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Modelling trends in food market integration: Method and an application to Tanzanian maize markets

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Abstract

Pushed by increasing availability of price data and extensive market liberalisation efforts in many developing countries, research on food market integration has evolved rapidly over the last two decades. Empirical methods to measure market integration diverged in two directions: on the one hand, there is the parity bounds model (PBM) using a switching regressions technique, while on the other hand the use of threshold autoregressive (TAR) models has been proposed. This article provides a discussion on the two methods and argues that TAR models are better able to capture the dynamics of the arbitrage process underlying interconnected markets. Furthermore, we extend the standard TAR model to include a time trend in both the threshold and the adjustment parameter. Using weekly maize price data on seven selected markets in Tanzania, we illustrate how both transaction cost and the speed of adjustment have changed during the nineties.
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Introduction

There is little disagreement on the benefits of a well-integrated market system. In general, producer marketing decisions are based on market price information, and poorly integrated markets may convey inaccurate price information, leading to inefficient product

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movements (Goodwin and Schroeder, 1991). For developing countries, there are some additional cases to be made for well integrated market systems. Linkages to marketing centres have been found to contribute significantly to rural households' escape out of poverty (Krishna, 2004; Krishna et al., 2004). Furthermore, the existence, extent and persistence of famines in market economies is also closely linked to market integration. Indeed, the answer to the central question how long an initially localised scarcity can be expected to persist depends entirely on how well the region is connected by arbitrage to other regions (Ravallion, 1986). Finally, the extent of market integration also has consequences for designing successful agricultural price stabilisation policies (Fackler and Goodwin, 2001).

Apart from the importance of market integration, two additional factors have spurred research in the field over the last two decades. First of all, in the wake of extensive economic reform and market liberalisation in many developing countries, market integration studies are needed to evaluate policy (Dercon, 1995). Secondly, time series data on prices in different locations are increasingly available, and at higher frequencies then ever before.[1] However, data on other factors affecting market integration (most notably transaction costs) have not followed this trend. This is why the challenge has been to assess the degree of market integration using only price data of a particular good in different markets. Studies using only price data to assess market interconnectedness have been labelled level I methods (Barrett, 1996).[2] Since the application in the present study relies solely on price data, we will mainly concentrate on level I methods here.

Markets are said to be integrated if they are connected by a process of arbitrage. This will be reflected in the price series of commodities in spatially separated markets. Thus, as a measure of market integration, the extent of co-movement between prices in different locations has been suggested. Initially, simple bivariate correlation coefficients have been suggested (Blyn, 1973), but the time series properties of the prices resulted in the preference of cointegration and error-correction models (Harriss, 1979; Ardeni, 1989; Goodwin and Schroeder, 1991; Palaskas and Harriss-White, 1993; Alexander and Wyeth, 1994; Dercon, 1995). Later, the non-linearity introduced in the adjustment of the prices by the existence of transaction costs prompted the search for more suitable models. Here, research seems to diverge in two directions: on the one hand, there is the parity bounds model (PBM) (Sexton et al., 1991; Baulch, 1997) and on the other hand, threshold autoregressive (TAR) models have been applied (Obstfeld and Taylor, 1997; Goodwin and Piggott, 2001).

In this paper, we argue that there are potentially serious problems with the distributional assumptions of the PBM. Furthermore, we feel that threshold models are better suited to capture the dynamic nature of market interlinkages. This is why we revisit the TAR model here, extending it to allow for a time trend in both the threshold and adjustment parameter. Using weekly price series data on maize in seven carefully selected markets in Tanzania, we then estimate (changes over time in) the transaction cost and speed of adjustment between these markets.

[1] Two noteworthy African sources of market information, clearly linked to famine relief, are the Africa Data Dissemination Service, which is part of the Famine Early Warning Systems Network and the IGAD Marketing Information System for the Greater Horn of Africa. A Latin American example is the Sistema de Información Agraria in Peru.

[2] Barrett (1996) defines three levels of methods used in the analysis of market integration. Level I methods only rely on price data. Level II methods combine transaction cost and price data. Level III methods combine trade flow and price data.

The paper is organized as follows. The next section briefly explains what is understood by market integration. Furthermore, the main econometric models used to measure it are described. In this section, there is also a small review of some empirical studies in developing countries to better situate the present study. ‘‘Models for measuring market integration: a discussion’’ provides a discussion on these models. ‘‘A threshold auto regression model with a time trend’’ presents the TAR model, and extends it to allow for a gradual change in market integration over time. In ‘‘An application to Tanzanian maize markets’’, we apply this model on weekly maize price data in selected Tanzanian markets. The last section concludes.

Market integration: theory, statistical models and previous empirical studies on Africa

The starting point for discussing market integration is the existence of separate regions, each with their own supplies and demands for a range of commodities. Because each product has its own supply and demand function, it is possible to identify autarkic prices in each region at each point in time (say P_t^{1A} and P_t^{2A}) for each homogeneous commodity. When free trade across the regions is introduced, the actual prices may differ from the autarchy prices. For instance, if the price difference between P_t^{1A} and P_t^{2A} exceeds the transaction costs at t (T_t) required to ship a unit of the good between the regions, profits can be made by shipping commodities from the region with the lowest price to the region with the highest price. This process will increase demand for the commodity in the region with the low price, while increasing supply in the market with the high price. The increase in demand (with unaltered supply) in the market with low autarchy price will drive up the actual price, while the increased supply (at a given level of demand) will decrease the actual price in the region with the high autarchy price. This process of arbitrage will persist until actual prices differ by exactly T_t.

Integrated markets are markets that are connected through such a process of arbitrage. However, if the price difference between two markets is lower than the transaction cost, rational traders will stop trading, otherwise they will incur a loss. In this case, actual prices are again determined by local demand and supply conditions. Prices will move independently, although it would be wrong to conclude from this that these markets are not integrated.

The first attempts to measure the extent of market integration did not consider the existence of transaction costs and took price co-movement as evidence for market integration. The first models use simple bivariate correlation coefficients (Blyn, 1973). Ravallion (1986) formulates a dynamic model of spatial price differentials, allowing differentiation between short-run market integration, long-run market integration and market segmentation. Realising that arbitrage takes time, he thus provides an alternative to the all-or-nothing approach of correlation coefficients. If evidence for long run market integration is found, he reformulates the model as an error-correction model. This model, together with the non-stationary nature of most price series gave rise to a whole series of studies that used cointegration techniques to test for long run market integration. When evidence of long run market integration is found, error-correction specifications are used to investigate the short run dynamics that are consistent with this long run relationship (e.g. Ardeni, 1989; Goodwin and Schroeder, 1991; Palaskas and Harriss-White, 1993; Alexander and Wyeth, 1994; Dercon, 1995; González-Rivera and Helfand, 2001; Rashid, 2004).

The first market integration study that explicitly acknowledges the existence of transaction costs was a model developed by Sexton et al. (1991), drawing on the work of Spiller and Huang (1986). Their model, essentially a switching regressions model, returns estimates for the transaction cost and the probabilities of being in a state of too little, too much or efficient arbitrage between two markets. Owing to Baulch (1997), this model has become very popular for measuring food market integration in developing countries as the parity bounds model (PBM), resulting in several studies using the underlying estimation framework (e.g. Fafchamps and Gavian, 1996; Barrett and Li, 2002; Park et al., 2002; Negassa et al., 2004).

The second model that incorporates transaction costs are threshold models, allowing for a different relationship between variables once a threshold has been surpassed. For studying food market integration, the self-exciting threshold autoregressive model (SETAR) is often used.[3] This model describes the adjustment of price differences between two markets over time. However, this adjustment process can be different according to this price difference being below or above the transaction cost (i.e. the threshold). Hence, they are conceptually closer to the dynamic models discussed above. In this study, we opt for such a model. It will be explained in detail in "A threshold auto regression model with a time trend".

The acknowledgement of the existence of transaction costs alters the way market integration is viewed. It essentially breaks the process of market integration into two components: transaction costs and the speed of price adjustment. For instance, a primary factor affecting market integration is an agent's cost and risk associated with trade between markets (Buccola, 1983). This would indeed alter the transaction costs between markets, but this does not automatically mean that the adjustment speed changes. The agent's access to market information, on the other hand, is more likely to influence the speed of adjustment than the transaction cost. For example, in the context of rural food markets, the existence of a telephone line between two markets might dramatically increase the speed of adjustment, without significantly affecting the transaction cost.

Let us now turn to empirical studies on market integration. Given the importance of market integration for food security mentioned in the introduction, it may seem surprising that there are not more studies on market integration in developing countries, especially for Sub Saharan Africa. Indeed, the most innovative studies on market integration are on markets in developed economies (e.g.: Spiller and Huang, 1986; Ardeni, 1989; Sexton et al., 1991; Goodwin and Schroeder, 1991; Goodwin and Piggott, 2001). One noteworthy exception is Ravallion (1986) who develops a dynamic model of price transmission using rice prices from Bangladesh.

If we zoom in on Sub Sahara Africa, according to the overview given in Fackler and Goodwin (2001), there are only nine studies on African markets, out of 61 studies published before 2000. None of the African studies listed there adequately handle transaction costs. They either use correlation coefficients or cointegration methods to assess market integration. More recently, some studies on African markets have emerged that do pay attention to the non-linearities caused by transaction costs using either switching regression techniques or TAR methods.

Ghanaian maize markets seem to be particularly popular in market integration analysis. Alderman (1993) analyses maize markets in Ghana using the standard cointegration analysis. Badiane and Shively (1998) extend the cointegration approach by modelling the implications of local price volatility as an autoregressive conditionally heteroscedastic

[3] Self-exciting threshold autoregressive (SETAR) models are TAR models where the transition depends on a lag of the process itself. The SETAR model should not be confused with the smooth transition autoregressive (STAR) model, which allows for a smooth transition between the different regimes.

(ARCH) process, using monthly price series in three Ghanaian maize markets. Abdulai (2000) uses a threshold model to investigate spatial price transmission for Ghanaian maize. However, his interest lies in testing asymmetries in price adjustment. Hence, he uses an asymmetric two regime TAR model that allows for different price adjustment when the price difference increases then when the price margin narrows. Ethiopia has also received some attention with Dercon (1995) looking for structural breaks using cointegration methods and Negassa et al. (2004) looking for trends in market integration using a switching regressions approach. Fafchamps and Gavian (1996) present results for Nigerian livestock markets using both the cointegration and switching regressions approach. Rashid (2004) uses a multivariate cointegration framework to test for market integration using weekly price data on selected Ugandan maize markets. Recently, Araujo et al. (2005) have analyzed the effects of a devaluation on cattle market integration in Burkina Faso using switching regressions.

As will be discussed later, all studies mentioned above assume a market setup where one market is indisputably a net-exporter and the other is net-importer. Trade always flows in the same direction. However, for agricultural commodities that are both a major staple and cash crop with a high trade volume, it is not uncommon for trade flows to reverse at certain periods during the year. Moreover, when the geographical region shows considerable variation, harvest seasons may differ between locations. An indication of the possibility that stock flows reverse is the fact that, for most of the market pairs we will use in the study, prices were never consistently higher in one market then in the other (the exception being the Dar es Salaam-Iringa trade route, where Iringa prices exceeded Dar es Salaam prices at only three points in time). Studies using cointegration methods have also noted that the price in the local market occasionally falls below the price in the central market, which raises the possibility of reverse stock flows (Badiane and Shively, 1998, footnote 8).

The present study proposes a method that is suitable for modelling market configurations where reversal of trade is possible. Moreover, instead of assuming a constant threshold as would be the case in the standard SETAR model, we extend the method by making the threshold a function of time. Furthermore, it uses high frequency time series data, which allows us to estimate the adjustment parameters more precisely by reducing the aggregation bias typical in studies using monthly price series data (Taylor, 2001).

Models for measuring market integration: a discussion

Although a significant improvement over the models that disregarded transaction cost, the PBM and TAR models have their shortcomings too. A first criticism on the PBM concerns its underlying distributional assumptions. The original model identifies three exhaustive regimes, based on the price difference between two markets. Either this price difference is equal to the transaction cost (regime 1), above the transaction cost (regime 2) or below the transaction cost (regime 3). In the switching regressions model, regime 1 is modelled as a constant (i.e. the transaction cost) plus a normally distributed error term. For regime 2, an additional error term is added, while for regime 3, the additional error term is subtracted. This additional error term is assumed to be half normal distributed truncated from below at zero. After formulating the corresponding density functions for each regime, probabilities are assigned to each regime, and the likelihood function can be specified. Maximizing the log of this function returns estimates for the probabilities of being in one of the tree regimes, the transaction cost, and the standard errors of both error terms (Sexton et al., 1991).

Now, suppose the price difference between two markets falls in regime 2, where it is larger than the transaction cost. Indeed, in this case there are profitable arbitrage opportunities that remain unexploited. It seems logical here to assume a half-normal distribution, because the probability of observing large deviations from the transaction cost is lower than the probability of observing smaller deviations. Obviously, economic reasoning suggests that in this regime, there are limits as to how big the discrepancy between the price margin and the transaction cost can become. However, this is not necessarily true for regime 3. If there is no trade between two markets because the price margin is lower than the transaction cost, there is no reason why a smaller deviation from the parity bounds should occur at a higher probability than a large deviation, as suggested by the half-normal distribution underlying the model. One would expect that in this regime, any price difference has the same probability of occurrence. The story is somehow different if there is trade occurring in this regime. In that case, it might be that temporarily too much trade is going on. These 'errors' will be corrected sooner or later; hence here a half-normal distribution seems to come closer to what economic theory predicts.[4]

The point made above is related to Fackler and Goodwin (2001, p. 1012), who argue that "[Switching regressions models] can be viewed as nothing more than flexible models of the price spread distribution. The believability of the regime interpretation rests very strongly on the believability of the distributional assumptions".[5] As explained above, in a setting where markets are not logically linked by continuous trade, there is no reason to assume any adjustment in regime 3. Even if the markets are logically connected by trade as in the original model, the assumption that the adjustment in both regime 2 and 3 is the same is weak, due to the so-called leverage effect (Deaton and Laroque, 1992).[6]

The parity bounds model is also static in nature.[7] It informs the researcher of the probabilities of being for instance off the parity bounds, but does tell us anything about how persistent these deviations from the equilibrium are. As already pointed out by Ravallion (1986, p. 103), "in many settings it will be implausible that trade adjusts instantaneously to spatial price differentials... But, given enough time, the short-run adjustments might exhibit a pattern which converges to such an equilibrium". Sluggishness in price adjustment,

[4] It is important to note that the original model was developed with such a market structure in mind. Sexton et al. (1991, p. 571) were looking at two markets where one was indisputably the exporter and the other the importer. They were looking at a situation of two markets that were linked by continuous trade, and their interpretation was that regime 3 reflects a situation where there is simply too much trade (glut). Most other studies using the PBM have analyses quite different market settings, including situations where reversal of trade is likely.

[5] Although they argue that the distributional assumptions are arbitrary because economic theory generally has little to say about the distribution, we feel that theory does say something about the type of adjustment that can be expected.

[6] This effect is created by the ability of traders to hold stocks. In times when the price difference is higher than transaction cost, traders will buy in the market with the low price and sell in the market with the high price. But when the price difference subsequently falls below the transaction cost, traders will, when possible, prefer to stock up instead of selling the goods and incurring a loss. This process obviously has consequences for the distributional assumptions. Note that the TAR model would be better suited to model this effect. In this case, a version of the model that allows for adjustment inside the band formed by the transaction costs like Eq. (2) can be used.

[7] This problem has been acknowledged from the beginning. For instance, Sexton et al. (1991) introduce some dynamics to their model by comparing the price of the exporting market to the lagged price of the importing market. However, this still not informs us on how persistent deviations from efficient arbitrage are.

delays in transportation and expectations formation under price uncertainty are mentioned as the prime causes for these delays in price adjustment. Indeed, one can imagine markets that are prone to frequent supply and demand shocks. Using a static model like the parity bounds model, one would observe a high frequency of inefficient arbitrage (i.e. too little or too much trade), and hence conclude that these markets are poorly integrated. If one would use a dynamic specification instead, one can assess the time it takes for prices to adjust to one another. If the price differences tend to be corrected quickly, one would come to a different conclusion than the one obtained by the PBM.

The TAR model has two main shortcomings. First of all, there is the assumption that the transaction cost is constant over time.[8] Another issue concerns inference on the threshold parameters. Chan (1993) has shown that the asymptotic distribution of the threshold parameter is neither normal nor nuisance parameter free, hence it is not possible to obtain standard errors and confidence intervals. Recurring to simulation based methods to obtain standard errors is not feasible in practice, as the grid search involved in the estimation takes too much time.

A threshold auto regression model with a time trend

Defining $m_t = p_t - p_{r,t}$ as the price difference between the market under investigation and the price in a reference market at time t, we set out by estimating how the price difference at time t responds to the price difference in the previous period:

$$\Delta m_t = \rho \cdot m_{t-1} + \varepsilon_t, \tag{1}$$

where $\Delta m_t = m_t - m_{t-1}$ and $\varepsilon_t \sim N(0, \sigma^2)$ is the estimated residual. The only parameter we estimate at this stage is ρ, which is the adjustment speed. It indicates the extent to which price differences in the previous period are 'corrected', and is the basis to calculate half-lives.[9]

This model does not incorporate the non-linear effects introduced by the existence of transaction costs between two markets. To account for the existence of transaction costs, we will estimate TAR models instead. One of the simplest TAR models is the following symmetric SETAR model:

$$\Delta m_t = \begin{cases} \rho_{\text{out}} m_{t-1} + \varepsilon_t & m_{t-1} > \theta, \\ \rho_{\text{in}} m_{t-1} + \varepsilon_t \quad \text{if} & -\theta \leqslant m_{t-1} \leqslant \theta, \\ \rho_{\text{out}} m_{t-1} + \varepsilon_t & m_{t-1} < -\theta, \end{cases} \tag{2}$$

where we now estimate two adjustment parameters, one for the adjustment inside the band formed by the threshold (ρ_{in}) and one for the adjustment outside this band (ρ_{out}), together with the transaction cost (θ). This model (or variants thereof) has been applied in numerous studies on market integration (e.g. Balke and Fomby, 1997; Obstfeld and Taylor, 1997; Goodwin and Piggott, 2001; Mancuso et al., 2003).

[8] Strictly speaking, this is also a shortcoming in switching regression models that only rely on price data. The subsequent PBM of Baulch (1997) relies on exogenous transaction cost data, and hence is a level II study. Similarly, one can also use transaction cost data in a TAR framework, which would allow a less restrictive threshold model, but again, this would result in a level II study. As said above, this study will only be concerned with what is possible within the first level of studies.

[9] A half-life is the time that is needed for a given shock to return to half its initial value: it is the solution for h in $m_{t+h} = \frac{m_t}{2}$. It is calculated as $h = \frac{\ln(0.5)}{\ln(1+\rho)}$.

As said above, theory predicts that within the band formed by the transaction cost (θ) there is no adjustment. In this region, our best guess of the price difference in the next period is therefore the price difference in the current period. We can exploit this theoretical property to increase identification of the parameters and impose unit root behaviour inside the band by setting $\rho_{\text{in}} = 0$:

$$\Delta m_t = \begin{cases} \rho_{\text{out}} m_{t-1} + \varepsilon_t & m_{t-1} > \theta, \\ \varepsilon_t & \text{if} \quad -\theta \leqslant m_{t-1} \leqslant \theta, \\ \rho_{\text{out}} m_{t-1} + \varepsilon_t & m_{t-1} < -\theta. \end{cases} \tag{3}$$

As mentioned in the previous section, one of the main objections to the TAR model is that the transaction cost is constant over time. Therefore, we will extend (3) to include a time trend in both the threshold and the adjustment parameter in the model. We model the threshold as a simple linear function of time:

$$\theta_t = \theta_0 + \frac{(\theta_T - \theta_0)}{T} \cdot t. \tag{4}$$

Here, t denotes time running from 0 to T. So, at $t = 0$, the threshold is θ_0 while for $t = T$ the threshold is θ_T. Like for the standard TAR model, θ_0 and θ_T is identified through a grid search over possible candidates for these thresholds. The pair that minimizes the sum of squared residuals is then used to estimate the final model.

We can also add a time trend to the adjustment parameter. The complete model can then be written as:

$$\Delta m_t = \begin{cases} \rho_{\text{out}} m_{t-1} + \rho'_{\text{out}} \cdot t \cdot m_{t-1} + \varepsilon_t & m_{t-1} > \theta_t, \\ \varepsilon_t & \text{if} \quad -\theta_t \leqslant m_{t-1} \leqslant \theta_t, \\ \rho_{\text{out}} m_{t-1} + \rho'_{\text{out}} \cdot t \cdot m_{t-1} + \varepsilon_t & m_{t-1} < -\theta_t, \end{cases} \tag{5}$$

Note that, instead of making the transaction cost and adjustment process a function of time, it would also be possible to include a dummy variable to capture sudden changes in these parameters. This is especially useful to capture the effects of structural breaks. For instance, if it is known that restrictions on trade have been removed at a particular point in time, the effect of such a sudden and dramatic shift in food marketing policy could be measured by adding a dummy from that moment onward. For less dramatic but continuous factors affecting market integrations, including a time trend is more appropriate (Negassa et al., 2004). Examples of such factors are the increase in the number of vehicles in the economy, improvements to the transportation infrastructure, gradual improvements in information dissemination (telecommunications, newspaper availability,...), etc.

An application to Tanzanian maize markets

The data and context

We will now use price data from seven geographically separated markets to illustrate the model discussed above. The data come from the Africa Data Dissemination Service, which is part of the Famine Early Warning Systems Network and is available on the internet. We decided to use data on white maize wholesale prices, as this is the main staple food in the region under investigation. To take out inflation, we did not use the difference in nominal price levels between two markets, but rather expressed the price difference as a share of average price level of the two markets.[10]

The reference market in our analysis is taken to be Iringa. Iringa is the regional capital of the region with the same name. The region is mainly inhabited by the Hehe tribe, which is known for their preference to white maize as a staple food. Climatic conditions in the region are also well suited for maize cultivation and Iringa serves as an important supply market for the rest of the country.

Iringa lies along the Tanzania-Zambian highway, about halfway between Morogoro to the east and Mbeya to the west. To the north, Iringa is connected by road to Dodoma, the administrative capital. Although the distance to Dodoma is relatively short, the road linking the two markets is in disrepair. We also included Songea, which lies at a considerable distance south of the TANZAM highway, but is connected by a fairly good road. Further east of Morogoro at the starting point of the TANZAM highway is Dar es Salaam, the commercial capital of Tanzania. And finally, we also included Sumbawanga, which is northwest of Mbeya, also a considerable distance off the TANZAM highway. Distances (in kilometres) by road between these different markets are reported in the table with the results (Table 1).

The data cover a period from 1989 to 2000. During this period, there is no significant structural change to maize marketing policy in Tanzania. According to Jayne and Jones (1997) food marketing and pricing policies in Tanzania have always been fairly market oriented. Furthermore, most structural reforms that affect maize market integration, most notably the relaxation and subsequent abolition of restrictions on grain movement, have happened in the eighties (1984 and 1987, respectively). Hence a gradual linear trend in both the threshold and adjustment parameters seems to be more suitable for this period than including dummies to capture structural breaks. Evidence of decreasing transaction cost or increased adjustment speed signals that there are small but continuous factors that contribute to the integration of markets.

Estimation results

We estimated three different models for price differences between the six markets and the reference market (Iringa). We first estimate the simple AR1 model of Eq. (1) where the change in the price difference is explained by the price difference in the previous period. Next, we estimate the standard TAR model without a time trend of Eq. (3). Finally, we estimate the TAR model with a trend in the threshold and the adjustment parameter as in Eq. (5). The estimation results are reported in Table 1, while Table 2 translates the

[10] One could ask if this is really necessary, since the arbitrage condition should hold for nominal prices as well. But since our estimation method exploits the information contained in the behavior of prices over time, inflation will affect the coefficient estimates. For instance, if there is positive inflation, price margins will be inflated proportionally, and changes in the price margin over time will show an upward bias proportional to the inflation rate. One way to deal with this is by adequately deflating the price series, using for instance a consumer price index. But these indices are typically only available as monthly averages, so one has to come up with a way to convert them to a weekly frequency, for instance through linear interpolation. However, as an anonymous reviewer pointed out, this could affect the time series properties of the series on which TAR models heavily rely. A more useful alternative was to take common inflation out by relating price margins to the (average) price level at each point in time. Henceforth, when we talk about the price difference between two markets, we mean the price difference relative to the average price level in the two markets.

Table 1
Estimation results

Market pair	Distance (km)	AR1 model	TAR model		TAR model with trend				N
		ρ	θ	ρ	$\theta(t=1)$	$\theta(t=502)$	ρ	$\rho*t$	
Dodoma-Iringa	272	−0.143**	2.15%	−0.145**	2.63%	1.26%	0.022	−0.0007612**	295
		(−4.91)		(−4.93)			(0.34)	(−2.98)	
Morogoro-Iringa	309	−0.077**	5.38%	−0.096**	6.43%	4.73%	−0.065	−0.000119	281
		(−3.48)		(−4.11)			(−1.21)	(−0.75)	
Mbeya-Iringa	355	−0.162**	2.29%	−0.170**	3.20%	2.04%	−0.056	−0.0004132+	363
		(−5.77)		(−5.98)			(−0.80)	(−1.87)	
Songea-Iringa	475	−0.078**	6.25%	−0.102**	6.60%	6.08%	−0.048	−0.0002415+	328
		(−3.66)		(−4.22)			(−1.13)	(−1.68)	
Dar es Salaam-Iringa	503	−0.030**	10.99%	−0.058**	11.71%	10.77%	0.027	−0.0003175*	371
		(−2.78)		(−4.03)			(0.69)	(−2.46)	
Sumbawanga-Iringa	677	−0.088**	7.57%	−0.118**	7.14%	3.19%	−0.163+	0.0001624	247
		(−3.16)		(−3.66)			(−1.70)	(0.58)	

Notes. Dependent variable is the change between two periods in the price difference of maize (expressed as the percentage of mean price in the two markets) between the two markets. All models are estimated without a constant. Rho (ρ) denotes the adjustment parameter on the lagged price difference (again expressed as the percentage of mean price in the two markets), theta (θ) is the threshold (also expressed as a percentage of mean price) and t is a time trend. The TAR models are three regime symmetric models with unit root behaviour imposed within the band formed by the thresholds. The thresholds are identified through a grid search over candidate thresholds with as model selection criterion the minimal sum of squared residuals. As starting values for the thresholds, at least 20% of the observations were either within or outside the band formed by the thresholds. t-ratios are in brackets. +, * and ** denote parameter estimates significantly different from zero at the 10%, 5% and 1% significance, respectively. N is the number of observations used in the estimation. Estimation was done using Stata 8.2. The code for the threshold models is available from the author on request.

Table 2
Thresholds and half-lives

Market pair	Distance (km)	AR1 model	TAR model		TAR model with trend				
		Half-life	*θ*	*Half-life*	$\theta(t=1)$	$\theta(t=502)$	*% change*	Half-live	*Half-life* $*\, t$
Dodoma-Iringa	272	4.5	565	4.4	693	333	−52	(∞)	1.5
Morogoro-Iringa	309	8.6	1759	6.7	2102	1545	−26	(10.3)	(5.2)
Mbeya-Iringa	355	3.9	599	3.7	836	533	−36	(12.0)	2.3
Songea-Iringa	475	8.5	1639	6.4	1731	1595	−8	(14.1)	3.7
Dar es Salaam-Iringa	503	22.8	3690	11.6	3921	3618	−8	(∞)	4.9
Sumbawanga-Iringa	677	7.5	2195	5.5	2070	925	−55	3.9	(8.2)

Note. Half-lives are expressed in weeks. Figures between brackets denote calculation of half-life was based on a coefficient that was estimated not significantly different from zero.

estimated adjustment parameters in the associated half-lives and reports the transaction costs in Tanzanian shillings.

For the simple AR1 model, fastest adjustment has been found between Mbeya and Iringa. Mbeya is the third largest city in Tanzania, and it is also a centre for the cross border trade with Malawi and Zambia. The adjustment speed of −0.16 implies a half-life of just under four weeks. Although distance between Dodoma and Iringa is much less, the adjustment speed between these two markets is lower, with a half-life of about four and a half weeks. This is most probably due to the bad shape the road that links these two markets is in. The markets of Songea and Sumbawanga are much further from Iringa and hence we find price adjustment to be significantly slower. It is also interesting to find that prices between Sumbawanga and Iringa adjust faster then on the Songea-Iringa route, despite the fact that Sumbawanga is further away. This is probably caused by the location of the two markets. Sumbawanga lies off the busy road linking Tanzania with Malawi and Zambia, and the road passes through to another important market on the shores of Lake Tanganyika, Kagera. Songea, on the other hand, lies secluded in the South, with the Livingsone Mountains and Lake Malawi to its West and Mozambique to its South. Given the distances, adjustment seems to be more sluggish to the markets in the east: it takes on average 8.5 weeks for a given price difference between Morogoro and Iringa to return to half its value, while the half-life between Dar es Salaam and Iringa is more than 22 weeks.

Next, we turn to the TAR estimates. There are now two different dimensions to market integration. On the one hand, there is the transaction cost and on the other hand, there is the speed of adjustment. As expected, the estimated transaction costs are generally proportional to the distance between the two markets. For instance, Dodoma-Iringa has the lowest estimate transaction cost of 565 shillings, or 2.15% of the average price of maize. Mbeya-Iringa has an estimated transaction cost of about 600 shillings. Sumbawanga has the highest estimated transaction cost of all the markets west of Iringa. Given the distance, transaction costs on the eastern trade route are significantly higher then for the other trade routes. There are some possible explanations for the high transaction costs between Iringa and markets to the east. The first is the fact that, at Mikumi, somewhere halfway between Iringa and Morogoro, traffic has to get up the escarpment dividing the southern highlands and the low lying coast region. This is a steep pass and the road is in bad condition due to the heavy traffic. A second factor increasing transaction costs is the presence of a multitude of police check posts between Iringa and Dar es Salaam, who stop every single truck. Often, bribes have to be paid to be able to carry on.[11] The higher transaction cost may also simply reflect the higher cost of living associated with Dar es Salaam.

It is also interesting to compare the estimates of the adjustment parameters in the TAR model to the estimates with the simple AR1 model. The adjustment parameters for the two eastern trade routes have increased dramatically (in absolute values), while for the Dodoma-Iringa and the Mbeya-Iringa trade routes, the changes are marginal. Both the Songea-Iringa route and the Sumbawanga-Iringa show a significant decrease. Note also that the sluggish adjustment of Songea-Iringa trade relative to Sumbawanga is not caused by a disproportionate transaction cost, but rather by a slower adjustment of the price differences. Judged by the speed at which price in different markets adjust to one another,

[11] A lot of trucks actually prefer to drive at night. Although this is much more dangerous, they prefer this to the hassle and cost of driving during daytime.

Mbeya is best integrated with Iringa, followed by Dodoma. Although the incorporation of transaction costs in the Dar es Salaam-Iringa trade route resulted in a doubling of the adjustment speed, price transmissions in this route remains slowest, with an associated half-life of more than 11 weeks.

Let us now turn to the model with a time trend included. We start by comparing the estimates of the transaction cost at the beginning of our sample to the estimates at the end of our sample.[12] For all trade routes, transaction costs have decreased over time. Over the entire period, transaction costs have been cut in half for Dodoma-Iringa and Sumbawanga-Iringa. For Mbeya-Iringa, the decrease in transaction costs was 36%, while for the Morogoro-Iringa route it decreased by 26%. The reduction in the transaction cost was lowest for the Songea-Iringa and the Dar es Salaam-Iringa trade routes, which both saw a reduction of about 8%.

Turning to the adjustment process, we see that there is evidence of a statistically significant increase in the speed of price adjustment in four out of six market pairs. For the Sumbawanga-Iringa trade route, the interaction between the adjustment and time is estimated to go in the wrong directions, though the coefficient did not prove significantly different from zero. For this route, the adjustment speed seemed to have remained constant at a half-life of just under four weeks. For the Morogoro-Iringa market pair, both the adjustment parameter and the interaction with time are estimated with the correct sign, but none of the estimates is statistically significant. The increase in the speed of adjustment is largest for the Dodoma-Iringa trade route. At the end of the period, it takes about one and a half week for a shock to adjust to half of its initial value, down from virtually no adjustment at the beginning of the period. For the Mbeya-Iringa trade route, while the half-life at the beginning of the sample was 12 weeks, this has come down to just over two weeks at the end of the period. Songea-Iringa also witnessed a significant increase in the adjustment speed. While it took on average 14 weeks at the beginning of the period for a shock to return to half its value, at the end of the period, it takes just under four weeks. For the Dar es Salaam-Iringa route, adjustment has been improving over time from virtually no adjustment to an adjustment speed with an associated half-live of about 5 weeks.

Overall, we see that the Iringa market is best integrated with the administrative capital, showing evidence of impressive reductions in both transaction costs and the time needed for prices to adjust to one another. We come to the same conclusion for the Mbeya-Iringa, although the reductions are less dramatic. In the Sumbawanga-Iringa trade route, we also witness substantial reductions in the transaction cost, but the speed of adjustment stays the same over the period under investigation. For Songea-Iringa, the reverse holds: the decrease in transaction cost is minimal, but there is a considerable increase in the speed of adjustment of price differences between the two markets once the price difference exceeds transaction costs.

Conclusions, policy implications and pathways for future research

In this paper, we argue that the threshold autoregressive model is a better tool to assess the degree of market integration than its rival, the parity bounds model. It allows the researcher to differentiate between two components critical to inter-market arbitrage:

[12] Our sample runs from the 37th week of 1989 to the 18th week of 1999.

transaction costs on the one hand and the speed of adjustment of market prices in spatially separated food markets on the other hand. Moreover, adding a simple time trend to both the threshold and the adjustment parameter allows us to break down changes in market integration in changes in these two components. We illustrate this using high frequency price data for seven maize markets in Tanzania.

We find that transaction costs are markedly higher between our reference market (Iringa) and the markets to its east. Dodoma seems to be best integrated with Iringa. Interestingly, this is due to a gradual increase of the speed of price adjustment and a gradual reduction of the transaction cost over time. If time trends are not accounted for, the Mbeya-Iringa trade route overtakes Iringa-Dodoma in the speed of price adjustment. For all six market pairs, we conclude that the transaction costs have decreased over time.

The results for a simple model that disregards transaction costs and does not include a time trend generates estimated half-lives ranging from 3.9 to more then 22 weeks. After appropriately modelling the non-linear adjustment caused by transaction costs, half-lives are down to 4–11 weeks. Subsequently adding a time trend, half-lives range from about one and a half week to about 5 weeks. Studies that do not include a time trend frequently find values for half-lives that are unreasonably high given the market settings. Half-lives from the order of 1 to 5 weeks seem much more reasonable then the ones we find without allowing the transaction costs and adjustment speed to change over time.

Given that the importance of price movements in the analysis of poverty and famines has been acknowledged decades ago (Sen, 1981) it is surprising famine prevention initiatives most often stop short of gathering and disseminating price data. Indeed, most famine early warning systems seem to attach more weight to meteorological and geological data and analysis then to analyzing the dynamics of prices and product movement. We feel studies like this can be a valuable addition to famine early warning systems. It should be possible to link the price data and resulting analysis to Geographic Information Systems (GIS) to produce interactive maps to help identify areas that are risk. It should, in principle, even be possible to link price movements to (food) poverty when prices of enough goods are gathered.

More specifically, for Tanzania this study has the potential to help government officials in their efforts to increase market performance in order to maintain food security. Although overall, market integration improved substantially over the period under analysis, the integration of individual trade routes show considerable heterogeneity. Government officials can use these findings and try to find out why, for instance, in the Dodoma-Iringa trade route market integration has improved both in terms of a declining transaction cost and an increasing speed of adjustment, despite a gradually deteriorating road linking the two markets. This could point to the fact that, in this trade route at least, labour cost is less important to traders than costs related to distance like fuel and informal trade taxes. Other issues deserving more attention is why the economic capital seems to be less well integrated with the hinterland, and more in particular why trade between the eastern markets involves transaction costs that seem way too high given the distances. One should try to identify the factors in this trade route that may make the journey comparatively more expensive. Furthermore, for markets that perform poor in terms of the speed of adjustment, policies that increase the flow of information should be considered.

Future research building on the present analysis could extend the method in several ways. First of all, it should be noted that the present analysis is essentially bivariate in nature, modelling trade between two markets over time. However, markets typically form part of a much broader market system and trade can flow from one market to the other via a third market. In such a setting, a multivariate approach, like the one employed in Sephton (2003) would be more appropriate.[13] A second issue is the transaction cost, which in this study is modelled as a linear function of time. One could ask whether it is realistic to assume that transaction costs decrease over time at a constant rate. Maybe it would be more appropriate to model transaction costs as a function that is declining at a decreasing rate over time. Furthermore, the present model also assumes homoscedasticity. However, the ability of traders to hold stocks can create a link between current-period price volatility and past prices (Deaton and Laroque, 1992), resulting in a pattern that can be better modelled using ARCH models (Badiane and Shively, 1998).

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[13] Note that with each market that is added to the analysis, an extra dimension is added to the grid search, which quickly renders the estimation impossible within a reasonable time frame.

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