143- Analysis of Effectiveness of Modern Information and Communication Technologies on Maize Marketing Efficiency in Selected Markets of Malawi

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ABSTRACT

Developing countries have been promoting initiatives that aim at reducing information asymmetry among market players especially smallholder farmers. Using co-integration error correction models, the study assessed effectiveness of modern Information and Communication Technologies (ICT) based market interventions in improving maize market efficiency in Malawi. Considering that efficient markets are integrated markets when price difference is only a factor of transaction costs, Threshold Autoregressive Error Correction (TAR) model assessed price transmission speed in pre – ICT and post – ICT periods in order to analyse effectiveness of modern ICTs. The spatial integration result shows that markets in Malawi were integrating. The results of TAR models in pre and post ICT periods shows that ICT based market interventions have positively influenced market integration and price transmission. Thus, modern ICTs have contributed to the reduction of search transaction costs leading to improved maize marketing efficiency. Based on the results, the study recommends the need to increase awareness of ICT based market interventions to all gender groups and improve market infrastructure in the country.

Keywords: ICT-based intervention, Threshold Autoregressive Error Correction, market integration, maize, Malawi

1.0 INTRODUCTION

Price and market signals are key instruments that facilitate coordination involved in resource allocation. Price information helps market participants to make effective decisions on production and consumption (Abraham, 2007). In well-functioning markets, prices serve to aggregate information dispersed among market participants (McMillan, 2002). This means that in a marketing system, price information serves as a feedback mechanism that coordinates the actions of market participants. Thus, efficiency in marketing would be shown by market integration through transaction costs indicated by the price differences in markets.

In agriculture, information is vital as it empowers farmers with bargaining power for better prices in the market. Information also brings stability in product supplies and prices in time and space thereby reducing transaction costs in input and output markets (Mukhebi *et. al.*, 2007). Stiglitz (1989) showed that imperfect information or absence of information impeded market entry and in extreme cases, markets cease to exist resulting in market inefficiency. This has the effect of lowering farm gate prices in surplus areas, resulting in reduced incomes for farmers and raising consumer food prices in deficit areas. Shepherd (1997) indicated that market information can be particularly valuable where countries are changing over from a state-controlled marketing system to one of private enterprise, in that farmers and small traders are made more aware of market opportunities. This implies that market efficiency should ensure that market prices are right in all markets and at all times i.e. prices are only differentiated by transaction cost between or among markets as indicated by the Law of One Price.

To ensure effective transmission of market information current efforts have focused on Information and Communications Technologies (ICTs). ICTs include broadcasting and internet clusters or interrelated systems of technological innovations in the field of microelectronics computing and electronic communications (Preston, 2003). ICTs have proven revolutionary in nature as far as creation, distribution, dissemination and repackaging of information and sharing of knowledge is concerned (Britz, *et. al.*, 2006). Basically, ICTs are a means of passing information from one person to the other using some technology; be it written, electronic or verbal. The modern ICT tools include newspapers, radio, telephone, fax, cell phone, market information centres (MIP) and computers (e-mail and internet) while the non-modern cover individual personal sharing of information. With ICT, available information can be stored, processed and transmitted easily and quickly thereby enhancing agricultural market efficiency.

Agricultural markets have for long not worked for the poor in Malawi despite agricultural sector being the engine of economic growth and requiring effective and efficient markets (Goletti and Babu, 1994 and Jayne *et. al.*, 2008). High productivity and access to efficient and better paying markets are important in enhancing the livelihood of the rural poor (Mukhebi *et. al.*, 2007). In late 1980s and early 1990s Malawi, like most African countries, implemented major policy changes under the structural adjustment programs. Both the communication and agricultural sectors were liberalized. The liberalization of agricultural commodity markets was intended to facilitate the functioning and effectiveness of rural markets. The liberalization, was also intended to equip smallholder farmers with successful marketing instruments and the ability to obtain market intelligence (information) so as to make rational decisions regarding crops to produce and markets to sell the product (McCrystal, 2007).

The liberalization has however introduced new marketing challenges such as poor access to reliable and timely market information or market information asymmetry especially among smallholder farmers. Since the lack of market information substantially increases transaction cost and reduces market efficiency (Barrett, 2008), in Malawi liberalization has led to poor access to timely and reliable markets as a result of information asymmetry where traders influence prices in local markets (Goletti and Babu, 1994 and Jayne e*t. al.*, 2008). Despite the challenges experienced from liberalized agricultural markets, the liberalization of the communications sector in 1994 has resulted in the introduction of more Frequency Modulation (FM) radio stations, television, mobile phone operators and the use of computers for internet and e-mail. This has allowed the underdeveloped and excluded areas and villages to have access to information including agricultural market information (GoM, 2006).

The agricultural marketing sector in Malawi is one of the sectors that has actively promoted the use of these modern ICTs to enhance the dissemination of market information among farmers, traders, middlemen and all other market participants. The development of institutions like Initiative for Development and Equity in African Agriculture (IDEAA) in 2004, for smallholder farmers and other market players, was aimed at improving access to timely and reliable information using modern ICTs leading to accessing efficient markets. These institutions are also helping to link producers, middlemen and consumers in agricultural markets through modern ICTs. Among market participants, smallholder farmers are trained on how to access information using mobile phones, actively participate in radio phone-in programs and visit MIPs. Smallholder farmers are also linked with potential buyers using these modern ICTs. Today the gap between those who can and cannot access ICT has been reduced. These initiatives aim at improving access to market and enhance marketing efficiency among smallholder farmers but little is known on the extent of the initiatives in improving the efficiency of markets in Malawi.

Many studies *(see Golleti and Babu, 1994; Chirwa, 2000; Sopo, 2008, Katengeza, 2008)* have been done on market efficiency in Malawi mainly using linear co-integration methods which have been criticized as being unreliable if (1) the transaction cost are non-stationary (*see Barrett, 1996; Barrett and Li, 2002*) and (2) if there are reversals in trade flows across markets (Barrett and 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. Considering how transaction cost influence prices in developing countries, this study was done to understand spatial market integration of maize markets in Malawi using models that factor in transaction cost. This paper uses threshold autoregressive error correction model to examine the relationship between 9 regional markets in Malawi. The markets are Karonga in Karonga District, Rumphi in Rumphi District and Mzuzu in Mzuzu City in the north; Lilongwe in Lilongwe District, Mitundu in Lilongwe District and Lizulu in Dedza District in the central; and Lunzu in Blantyre District, Luncheza in Thyolo District and Bangula in Nsanje District in the Southern Region.

This paper is organized as follows. The next section gives a review of methodologies applied in agricultural market integration studies then discusses the models used in this paper. The fourth section gives the estimated results while the fifth section is the conclusion.

2.0 METHODOLOGY

2.1 Models for ICT Based Market Interventions and Spatial Co-Integration

To analyse the spatial price integration and price transmission, error correction models were used. Co-integration analysis tools and both linear and threshold price transmission tools were applied to assess the effect of ICT in price integration by comparing the threshold models to the standard linear model in pre and post ICT periods. Before assessing price transmission, long-run co-integration and Granger causality test were applied to the whole sample to determine the co-integrating market and the direction of causality for the whole period. This assisted in determining the long-run co-integrating markets before price transmission was assessed in pre and post ICT periods.

2.1.1 Long-run bivariate co – integration

To check for statistical properties, the Augmented Dickey – Fuller (ADF) test was used for price stationarity, as a unit root test. To determine appropriate lag length, Akaike Information Criterion (AIC) was used. This was done to reduce the sum of squares and to ensure that the error process in estimating equation is residually uncorrelated (Gujarati, 2004). Considering the significant influence of trend factors in price series, the analysis included trend analysis in stationarity test.

To assess the long run market integration, Johansen vector error correction test was used. This assessed integration of bivariate price series between markets with null hypothesis of *r* co-integrating vectors against the alternative of *r + 1* (Uchezuba, 2005). After determining the bivariate co-integrating markets, the causal relationship between co-integrating maize price series was assessed using Granger Causality test. This is a measure of price predictability. That is, price movements in one market can be used to forecast price changes in other markets.

2.1.2 Spatial price transmission

Information services aim at improving price adjustment between markets. Based on the estimated co-integrating vectors between markets, autoregressive error correction method was used to estimate price transmission adjustment factors. The model assumed symmetric price transmission but the direction of trade flow in the markets was determined by the Granger Causality test. Spatial price transmission was estimated using both linear autoregressive (AR) and threshold autoregressive (TAR) error correction models. These were applied to compare models that consider transaction costs against liner models in assessing market efficiency in pre and post ICT periods.

2.1.3 Standard linear autoregressive (AR) 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 at time *t* and at location *i* of a given quantity;

P_{jt} is the retail price at time *t* and at location *j* of a given quantity;

β is 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 behavior of η_t That is, η_t is referred to as the deviation between prices in two different markets. When $\beta = 1$, 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 price adjustment is based on how the deviation ($\eta_t = P_{it} - P_{jt}$) at time *t* corresponds to 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

ω_t is 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 lagged price difference. It indicates the extent to which price differences in the previous period are ‘corrected’ back to equilibrium price. The model was applied in both pre and post ICT periods.

2.1.4 Threshold autoregressive (TAR) error correction model

The applied standard linear autoregressive error correction method is known to be restrictive for investigating spatial maize price transmission. The method fails to allow for a zone of trade inactivity or the ‘parity bound’ when price spreads fall below a threshold that reflects transfer cost between markets. Thus if markets are integrated, the price differential or spread between markets cannot exceed the transfer cost (Alexander and Wyeth, 1994). To analyze symmetrical price adjustment further, the study used threshold autoregressive (TAR) error correction model. This was compared with the standard AR model in pre and post ICT periods.

Assuming 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):

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

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

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

where:

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

The first regime occurs when there is no trade between markets hence the absolute value of the price spread should be less than transfer cost. The second regime implies that if trade flows from *i* to *j*, then the price in *j* market should be to equal the price in *i* plus transfer cost. The third regime indicates that if trade flows from *j* to *i*, then the price in *i* market should be equal to the price in *j* plus the transfer cost (Myers, 2008).

To test these regimes, threshold autoregressive error correction model was used. This model can allow for the deviations from the 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	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 long transfer costs. To evaluate the effectiveness of spatial price transmission the primary interest is in regime 1, the size of the parity bound and regime 2, 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.

Threshold error correction model can be straightforward if price spread and transfer cost data are observable. However, the used data does not have transfer costs as separate data hence an auxiliary model for long run transfer costs c_t, which captures trends and variations over time can be used. Thus the long run transfer cost threshold can be presented 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*

Note: If $\delta_2 = 0$ then δ_0 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.

The price variable of market *i* (p_{it}) is included to allow for the fact that some marginal transfer costs[3] may vary with the price of the product.

This model may not capture all the short run movements in transfer cost 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 inter-regional trade activity between the markets. To evaluate effectively the 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 transfer cost. 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 incentive to increase trade flow until the price spread returns to the parity bound.

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

This means that for effective spatial price transmission we cannot have $\alpha \geq 0$ (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. $\alpha \geq 0$) 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, ……,K it would imply immediate adjustment although 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 and the closer 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*).

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

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

2.2. Data type and sources

The nominal maize retail prices for the selected nine markets in all the three regions were sourced from Ministry of Agriculture and Food Security (MoAFS) and Initiative for Development and Equity in African Agriculture (IDEAA) offices. The study used maize prices because it is synonymous with food security in Malawi. The data was used to assess effectiveness of modern ICT in post ICT period (January 2004 to December 2009). Monthly nominal retail price data was available from January 1992 to December 2009 and it was deflated using food CPI index for the specified period. The food CPI was used because maize contributes 60 percent in the Malawian food CPI index. The real maize price data was entered and cleaned in Excel. The data was analyzed in SPSS and STATA

3.0 ESTIMATED RESULTS

Spatial integration of nine markets in Malawi was analyzed using monthly real maize retail price data valued in Malawi Kwacha (MK)[4]. From the co-integrating markets, price transmission analysis was compared in pre and post ICT market intervention periods.

[4] At the time of research, US$1.00 was equivalent to MK 152.00

3.1 Long-run Co-integration and Price Transmission

Modern ICTs were introduced to improve co-integration and price transmission, thereby contributing to market efficiency. To assess the effect of modern ICTs on price transmission, basic trend analysis and stationarity test were done for the whole period. After determining data stationarity, long-run bivariate co-integrating markets and the direction of causality were determined for the whole period (1992 – 2009). Based on the long-run bivariate co-integrating markets and the direction of causality in the whole period, price transmission was assessed in pre and post ICT periods.

The trend analysis results in appendix 1 show a positive sign in all markets with an R-squared of greater than 33 percent. Thus, the trend factors were significant in the specified period. The stationarity test showed that the analysis without trend had almost all price series being integrated of order zero I(0) at 5 percent significance level except for Rumphi, Mzuzu and Lilongwe. Considering the significance of trends, the results with trend indicate that all markets were stationary or integrated of order zero I(0) at 5 percent significance level. Following Shahidur (2004), further co-integration analysis includes markets with same order of integration. Thus, all markets were included in co-integration analysis with trend.

3.2 Long-run co-integration

The approach for testing 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 long-run bivariate co-integration was done for the whole period to determine the co-integrating markets in the sample. Table 1 shows the bivariate co-integrating markets.

Karonga District in the north is separated from the Central and Southern region by the Chiweta mountain range while Luncheza and Bangula markets in the south are separated from the country by Chikhwawa Mountains (Goletti and Babu, 1994).Despite the geographical size, Karonga market was integrating with almost all markets including Luncheza and Bangula markets. Jayne *et. al.* (2008) observed that during lean period of maize supply in Malawi (from December to March), primary assemblers travel to remote areas and border districts to acquire maize supplies. Thus, Karonga market would integrate with Luncheza and Bangula markets when supply is influenced by informal imports. This is also the case with Rumphi and Luncheza markets. Where the integration between Rumphi and Luncheza happens when informal imports supply maize in border districts and primary assemblers move the crop to low supplied areas.

Table 1: Bivariate Co-integration coefficients of maize markets

Market j I	Karonga	Rumphi	Mzuzu	Mitundu	Lilongwe	Lizulu	Lunzu	Luncheza	Bangula
Karonga	**0.000**								
Rumphi	31.262*	**0.000**							
Mzuzu	30.323*	11.149	**0.000**						
Mitundu	32.229*	15.311	13.770	**0.000**					
Lilongwe	11.746	15.115	21.314*	35.370*	**0.000**				
Lizulu	19.128*	23.704*	15.391	44.254*	17.022	**0.000**			
Lunzu	21.363*	17.798	16.845	23.990*	9.723	19.172*	**0.000**		
Luncheza	25.164*	20.426*	16.769	22.735*	13.232	20.192*	11.548	**0.000**	
Bangula	19.358*	10.938	11.868	14.931	16.587	12.520	26.425*	24.820*	**0.000**

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

Lunzu and Lizulu markets lie along the main road running across the country from the Northern to the Southern Region. The accessibility of these markets along the road creates a high probability of co-integrating with other regional markets as revealed by the results. Mitundu area in Lilongwe is one of the major maize producing areas (Lilongwe District Assembly, 2006). During post-harvest period (from April to May), supply is high and prices are low in main producing areas like Mitundu (Jayne *et. al.*, 2008). At Mitundu market, primary assemblers[5] acquire maize from smallholder farmers and transport it to urban markets or low producing areas. Considering that Karonga is a major producer of rice and not maize, the integration with Mitundu implies the link in maize supply from Mitundu (a high producing area) to Karonga that influences prices between the markets.

Lilongwe and Mzuzu are markets located in major cities in the two regions, where there is low maize production. The supply of maize to these areas depends on production from district and remote areas (Jayne e*t. al.*, 2008). The co-integration of Lilongwe and Mzuzu markets shows the integration of urban markets in Central and Northern Regions that are supplied by remote areas. As city markets, the co-integration is influenced by demand of the urban population.

3.3 Determining 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 that shows the existence (or not) of relation between two economic time series. Based on the co-integrating markets, the analysis allows for causality test to determine causal relationship between markets (Goletti and Babu, 1994). Using Granger Causality test, Table 2 shows the causal relationship between co-integrating markets for the whole period. From Table 2, there are eight unidirectional causal relationships and the rest are independent relationships. In the regional markets, Karonga was observed to Granger cause Rumphi market

[5] The primary assemblers include small scale traders on bicycle, local buyers in rural market, mobile buyers, and agents buying for large trading companies (Jayne *et. al.*, 2008)

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.

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
	Luncheza	0.007	0.930	0.732	0.393	Independent
	Bangula	9.852	0.002***	0.003	0.954	**Unidirectional**
Rumphi	Lunzu	3.105	0.080*	0.128	0.720	**Unidirectional**
	Luncheza	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
	Luncheza	1.574	0.211	0.548	0.460	Independent
Lizulu	Lunzu	6.119	0.014***	0.026	0.872	**Unidirectional**
Lizulu	Luncheza	0.169	0.681	1.879	0.197	Independent
Lunzu	Bangula	2.318	0.129	0.105	0.745	Independent
Luncheza	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% and 10% 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*)

In Central Region, Mitundu market Granger caused Lilongwe and Lizulu markets. Being a major producer of maize, Mitundu market is a major supplier of maize to Lilongwe urban market. This signifies the co-integration between Mitundu and Lilongwe markets causing market integration. Although Dedza District produces maize, geographical size results in low maize production among smallholder farmers. Thus, the supply of maize to Lizulu market partly depends on supply from Lilongwe District especially Mitundu market. There was no unidirectional causal relationship in the Southern Region. This might have arisen from the fact that maize production and supply have been low in the specified markets to Granger cause each other. Luncheza and Bangula are low producing areas while Lunzu is an urban market.

Among the regions, Mitundu and Bangula markets Granger caused Karonga market while Lunzu and Luncheza Granger caused Rumphi market prices. Lunzu Granger caused Lizulu. The regional market causality signifies the integration of markets across the country, such as Luncheza and Rumphi; Bangula and Karonga. The casual relationship between Lunzu and Lizulu means that prices in Lizulu can be predicted based on Lunzu prices but not the other way round. Although there were only eight unidirectional causality, the independent causality in other co-integrating markets does not imply a total absence of price transmission. This might mean price signals are transmitted instantaneously under special conditions like relief or donation supply as indicated by Abdulai (2000).

3.4 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 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 and Babu, 1994).

3.4.1 Pre-ICT price adjustment results

Table 3 shows that the fastest significant price adjustment factor was observed in Lizulu-Luncheza market link both in AR and TAR models. The adjustment factor of 0.05 in AR model implies that it took 12.5 weeks for half of the price shock to return to the equilibrium price. In TAR model, the estimated adjustment factor of 0.07 implies that it took 9.3 weeks for half of the price shock to return to the equilibrium neutral price band. In the TAR model, the estimated transaction cost was 3.1 percent of the mean price in the markets. This indicates that price adjustment speed is faster in TAR model because it considers the threshold where there is no price adjustment. As indicated by Van Campenhout (2007) and Goodwin and 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.

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

Market Pair	Pre –ICT						Post - ICT				
	Distance (km)	AR Model		TAR Model			AR Model		TAR Model		
		ρ	Half-Life	δ	ρ	Half-Life	ρ	Half-Life	δ	ρ	Half-Life
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)	8.54	4.038	-0.124*** (0.015)	5.23	-0.069* (0.026)	9.69	3.5719	- 0.084* (0.024)	7.90
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 – Luncheza	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	2.1822	-0.035*** (0.009)	19.5	-0.001 (0.036)	692.8	1.6510	-0.003 (0.037)	203.7

Note: ρ denotes adjustment parameter on the lagged price difference (expressed as a percentage of mean prices in the two markets), δ is the estimated thresholds, expressed as percentage of mean price in the two markets

Figures in parenthesis are standard errors. *** and ** denote significance levels at 1 percent and 5 percent, respectively.

As observed by Van Campenhout (2007), it was taking few weeks for price to adjust back to the parity price band in TAR model than in AR model. This signifies that considering transaction costs when assessing price adjustment is important. As indicated by Abdulai (2000) in developing countries, vast distances and poor infrastructure lead to high transaction cost, 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 TAR models are appropriate because price equalizing arbitrage is triggered only when shocks result in price differences that exceed the neutral band as opposed to AR models that do not consider transaction costs.

3.4.2 Post-ICT price adjustment results

The fastest significant price adjustment in post-ICT was observed in Mitundu – Lizulu market link. In 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 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 half way back to parity bound or threshold that covers transaction costs (Myers, 2008). The estimated threshold was 1.94 percent of the mean price. This entails that influencing factors that reduce transaction costs also influence the speed of price adjustment if there is a shock in the markets.

In Karonga – Rumphi market link the estimated price adjustment factor was 0.148 indicating half-life of 4.3 weeks in standard AR. This shows that it took 4.3 weeks for a price shock to adjust half way back to the equilibrium price. In TAR model, the adjustment factor of 0.189 implied 3.3 weeks half-life. This means that price adjustment is faster in TAR model because it took only 3.3 weeks for half of the price shock to return to parity bound compared to 4.3 weeks half-life in AR model. This agrees with Goodwin and 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 (Abdulai, 2000).

3.4.3 Comparison between pre – ICT and post – ICT price adjustment results

Considering that 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 effectiveness of modern ICTs in post – ICT period. The analysis used the market links that were significant in pre and post ICT periods. From Table 5, the co-integrating links that were significant in both periods were Karonga-Rumphi; Karonga – Mitundu; Karonga – Bangula; Mitundu-Lilongwe and Mitundu-Lizulu.

In Karonga - Rumphi pre ICT market link, the estimated price adjustment factor of 0.043 implied 15.8 weeks half-life and estimated threshold of 2.5 percent of mean price. In 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 mean price. This shows that in post ICT period, prices were adjusting faster than in pre ICT period. That is, improving information services influence transaction costs thereby improving market efficiency and participation. Thus, the introduction of modern ICTs improved price adjustment. As observed by Sopo (2008), the introduction of market information systems improves the co-integration of spatially separated maize markets and improves price transmission in Malawi. This also concurs with Katengeza (2008), who observed that price adjustment factor was faster in post ICT period for spatially separated rice markets in Malawi. In the Mitundu – Lizulu market link, price adjustment was also faster in post-ICT with a half-life of 2.9, weeks only compared to the pre ICT period. This agrees with Jansen (2007), who observed that availability of information through mobile phones reduces price dispersion between markets, reduce transaction costs and increase price adjustment even in distant markets.

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

4.0 CONCLUSION AND POLICY RECOMMENDATION

The main objective of this study was to analyse the effectiveness of ICT based market interventions on maize marketing efficiency in Malawi. The focus was on how the use of modern ICTs improved market efficiency among spatially separated maize market in Malawi. Assuming symmetric price adjustment, spatial price adjustment results show that adjustment was faster in TAR models than AR models. This signifies that transaction costs are significant in estimating spatial price linkages. Comparing TAR models in pre and post ICT periods showed that estimated thresholds were lower in post ICT TAR models and that it took fewer weeks for a shock to return half-way back to parity bound. Therefore, the results signify that modern ICT based market interventions influenced reduction in search transaction cost thereby improving maize marketing efficiency in the post ICT period. Although price adjustment was faster in post-

ICT period, the adjustment was not instantaneous. This can be attributed to, among other factors, transportation transaction costs and market charges related to volume of trade.

Considering the importance of reducing transaction cost in market integration and market efficiency, the study recommends the need to enhance use of modern ICTs especially at farm gate. There is need to enhance dissemination of modern ICTs to all producers in order to equip then with variable marketing information. Further, there is need to improve the market infrastructure to complement the efforts in reducing market information asymmetry. 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. Therefore, further studies can apply parity bound models and threshold vector error correction models that take into account asymmetric price transmission and estimate thresholds that vary over period of study.

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APPENDIX

Appendix 1: Maize Market Real Price Trend Analysis

Market	Trend coefficient	t-statistic of linear trend	R-squared of trend equation (%)
Karonga	0.0523	12.60	42.6
Rumphi	0.0654	15.70	53.5
Mzuzu	0.0515	13.81	47.1
Mitundu	0.0542	12.08	40.5
Lilongwe	0.0547	11.87	39.6
Lizulu	0.0530	11.40	37.7
Lunzu	0.0539	10.30	33.1
Luncheza	0.0601	10.49	33.9
Bangula	0.0743	14.25	48.6

Appendix 2: Unit Root Test for Real Maize Market Prices

Market	Real market price before differencing without trend					Real market price before differencing with trend				
				Critical Values					Critical Values	
	t-statistic	No of lags	Order of Integration	1%	5%	*t*-statistic	No of lags	Order of Integration	1%	5%
Karonga	-3.646 (0.004)	1	I (0)	-3.47	-2.88	-5.149 (0.000)	1	I (0)	-4.00	-3.44
Rumphi	-2.339 (0.159)	4	NS	-3.47	-2.88	-3.760 (0.032)	4	I (0)	-4.00	-3.44
Mzuzu	-2.045 (0.267)	7	NS	-3.47	-2.88	-3.568 (0.033)	7	I (0)	-4.00	-3.44
Mitundu	-3.925 (0.002)	1	I (0)	-3.47	-2.88	-5.402 (0.000)	1	I (0)	-4.00	-3.44
Lilongwe	-2.437 (0.131)	4	NS	-3.47	-2.88	-3.615 (0.028)	4	I (0)	-4.00	-3.44
Lizulu	-3.333 (0.013)	1	I (0)	-3.47	-2.88	-4.397 (0.002)	1	I (0)	-4.00	-3.44
Lunzu	-3.758 (0.003)	1	I (0)	-3.47	-2.88	-4.746 (0.001)	1	I (0)	-4.00	-3.44
Luncheza	-3.794 (0.003)	2	I (0)	-3.47	-2.88	-4.928 (0.000)	2	I (0)	-4.00	-3.44
Bangula	-3.750 (0.004)	1	I (0)	-3.47	-2.88	-5.770 (0.000)	1	I (0)	-4.00	-3.44

Note: The values in parenthesis are *P-values*

NS = Not Stationary

I (0) = Integrated of order zero (Stationary)