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Analysis of the effectiveness of modern information and communication technologies on maize marketing efficiency in Malawi markets

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ABSTRACT

In 2004, the government of Malawi introduced the Malawi Agriculture Commodity Exchange under the Initiative for Development and Equity in African Agriculture program, which promoted modern information and communication technologies (ICT) to improve access to agricultural market information for both suppliers and buyers of market produce. Using co-integration error correction models, this study assesses the effectiveness of modern ICT-based market interventions in improving maize market efficiency in Malawi. A Threshold Autoregressive Error Correction model was used to assess price transmission speed. Comparisons were made of the speed of price transmission in the periods before and after the introduction of ICT technologies by the Malawi Agriculture Commodity Exchange – Initiative for Development and Equity in African Agriculture in 2004. The spatial integration results show that maize markets in Malawi were better integrated following the introduction of ICT-based market interventions. Furthermore, the study results for pre- and post-ICT interventions shows that ICT-based market interventions positively influenced market integration and price transmission, contributing to a reduction of market search transaction costs which lead to improved maize marketing efficiency. Based on the results, increased investments to enhance the awareness and use of ICT-based market interventions and to improve market infrastructure in the country are recommended.

Keywords: **information and communication technologies (ICT), transaction costs, Threshold Autoregressive Error Correction model, price transmission, spatial integration**

1. AGRICULTURAL MARKETING IN MALAWI

In Malawi, agriculture plays a critical role both at macroeconomic and microeconomic levels. Despite this, agricultural markets do not work efficiently for smallholder farmers (Goletti & Babu 1994; Jayne et al. 2008). In late 1980s and early 1990s, like most African countries, Malawi implemented major policy changes under the Structural Adjustment Programs. During this time both the communication and agricultural sectors were liberalized. The liberalization of agricultural commodity markets was intended to facilitate improved functioning and effectiveness of rural markets and equip smallholder farmers with successful marketing instruments. However, this introduced a new marketing challenge – that of poor access to reliable and timely market information for smallholder farmers and increased asymmetry in the market information farmers have vis-à-vis that possessed by agricultural commodity traders. Since the lack of market information substantially increases transaction costs and reduces market efficiency (Barrett 2008), market liberalization in Malawi has not solved the problems of inefficient and unreliable agricultural output markets due to this information asymmetry where traders are able to influence prices in local markets (Goletti & Babu 1994; Jayne et al. 2008). Despite the challenges experienced in the liberalization of agricultural markets, the liberalization of the communications sector in 1994 resulted in the introduction of more FM radio stations, television, and mobile phone operators and the increased use of computers for internet and e-mail. This has resulted in increased usage of mobile and fixed telephones from 2.6 percent of the population using telephones in 2005 to about 27 percent in 2011 (GoM 2013). These ICT advances have brought about changes in the way business is conducted in Malawi by improving access for all to information, including agricultural market information.

The agricultural marketing sub-sector in Malawi is one of the sectors that has actively promoted the use of modern ICTs to enhance the dissemination of market information to farmers, traders, middlemen and all other market participants. In 2004, the government of Malawi introduced the Malawi Agriculture Commodity Exchange (MACE) under the Initiative for Development and Equity in African Agriculture (IDEAA). The initiative targeted smallholder farmers and other market players with market information through Short Messaging Services (SMS) to mobile phones, a website, radio programs, and displaying price information on chalkboards at Market Information Points (MIPs). The aim was to improve access to timely and reliable information using modern ICTs to foster improved market linkages. Among market participants, smallholder farmers were trained on how to access information using mobile phones, to actively participate in radio phone-in programs, and to visit and benefit from MIPs. This reduced the gap between those who can and cannot access information through ICTs in Malawi. Although the initiative aimed at improving access to markets and enhancing marketing efficiency among smallholder farmers, little is known of the extent to which the initiatives improved market efficiency in Malawi.[1]

Studies on market efficiency and market integration in Malawi have been done by Goletti & Babu (1994); Chirwa (2000); Sopo (2008); and Katengeza (2008). However these studies have mostly focused on market value chains, spatial and inter-temporal linear co-integration of market prices before and after introducing modern ICTs in agricultural marketing, and price margins after liberalization. Although the linear co-integration approach has been applied widely to assess agricultural commodity market integration in Malawi, the methodology has been criticized as being unreliable if transaction costs are non-stationary (Barrett 1996; Barrett & Li 2002) or if there are reversals in trade flows across markets (Barrett & Li 2002). Considering these challenges over the years, methodologies like threshold error correction models and parity bound models have been developed. These models capture transaction costs when assessing market efficiency.

In Malawi, information asymmetry among smallholder farmers coupled with high transport and search costs affects prices, resulting in inefficiency in agricultural markets (Jayne et al. 2008). Search methods rely principally on costly personal visits to producers and local markets by traders. Since agricultural production among smallholder farmers is low, consolidating sufficient quantities of a commodity for transportation and storage is also a challenge. Hence, many traders are unable to achieve returns to scale (Fafchamps & Gabre-Madhin 2006). Considering how transaction costs influence market prices, this study was done to understand how the spatial integration of nine maize markets in Malawi changed after improving access to market information for both producers and traders through modern ICTs in Malawi. For this analysis, the threshold autoregressive error correction model that factors in transaction costs was used. The selected regional maize markets examined are Karonga, Rumphi, and Mzuzu in Northern region; Lilongwe, Mitundu (Lilongwe district), and Lizulu (Dedza district) in Central region; and Lunzu (Blantyre district), Luchenza (Thyolo district), and Bangula (Nsanje district) in Southern Region. These markets were purposively targeted because the IDEAA-MACE program was working in and had well established MIPs in all of them after 2004.

Monthly retail nominal maize price data from January 1992 to December 2009 was used. These data were collected from local Ministry of Agriculture and Food Security (MoAFS) and IDEAA offices. The price series were used to assess maize market efficiency in the pre-ICT period (January 1992 to December 2003) and in the post-ICT period (January 2004 to December 2009). Where there were gaps in the price data, an extrapolation method was applied. Considering that

[1] Market efficiency ensures that market prices are right in all markets and at all times. Market prices are right if they are only differentiated by the transaction costs of moving goods between or among markets, as indicated by the Law of One Price.

nominal prices do not account for any price inflation, the Food Consumer Price Index[2] (CPI, year 2000 = 100) for Malawi was used to deflate nominal prices using the splicing method. The Food CPI was used, because maize has a weight of 60 percent in the Food CPI.

2. STUDY METHODOLOGY

To analyze spatial price integration and price transmission in these maize markets, error correction models were used. The Johansen vector error correction test was used to assess long-run bivariate co-integration markets. The Granger Causality test was used to identify causal relationships between integrating markets. The causal relationship was tested at three different levels, i.e., unidirectional, bidirectional, and independent. Based on the estimated co-integrating vectors between markets, an autoregressive error correction method was used to estimate price transmission adjustment factors. Since information services aim at improving price adjustments between markets, spatial price transmission was estimated and compared between the linear autoregressive (AR) and threshold autoregressive (TAR) error correction models. The models assume symmetric price transmission, but the direction of trade flow in the markets was determined by the Granger Causality test. In assessing market efficiency, these models were applied to compare those that consider transaction costs against the linear models that do not in the pre- and post-ICT periods, i.e., before and after 2004.

Standard linear autoregressive error correction model

The standard linear autoregressive error correction model can be expressed as follows.

$$P_{it} = \beta P_{jt} + \eta_t \qquad (1)$$

where P_{it} is the retail price of a given quantity at time t and at location i; P_{jt} is the retail price of a given quantity at time t and at location j; β are parameters to be estimated; and η_t is the error terms, *iid* $\sim N(0, \sigma)$. The error term η_t is used to define the error correction model, since integration of P_{it} and P_{jt} depends on the behavior of the error term. That is, η_t is referred to as the deviation between prices in the two different markets. When β=1, the deviation η_t becomes non-stationary, leading to no integration between the price series. Thus, co-integration depends on the autoregressive behavior of the deviation (η_t) (Uchezuba 2005).

The estimation of the price adjustment is based on how the deviation ($\eta_t = P_{it} - P_{jt}$) at time t corresponds to the price difference in the previous period, as presented in equation (2).

$$\Delta\eta_t = \rho\eta_{t-1} + \omega_t \qquad (2)$$

where $\eta_t = P_{it} - P_{jt}$ is the price spread between markets at period t; Δ is the first difference operator and $\Delta\eta_t$ is difference in price spreads $\eta_t - \eta_{t-1}$; ρ is the coefficient; and ω_t is the zero-mean serially uncorrelated error term. Linear autoregressive error correction was used to assess price transmission between maize market prices in pre- and post-ICT periods. Using equation *(2)*, the estimated ρ shows the adjustment parameter on the lagged price difference. It indicates the extent to which price differences in the previous period are 'corrected' back to the equilibrium price. The model was applied in both the pre- and post-ICT periods.

Threshold autoregressive error correction model

The applied standard linear autoregressive error correction method is known to be restrictive for investigating spatial maize price transmission. To analyze symmetrical price adjustment further, the study used the threshold autoregressive (TAR) error correction model. This was compared with the standard linear autoregressive (AR) model in pre- and post-ICT periods. Assuming that η_t from equation (1) follows a threshold autoregressive behavior, spatial price transmission in long-run equilibrium under competitive behavior is given as follows (Myers 2008):

$$|P_{it} - P_{jt}| < c \qquad \text{If } q = 0 \text{ (Regime 1)} \qquad (3)$$

$$P_{it} - P_{jt} = c \qquad \text{If } q > 0 \text{ (Regime 2)} \qquad (4)$$

$$P_{it} - P_{jt} = -c \qquad \text{If } q < 0 \text{ (Regime 3)} \qquad (5)$$

where P_{it} is the price in market i at time t; P_{jt} is the price in market j at time t; and q is the quantity of commodity traded between the markets in both (two-way) directions. If q > 0, the commodity is traded from market i to j. If q < 0, the commodity is traded from market j to i. c is the marginal transfer cost and is assumed to be symmetric irrespective of the direction of trade flow.

The first regime occurs when there is no trade between markets, so the absolute value of the price spread should be less than the transfer cost. The second regime implies that if trade flows from i to j, then the price in j market should be equal to the price in i plus the transfer cost. The third regime indicates that if trade flows from j to i, then the price in i market

[2] The CPI data was sourced online from the National Statistical Office: http://www.nsomalawi.mw/latest-publications/consumer-price-indices.

should be equal to the price in *j* plus the transfer cost (Myers 2008). To test these regimes, the threshold autoregressive error correction model was used. This model allows for deviations from market efficiency conditions to occur. Following Myers (2008), the threshold autoregressive error correction model can be presented as:

$$\Delta\eta_t = \alpha + \beta_0\eta_{t-1} + \sum_{k=1}^{K}\beta_k\Delta\eta_{t-k} + \varepsilon_t \qquad \text{If } |\eta_t| \le c_t \text{ (Regime 1)} \qquad (6)$$

$$\Delta(\eta_t - c_t) = \alpha(\eta_{t-1} - c_{t-1}) + \sum_{k=1}^{K}\alpha_k\Delta(\eta_{t-k} - c_{t-k}) + \varepsilon_t \qquad \text{If } \eta_t > c_t \text{ (Regime 2)} \qquad (7)$$

$$\Delta(\eta_t + c_t) = \alpha(\eta_{t-1} + c_{t-1}) + \sum_{k=1}^{K}\alpha_k\Delta(\eta_{t-k} - c_{t-k}) + \varepsilon_t \qquad \text{If } \eta_t < -c_t \text{ (Regime 3)} \qquad (8)$$

Where $\eta_t = P_{it} - P_{jt}$ is the price spread between markets at period *t*; Δ is the first difference operator, $\Delta\eta_t = \eta_t - \eta_{t-1}$; c_t is the long run transfer cost at *t*; and ε_t is the zero-mean serially uncorrelated error term. There is a non-linearity at the threshold which allows the price spread to display different behavior inside versus outside a 'parity bound' defined by the long run transfer costs. To evaluate the effectiveness of spatial price transmission, the primary interest is in regime 1 and the size of the parity bound, and in regime 2 and the behavior of price spreads when they are outside the bounds. In particular, if the spreads deviate from the parity bound, the point is to know how long it takes for them to return to the bound.

Use of the threshold error correction model can be straightforward if the price spread and transfer cost data are observable. However, the data used here does not have transfer costs as separate data. Consequently, an auxiliary model for long run transfer costs, c_t, which captures trends and variations over time can be used. The long run transfer cost threshold is calculated as:

$$c_t = \delta_0 + (\delta_1 - \delta_0)\frac{t}{(T-1)} + \delta_2 p_{it} \qquad (9)$$

where *t* is the time index *t* = 0,1,2,……, T-1; and *T* is the total number of price observations. P_{it} is the price in market *I* at time *t*.[3] The price variable of market *i* (ρ_{it}) is included to allow for the fact that some marginal transfer costs may vary with the price of the product.[4] This model may not capture all of the short run movements in transfer costs, but should capture long run changes and trends. That is, if the estimate of the threshold long run transfer cost, c_t, from the model is a reasonable estimate of actual average transfer cost between the markets, then the results suggest long run efficient, competitive trade activity between the markets.

To evaluate effectively spatial price transmission, the focus is on regimes 1 and 2. In regime 1 (the price spread is inside the parity bound), trade flow should be zero (Myers 2008). This implies that movements in the price spread follow an arbitrary stochastic process that depends on autarky supply and demand conditions in the two markets and not on transfer costs. It might be expected that $\alpha \approx \beta_0 \approx 0$, which would imply that price spread inside the parity bound follows a random walk without drift (i.e. price spread changes randomly inside the parity bound).

For regimes 2 and 3 (outside the parity bound), price transmission is not fully efficient because there should be an incentive to increase trade flow until the price spread returns to the parity bound. This means that for effective spatial price transmission, we cannot have $\alpha \ge 0$ (because then η_t and c_t would be unrelated in the long run and there would be no tendency for spatial price spreads to return to the parity bound). This sufficient condition for ineffective spatial price transmission, i.e., $\alpha \ge 0$, is testable (Myers 2008).

Thus, if $\alpha < 0$, there is a long run equilibrium relationship between η_t and c_t, and the size of α determines the spread of adjustment of the price spread back to the parity bound. Furthermore, when $\alpha = -1$ and $\delta_k = 0$ for $k = 1, 2, \ldots\ldots, K$, it would imply immediate adjustment, although the price spread never moves systematically outside the parity bound. For values of α between 0 and -1, the closer α is to 0, the slower the adjustment, while the closer α is to -1, the faster the adjustment. If the adjustment is fast, it implies more effective spatial price transmission.

Although the value of α gives the rate of price adjustment, it does not show the value of adjustment. Therefore, a measure that helps interpret the spread of adjustment of price spreads back to the parity bound in regimes 2 and 3 is referred to as the half-life (*h*).

$$h = \ln(0.5) / \ln(\alpha - 1) \qquad (10)$$

[3] If $\delta_2 = 0$, then δ_2 is the long run transfer cost at the beginning of the sample and δ_1 is long run transfer cost at the end of the sample, after allowing for a linear time trend.

[4] Particularly for costs related to revenue rather than volume, such as credit costs or volume discounts.

The half-life is the time it takes for trade to increase and drive the price spread halfway back to the parity bound, when there is a supply or demand shock that raises price spread above the parity bound. This assumes that there is no other shock within the period of adjustment. If the half-life is shorter, it implies more effective price transmission (Myers 2008).

3. RESULTS AND DISCUSSION

Spatial integration of nine markets in Malawi was analyzed using monthly real maize retail price data from January 1992 to December 2009 valued in Malawi Kwacha (MK)[5]. From the co-integrating markets, price transmission analysis was compared in pre- (January 1992 to December 2003) and post-ICT (January 2004 to December 2009) market intervention periods. Agricultural production is mainly done in one rainy season in Malawi with harvest in the March to June period. This results in agricultural prices exhibiting a seasonal distribution, with additional variations due to other factors like natural disasters and changes in transport and marketing infrastructure, among others. To understand the data, descriptive analysis of the price series was done over the pre- and post-ICT periods.

Lilongwe and Lunzu markets had the highest real market prices in the pre-ICT period with averages of MK 28.99 (US$ 0.19) and MK 26.96 (US $0.18) per kilogram of maize grain, respectively. From the estimated coefficient of variation, prices in all markets had a variation of between 34 and 57 percent. In the post-ICT period, Luchenza and Bangula markets had the highest observed average market prices of MK 95.45 (US$ 0.63) and MK 94.84 (US$ 0.62), respectively.

Trend analysis and stationarity tests were done for the period January 1992 to December 2009. The trend analysis for monthly real prices showed positive signs in all markets. This implies that maize market real prices have been increasing over time in all the specified markets. Further, trend factors had influence of more than 33 percent but less than 55 percent on changes in the real prices of maize as shown by the R-squared of the trend equation. Hence, trend factors were significant in the specified period (Goodwin 1994).

The data on real maize prices from 1992 to 2009 was tested for stationarity as a pre-condition for co-integration analysis using the Augmented Dickey Fuller (ADF) method. The appropriate lag length was selected based on the resultant Akaike Information Criteria (AIC). Considering the significance of trends in maize market, the stationarity test was done both with and without trend entered as a time variable. The results showed that the analysis without trend had almost all price series being integrated of order zero I(0) at the 5 percent significance level, except for Rumphi, Mzuzu, and Lilongwe. Considering the significance of price trends, the results with trend indicate that all markets were stationary or integrated of order zero I (0) at the 5 percent significance level. This implies that all market series were stationary when the trend factor is included in the analysis. Following Rashid (2004), further co-integration analysis included markets with the same order of integration. Thus, all markets were included in the co-integration analysis with trend.

Long-run co-integration

The approach for testing the integration of spatially separated markets is based on the fact that deviations from equilibrium conditions of two non-stationary variables should be stationary. This implies that, while price series may wander extensively, pairs should not diverge from one another in the long run (Abdulai 2006). The bivariate co-integration analysis used the eigenvalue and trace statistic in the Johansen vector error correction model to test the spatial integration of two markets based on their maximum co-integrating rank (*r*). The long-run bivariate co-integration was done for the whole period to determine the co-integrating markets in the sample. Table 1 shows the results.

Table 1—Bivariate co-integration coefficients of maize markets

Market	Karonga	Rumphi	Mzuzu	Mitundu	Lilongwe	Lizulu	Lunzu	Luchenza	Bangula
Karonga	--								
Rumphi	31.262 *	--							
Mzuzu	30.323 *	11.149	--						
Mitundu	32.229 *	15.311	13.770	--					
Lilongwe	11.746	15.115	21.314 *	35.370 *	--				
Lizulu	19.128 *	23.704 *	15.391	44.254 *	17.022	--			
Lunzu	21.363 *	17.798	16.845	23.990 *	9.723	19.172 *	--		
Luchenza	25.164 *	20.426 *	16.769	22.735 *	13.232	20.192 *	11.548	--	
Bangula	19.358 *	10.938	11.868	14.931	16.587	12.520	26.425 *	24.820 *	--

Note: The asterisk * show the co-integrating relationship between markets *i* and *j* at a 5 percent statistical significance level. An integrating link *(r = 1)* is the one in which the trace statistic value is greater than the critical value. The critical value at the 5 percent significance level is 18.17.

[5] At the time of research in 2010, US$1.00 was equivalent to MK 152.00. Historical Exchange Rates for the Malawi kwacha can be found at http://www.rbm.mw/stats_financials.aspx.

Within the regions, the bivariate co-integrating markets are Karonga with Rumphi and Mzuzu in the north; Mitundu with Lilongwe and Lizulu in Central region; and Bangula with Lunzu and Luchenza in the south. This implies that markets in each region were integrated.

Causal relationship between co-integrating markets

Co-integration of markets is an indicative measure of non-segmentation between two price series. It is a good tool to show the existence (or not) of any relation between two economic time series. Based on the co-integrating markets, the analysis allows for a causality test to determine whether there is a causal relationship between markets (Goletti & Babu 1994). Using the Granger Causality test, Table 2 shows the causal relationship between co-integrating markets for the whole period considered.

Table 2—Granger causality relationship between co-integrating markets

Market *i*	Market *j*	F_1	Prob > F_1	F_2	Prob > F_2	Direction of causality
Karonga	Rumphi	1.470	0.228	5.776	0.017**	**Unidirectional**
	Mzuzu	1.662	0.199	2.429	0.120	Independent
	Mitundu	6.520	0.011**	0.272	0.603	**Unidirectional**
	Lizulu	2.179	0.142	0.162	0.688	Independent
	Lunzu	0.130	0.719	0.086	0.769	Independent
	Luchenza	0.007	0.930	0.732	0.393	Independent
	Bangula	9.852	0.002***	0.003	0.954	**Unidirectional**
Rumphi	Lizulu	3.105	0.080*	0.128	0.720	**Unidirectional**
	Luchenza	8.348	0.004***	0.351	0.554	**Unidirectional**
Mzuzu	Lilongwe	0.125	0.723	0.281	0.596	Independent
Mitundu	Lilongwe	0.419	0.518	9.721	0.002***	**Unidirectional**
	Lizulu	1.042	0.309	2.564	0.100*	**Unidirectional**
	Lunzu	0.589	0.444	0.388	0.534	Independent
	Luchenza	1.574	0.211	0.548	0.460	Independent
Lizulu	Lunzu	6.119	0.014***	0.026	0.872	**Unidirectional**
	Luchenza	0.169	0.681	1.879	0.197	Independent
Lunzu	Bangula	2.318	0.129	0.105	0.745	Independent
Luchenza	Bangula	0.478	0.490	0.718	0.398	Independent

Note: Values with asterisk (*) show granger causality. That is, Prob > f is higher at 1 (***), 5 (**), or 10 (*) percent statistical significance levels, and we fail to accept the null hypothesis. H_o: $F_1 \neq 0$ (Market *j* does not Granger cause market *i*); H_o: $F_2 \neq 0$ (market *i* does not Granger cause market *j*)

From the table, there are eight unidirectional causal relationships, with the rest being independent relationships. In the regional markets, Karonga was observed to Granger cause Rumphi market, but there was an independent causal relationship between Karonga and Mzuzu. Since Karonga mainly produces rice, it cannot Granger cause Mzuzu market, which is an urban market. At the same time, Mzuzu did not Granger cause Karonga market.

Symmetric spatial price transmission

Co-integration and Granger causality test shows the co-movement of prices and the direction of causality, respectively. However, the analysis is not sufficiently powerful to highlight how strong the relationship is between the two markets and how long it takes for a shock to be transmitted from one market to another (Goletti & Babu 1994). Assuming symmetric price transmission, the analysis used the co-integrating markets with unidirectional causality method to estimate price transmission. Using both the standard AR and TAR error correction models, the analysis compared price transmission in pre- and post-ICT periods in Malawi to assess the effectiveness of modern ICTs in the post-ICT period to better integrate maize markets in Malawi. The models were estimated without a constant. The results on price adjustment factors and half-life (in weeks) are presented in Table 3. The TAR model is a three regime symmetric model with unit root behavior imposed within the band formed by the thresholds. The thresholds are estimated through a grid search.

The results for the pre-ICT period shows that the fastest significant price adjustment factor was observed for the Rumphi – Luchenza market link both in the AR and the TAR models. The adjustment factor of 0.05 in the AR model implies that it took 13.5 weeks for half of the price shock to return to the equilibrium price. In the TAR model, the estimated adjustment factor of 0.07 implies that it took 9.7 weeks for half of the price shock to return to the equilibrium neutral price band. In the TAR model, the estimated transaction cost was 3.2 percent of the mean price in the markets. This indicates that the price adjustment speed is faster in the TAR model, because it considers the threshold where there is no price adjustment.

The fastest significant price adjustment in the post-ICT period was observed in the Mitundu – Lizulu market link. In the standard AR model, the adjustment factor was 0.186, which implied a half-life of 3.4 weeks. This means that, when transaction costs are not considered in estimating the speed of price adjustment, it takes 3.4 weeks for half of the price shock to return to the equilibrium price. In the TAR model, the significant adjustment factor was 0.209 percent, which implied a half-life of 2.9 weeks. The estimated half-life shows that it took 2.9 weeks for a price shock in Mitundu market to return halfway back to the parity bound or threshold that covers transaction costs (Myers 2008). The estimated threshold was 1.94 percent of the mean price. This implies that influencing factors that reduce transaction costs also influence the speed of price adjustment if there is a shock in the markets. As indicated by Van Campenhout (2007) and Goodwin & Piggott (2001), TAR models are more appropriate in estimating price adjustment because they represent the amount that proportional price differences must exceed to cross the threshold and trigger the ‘outside-band’ regime adjustments. Except for the Mitundu – Lizulu link and the Lizulu – Lunzu link, all the other co-integration market combinations show significant price adjustment factor of approximately 0.30, implying half-lives of between 22.8 and 27.4 weeks in the standard AR model.

As indicated by Abdulai (2000), in developing countries vast distances and poor infrastructure lead to high transaction costs for market participants, thereby making arbitrage unprofitable and isolating markets. These transaction costs may lead to a neutral band within which prices are not linked to one another. Therefore, the TAR models are appropriate because price equalizing arbitrage is triggered only when shocks result in price differences that exceed the neutral band, in contrast to the AR models that do not consider transaction costs. This agrees with Goodwin & Piggott (2001), who observed that threshold models suggest much faster adjustments in response to price deviations from equilibrium price band than in cases where thresholds are ignored. Since vast distances and poor infrastructure lead to high transaction costs, especially in developing country, TAR models are appropriate in estimating price adjustment in such contexts.

Table 3—Price adjustment factors in AR and TAR error correction models

		Pre-ICT					Post-ICT				
		AR Model		TAR Model			AR Model		TAR Model		
Market pair	Distance (km)	ρ	Half-life (wks)	δ	ρ	Half-life (wks)	ρ	Half-life (wks)	δ	ρ	Half-life (wks)
Karonga – Rumphi	176	-0.029*** (0.010)	23.6	2.533	-0.043*** (0.009)	15.8	-0.148*** (0.025)	4.3	3.006	-0.189*** (0.023)	3.3
Karonga – Mitundu	620	-0.030*** (0.010)	22.8	3.107	-0.041*** (0.009)	16.6	-0.065** (0.033)	10.3	2.878	-0.078** (0.034)	8.5
Karonga – Bangula	804	-0.078*** (0.018)	8.5	4.038	-0.124*** (0.015)	5.2	-0.069* (0.026)	9.7	3.572	- 0.084* (0.024)	7.9
Rumphi – Lunzu	545	-0.025*** (0.005)	27.4	3.960	-0.034*** (0.006)	20.0	0.057 (0.041)	11.8	3.392	0.069 (0.045)	9.7
Rumphi – Luchenza	821	-0.050*** (0.106)	13.5	3.167	-0.069*** (0.115)	9.7	-0.004 (0.024)	173.0	4.421	-0.009 (0.026)	76.7
Mitundu – Lilongwe	30	-0.030*** (0.010)	22.8	4.129	-0.045*** (0.012)	15.1	-0.120*** (0.039)	5.4	3.556	-0.142*** (0.041)	4.5
Mitundu – Lizulu	90	-0.014*** (0.006)	49.2	1.740	-0.019*** (0.007)	36.1	-0.186*** (0.060)	3.4	1.944	-0.209*** (0.062)	2.9
Lizulu – Lunzu	201	-0.024*** (0.008)	28.5	2.182	-0.035*** (0.009)	19.5	-0.001 (0.036)	692.8	1.651	-0.003 (0.037)	203.7

Note: ρ denotes the adjustment parameter on the lagged price difference (expressed as a percentage of mean prices in the two markets), and δ is the estimated threshold, expressed as a percentage of the mean price in the two markets. Figures in parenthesis are standard errors. *** and ** denote significance levels at 1 percent and 5 percent, respectively. The unit for the half-life parameter is weeks.

Considering that the availability of information reduces transaction cost by reducing search cost, the analysis compared the TAR models in pre- and post-ICT periods in order to assess the effectiveness of modern ICTs in the post-ICT period. The analysis used the market links that were significant in the pre- and post-ICT periods. From Table 3, the co-integrating links that were significant in both periods were Karonga-Rumphi; Karonga-Mitundu; Karonga-Bangula; Mitundu-Lilongwe, and Mitundu-Lizulu.

For the pre-ICT Karonga-Rumphi market link, the estimated price adjustment factor of 0.043 implied a 15.8 weeks half-life and estimated threshold of 2.5 percent of the mean maize price. In the post-ICT period, the estimated price adjustment factor of 0.189 indicated 3.3 weeks half-life and estimated threshold of 3.0 percent of the mean price. This shows that in the post-ICT period, prices in these two markets were adjusting faster than before. For the Mitundu-Lizulu market link, price adjustment was also faster in the post-ICT period with a half-life of 2.9 weeks, compared to a half-life of 36.1 weeks in the pre-ICT period. The Mitundu-Lilongwe market link also shows faster price adjustment in the post-ICT period using the TAR models. With a price adjustment parameter value of 0.045 in the pre-ICT period, it took 15.1 weeks for half of the price shock in Mitundu to be adjusted in the Lilongwe market with an estimated threshold of 4.1 percent of the mean price. In contrast, in the post-ICT period, it was taking only 4.5 weeks for a price shock to be adjusted from Mitundu to Lilongwe, with an estimated threshold of 3.6 percent of the mean price. Similarly, the integration between Karonga and Mitundu markets, located over 600 km apart, shows faster adjustment in the post-ICT period than in the pre-ICT period. The only market pair in which improvements in price adjustment were not seen in the post-ICT period is the Karonga-Bangula pair, one of the most distant market pairs considered in this study.

Broadly, these findings show that the increased availability of information assists in reducing transaction costs and increases the speed by which prices adjust even in relatively distant markets (Jensen, 2007; Katengeza, 2008). Thus, improving information services influenced transaction costs, thereby improving market efficiency and participation. Overall, these results indicate that the introduction of modern ICTs effectively improved maize marketing efficiency in Malawi.

However, although the price adjustment was faster in the post-ICT period, the adjustment was not instantaneous. This implies that reduction in transaction costs is not only a factor of reducing the search cost or reducing information asymmetry, but a combination of several other factors as well. As observed by Myers (2008), price transmission not being instantaneous might be because (i) TAR models measure deviations from long-run transfer costs, but not unmeasured short-run deviations from long-run levels, like might results from a temporary increase or decrease in fuel costs; (ii) that it is possible that some transport routes between markets become temporarily impassable due to weather; and (iii) trade volumes become high enough that the transportation system reaches a capacity constraint. Thus, higher cost alternative routes are used, which increase transfer costs above their long-run equilibrium level and increase price spreads. These scenarios would indicate an efficient response to a temporary increase in transfer cost that is not reflected in long-run transfer costs. Therefore, the slow adjustments might be a result of other transportation and transaction costs being imposed on maize trade between the markets being considered.

4. CONCLUSIONS AND POLICY RECOMMENDATIONS

The main objective of this study was to analyze the effectiveness of ICT-based market interventions on maize marketing efficiency in Malawi. The focus was on the use of modern ICTs for improved market efficiency among spatially separated maize markets in Malawi. Assuming symmetric price adjustment, the spatial price adjustment analysis results show that adjustment was faster in Threshold Autoregressive models than in Linear Autoregressive models. This signifies that transaction costs are significant in estimating spatial price linkages. Comparing threshold models in the pre- and post-ICT periods, the analysis showed that estimated thresholds were lower in the post-ICT period and that it took fewer weeks for a shock to return half-way back to parity bound. Therefore, the results can be interpreted to indicate that modern ICT-based market interventions resulted in a reduction in search transaction costs, thereby improving maize marketing efficiency in the post-ICT period. However, although price adjustments were faster in the post-ICT period, adjustments were not instantaneous. This can be attributed to, among other factors, changes in transportation costs and market charges related to volumes of trade.

Considering the importance of reducing transaction costs for improving market integration and market efficiency, the study recommends increasing and enhancing the use of modern ICTs in agricultural markets in Malawi, especially by farmers. There is a need to enhance dissemination of modern ICTs to all producers in order to equip then with timely marketing information. Further, there is a need to improve the market infrastructure to complement efforts made to reducing market information asymmetry between farmers and traders. The study looked at spatial integration and price transmission for nine selected markets using the standard linear and threshold autoregressive error correction models. It also assumed symmetric price transmission and constant thresholds throughout the study period. Future studies might apply parity bound models and threshold vector error correction models that take into account asymmetric price transmission and estimate thresholds that vary over the period of study. Others studies can also compare price transmission between markets where chalkboard and internet based Market Information Points are fully established against where general modern ICTs tools like radio, newspaper and mobile SMS messaging for market information provision are not being promoted.

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