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Impacts of the 2016/17 Food Insecurity Response Program on Maize Prices in Malawi

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ABSTRACT

In early 2016, Malawi suffered its second consecutive year of harvest failure. An emergency was declared in April 2016 and the resulting humanitarian response, known as the Food Insecurity Response Program (FIRP), was of unprecedented scale: almost 40 percent of the population received in-kind food or cash transfers (or both) at an estimated cost of US$ 287 million. Yet despite the extensive nature of the response, prices for the main food staple, maize, stayed relatively 'flat' throughout most of the year and then declined during the pre-harvest lean season. This paper examines what explains this paradox, focusing on why in-kind food distribution did not depress maize prices while cash transfers did not raise them. Using daily information on maize prices, and food and cash transfers from ten major markets during the height of the FIRP, we employ time series methods to analyze the properties of the series and model the formation of maize prices using autoregressive distributed lag models. We find limited evidence of price linkages between markets and almost no impact of food distribution and cash transfers on maize prices. Sen's distinction between direct and trade-based entitlements is used to help explain this paradox.

Keywords: Malawi, maize prices, food transfers, cash transfers

1. INTRODUCTION

In early 2016, Malawi, suffered its second consecutive year of harvest failure: with maize production estimated to be 2.4 million metric tons (MT) compared to 3.2 million MT in a normal year. The President of Malawi declared an emergency on 12 April 2016 and appealed for assistance totaling US$395 million from the international community and private sector. The resulting humanitarian response, known in Malawi as the Food Insecurity Response Program (FIRP), was of unprecedented scale with almost 40 percent of the population receiving either in-kind food or cash transfers or some combination of the two, delivered through various modalities (cereals and oil in-kind, maize vouchers, cash, and mobile money). The final cost of the FIRP is estimated to have been US$ 287 million, of which 23 percent was financed by the Government of Malawi and the remainder by its international development partners (in particular, the United States and the United Kingdom). Yet despite the extensive nature of the response, prices for Malawi's main food staple, maize, stayed relatively 'flat' throughout the year and even declined during the pre-harvest lean season. This paper examines what explains this surprising fact, focusing on why food distribution in-kind did not depress maize prices while cash transfers did not raise them.

The paper conducts a rigorous analysis of maize price formation in the ten markets for which we have daily information on maize prices, in-kind food distribution and cash transfers during the height of the 2016/17 humanitarian response. Such high-frequency data is rarely available in developing countries: the vast majority of quantitative analyses of the possible disincentive effects of food aid in these countries use either monthly or annual prices.[1] Advanced time series methods are used to analyze the properties of these series and model the formation of maize prices using autoregressive distributed lag models. While these models track daily maize prices rather well, we find limited evidence of price linkages between markets and almost no impact of food and cash transfers on maize price formation during the December 2016 to March 2017 period.

Context

As noted above, the 2016/17 FIRP in Malawi was of unprecedented scale. It was also dominated by in-kind food transfers. The Malawi Vulnerability and Assessment Committee (MVAC) assessment of May 2016 envisaged 6.5 million beneficiaries, of whom 4.7 million would receive in-kind food transfers and 1.8 million would receive cash transfers. This was modified to 6.7 million beneficiaries in October 2016, with in-kind food beneficiaries increased to 5.4 million and cash beneficiaries decreased to 1.4 million. In addition, a hybrid modality involving maize vouchers plus cash for the non-maize ration was introduced from December 2016 onwards. In-kind food distribution was coordinated by the World Food Programme (WFP) and delivered through their 18 district-level cooperating partners while cash transfers (and vouchers) were split between WFP and a Cash Transfer Consortium led by five international non-governmental organizations.[2] Figure 1 shows the number of beneficiaries by mode of assistance during the FIRP implementation period.

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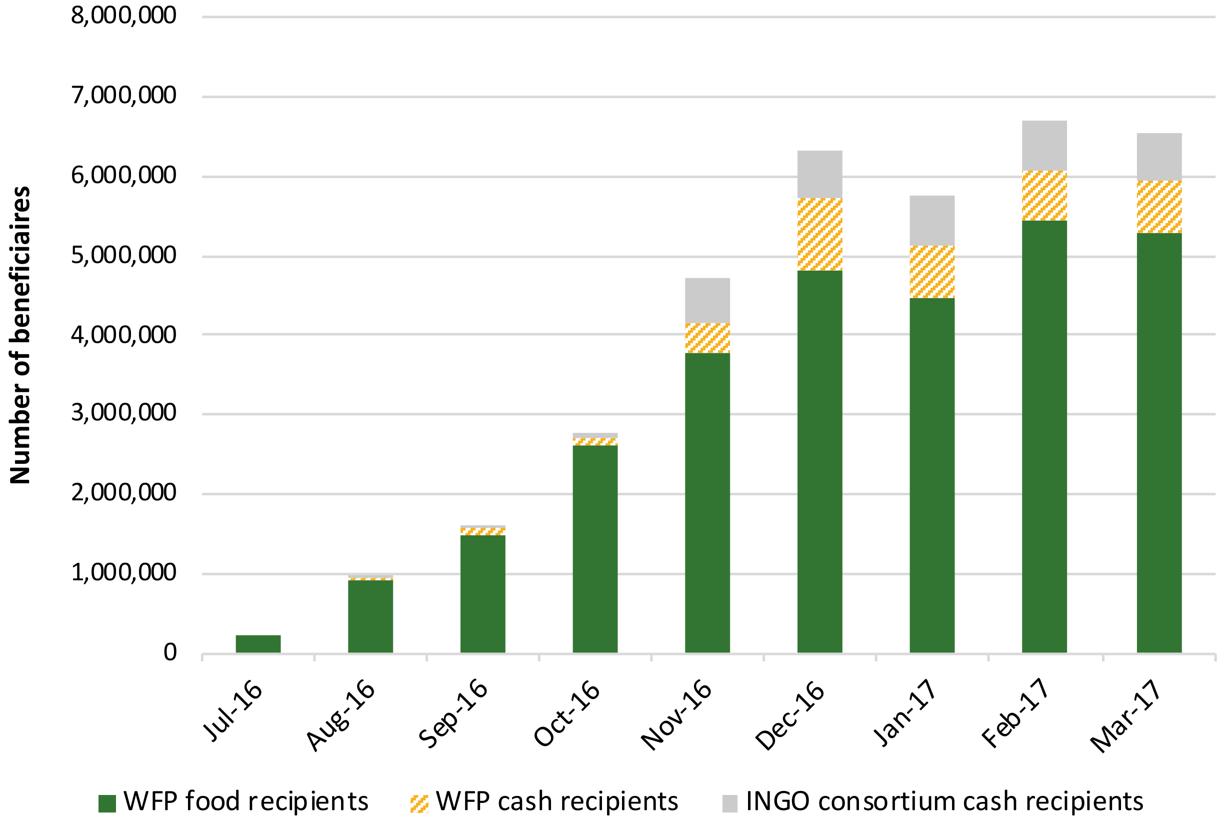
1 See the seminal paper by Schultz (1960), and, inter alia, Maxwell and Singer (1979), Bezuneh, Deaton and Norton (1988), Lavy (1990), Donnovan et al. (1999), and Abdulai, Barrett and Hoddinott (2005).

2 The members of the INGO Cash Transfer Consortium were Concern Worldwide, Oxfam, GOAL, Save the Children and United Purpose (formerly Concern Universal).

Figure 1. Beneficiaries assisted per month during the 2016/17 FIRP.

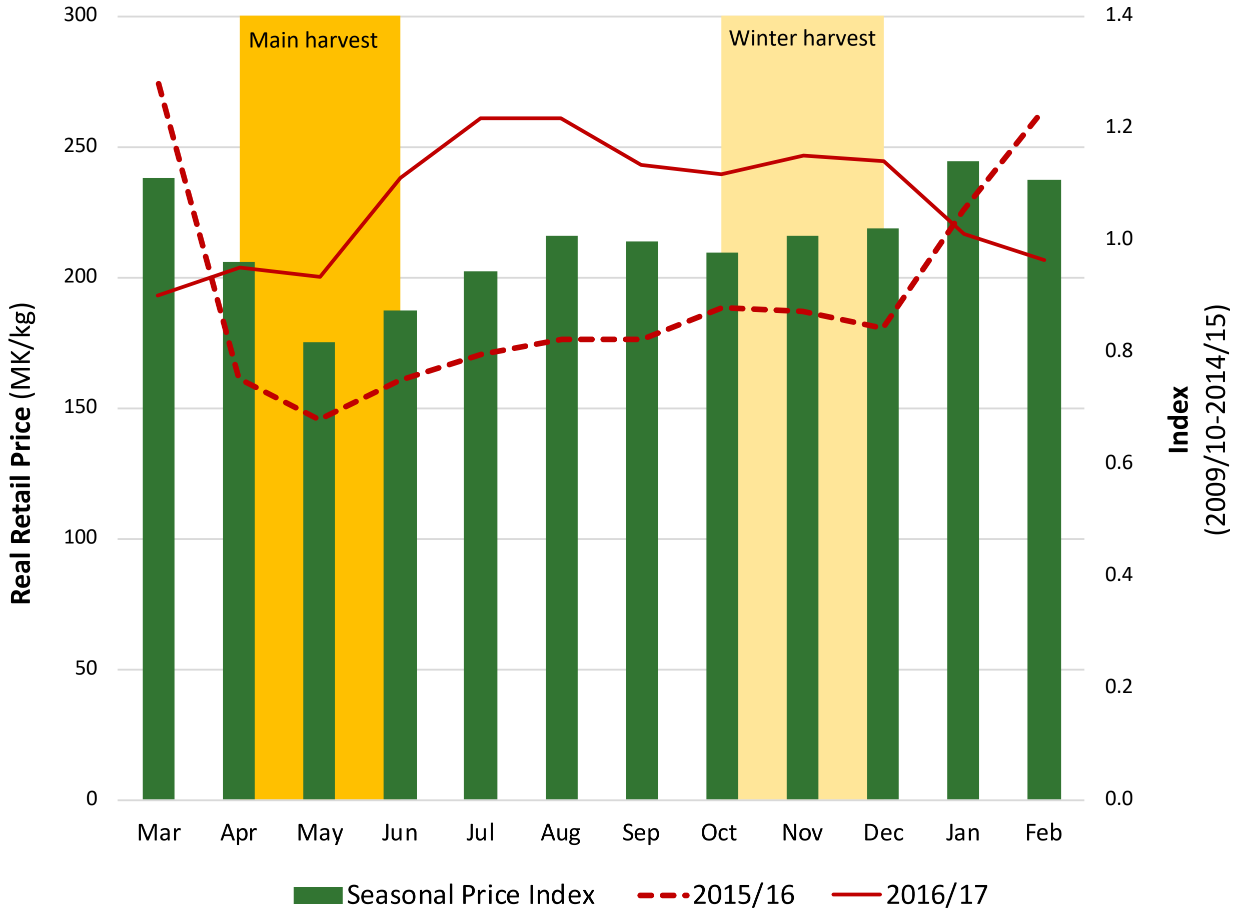


Source: based on WFP 2017b.

Extrapolating from MoAIWD (2016), we estimate that in-kind food transfers (excluding vouchers) represented 8.9 to 9.9 percent of Malawi's annual maize consumption requirements, while cash transfers represented less than 2 percent (1.5 to 1.7%) percent of maize consumption.

Figure 2 compares monthly retail maize price patterns in real (inflation adjusted) terms during the 2016/17 response with those of 2015/16 and a seasonal price index based on maize prices during preceding five years. Maize prices reached their highest level in July and August 2016, and then declined. This was contrary to the usual seasonal price pattern, in which maize prices usually peak between January and March – the lean season before the main maize harvest.

Figure 2. Seasonal price patterns for maize compared to maize prices, 2015/16 and 2016/17.



Source: Authors' construction from monthly prices of the Government of Malawi's Agricultural Market Information System.

Private sector participation in the FIRP began mid-2016, when the major private sector grain traders (Export Trading Group, Mulli Brothers, Farmer's World, Rab Processors, etc.) started actively procuring maize both locally and from neighbouring countries. Most of the 100,000 MT of 'local' maize purchased by the National Food Research Agency, which manages the Strategic Grain Reserve (SGR), and 95,000 MT purchased by ADMARC came from these large private sector traders.[3] These purchases, along with more than 85,000 MT of speculative purchases by the grain traders themselves, drove the real maize price up to a seasonally uncharacteristic peak in July and August 2016 (Figure 1). At this time, maize in the border town of Mchinji, most of it cross-border imports, was selling at a MK 35/kg premium over prices in the neighbouring Zambian town of Chipata.

Having accumulated substantial stocks, the private sector was then unable to sell a large portion of these at the high prices they had anticipated during the last quarter of 2016. Liquidation of their maize stocks by these firms on the open market, combined with continuing unofficial cross-border imports, contributed to falling prices for maize during the pre-harvest lean season in the first quarter of 2017, again contrary to the usual seasonal pattern (Figure 2). These price trends, along with the extensive

3 According to reliable sources, much of the 100,000 MT procured for the SGR (and possibly some of WFP's 'local' procurement) came from informal imports from Zambia despite that country's maize export ban.

nature of the humanitarian response, led FEWS NET (2017) to revise downward its rating for central and southern Malawi to 'stressed' (IPC classification 2) in January 2017.[4] By March 2017, the average real maize price in Malawi was well below the peak reached at the height of the lean season in 2016 (as well as below the usual seasonal price pattern).

One of the factors influencing the unexpected decline of real maize prices from November onwards may have been the switch from cash to maize vouchers following the MVAC update report of October 2016. This update recommended that the number of beneficiaries receiving cash transfers be reduced from 1.8 million to 1.4 million, with a hybrid modality consisting of a voucher for one 50 kg bag of maize plus cash for the remainder of the ration. Consequently, WFP changed its mode of transfer from cash to the hybrid modality in 33 Traditional Authorities (TAs), and to in-kind food only in 18 TAs starting in December 2016. Meanwhile, the International NGO Social Cash Transfer Consortium signed an agreement with Rab Processors (one of the large grain traders in Malawi) to supply maize in the 51 TAs where the NGOs had initially only provided cash from January 2017. These arrangements are reported to have worked relatively smoothly, despite problems with the verification of electronic vouchers in the field and some roads being impassable during the rainy season.

2. DATA AND METHODOLOGY

Data

The study uses three sources of data, covering the period from November 2016 to March 2017. Retail maize price data was obtained from IFPRI's maize price monitoring in 15 markets covering six days in a week, excluding Sundays. In-kind food distribution data was obtained from WFP, comprising distribution dates, locations, and total volume of in-kind distribution in the districts that overlapped with markets covered by IFPRI'S daily maize price monitoring. Cash transfer distribution data was obtained from the International NGO (INGO) Cash Transfer Consortium, led by Save the Children. The INGO data comprises the actual distribution dates, locations, and total values in the seven districts that overlap with the markets in IFPRI's daily maize price monitoring.

Table 1 shows the amount of cash and food distributed by WFP and the INGO consortium in each district between 1 November 2016 and 31 March 2017. During this time, Chikwawa, Blantyre, Mulanje and Nsanje districts in southern Malawi received substantial quantities of food aid, while Lilongwe, Dowa, Mchinji and Dedza districts in central Malawi received the largest amount of cash transfers. It should be noted that, except for Mchinji (cash only) and Mzimba districts (food only), most districts received a mixture of both food and cash.

4 The January FEWSNET report also notes that: 'Were the humanitarian response not present, these areas would experience Crisis (IPC Phase 3) and Emergency (IPC Phase 4) outcomes.'

Table 1. Cash and food distributed by district, 1 November 2016 to 31 March 2017.

District	Cash (MK million)	District	Food (MT)
Lilongwe	2,880	Chikwawa	18,703
Dowa	1,760	Blantyre	14,559
Mchinji	1,530	Lilongwe	9,382
Dedza	1,520	Mulanje	9,168
Mulanje	843	Nsanje	9,108
Blantyre	566	Dedza	3,934
Chikwawa	470	Dowa	3,723
Mwanza	169	Mzimba	3,239
Nsanje	169	Mwanza	1,037
Mzimba	-	Mchinji	-

Source: WFP; INGO Cash Transfer Consortium.
Note: Cash includes WFP and INGO transfers; maize vouchers are also included in food transfers.

Figure 3 shows time series plots of daily maize prices and cash and food distribution in selected markets. In these graphs, retail prices are shown by the blue lines, in-kind food distribution by the downward brown bars, and cash transfers (expressed in terms on metric tons of maize at the prevailing market price) by the upward green bars. At this, admittedly descriptive, level it is very hard to visually detect any consistent trends between food and cash transfers and the level of retail maize prices.

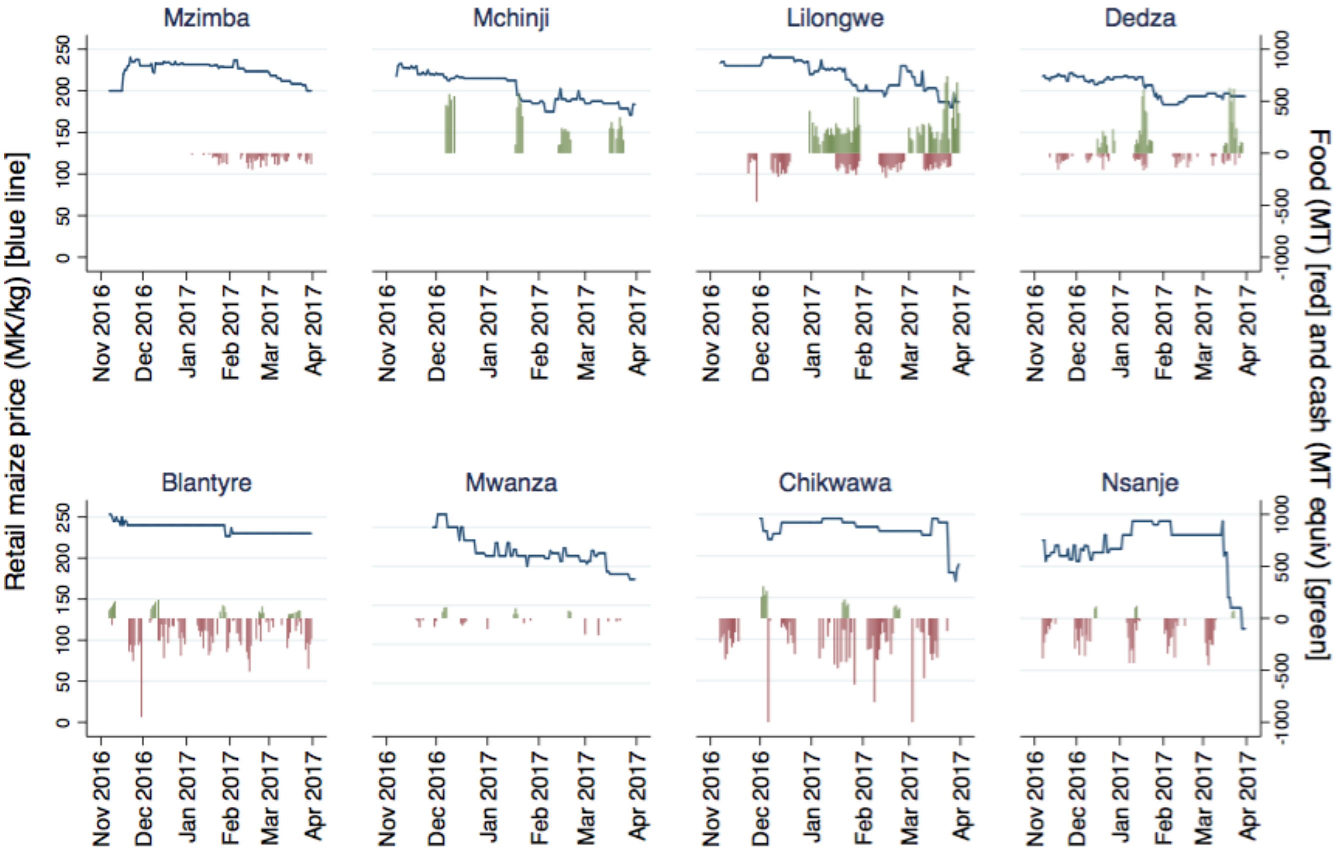
Methodology

The aim of the study is to estimate the impact that different modes of humanitarian assistance had on daily maize prices in selected markets in Malawi. We follow a time series analysis conceptual framework which includes assessing stationary using unit root tests, Granger causality and cointegration tests, model selection and estimation of autoregressive distributed lag and error correction models. The time series analysis was conducted using the software packages Stata/SE15.0 and EViews 9.5.

The choice of which model to use to estimate the impact of food and cash transfers on maize prices depends on several considerations which take account of the stationarity and cointegration relationships in the underlying data. Firstly, when all the series are stationary or I(0), it is possible to simply model the data in levels using a single equation auto-regressive distributed lag (ARL) model or multiple equation vector autoregression (VAR) model. Secondly, when all series are integrated of the order one (i.e., I(1)) but not cointegrated, ordinary least squares (OLS) in first differences or VAR estimation can be used. Thirdly, when all the series are integrated of order one and cointegrated, it is appropriate to estimate the long-run relationship between the variables using an error-correction model (ECM), from which both the short-run and long-run dynamics of the relationship between the variables can be found (Engle and Granger, 1987). Finally, when the series have different orders of integration, such as I(0) and I(1), with cointegration among some of the I(1) variables, then an auto-regressive distributed lag (ARDL) model is appropriate. The paper focuses on the ARDL model because the tests of the variables suggest it is the most appropriate methodology. Moreover, as noted by Pesaran and Shin (1999) and Pesaran *et al*. (2001), the ARDL model has a number of advantages over conventional error correction models. Specifically: (i) the ARDL can be used with a mixture of I(0) and I(1) series; (ii) it involves a single-equation set-up, making it simple to implement and interpret; and, (iii) it is possible to assign different lag-lengths to the different variables which enter the model.[5]

5 Note that advantages (ii) and (iii) also apply to error-correction models, while (iii) applies to ARL and VAR models. However, the asympotitics of none of these models can handle time series with different orders of integration.

Figure 3. Time series plots of daily maize prices, cash, and food distribution in selected markets, November 2016 to March 2017.



Source: IFPRI Price Monitoring, WFP, and INGO Cash Transfers Consortium.
Note: Retail maize prices (MK/kg) = blue line; food transfers (MT) = red bars; cash transfers (MT equivalents) = green bars.

The generic form of an ARDL regression model is given as follows:

$$Y_t = \beta_1 Y_{t-1} + ... + \beta_k Y_{t-p} + \alpha_0 X_t + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + ... + \alpha_q X_{t-q} + \varepsilon_t \quad (1)$$

where X_t and Y_t are time series and ε_t is a random "disturbance" term. The term "autoregressive" implies that Y_t is explained (in part) by lagged values of itself. The model also has a "distributed lag" component, in the form of successive lags of the "t" explanatory variable. Exogenous variables that are either I(0) or I(1) can be added to the model to improve its fit.

We adapt this generic ARDL model to maize price formation, by replacing Y and X with maize prices (P) in two markets denoted by the superscripts m and n, and adding in-kind food distribution (F) and cash transfers (C) in market m as exogenous variables, thereby obtaining the following estimation equation:

$$P_t^m = \beta_0 + \sum_{i=1}^{p} \beta_i P_{t-i}^m + \sum_{i=0}^{k} \phi_i P_{t-i}^n + \sum_{i=0}^{f} \delta_i F_{t-i}^m + \sum_{i=0}^{c} \gamma_i C_{t-i}^m + \varepsilon_t \quad (2)$$

where P_t^m and P_t^n represent the price of maize in markets m and n at time t, F_t^m denotes in-kind food transfers and C_t^m denotes cash transfers in market m. To detect whether or food and cash transfers impact on maize prices in market m, Wald tests may then be conducted on the coefficients δ_i and γ_i .

3. EMPIRICAL RESULTS

Stationary Tests

As a first step, we investigated the properties of daily maize prices using unit root tests. Stationarity tests were based on the Augmented Dickey Fuller and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests with robustness checks done using the Phillips-Perron unit-root test and the modified augmented Dickey Fuller test, which uses GLS. The null hypothesis of the Augmented Dickey Fuller (ADF) test is that the variable is non-stationary (contains a unit root), while the alternative hypothesis is that the variable was generated by a stationary process. In contrast, the KPSS test has the null hypothesis of stationarity. The KPSS is often used in conjunction with the ADF test to investigate the possibility that a series is fractionally integrated, namely neither I(1) nor I(0) (see Lee and Schmidt, 1996). We include lagged terms of the dependent variables to control for serial correlation with the number of lagged terms chosen using Stata's *varsoc* command. The tests also included a trend term since the price data shows a clear downward trend in most series.

Table 2 shows that all series are integrated of order 1, except for Lunzu which is *I(0)* according to the ADF test but I(1) based on the KPSS test. Therefore, our unit root tests indicate that all maize price times series are non-stationary with the possible exception of Lunzu, whose stationarity test is inconclusive. The results of the Phillips-Perron unit-root test (not shown) gives similar results to the ADF test, while the modified augmented Dickey Fuller test (also not shown) agrees with the KPSS test. This is where the ARDL model, and the accompanying bounds testing methodology, become quite useful–as seen below in the selection of the most appropriate estimation model.

Table 2. Univariate tests for stationarity

Market	ADF test	Test statistic	KPSS test	Test statistic
Chikwawa	I(1)	-7.755***	I(1)	0.045***
Chimbiya	I(1)	-9.354***	I(1)	0.080***
Lunzu	I(0)	-3.511**	I(1)	0.045***
Mchinji	I(1)	-6.492***	I(1)	0.058***
Mitundu	I(1)	-7.490***	I(1)	0.041***
Mponela	I(1)	-7.951***	I(1)	0.052***
Mulanje	I(1)	-8.294***	I(1)	0.023***
Mwanza	I(1)	-6.808***	I(1)	0.048***
Mzimba	I(1)	-8.611***	I(1)	0.048***
Nsanje	I(1)	-4.413***	I(1)	0.150***

Source: Authors' estimation.
*Note: *** and ** indicate significance at 1% and 5% levels.*

Granger Causality tests

We investigate linkages between maize prices in different markets by performing pairwise Granger causality tests for each equation specified in our vector autoregressive model (VAR). A time series X is said to 'Granger cause' another time series Y, if current and lagged values of X improve prediction of Y(Granger, 1969). When applied to maize prices, this approach allows assessment of the extent to which maize prices in some market 'lead' or 'lag' maize prices in other markets. It should be clearly noted that Granger causality does not necessarily indicate a deterministic cause and effect relationship.

The presence or absence of Granger causality can be tested by estimating the following equations for a VAR model simultaneously:

$$P_i^m = a_0 + \sum_{i=1}^{k} a_i P_{t-i}^m + \sum_{i=1}^{k} b_i P_{t-i}^n + u_t \quad (3)$$

$$P_i^n = c_0 + \sum_{i=1}^{k} c_i P_{t-i}^n + \sum_{i=1}^{k} d_i P_{t-i}^m + v_t \quad (4)$$

Note that the Granger causality tests were performed on the first differences of prices (as opposed to the levels) given that the maize price series were mostly non-stationary.

Table 3 shows that most of the market pairs exhibit uni-directional Granger causality. Bi-directional causality occurs for two market pairs, namely Chimbiya-Mponela and Lunzu-Chimbiya. In general, the Granger causality tests are consistent with the bivariate pairwise correlations at lag 0 (see Appendix). The market linkages revealed by these Granger Causality tests are visually presented in Figure 4.

Table 3. System Granger Causality Tests (first differences)

Origin Market	Destination Market	Prob > chi2
Mponela	Lunzu	0.002
Chimbiya	Mponela	0.003
Mulanje	Mchinji	0.006
Mponela	Chimbiya	0.007
Lunzu	Chimbiya	0.015
Chimbiya	Mchinji	0.023
Mzimba	Mchinji	0.028
Mwanza	Chimbiya	0.060
Mwanza	Nsanje	0.064
Mitundu	Mchinji	0.097
Chimbiya	Lunzu	0.098

Source: Authors' estimation.

It is noticeable from Table 3 and Figure 4 that the direction of most linkages is from the central to the southern region of Malawi. Although it is not a particularly large market, Chimbiya market (near Dedza) appears to occupy a strategic position in the price formation process.[6] Mchinji and Mwanza also play important roles in the formation of maize prices. Both are border towns, through which significant, though unquantifiable, flows of maize are known to have entered Malawi during late 2016 and early 2017 (FEWS NET, 2017).

It is also apparent that Mzimba and Nsanje markets exhibit rather weak linkages with other markets. There is only weak Granger causality from Mzimba to Mchinji and from Mwanza to Nsanje. In the case of Nsanje, this is relatively easy to understand, as Nsanje was the district in which the food crisis was most severe and where the duration of the response was the longest. Furthermore, no Granger causality was

6 Chimbiya's importance in the price formation process is also confirmed by interviews with traders in southern Malawi, who state that they regularly procure from Chimbiya rather than nearer wholesale markets (such as Lunzu) because traders in Chimbiya offer more competitive price and will arrange for delivery to locations.

found between nearby Chikwawa, which received the most in-kind food of all the districts considered here, and any of the other markets. Maize prices in Mzimba in central Malawi, only Granger cause those in Mchinji on the border with Zambia, but not prices in the neighboring, though small market, of Mponela.

Figure 4. Granger Causality between markets (first differences).

Source: Authors.

Cointegration

Before choosing an appropriate time series model, it is necessary to determine the number of cointegrating equations. There are three main ways of determining the number of cointegrating equations in a vector error correction model (VECM), conditional on a trend specification and lag order. These three approaches are the Johansen's "trace" statistic method, the "maximum eigenvalue" statistic method, and an information criterion based method–such as the Schwarz Bayesian information criterion (SBIC), the Hannan and Quinn information criterion (HQIC) and the Akaike information criterion (AIC). Most software packages calculate and report the trace statistic by default. It is, however, common in the literature to use results from the two other approaches to confirm results based on the first approach.

There exists a relationship between Granger Causality and cointegration. Specifically, according to the Granger-Engle representation theorem, if two series, X and Y, are cointegrated, there must exist Granger causality either from X to Y, or from Y to X, or in both directions (Engle & Granger, 1987). However, the presence of Granger causality in either or both directions between $X$and Y does not necessarily imply that the series will be cointegrated.

The cointegration tests were first conducted on market pairs with linkages informed by the Granger Causality tests described above. The results are presented in Table 4. Cointegration tests based on the full list of markets indicate that there are up to five cointegrating relationships among the markets of interest.

Table 4. ADF Cointegration Tests

Market pair	Cointegration result
Mitundu-Mchinji	Series are cointegrated
Chimbiya-Mchinji	Series are cointegrated
Chimbiya-Mponela	Series are cointegrated
Mitundu-Mponela	Series are cointegrated
Chimbiya-Lunzu	Series are cointegrated
Nsanje-Chikwawa	Series are cointegrated
Chikwawa-Mulanje	Series are cointegrated
Chimbiya-Mitundu	Series are not cointegrated
Mchinji-Mzimba	Series are not cointegrated
Mponela-Mzimba	Series are not cointegrated
Chimbiya-Mzimba	Series are not cointegrated
Lunzu-Mwanza	Series are not cointegrated
Lunzu-Mulanje	Series are not cointegrated
Lunzu-Nsanje	Series are not cointegrated
Nsanje-Mwanza	Series are not cointegrated

Source: Authors' estimation.

ARDL Estimation Results

The estimation results for the ARDL model outlined above are reported in Table 5. The market pairs for which ARDL models were estimated correspond to the pairs of markets for which Granger causality and cointegration was established in Tables 3 and 4. For each market pair, the dependent variable is the logarithm of the maize price for the first market in the pair and is explained by the past values of that price, as well as current and past values of the logarithm of maize prices in the second market of the pair. Current and past values of food and cash distribution enter the model as exogenous variables, with a maximum lag of 1. The optimal lag order for the ARDL model, as reported in the table, is chosen using the Akaike information criterion (AIC), which tends to select a simpler model specification than other information criteria.

Table 5. ARDL Model Summary

Market pair	Selected model	Presence of structural break	Trend term included
Chimbiya-Mchinji	ARDL(1, 4)	No	Yes
Mitundu-Mchinji	ARDL(2, 1)	No	No
Chimbiya-Mponela	ARDL(8, 4)	No	No
Mitundu-Mponela	ARDL(1, 2)	Yes	No
Chimbiya-Lunzu	ARDL(1, 0)	No	No
Nsanje-Chikwawa	ARDL(4, 2)	Yes	Yes
Chikwawa-Mulanje	ARDL(7, 0)	Yes	Yes

Source: Authors' estimation.

To ensure the ensure stability of the regression coefficients, we apply CUSUM squared tests to check for the presence of structural breaks. The test is based on the cumulative sum of squared recursive residuals plotted against the break dates. If the CUSUM statistic stays within the 5 percent level of significance, then the coefficients are said to be stable. The results suggest structural breaks for Mitundu-Mponela, and Nsanje-Chikwawa market pairs. The break takes a value of 1 for dates after and 0 before the break, which occur in late January or early February 2017. There is also evidence of a structural break in the Chikwawa-Mulanje pair but adding a break dummy to the ARDL does not improve the ARDL model.

The residual diagnostics based on autocorrelation, partial autocorrelation and Box-Pierce Q statistics indicate that there is no serial correlation, implying that our estimators are consistent. Appendix 2 below show the "Actual / Fitted / Residuals" plots of our model. The plots suggest a good fit.

As a robustness check, we apply the bounds testing methodology of Pesaran and Shin (1999) and Pesaran et al. (2001) between the selected market pairs. The ARDL bounds testing methodology handles complicated situations when it is not clear whether the time series are all integrated of the same order or when there is cointegration among some, but not all, variables. A key assumption of the ARDL bounds test is that the residuals are serially independent–a condition already met in the residual diagnostics. The F statistics for the bounds test are presented in Table 6 below, along with the lower and upper bounds for the test at the 10 and 5 percent significance levels. When the F statistic is greater than the lower and upper bounds (critical values), we may conclude that a long-run relationship exists. From F statistics in the table, it can be seen that there are long-run relationships between maize prices in Chimbiya-Mchinji, Mitundu-Mponela, and Chikwawa-Mulanje. There is no evidence of a long-run price relationship for two pairs of markets: Chimbiya-Lunzu and Nsanje-Chikwawa. For the two remaining market pairs, the bounds test results are inconclusive.

Table 6. ARDL Bounds Tests

	Chimbiya-Mchinji	Mitundu-Mchinji	Chimbiya-Mponela	Mitundu-Mponela	Chimbiya-Lunzu	Nsanje-Chikwawa	Chikwawa-Mulanje
F-Stat	8.91	3.60	4.63	14.74	1.08	2.24	6.74
Observations	141	143	126	127	144	119	113
I(0) bound							
10%	4.05	3.02	4.04	4.04	3.02	4.05	4.04
5%	4.68	3.62	4.94	4.94	3.62	4.68	4.94
I(1) bound							
10%	4.49	3.51	4.78	4.78	3.51	4.49	4.78
5%	5.15	4.16	5.73	5.73	4.16	5.15	5.73
Long-run relationship	**Yes**	**?**	**?**	**Yes**	**No**	**No**	**Yes**

Source: Authors' estimation.

The main ARDL estimation results are presented in Table 7, in which the long-run coefficients from the cointegrating equation together with the associated standard errors and p-values are reported. The error-correction coefficients are all negative (as would be expected) and are statistically significant for all market pairs except for Chikwawa-Mulanje. The size of the error correction terms for most of the markets indicate there is a relatively quick adjustment in the prices of maize between markets, except for Chimbiya-Lunzu and Nsanje-Chikwawa for which no LR relationship exists according to the bounds tests in Table 6. The long-run (LR) coefficients indicate a long-run relationship between prices that is close to one for the first three market pairs. For example, a 10 percent change in the price of maize in Mchinji will result in a long-run change of 9.9 percent in the retail price of maize in Chimbiya. For two of the remaining for market pairs, wide standard errors mean that the LR coefficient could be equal to one, while for Mitundu-Mponela, a maize price change of 10 percent in Mponela is associated with a 21 percent increase in maize prices in Mitundu. However, the extent of price adjustment for Chikwawa and Mulanje, is only 0.0018 indicating that only a small fraction of price changes in Mulanje are passed on to consumers in Chikwawa.

Table 7. ARDL results

Market pair	EC coefficient	Std-error	P-value	LR coefficient	Std-error	P-value
Chimbiya-Mchinji	-0.2304	0.046	0.000	0.9875	0.123	0.000
Mitundu-Mchinji	-0.1539	0.035	0.000	0.9809	0.242	0.000
Chimbiya-Mponela	-0.1276	0.041	0.002	0.9924	0.136	0.000
Mitundu-Mponela	-0.2428	0.052	0.000	2.1417	0.230	0.000
Chimbiya-Lunzu	-0.0398	0.022	0.067	1.4138	1.106	0.203
Nsanje-Chikwawa	-0.0411	0.013	0.002	1.4461	1.665	0.387
Chikwawa-Mulanje	-0.1441	0.037	0.000	0.0018	0.002	0.312

Source: Authors' estimation.

The size of the coefficients presented in Table 8, indicate that both current and past values of cash and food distributed have little impact on daily maize prices. All but one of these coefficients is statistically indistinguishable from zero, and the one exception (the coefficient on lagged cash transfers in Chikwawa) is so close to zero as to be economically unimportant. Furthermore, the p-values of the Wald-tests in the last column of Table 8 indicate that that the null hypothesis of equality to zero cannot be rejected for all market pairs except for the Chimbiya-Mponela pair. In Chimbiya-Mponela, the Wald tests can be reject at the 2 percent level but the individual coefficients on current day's and past day's food and cash distribution are so small as to be economically unimportant. Furthermore, these results are robust to several different specifications of the ARDL models. Given the scale of 2016-17 humanitarian response in Malawi, this finding is rather surprising: some possible explanations are discussed in the concluding section below.

Table 8. Effects of food distribution and cash transfers on daily prices

Market pair	Food (t) (SE)	Food (t-1) (SE)	Cash (t) (SE)	Cash (t-1) (SE)	Wald F Stat (p value)
Chimbiya-Mchinji	-0.0002	0.0001	0.0002	0.0000	0.7371
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.5683)
Mitundu-Mchinji	-0.0007	0.0006	-0.0003	-0.0001	0.4909
	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.7424)
Chimbiya-Mponela	0.0000	0.0001	0.0002	0.0001	3.1960**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0160)
Mitundu-Mponela	-0.0007	0.0005	0.0000	0.0003	1.7958
	(0.0006)	(0.0006)	(0.0004)	(0.0004)	(0.6960)
Chimbiya-Lunzu	0.0000	0.0002	0.0002	-0.0002	0.6868
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.6023)
Nsanje-Chikwawa	0.0000	0.0003	0.0006	-0.0004	0.2280
	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.9222)
Chikwawa-Mulanje	0.0002	-0.0002	0.0001	-0.0007*	1.9206
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.1124)

Source: Authors' estimation.
*Note: * and ** respectively indicate significance at the 10% and 5% levels.*

4. CONCLUSIONS

Overall our pricing analysis indicates that maize markets in Malawi are quite poorly linked, with only eight market pairs being connected in terms of Granger causality and seven pairs connected in terms of cointegration. Bivariate correlation coefficients are also generally low between markets. While our ARDL models track maize prices quite closely, bounds tests for long-run relationships between daily maize prices only held between three pairs of markets, with inconclusive results for two more market pairs.

There is evidence of a structural break having occurred between three-market pairs in mid-January to early February, which broadly corresponds to the introduction of maize vouchers in previous cash-only locations (WFP, 2017a). For these locations, which comprised about 18 percent of the total food response, the switch from cash to vouchers may have served to dampen maize prices during the peak lean season.[7] In addition, sharing of food and cash transfers by many beneficiaries, of which there is considerable qualitative evidence, will also have diluted the inflationary impact of cash transfers.[8]

What is particularly surprising, given that the volume of in-kind food transfers represented nine to ten percent of maize consumption requirements, is that food transfers had negligible impacts on daily maize prices in all but one of the markets considered. This is likely because in-kind beneficiaries–who WFP (2017b) report derived 67 percent of their maize consumption needs from food transfers and another 19 percent from own production–had little need to rely on maize purchases. In addition, because in-kind maize transfers were provided along with other commodities (cooking oil and pulses for all households, plus 'super-cereals' for households with children under two years old and/or pregnant and lactating women), there was less need for MVAC beneficiaries to sell some of the maize they received in order meet to their non-maize food needs. Similarly, those who received maize vouchers after the switch in January 2017, still received cash for their non-maize needs. Since most of the households who received in-kind food transfers or maize vouchers had extremely limited purchasing power, food transfers enhanced their direct entitlements, thereby reducing hunger and saving lives, while having little impact on markets and trade as only a small fraction of the maize distributed was sold.

Put differently, recalling Sen's (1981) distinction between direct and trade-based entitlements, most of the households who received in-kind food transfers had extremely limited purchasing power. Therefore, food transfers enhanced their direct entitlements, thereby reducing hunger and saving lives, while having little impact on markets and trade-based entitlements because so little of the maize distributed was sold.

7 Although cash transfers could, in principle, be spent on foods others than maize and even essential non-food items, WFP (2017a) found that most cash beneficiaries were spending more than the notional amount for cereals on maize alone.

8 See IFPRI (2017) and Margolies et al. (2017).

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APPENDICES

Table A1. Bivariate Correlation Coefficients for Key Market Pairs

A. Levels

	Chikwawa	Chimbiya	Lunzu	Mchinji	Mitundu	Mponela	Mulanje	Mwanza	Mzimba	Nsanje
Chikwawa	1									
Chimbiya	0.3196*	1								
Lunzu	0.3868*	0.8504*	1							
Mchinji	0.3947*	0.9084*	0.8581*	1						
Mitundu	0.3983*	0.7917*	0.7474*	0.8387*	1					
Mponela	0.2410*	0.8985*	0.8347*	0.8934*	0.8281*	1				
Mulanje	0.5766*	0.5530*	0.7268*	0.6800*	0.6730*	0.5575*	1			
Mwanza	0.2528*	0.5566*	0.5921*	0.7169*	0.7620*	0.7008*	0.6720*	1		
Mzimba	0.6043*	0.2598*	0.1510	0.2479*	0.4419*	0.5603*	0.9504*	0.6409*	1	
Nsanje	0.6029*	-0.0225	0.0864	0.0580	0.2753*	-0.0537	0.5672*	0.2745*	0.4943*	1

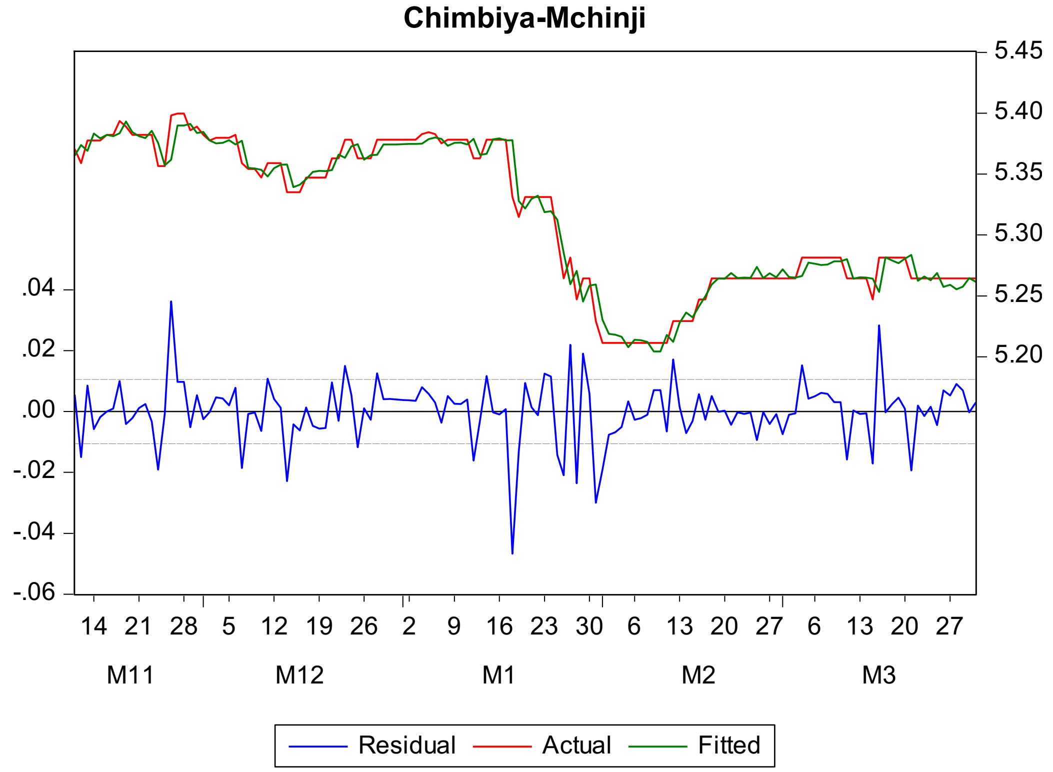
Source: Authors.
*Note: * indicates correlation coefficients significant at the 5% level*

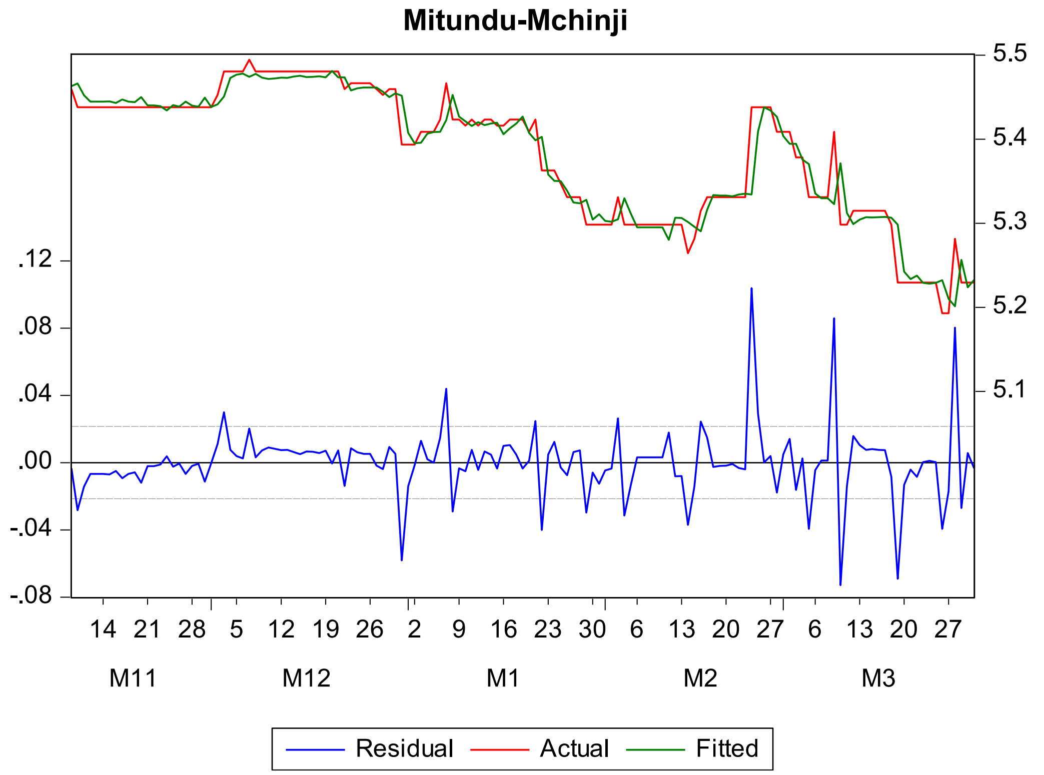
B. First differences

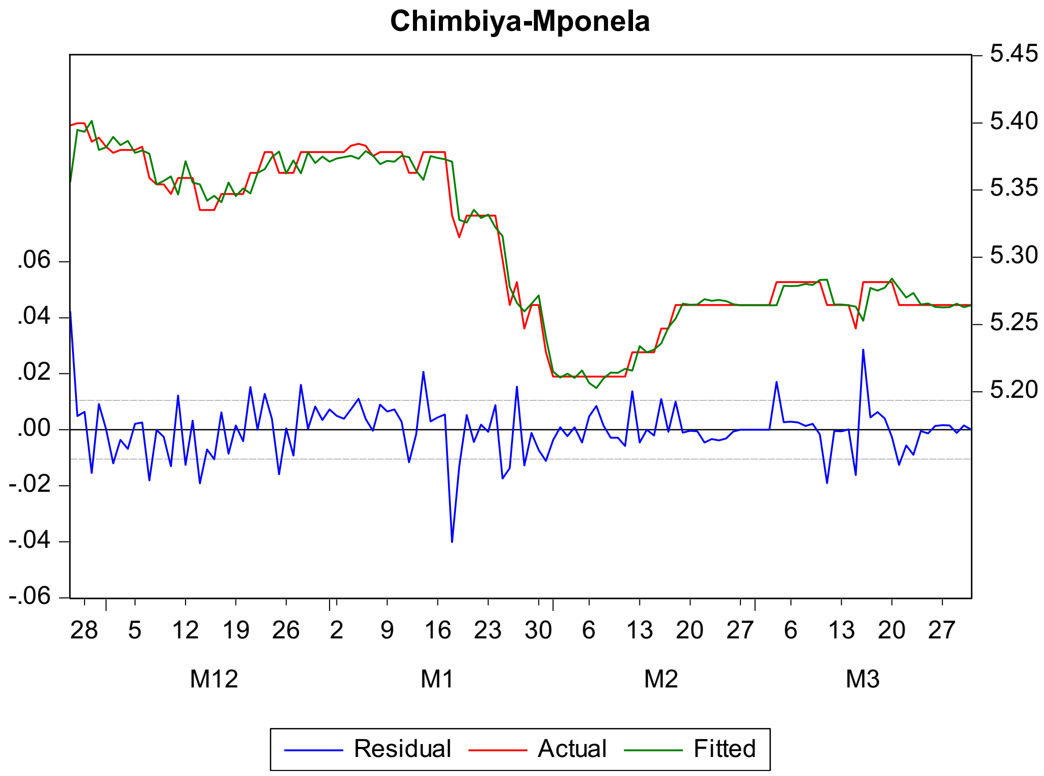
	Chikwawa	Chimbiya	Lunzu	Mchinji	Mitundu	Mponela	Mulanje	Mwanza	Mzimba	Nsanje
Chikwawa	1									
Chimbiya	-0.0796	1								
Lunzu	-0.0036	-0.0546	1							
Mchinji	0.0520	0.1057	0.1077	1						
Mitundu	-0.0174	-0.0032	0.0417	-0.0942	1					
Mponela	-0.0263	0.1133	0.0213	0.0224	0.0595	1				
Mulanje	-0.0083	0.0256	-0.0090	-0.0962	-0.1660	0.0007	1			
Mwanza	-0.0267	0.0316	-0.0044	0.0922	0.1014	-0.1244	0.1165	1		
Mzimba	0.0468	0.0295	-0.2210*	-0.0005	-0.0273	0.0707	0.1471	0.1723	1	
Nsanje	0.1329	-0.1224	0.0163	-0.0472	0.1626	0.0056	-0.0148	0.0129	-0.0409	1

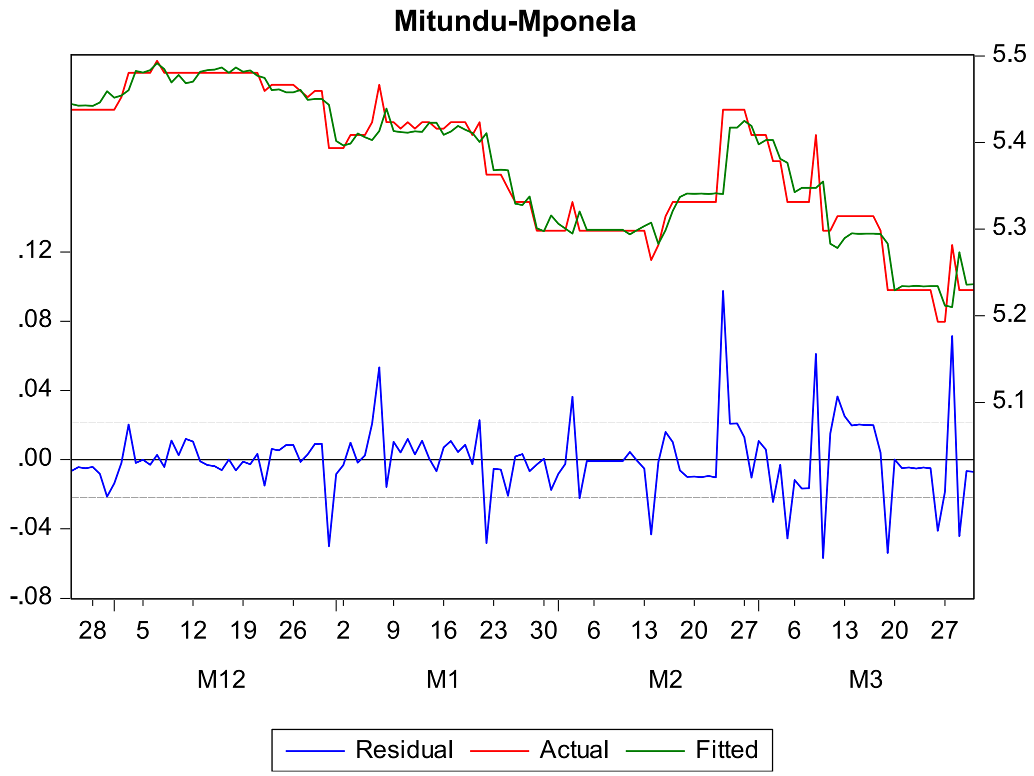
Source: Authors.
*Note: * indicates correlation coefficients significant at the 5% level.*

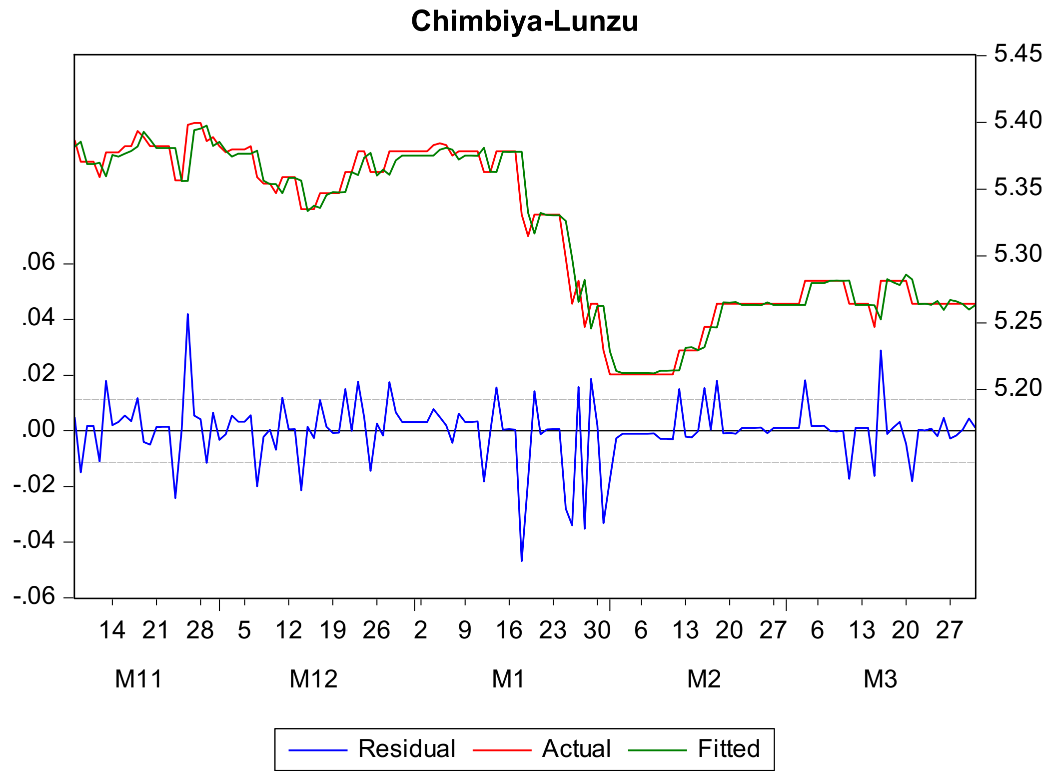
Figure A1. Actual/Fitted/Residual plots for key market pairs



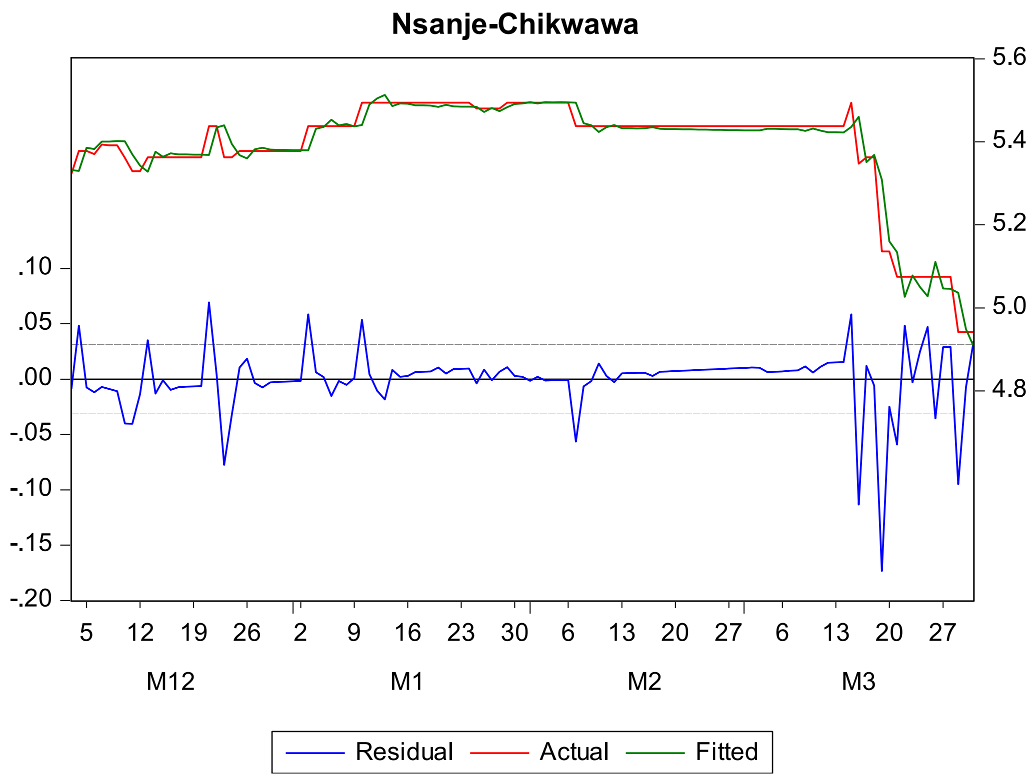



Chimbiya-Mponela
5.45
5.40
5.35
5.30
5.25
5.20
.06
.04
.02
.00
-.02
-.04
-.06
28 5 12 19 26 2 9 16 23 30 6 13 20 27 6 13 20 27
M12
M1
M2
M3
Residual
Actual
Fitted

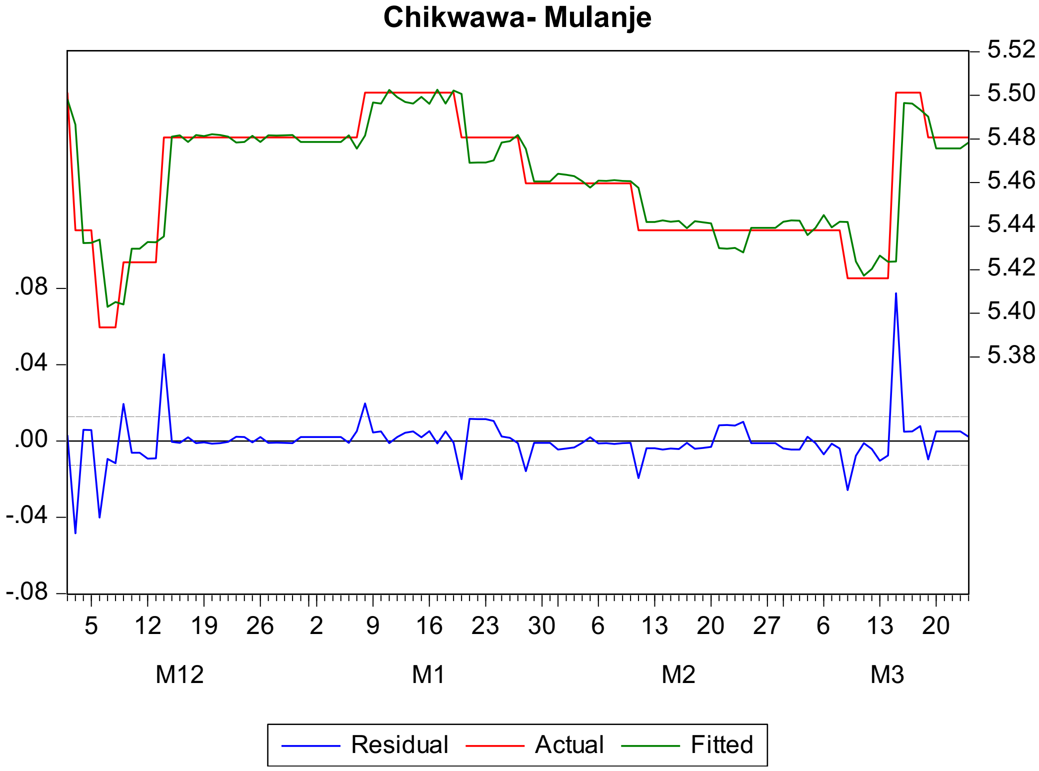

Mitundu-Mponela
5.5
5.4
5.3
5.2
5.1
.12
.08
.04
.00
-.04
-.08
28 5 12 19 26 2 9 16 23 30 6 13 20 27 6 13 20 27
M12
M1
M2
M3
Residual
Actual
Fitted



Chimbiya-Lunzu
5.45
5.40
5.35
5.30
5.25
5.20
.06
.04
.02
.00
-.02
-.04
-.06
14 21 28 5 12 19 26 2 9 16 23 30 6 13 20 27 6 13 20 27
M11 M12 M1 M2 M3
Residual Actual Fitted



Nsanje-Chikwawa
5.6
5.4
5.2
5.0
4.8
.10
.05
.00
-.05
-.10
-.15
-.20
5 12 19 26 2 9 16 23 30 6 13 20 27 6 13 20 27
M12 M1 M2 M3
Residual Actual Fitted



Source: Authors' estimation.

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