \mathrm{r}_{j,} 0\right) \tag{2}$$

From the above expression, the asymmetric long-run equilibrium relation can then be tested via:

$$p_t = r_0 + \beta^+ r_t^+ + \beta^- r_t^- + u_t , \tag{3}$$

where β^+ and β^- are long-run parameters that represent, respectively, the effect of positive and negative changes in rainfall on food crop price.

Next, we combined the linear ARDL(p,q) in Eq. 1 and the asymmetric long-run relationship in Eq. 3 to obtain the NARDL (p,q), expressed as follows:

$$\Delta p_t = a_0 + \rho p_{t-1} + \theta^+ r_{t-1}^+ + \theta^- r_{t-1}^- + \sum_{j=1}^{p-1} a_j \Delta p_{t-j} + \sum_{j=0}^{q-1} \left(\gamma_j^+ \Delta r_{t-j}^+ + \gamma_j^- \Delta r_{t-j}^- \right) + \phi z_t + \varepsilon_t , \tag{4}$$

where $\theta^+ = {}^{-\rho}\!/_{\beta^+}$ and $\theta^- = {}^{-\rho}\!/_{\beta^-}$. The null hypothesis of no cointegration is $\theta^+ = \theta^- = 0$, which was tested using the F_{PSS}-test statistic of M. H. Pesaran et al.'s (2001) bound test. Long-run symmetry requires $\beta^+ = \beta^-$, which was tested by means of the F-test. Short-run symmetry in its strong form requires $\gamma_j^+ = \gamma_j^-$ for $j = 1,...,q-1$. The less restrictive (weak) form, on the other hand, requires $\sum_{j=0}^{q-1} \gamma_j^+ = \sum_{j=0}^{q-1} \gamma_j^-$. Following recent empirical literature (for instance, Fousekis et al., 2016), we tested the less restrictive form of short-run symmetry.

Furthermore, we captured the asymmetric responses to positive and negative rainfall shocks by cumulative dynamic multipliers ($\mathrm{m}_h^+$and m_h^-) at horizons $h = 0,1,...,H$. These multipliers show the change in the food crop price following a (positive or negative) rainfall shock. They are defined as follows:

$$\mathrm{m}_{h,r}^{+} = \sum_{j=0}^{h} \frac{\partial p_{t+j}}{\partial \mathrm{r}_t^{+}} \quad \text{and} \quad \mathrm{m}_{h,r}^{-} = \sum_{j=0}^{h} \frac{\partial p_{t+j}}{\partial \mathrm{r}_t^{-}}, \qquad (5)$$

when $h \to \infty$, $\mathrm{m}_h^{+} \to \beta^{+}$ and $\mathrm{m}_h^{-} \to \beta^{-}$, where β^{+} and β^{-} are the asymmetric long-run coefficients. The multipliers represent nonlinear dynamic adjustments in food crop price following rainfall shocks. We used bootstrap confidence bands to test for asymmetries at different horizons.

2. Data and descriptive statistics

Data on the monthly average price of beans, potatoes and cassava roots were obtained from the National Institute of Statistics of Rwanda (NISR). These are nominal retail prices that prevail on the markets in the country as shown in Figure 1. From these nominal prices, we computed real prices using the consumer price index (CPI), taking January 2005, as the base. The data series on rainfall were extracted from the World Bank's climate change knowledge portal. Table 1 in Appendix presents descriptive statistics (mean, standard deviation, minimum, maximum and coefficient of variation) for the real prices of cassava roots, potatoes and beans and the amount of rainfall in the study period. The statistics are presented month-wise to capture rainfall seasonality. Looking at the mean rainfall, there was an increase from January to April and a small decrease in May, followed by the lowest levels of rain during June, July and August, and then an increase from September to December. This distribution corresponds to the three agricultural seasons in Rwanda. To control for this observed seasonality, we included seasonal dummies in our regression analysis.

2.1. Unit root tests. The ARDL framework is applicable irrespective of whether the series is purely I(0), purely I(1) or mutually cointegrated (M. H. Pesaran et al., 2001). Hence, it must be ensured that the order of integration of the series is not higher than one. Accordingly, we tested the null hypothesis of a unit root using the modified Dickey-Fuller (DF) Generalized Least Square t-test (hereafter referred to as DF-GLS), as suggested by Elliot, Rothenberg, and Stock (1996), and the Zivot and Andrews (ZA) unit root test (Zivot & Andrews, 2002).

Table 2. Unit root tests

Variables	Level		First difference		
	DF-GLS	ZA	DF-GLS	ZA	Break point
Cassava roots	-2.53(3)	-4.74 (3)	-3.51***(5)	-6.01*** (2)	2003m3
Potato	-1.64(9)	-5.05*(3)	-6.05***(4)	-11.02***(2)	2007m9
Beans	-1.43 (10)	-6.53***(1)	-6.77***(1)	-8.81*** (2)	2007m3
Rainfall	-1.37 (11)	-9.11***(2)	-9.57***(1)	-10.09***(3)	2002m6

Notes: superscripts *, **and *** indicate rejection of the null hypothesis of a unit root at the 10, 5 and 1% significance levels, respectively. The optimal lag length is given in brackets, and is based on the Schwarz Information Criterion.

The DF-GLS test is more efficient, especially when an unknown mean or trend is present in the series. The ZA test allows for an alternative hypothesis that the series is trend-stationary with a one-time break in the level or trend or both.

Table 2 presents the results. The DF-GLS test suggested that all the series had unit roots in levels, but that the first differences were stationary, i.e., they were all I(1). The ZA unit root test suggested that, except for cassava roots, other series were stationary around an intercept shift or both an intercept shift and a trend break. The last column of the table shows the month and the year of the break point for each series. Overall, the series were either I(0) or I(1), which makes the ARDL framework appropriate.

3. Empirical results and discussion

Table 3 presents estimates of the parameters in Eq. (4) for the price of beans, potato and cassava roots. The parameter restimates and p-values are shown. The first column contains short-run elasticities of asymmetric (positive and negative) effects of rainfall on the price of beans. The estimates indicated that positive changes in rainfall were associated with a significant decrease in the price of beans and that these effects emerged in the third month from the time when the rainfall period started. Therefore, the figures 0.63 and 1.09 are parameter elasticities, meaning that a 10% increase in rainfall (expressed in mm) induces a reduction by 0.63% and 1.09% in the price of beans in the third and fourth months, respectively.

On the other hand, a decrease in rainfall induced an instant increase in the price of beans. This means that rainfall shortage affects crop yield negatively, reduces supply on the market and eventually increases the price of beans. This suggests that crop yield depends heavily on amount of rainfall and its variability. Weather variability has previously been found to be an important determinant of farmer cropping decisions (Wood et al., 2014) and of crop yields (Lobell et al., 2011). Climate variability affects the stability of food supplies and vulnerable people's ability to access food at affordable prices (Schmidhuber & Tubiello, 2007).

The second column of Table 3 contains the short-run elasticities of asymmetric (positive and negative) effects of rainfall on the price of potatoes. Unlike the price of beans, the effect of rainfall changes in either directions is associated with a reduction in potato prices. One tentative explanation relates to the fact that crop yield depends on both rainfall and sunshine.

Potato farmers need moderate rain and sunshine interchangeably. Therefore, by controlling for farming season, we were able to show that rainfall does not exclusively influence potato supply, and, hence, its price.

Table 3. Dynamic asymmetries in the price of beans, potatoes and cassava roots

Beans		Potatoes		Cassava roots	
Variable	Estimate	Variable	Estimate	Variable	Estimate
$Pbeans_{t-1}$	-0.197***	$Ppotato_{t-1}$	-0.261***	$Pcassava_{t-1}$	-0.230***
	(0.046)		(0.064)		(0.070)
$\Delta Pbeans_{t-3}$	-0.163**	$\Delta Ppotato_{t-1}$	0.377***	$\Delta Pcassava_{t-1}$	-0.238**
	(0.076)		(0.088)		(0.106)
$\Delta rain^{+}_{t-3}$	-0.063***	$\Delta Ppotato_{t-2}$	-0.164*	$\Delta Pcassava_{t-5}$	0.249**
	(0.024)		(0.093)		(0.109)
$\Delta rain^{+}_{t-4}$	-0.109***	$rain^{+}_{t-1}$	-0.047*	$\Delta rain^{+}_{t-1}$	0.191**
	(0.020)		(0.025)		(0.089)
$\Delta rain^{-}_{t-1}$	0.054*	$rain^{+}_{t-3}$	-0.047**	$\Delta rain^{-}_{t-2}$	0.181**
	(0.032)		(0.021)		(0.089)
$\Delta rain^{-}_{t-2}$	0.064**	$rain^{-}_{t-1}$	-0.051**	$\Delta rain^{-}_{t-3}$	0.188**
	(0.029)		(0.025)		(0.082)
$\Delta rain^{-}_{t-3}$	0.070***	$\Delta rain^{-}_{t}$	-0.028*	$\Delta rain^{+}_{t-4}$	0.164**
	(0.022)		(0.016)		(0.076)
$Season\ A$	0.042	$Season\ A$	-0.028	$Season\ A$	0.052
	(0.039)		(0.034)		(0.057)
$Season\ B$	-0.086**	$Season\ B$	-0.005	$Season\ B$	0.016
	(0.033)		(0.030)		(0.055)
$Constant$	2.501***	$Constant$	2.505***	$Constant$	1.466
	(0.810)		(0.780)		(1.112)

Notes: superscripts *, ** and *** indicate rejection of the null hypothesis at 10, 5 and 1% significance level, respectively. All the variables are in natural logarithm, so the coefficients can be interpreted as elasticities.

The role of agricultural seasons is of paramount importance in determination of the degree of food price transmission in Rwanda, since crop farming depends heavily on rainfall. The parameter estimates on agricultural seasons indicated that the price of beans and cassava roots increased by 4.2% and 5.2%, respectively, in season A relative to season C. It is worth mentioning that during season C there was a substantial food price decrease, as farmers in Rwanda harvest most of their crops in this season. Because these farmers have no or limited access to crop storage, they tend to sell their produce as soon as they harvest it, especially food crops like potatoes that are difficult to store. Consequently, an increase in demand for food cropsand eventually a hike in their market prices in the following season can be expected, not only for urban households, which depend entirely on food purchases, but also for rural households that buy food crops that they may usually produce but cannot store.

Moreover, the results showed that price of beans was 8.6% lower during season B than in season C. One tentative explanation for the lower prices in season B is that beans are harvested during January-February and the market price falls immediately, since most rural households then become sellers rather than buyers.

On the other hand, the seasonality effects on potato prices were relatively low. However, we did not expect significant differences in potato prices across seasons, mainly because potatoes are produced throughout the year, mostly in Northern Rwanda. The differences in the price of food crops across seasons highlight the need for crop storage facilities in the country. The importance of seasons in explaining the effects of climate change on agricultural output has also been demonstrated for South Africa by Benhin (2008) who reported that a fall in precipitation leads to a fall in net crop revenue, but with significant seasonal differences in impacts.

In the last column of Table 3, we present short-run elasticities of asymmetric (positive and negative) effects of rainfall and other controls on the price of cassava roots. As the estimates show, rainfall changes in either direction are associated with increased crop prices. This implies that positive/negative rainfall changes may affect the supply of cassava roots negatively and eventually increase the price. Under these circumstances, we can say that crop yield depends not only on quantity of rainfall per se, but also on its variability. Another important aspect that needs to be considered here is that during the rainy season, farmers need to buy seeds, leading to an upward trend in prices and explaining the observed positive effect of rainfall on food crop prices (Table 3). Moreover, it is important to highlight the effect of expectations;low levels of rainfall are a signal to the farmer to anticipate an increase in future food prices. A rational farmer would then delay selling their harvested crop, which would result in even higher food prices on the market. All these factors explain the positive coefficients obtained in this study.

The upper part of Table 4 presents long-run asymmetric effects of rainfall effects on the price of the three main food crops. The middle part of the table presents the results of tests of the significance of these asymmetries, which indicate strong significance of both short-run and long-run asymmetries, especially for the price of beans. The lower part of the table provides diagnostic statistics on the validity of the NARDL model estimates.

The estimated long-run effect (β^{+}) of rainfall on crop prices was -0.438, -0.252 and -0.179 for cassava roots, beans and potatoes, respectively. This implies that in the long-run, a 1% increase (decrease) in rainfall is associated with a 0.44%, 0.25% and 0.18% decrease (increase) in the price of cassava roots, beans and potatoes, respectively. On other hand, the estimated β^{-} was 0.76%, 0.27% and 0.19%, respectively, meaning that a 1% decrease (increase) in rainfall is associated with a 0.76%, 0.27% and 0.19% increase (decrease) in the price of cassava roots, beans and potatoes, respectively, in the long run. Looking at both scenarios, the results show that negative shocks in rainfall are transmitted to crop prices with substantially greater intensity than positive shocks in rainfall. In particular, the negative long-run elasticity of rainfall shocks on cassava root prices was roughly 32 percentage points higher than that of positive rainfall shocks.

Table 4. Asymmetric statistics on rainfall effects of food prices

	Cassava roots	Beans	Potatoes
	Coef.	Coef.	Coef.
Long-run positive effects^{+}	-0.438	-0.252	-0.179*
	(0.194)	(0.134)	(0.095)
Long-run negative effects^{-}	0.766*	0.268	0.196*
	(0.071)	(0.114)	(0.070)
Long-run and short-run asymmetry tests			
Rainfall_F.stat$_{LR}$	3.08*	17.44***	43.48***
	(0.083)	(0.000)	(0.000)
Rainfall_F.stat$_{SR}$	8.01***	18.58***	0.92
	(0.006)	(0.000)	(0.340)
Diagnostic statistics of the NARDL model			
R_Squared	0.394	0.549	0.595
Observation	142	151	150
Bound test	1.697	8.380***	3.374**
Chi_ARCH	0.059	0.262	0.218
	(0.808)	(0.608)	(0.640)
Chi_SC	0.025	6.428	2.460
	(0.874)	(0.11)	(0.117)

Notes: the superscripts + and – represent, respectively, the positive and negative partial sums.

The F.stat$_{LR}$ is the F-statistic for log-run symmetry in Eq. (4) that $\hat{\beta}^{+} = \hat{\beta}^{-}$ and F.stat$_{SR}$ is the short-run F-statistic for the null of less restrictive (weak) form symmetry defined as $\sum_{j=0}^{q-1} \gamma_j^{+} = \sum_{j=0}^{q-1} \gamma_j^{-}$

The Bound Test for levels relationship is an additional proof for testing long-run relationships between food crop prices and rainfall. Chi_ARCH is a test for autoregressive conditional heteroscedasticity, while Chi_SC is a test for serial correlation. P-values are in brackets. Superscripts *, ** and *** indicate rejection of the null hypothesis at 10, 5 and 1% significance level, respectively.

An effect of rainfall on food crop prices has also been found in other Sub-Sahara African countries. For instance, in a study in Ethiopia, Hill and Porter (2017) found that rainfall shortage caused sudden increases in food prices and a 9% reduction in consumption for rural households.

The tests of short-run and long-run asymmetry are also presented in Table 4. The null hypothesis of long-run asymmetry ($\beta^{+}=\beta^{-}$) was rejected for all three food crops. Similarly, short-run (weak) symmetry was rejected, except for potatoes. In the lower part of the table, various diagnostic tests are reported. To judge the goodness of fit, R-squared was used. The bound test [5] was highly significant and indicated rejection of the null hypothesis that the coefficients of the lagged level variables are jointly equal to zero. This is significant evidence of the existence of a long-run cointegrating relationship between the variables in the model. The null hypothesis of homoscedasticity could not be rejected for all three food crop model estimates. Moreover, the test of serial correlation (Chi_SC) indicated no evidence of serial correlation. The bound test indicated a very significant long-run cointegrating relationship between rainfall and potato and bean prices.

For further analysis, we derived cumulative effects of rainfall on the food crop prices. These multipliers showed the change in the food crop price following a (positive or negative) rainfall shock. Figure 3 shows the change in the price of cassava roots following a rainfall shock. As can be seen, in line with results in Table 4, the price of cassava roots responded positively to a reduction in rainfall, while the response was negative following an increase in rainfall. This highlights the presence of asymmetries in the relationship. Figure 3 also shows the path towards the equilibrium correction, which was achieved after 20 months for a positive shock and around 27 months following a negative shock.

Figure 4 depicts the change in the price of beans following a shock in rainfall. It was found that the effect on bean prices was very asymmetric, with the response to an increase in rainfall being larger than the response to a decrease (negative shock).

However, a negative shock was more persistent, since the equilibrium correction was achieved after 4 months following a positive change, while the effect of a negative shock extended beyond 6 months.

Figure 5 shows the change in the price of potatoes following a shock in rainfall. Here, potato prices responded asymmetrically to rainfall shocks, but at almost the same rate. Equilibrium was achieved after 4 months.

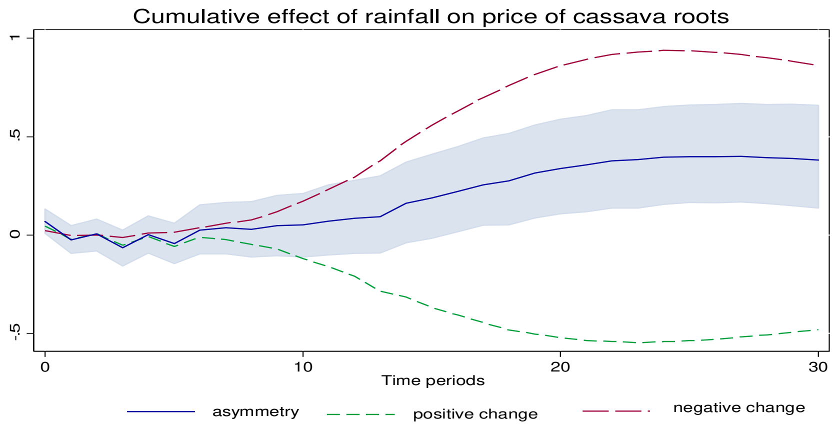

Fig. 3. Dynamic multipliers. Effect of rainfall on cassava root prices

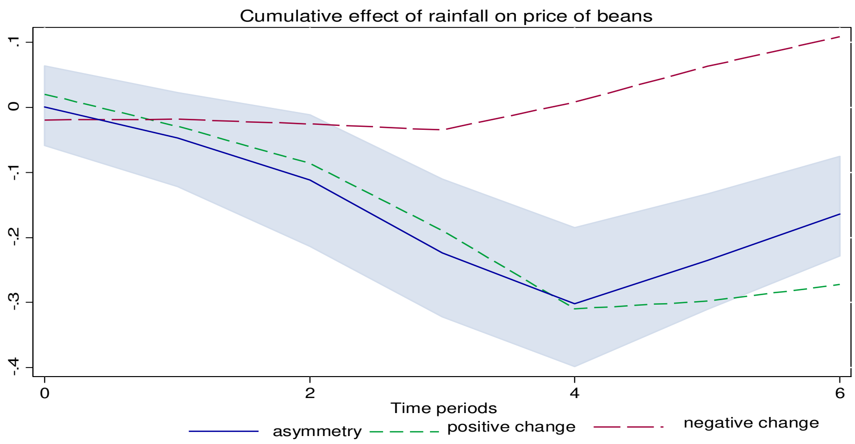

Fig. 4. Dynamic multipliers. Effect of rainfall on bean prices

[5] Pesaran et al. (2001) propose using the usual F-test. Unlike the usual F-test, however, the critical values of the bound test depend upon the integrating properties of the variables. If all variables in the model are I(0), the decision is then based on a lower bound critical value. On the other hand, if all variables are I(1), one has to refer to the upper bound critical value. The latter critical values are also valid in the presence of a mixture of I(0) and I(1) variables in the model.

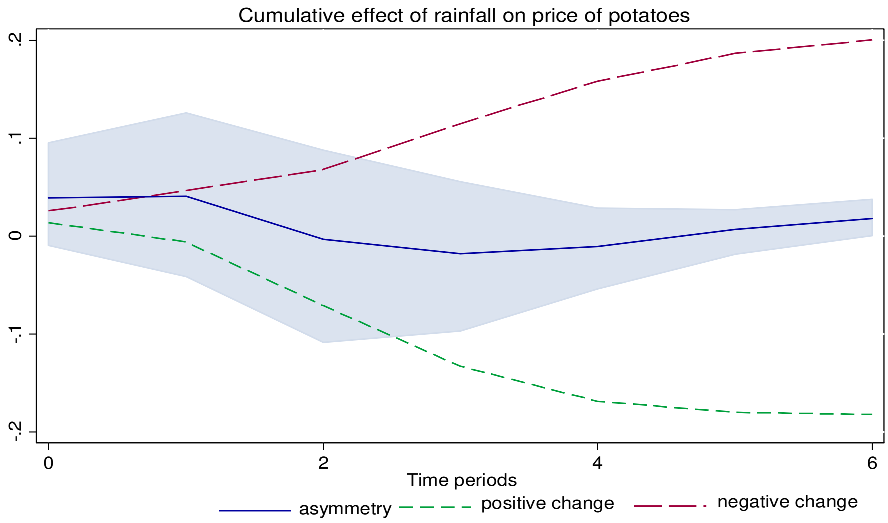

Fig. 5. Dynamic multipliers. Effect of rainfall on potato prices

Conclusion

This study investigated the dynamic and asymmetric effect of rainfall on food crop prices with an application to Rwanda, a landlocked country with rain-fed agriculture. More specifically, it examined whether both short- and long-run rainfall changes significantly affect staple food prices in Rwanda.

The nonlinear ARDL framework, a relatively recent methodology that incorporates an error correction mechanism and allows estimation of asymmetric long-run and short-run dynamic coefficients in a cointegration framework, was applied to examine the price of beans, potatoes and cassava roots, three very important staple foods in Rwanda. The findings indicate that food crop prices are vulnerable to rainfall shocks and that the effect is asymmetric in both the short and long run. Considering the sensitivity of food crop prices to rainfall, it is essential to adopt climate adaptation strategies in the agriculture sector and to provide farmers with improved seeds that can resist rainfall shortages.

We also found evidence of seasonality, whereby prices fall during the harvest season and rise thereafter. This highlights the necessity for crop storage systems in Rwanda to help to smooth food prices across the agricultural year. This would break the recurring cycle, whereby farmers sell their produce at low prices and buy it later at very high prices, and thus significantly improve the livelihood of agrarian households. These findings add to the recent literature on the effect of climate-related factors on food crop prices and higlight the need to develop and distribute foodcrop varieties and crop technologies that reduce the vulnerability of farming to rainfall shocks.

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Appendix

Table 1. Descriptive statistics on key variables of interest in the study (real prices are expressed in Rwandan Francs; rainfall is in millimetres)

		Cassava roots	Potato	Dry beans	Rainfall
January	Mean	93.55	81.37	193.59	108.13
	SD	36.73	40.42	90.30	44.36
	Min	33.6	30.90	80.00	45.67
	Max	139.5	157.30	317.90	195.70
	CV	0.39	0.50	0.47	0.41
February	Mean	94.54	89.35	185.25	110.83
	SD	38.05	45.16	87.32	62.71
	Min	33.1	30.90	78.10	60.53
	Max	153.8	177.40	294.20	293.25
	CV	0.40	0.51	0.47	0.57
March	Mean	100.68	95.88	193.71	133.07
	SD	38.04	48.94	91.45	31.25
	Min	37.8	34.20	78.10	68.57
	Max	156.1	200.90	311.90	180.50
	CV	0.38	0.51	0.47	0.23
April	Mean	99.68	97.38	204.85	150.65
	SD	37.80	49.39	98.14	33.82
	Min	35.6	35.20	80.30	95.68
	Max	158.1	192.50	336.80	224.25
	CV	0.38	0.51	0.48	0.22
May	Mean	101.9	94.02	207.82	109.97
	SD	40.22	48.51	100.60	31.16
	Min	38	33.60	84.10	71.81
	Max	156.4	180.40	362.50	172.64
	CV	0.39	0.52	0.48	0.28
June	Mean	101.55	96.52	205.70	32.25
	SD	41.64	49.11	98.82	27.72
	Min	35.9	31.10	89.80	4.76
	Max	157.5	172.40	362.80	85.43
	CV	0.41	0.51	0.48	0.86
July	Mean	101.56	99.11	216.09	15.63
	SD	40.65	45.25	98.35	4.20
	Min	42	36.10	101.10	8.69
	Max	168.1	178.50	345.70	18.97
	CV	0.40	0.46	0.46	0.27
August	Mean	102.65	107.59	232.33	43.16
	SD	40.32	48.56	104.91	19.78
	Min	43.2	40.90	103.80	13.16
	Max	174.3	198.90	377.20	89.86
	CV	0.39	0.45	0.45	0.46
September	Mean	107.22	117.21	246.12	89.40
	SD	42.26	56.47	109.81	27.70
	Min	47.7	44.30	114.50	50.06
	Max	178.2	217.50	395.10	136.32
	CV	0.39	0.48	0.45	0.31
October	Mean	106.11	116.29	260.19	125.91
	SD	39.67	54.18	105.39	30.42
	Min	42.8	42.60	104.30	88.54
	Max	173.5	216.70	384.20	196.41
	CV	0.37	0.47	0.41	0.24

Table 1 (cont.). Descriptive statistics on key variables of interest in the study (real prices are expressed in Rwandan Francs; rainfall is in millimetres)

		Cassava roots	Potato	Dry beans	Rainfall
November	Mean	105.86	103.31	268.93	147.62
	SD	40.37	45.70	110.61	42.99
	Min	45.7	37.30	102.00	82.04
	Max	172	178.00	444.00	239.83
	CV	0.38	0.44	0.41	0.29
December	Mean	103.03	89.55	251.52	120.29
	SD	40.44	38.84	98.33	31.86
	Min	37.4	35.40	92.40	55.55
	Max	168.6	155.40	405.60	184.96
	CV	0.39	0.43	0.39	0.26

Source: authors' calculations. SD = standard deviation, CV = coefficient of variation.