American Journal of Agricultural Economics Advance Access published December 4, 2011

Multiple-Regime Spatial Price Transmission with an Application to Maize Markets in Southern Africa

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Conventional threshold models of price transmission allow for different speeds of adjustment to equilibria depending on the magnitude of price differentials between markets. However, these models typically assume only one underlying long-run equilibrium price relationship. In this article we develop a framework for allowing multiple equilibria and multiple speeds of adjustment with regime separation depending on the magnitude of trade flows between regions, rather than the magnitude of price differentials. Applying this framework to maize price transmission between South Africa and Zambia shows no transmission during periods of high imports, when the government was heavily involved in maize importation, but stronger transmission during periods of low imports when the government was not importing.

Key words: maize, multiple thresholds, price transmission, South Africa, Zambia.

JEL Classification: C4, Q11, Q17, Q18.

Commodity trade flows between spatially-separated markets link regional markets and also facilitate the efficient transmission of supply/demand shocks in any one market to prices in other markets in the spatial network (Fackler and Goodwin 2001). The level of commodity stocks in both exporting and importing regions, along with the possibility of transport capacity constraints, can also play an important role in spatial price transmission (Wright and Williams 1989; Coleman 2009a and 2009b). Spatial price transmission may also take place in the absence of trade flows based on the inter-regional flows of information about relative supply and demand conditions in different regions, as well as the likelihood of future trade flows and stock adjustments (Stephens, et al. 2008).

The nature and extent of spatial maize price transmission has become an important food policy issue in Southern Africa. Indeed, maize is the primary food staple in the region, and the Republic of South Africa (RSA) is the only consistent producer of surplus maize. Most other countries in the region are nearly self-sufficient in maize in normal years, but require imports from RSA (or sometimes from other countries outside the region) during poor growing seasons. This is certainly the case for Zambia, the focus country of the application. In years of domestic shortage, the maize price in Zambia should rise relative to the RSA price, which provides an incentive for imports to take place. As imports occur, further changes in the RSA price might then be expected to be transmitted to domestic prices in Zambia.

However, there is clearly great controversy surrounding how effective private sector traders in Zambia (and other importing countries in the region) are in organizing timely imports and facilitating spatial price transmission. Governments often argue that private sector trade and storage is not sufficiently developed to undertake the necessary imports in a timely manner, leading to severe domestic shortages and prices that surge above the RSA price, plus transfer costs (Bird, Booth, and Pratt 2003). Alternatively, the private traders and many economists argue that government tariff and licensing requirements, combined with unpredictable discretionary imports by the government itself (or its parastatal maize marketing board) create disincentives for the private sector to play an effective

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Amer. J. Agr. Econ. 00(0): 1–15; doi: 10.1093/ajae/aar123
Received October 2011

role in organizing imports, managing stocks, or encouraging appropriate price transmission (Tschirley and Jayne, 2010). This issue has become even more important recently because the global commodity price boom has made the governments of countries like Zambia even more sensitive to higher global maize prices being transmitted to local domestic food markets due to the resulting implications for food security and social instability.

This article reports an econometric investigation into the nature and extent of maize price transmission between RSA and Zambia. Our empirical approach is rooted in the dynamic regression model of spatial price transmission (Ravallion, 1986).[1] However, Ravallion's seminal spatial dynamic regression model has been extended in light of econometric developments in unit root and cointegration methods, and it is now common to investigate these dynamic regressions in a cointegration framework (e.g., Alderman 1993; Golletti and Babu 1994; Minot 2010). A more recent development in the spatial dynamic regression literature is the realization that the speed of adjustment to shocks may differ depending on whether the magnitude of the shock exceeds a threshold representing transfer costs between regions. These threshold autoregression (TAR) and threshold cointegration (TCI) models allow for more rapid price adjustments when regional price differences are large enough to exceed an estimated threshold representing transfer costs, and slower or no adjustment when price differences are below the threshold (Abdulai 2000; Goodwin and Piggott 2001, Sarno, Taylor, and Chowdury 2004). The TAR and TIC models provide a more flexible framework which allows for regime-dependent speeds of price adjustment. However, these models have usually been applied using price data only, and assuming constant threshold parameters, which is tantamount to the restrictive assumption that transfer costs are constant over time.[2] Furthermore, these TAR and TIC models assume there is only one (regime-independent) long-run spatial price equilibrium, even though we might expect equilibrium price relationships to differ depending on the quantity of trade flowing between regions, who is doing the importing (the government or the private sector), and whether transport capacity constraints are binding (Stephens et al. 2008; Coleman 2009b).

The empirical framework developed in this article follows in the tradition of TAR and TCI models, but differs in two important ways from most previous research on price transmission using these methods. First, we include an estimate of transfer costs directly into the model, which helps overcome the limitation of the usual (often implicit) assumption of constant transfer costs. Second, and more importantly, we use trade flow data as our threshold variable and allow for multiple thresholds and price transmission regimes, thereby allowing price transmission performance to differ depending on the magnitude of trade flows between regions. This is a natural formulation that should provide more detailed information than threshold models based on the size of price differentials alone, because the size of trade flows is an important economic determinant of the nature of price transmission between the spatially-separated markets. Furthermore, unlike in standard TAR and TIC models, we also allow for the possibility that underlying long-run equilibrium relationships and speeds of adjustment can both shift between regimes. This adds valuable flexibility that should provide better inferences on both the nature of long-run price transmission and the speed of adjustment in different regimes. For example, Coleman (2009b) shows how spatial equilibrium price relationships can change dramatically as trade flows reach an upper bound (threshold) on transportation capacity. Furthermore, if governments have been involved in direct importation (as is the case for maize in Zambia) we might also expect spatial equilibrium price relationships to be quite different when the government is importing versus when imports are being undertaken by private sector traders.

[1] An alternative empirical approach to spatial price transmission is the switching regression model of Spiller and Huang (1986), which was first applied to agricultural markets by Sexton, Kling, and Carmen (1991). Switching regressions estimate the probability of being in different spatial arbitrage regimes, some of which are associated with spatial price efficiency and some with spatial inefficiency. The basic approach has been extended by Barrett and Li (2002) to account for different arbitrage regimes depending on the existence and direction of trade flows, and by Negassa and Myers (2007) to allow changes in government marketing policies to have an effect on the probability of being in different arbitrage regimes. However, switching regressions have been criticized for not incorporating dynamic adjustment between alternative arbitrage regimes in response to supply or demand shocks, a feature which appears to be important in the current context. Therefore, the dynamic regression approach is used as the basis for our empirical approach here.

[2] Or, at best, allowing threshold parameters (and hence transfer costs) to change smoothly over time; see Van Campenhout (2007).

A study that is closest to our approach was undertaken by Stephens et al. (2008), who use a switching error correction model to allow both the equilibrium (cointegrating) relationship and the speed of adjustment to vary across regimes. However, the authors restrict the possibilities to two regimes exogenously defined by a zero trade threshold (i.e., two regimes, a trade regime and a no-trade regime). In our study, however, we allow for multiple regimes and estimate threshold values rather than imposing them *a priori*. Our approach is more flexible because, as discussed above, it is intuitive that trade thresholds other than zero may influence spatial price transmission, especially when there are transport capacity constraints and direct government imports.

In the remainder of the article we first outline our conceptual framework and empirical approach. The model is a multiple-regime dynamic regression and threshold identification and estimation using the Gonzalo and Pitarakis (2002) penalty function approach. After outlining the model and estimation procedure, we provide an application to maize price transmission between RSA and Zambia.

Conceptual Framework

Let p_t be the domestic price of maize in a maize deficit country (e.g., Zambia) at time t, and s_t be the landed price of imported maize from a surplus country (e.g., RSA), including transfer costs and any import duties required to bring the commodity to the domestic location. Both prices are expressed in the same currency and quantity units (USD/metric ton). We allow for an arbitrary number of different price transmission regimes indexed by $i = 1, 2, \ldots, n$. The potential long-run spatial price relationship in each regime is assumed to be represented by:[3]

$$(1) \qquad p_t = \alpha_i + \beta_i s_t + u_{it} \quad \text{for } i = 1, 2, \ldots, n$$

where the intercepts α_i, slopes β_i, and the stochastic properties of the errors u_{it} may differ across regimes. In particular, the u_{it}'s for each regime may be stationary (indicating that a long-run equilibrium spatial price relationship exists) or nonstationary (no long-run equilibrium). The u_{it}'s may also be serially uncorrelated (rapid adjustment to equilibrium, if it exists) or serially correlated (slower adjustment to equilibrium).

This model can accommodate many different types of spatial price transmission regimes. For example, if a regime is characterized by rapid transport, positive and unconstrained trade flows, and trade is being undertaken by efficient private sector arbitragers, then we might expect $\alpha_i = 0$, $\beta_i = 1$, and u_{it} stationary with very little serial correlation (Williams and Wright 1991; Coleman 2009a). If a regime is characterized by zero trade between regions, then u_{it} may still be stationary, indicating the existence of a long-run equilibrium relationship due to the information flows between regions and the potential for trade (Stephens et al. 2008). But in this case u_{it} might be more serially correlated (slower speed of adjustment to equilibrium) and β_i might deviate from one (i.e., less than perfect long-run spatial price transmission).[4] If a regime is characterized by efficient private sector arbitragers with positive trade flows but there is a binding transport capacity constraint, then u_{it} might be nonstationary because the spatial price relationship will reflect an unobserved excess return to transport owners (Coleman 2009b), which could itself be nonstationary. In this case there might be no long-run equilibrium when looking at the relationship between s_t and p_t alone. Similarly, if a regime is characterized by high government imports which crowd out private sector imports, then we might expect u_{it} to be nonstationary because the objective of the government imports (which are typically sold domestically at a subsidized price) is to lower domestic prices relative to the price of imports (i.e., to *break* the equilibrium link between domestic prices and the price of imports). Each of these possible situations can potentially be captured by the multiple regime model (1).

Equation (1) is not a complete model of inter-regional price relationships in each regime because: (a) s_t will generally be endogenous; and (b) the stochastic structure of u_{it} has not yet been pinned down. To complete the model, we add an equation for s_t and provide a general structure for the error dynamics. In our application below strong evidence is presented that s_t is non-stationary in all regimes, so we complete the model under this assumption. However, extension to the alternative case of stationary s_t is straightforward.

[3] The relationship is "potential" because it is possible that u_{it} is non-stationary, in which case no long-run equilibrium exists.

[4] This might occur because the equilibrium link is based on information flows rather than physical trade flows.

Assuming s_t is non-stationary in all regimes we specify a set of regime-specific reduced-form equations:

$$\Delta s_t = \gamma_i + v_{it} \quad \text{for } i = 1, 2, \ldots, n \tag{2}$$

where the γ_i's are parameters and the v_{it}'s are zero mean and stationary but may be serially correlated and also correlated with the u_{it} at all lags (i.e., u_{it} and v_{it} are allowed to share a rich and interrelated dynamic correlation structure). Under these assumptions, (1) and (2) imply an estimation equation that has the structure of a single equation error correction model (SEECM):[5]

$$\begin{aligned}\Delta p_t = \mu_i + \beta_i \Delta s_t + \rho_i \Delta s_t + \lambda_i (p_{t-1} \\ - \beta_i s_{t-1}) + \sum_{j=1}^{m} a_{ij} (\Delta p_{t-j} \\ - \beta_i \Delta s_{t-j}) + \sum_{j=1}^{m} b_{ij} \Delta s_{t-j} + \varepsilon_t\end{aligned} \tag{3}$$

where the μ_i are composite constant terms that depend on α_i and γ_i, the ρ_i are measures of the within-regime contemporaneous correlation between u_{it} and v_{it}, the λ_i, a_{ij} and b_{ij} are parameters representing the dynamics of the adjustment process, and the ε_t is serially uncorrelated and uncorrelated with Δs_t by construction.[6] Notice that all parameters (both those representing the dynamics and those representing the potential long-run equilibrium relationship) are allowed to vary across regimes $i = 1, 2, \ldots, n$.

Equation (3) assumes p_t and s_t are non-stationary and cointegrated, in which case the parameters are just identified and non-linear least squares (NLS) estimation provides optimal Gaussian inference (Phillips and Loretan 1991).[7] Under these assumptions β_i is the regime-specific long-run spatial price transmission parameter indicating the long-run increase in the domestic price p that can be expected to be associated with a unit price increase in the RSA price s, provided transmission remains in regime i. Similarly, λ_i is the regime-specific speed of adjustment parameter indicating how long it takes for the long-run equilibrium to re-establish itself after a shock, again provided transmission remains in regime i. The speed of adjustment is usually measured by the half-life $hl_i = \ln(0.5)/\ln(1 + \lambda_i)$, which is an estimate of the number of periods it takes for half of the adjustment back to long-run equilibrium to occur.

Under appropriate restrictions, (3) can also accommodate cases in which no long-run spatial price transmission occurs in some regimes. In particular, if p_t and s_t are both non-stationary but *not* cointegrated in regime i, then $\lambda_i = 0$ and β_i is under-identified. In this case there is no long-run equilibrium between the prices and no long-run spatial price transmission occurs in regime i. If s_t is non-stationary but p_t is stationary, then $\beta_i = 0$, and again there is no long-run price transmission in regime i.

Estimation and Testing

The goals of the analysis are: (1) to identify different price transmission regimes; and (2) to generate estimates of the degree of long-run transmission (i.e., the magnitude of β_i) and the speed of adjustment to equilibrium (the magnitude of λ_i) that are specific to each price transmission regime. We first discuss regime identification and estimation, and then turn to estimating the degree of spatial price transmission in each regime.

Regime Identification and Estimation

To identify and estimate the regime, first note that (3) can be written in compact form as $\Delta p_t = f(\mathbf{X}_t, \boldsymbol{\theta}_i) + \varepsilon_t$, where $\mathbf{X_t}$ are the explanatory variables and $\boldsymbol{\theta}_i$ is the associated parameter vector. Using this notation we define a multiple-regime threshold model as:

$$\Delta p_t = f(\mathbf{X}_t, \boldsymbol{\theta}_i) + \varepsilon_t \quad \mathbf{q}_t \in R_i(\boldsymbol{\delta}) \tag{4}$$

where $i = 1, 2, \ldots, n$ indexes a set of multiple regimes defined by values of the exogenous threshold variable vector $\mathbf{q_t}$ lying in a set of non-intersecting and exhaustive sets $R_i(\boldsymbol{\delta})$, defined by the parameter vector $\boldsymbol{\delta}$. A simple example would be a two-regime model based

[5] See Phillips and Loretan (1991) for a detailed derivation of the SEECM from equations of the form (1) and (2). Another option would be to derive a vector error correction form for estimation. However, the SEECM facilitates threshold estimation and so is more convenient for the current application.

[6] This specification does *not* assume that s_t is exogenous to p_t, which would only be true if $\rho_i = 0$ (i.e., u_{it} and v_{it} are not contemporaneously correlated). Thus, the model allows for the possibility of bi-directional price transmission.

[7] In particular, standard errors from NLS estimation of (3) are appropriate for hypothesis testing and confidence interval estimation, including inference on β_i and λ_i.

on the level of imports:

$$\text{(5a)} \quad \Delta p_t = f(\mathbf{X}_t, \boldsymbol{\theta}_1) + \varepsilon_t \quad q_{1t} \le \delta_1$$

$$\text{(5b)} \quad \Delta p_t = f(\mathbf{X}_t, \boldsymbol{\theta}_2) + \varepsilon_t \quad q_{1t} > \delta_1$$

where q_{1t} represents imports into the country of interest and δ_1 is the critical threshold import level above which the price transmission process changes. In general, however, (4) allows for multiple regimes and multiple threshold variables and parameters.

Threshold estimation proceeds through concentration. Let $S_T(\boldsymbol{\delta})$ be the minimized residual sum of squares function from estimating the set of parameters $\boldsymbol{\theta}_i$ in (4) using a sample of T observations, conditional on a given regime definition parameter vector $\boldsymbol{\delta}$. Then the estimated regime parameters are given by:

$$\text{(6)} \quad \hat{\boldsymbol{\delta}} = \arg\min_{\boldsymbol{\delta}} S_T(\boldsymbol{\delta})$$

which is computed with a grid search procedure over the threshold parameter space, conditional on ensuring a minimum number of observations in each regime. This estimation procedure has been explained in detail elsewhere (e.g., Hansen 2000).

Despite the ease of estimation, testing to determine the number thresholds is difficult because of the well-known problem of underidentified nuisance parameters under the null of no thresholds (Davies, 1987; Hansen, 1996; and Balagtas and Holt, 2008). Hansen (1996) has developed an alternative bootstrap method for testing the null of no threshold (one regime) against a one threshold (two-regime) alternative. But although this same test has been applied to test for multiple regimes sequentially, there is no distribution theory to support this (see Gonzalo and Piterakis 2002).

An alternative procedure for identifying multiple regimes has been developed by Gonzalo and Pitarakis (2002), hereafter GP, who suggest using the BIC-like criterion function:

$$\text{(7)} \quad Q_T(n-1) = \max_{\boldsymbol{\delta}} \log\left[\frac{S_T}{S_T(\boldsymbol{\delta})}\right] - \frac{\ln(T)}{T} k(n-1)$$

where S_T is the residual sum of squares for the single regime (no threshold) model, k is the number of parameters to be estimated in the single regime model, and $(n-1)$ is the number of threshold parameters to be estimated. Multiplying T times the first component on the right hand side of (7) provides the conventional likelihood ratio (LR) statistic for testing the null of a single regime (no threshold parameters) against the alternative of $(n-1)$ threshold parameters. Therefore, this LR statistic forms the basis for model selection. But instead of using the conventional LR test, whose distribution in this context is unknown, selecting the number of regimes is based on the inclusion of a penalty function that penalizes over-parameterization of thresholds relative to the sample size. This penalty function is analogous to the BIC criterion for choosing lag lengths. GP recommend threshold and regime selection based on:

$$\text{(8)} \quad \hat{n} - 1 = \arg\max_{1 \le n \le N-1} Q_T(n-1)$$

where N is a maximum number of regimes to be considered. Gonzalo and Pitarakis also provide simulation evidence to suggest this criterion performs well in selecting the appropriate number of thresholds and regimes in many environments.

Because we want to evaluate multiple thresholds, we apply the GP penalty function approach for choosing the number of thresholds. However, for comparing no thresholds with one, we also apply the Hansen (1996) bootstrap test as a consistency check.

It is important to note that the SEECM model (3) can be used in this threshold identification and estimation procedure even if some price transmission regimes feature prices that are not cointegrated (no long-run spatial price transmission). This is because (3) is just identified and so has exactly the same reduced form (and therefore exactly the same residual sum of squares) under the assumption of no cointegration as it does under the assumption of cointegration (Phillips and Loretan 1991). Therefore, threshold selection can proceed based on (3) even if there is no long-run price transmission in some regimes.

Regime-Specific Estimation and Testing

Regime-specific estimation and testing on the long-run spatial price transmission parameters β_i, and speed of adjustment parameters λ_i, would be straightforward under the assumption that prices are cointegrated in every regime. In this case we could just apply (3) to the relevant data sub-sample associated

Table 1. Data Summary Statistics

Variable	No. of Obs.	Mean	Std. Dev.	Min.	Max.
RSA Price (USD/MT)	187	156.8	43.9	74	280
Zambia Price (USD/MT)	187	200.2	66.3	86.5	389
Transport Costs RSA-Zambia (USD/MT)	187	96.3	32.4	51	230
Imports RSA-Zambia (MT)	187	3,352.3	7,218.7	0	41,560
Imports RSA-Malawi (MT)	187	1,535.2	5,010.3	0	52,298
Imports RSA-DRC (MT)	187	214.4	421.6	0	2002

with each regime to obtain the regime-specific parameter estimates. However, if we want to allow for the possibility that there is no cointegration in some regimes, things become more complicated. This is because (3) would not provide valid estimates of β_i and λ_i when there is no cointegration (because the identification restrictions would be invalid).

One way to proceed would be to undertake preliminary regime-specific unit root and cointegration tests to decide if a particular regime features cointegration or not. Then, if cointegration is found, one would estimate (3). If not, one would stop and conclude that there is no long-run spatial price transmission in that regime. The problem is that this is a non-standard testing environment because the conventional distributions for unit root and cointegration tests assume a single-regime environment, whereas in our model we have multiple regimes and possible multiple switches between regimes in any data sample. In the absence of an explicit distribution theory that accounts for the regime-switching, we undertook a simulation study to evaluate the performance of standard unit root and cointegration tests applied to data from a particular regime when the sample is generated from a multiple-regime threshold model. Results from the simulation are reported in the appendix, and show that the regime-specific tests are indeed biased and, in our simulations, the bias favors over-acceptance of the null of non-stationarity (no cointegration). This suggests that regime-specific tests for cointegration may be biased in favor of finding no long-run equilibrium relationship, and therefore no long-run spatial price transmission.

Given the difficulties with this testing environment, we take a conservative approach to regime-specific estimation and testing. First, we do report regime-specific unit root and cointegration tests for each regime identified with the regime selection procedure. Even though these tests are biased, the size of their p-values can still provide an informal idea of the likelihood of non-stationarity and cointegration in different regimes, though obviously these p-values need to be interpreted with caution. Second, irrespective of the unit root and cointegration testing results, we proceed to regime-specific estimates of (3) under the assumption of cointegration in every regime. Assuming a long-run equilibrium exists in every regime (while still allowing the nature of that equilibrium to differ across regimes) provides the maximum opportunity for finding that price transmission exists in the most regimes. Therefore, we would argue that this approach will provide an upper bound on the extent of price transmission between the markets.

Data and Background

Summary statistics for the data used in our application to RSA and Zambia are reported in table 1. Monthly maize prices for each country were obtained from national price reporting systems for RSA and Zambia covering the period January 1994 to July 2009. The Johannesburg Stock Exchange collects monthly white maize prices for RSA, and Zambia's Central Statistical Office collects monthly white maize retail prices in various regional markets throughout Zambia. For our purposes, we focus on retail maize prices in Zambia's capital city of Lusaka.

Transport costs from RSA to Lusaka were obtained from the Hauliers Association of Zambia up to September 2007. After September 2007, transport costs are based on thrice-annual interviews of three to four trading firms that import grain from RSA to Zambia. Official import duties for maize imports into Zambia varied little over the sample period, and can therefore be captured adequately by the α_i and β_i parameters in the long-run spatial price relationships.

Monthly trade flow data was obtained from the South Africa Revenue Service (SARS

2010), which records the monthly trade of all commodities exported from South Africa to neighboring countries. There is potential for commercial (private sector) maize imports from RSA to Zambia, and such imports are reported to have occurred during some periods over the sample (Tschirley and Jayne 2010). However, during periods when imports were relatively high, virtually all the activity was initiated and coordinated by the Government of Zambia in response to anticipated production shortfalls predicted by national early warning systems (Tschirley and Jayne 2010). The resulting imports were then sold to registered maize millers and other industrial buyers at subsidized prices (with the subsidy being the difference between the landed cost of importing maize from South Africa, minus the government-specified selling price to industrial buyers). Thus, during periods of relatively high maize imports, when the government was dominating the trade, subsidies were being used to lower domestic prices relative to RSA prices.

Unfortunately, reliable monthly data separating government from private sector imports are not available for Zambia (or other countries in the region). The only monthly trade flow data available are total flows out of RSA. However, annual trade data from Zambia show that the government was heavily involved in direct maize importation during periods of major domestic production shortfalls (e.g., 1998/99, 2001/02, 2002/03, 2005/06 and 2008/09) when imports from RSA were at their highest (Ministry of Agriculture and Cooperatives 2011). This pattern of government involvement in maize imports from RSA plays a major role in our interpretation of the price transmission empirical results reported below.

Application to South Africa-Zambia Maize Price Transmission

We apply the modeling procedure to investigate maize price transmission between RSA and Zambia. The volume of maize traded between RSA and Zambia is the primary candidate for a threshold variable because economic theory suggests the level of such trade will be a major determinant of spatial price transmission. However, we also investigate other potential threshold variables as a consistency check; specifically, we examine imports from RSA into the Democratic Republic of the Congo (DRC) and Malawi, respectively, as well as time.[8] Trade flows from RSA to neighboring countries are considered because cross-border maize trade between Zambia and its neighbors opens the potential for indirect price transmission when imports are flowing from RSA into the DRC or Malawi. Current period trade flows may not be exogenous to current prices, as is required for threshold estimation. However, the trade flow data identifies when imports leave RSA, and it takes time for transport to occur. So exogeneity of current trade flows may be a reasonable assumption, especially when trade volumes are relatively low. Furthermore, using lagged trade flows as the threshold variable produces very similar results to current trade flows, so any endogeneity in the current trade flow data does not appear to have a major influence on the results. Evaluating time as a possible threshold variable allows for structural change in the maize price transmission process that may occur due to changes in transport capacity and/or changes in government policies not captured by the trade flow data. The SEECM model (3) was used for threshold selection and estimation, and including one lagged first difference (i.e., $m = 1$) was found to be sufficient to eliminate autocorrelation in the residuals from every estimated regime in this application.

Threshold selection proceeds sequentially. We first evaluate each of the candidate threshold variables as a possible determinant of the first threshold (see the top part of table 2). Optimal single threshold parameter estimates for each potential threshold variable (*qzam*, *qdrc*, and *qmal* for metric tons of imports from RSA into each country, along with time) are provided, along with the sample size for the lower and upper regime estimates and the optimal GP BIC value. For the single threshold case we also provide the Hansen (1996) bootstrapped p-value for testing the null of no thresholds against the alternative of a single threshold.[9] Two threshold variables, *qzam* and *qmal*, provide positive GP BIC values, indicating an initial threshold could be defined by either of these variables. The bootstrapped p-value confirms strong rejection of

[8] The work of Coleman (2009a and 2009b) suggests maize stock levels may also be potential threshold variables. However, commercial maize stocks in Zambia are negligible, with most stockholding being undertaken either by smallholder households or the government. Furthermore, reliable stocks data are not available, so maize stocks could not be investigated as a potential threshold variable.

[9] The bootstrapped p-value for this test is not used in the case of multiple thresholds because there is no distribution theory for the test statistic in this case.

Table 2. Price Transmission Threshold Estimation and Testing Results

Variable	Statistic				
	Threshold Estimate	T (Low)	T (Up)	GP BIC value	Bootstrap p-value
First Threshold					
- *qzam*	20.0	86	99	0.0142	0.000
- *qdrc*	158.3	135	50	−0.0462	0.018
- *qmal*	0.3	82	103	0.0181	0.000
- time	Mar, 06	145	40	−0.0552	0.043
Second Threshold (over $qzam \leq 20$*)*					
- *qzam*	2	69	17	−0.1145	—
- *qdrc*	43.1	64	22	−0.1099	—
- *qmal*	1.23	63	23	−0.1062	—
- time	Nov, 95	17	69	−0.0518	—
Second Threshold (over $qzam > 20$*)*					
- *qzam*	6934	70	29	0.0213	—
- *qdrc*	300	68	31	−0.0259	—
- *qmal*	0	19	80	−0.0428	—
- time	Aug, 06	78	21	−0.0481	—
Third Threshold (over $20 < qzam \leq 6934$*)*					
- *qzam*	3169	56	14	−0.0666	—
- *qdrc*	104	42	28	−0.0626	—
- *qmal*	0	17	53	−0.0840	—
- time	July, 06	51	19	−0.0749	—

the no threshold null against a single threshold for both *qzam* and *qmal* (p-values = 0.000).[10] Although the GP BIC value is slightly higher for *qmal* than *qzam*, we chose 20 metric tons of imports from RSA to Zambia as the first threshold on the strong *a priori* grounds that imports entering Zambia directly are likely to be the most important determinant of regime shifts in price transmission between RSA and Zambia. We investigate other potential threshold variables again when considering the possibility of a second threshold.

Given that the threshold of 20 metric tons is close to zero, we also investigated zero imports from RSA to Zambia as a candidate for the first threshold. The GP BIC value for a threshold at zero is −.1179, indicating no threshold at zero. Evidently, even a small amount of imports can be an important factor when determining the spatial price transmission regime.[11] Therefore, the first threshold is chosen to be $qzam = 20$ metric tons per month, which defines the two regimes as $qzam \leq 20$ and $qzam > 20$.

Next, we investigate the possibility of a second threshold within each of the two regimes already defined (see the middle part of table 2). Within the lower regime ($qzam \leq 20$) there is no evidence of a second threshold using any of the four threshold variables because all of the GP BIC values are negative. Within the upper regime ($qzam > 20$) there is a positive GP BIC value at $qzam = 6,934$ metric tons, indicating support for a second threshold at this level of imports into Zambia. GP BIC values for all other threshold variables are negative, indicating no support for additional thresholds.

A third threshold is also possible. The lower regime ($qzam \leq 20$) was already investigated and no additional threshold was found, and the upper regime ($qzam > 6,934$) only has 29 observations, which is too few to identify an additional threshold. However, we investigated the possibility of an additional threshold within the middle regime ($20 < qzam \leq 6,934$) which has 70 observations. In this case, however, all GP BIC values are negative, indicating no additional threshold (see the bottom part of table 2).

To summarize, the GP BIC criterion suggests two thresholds, both defined by the level of direct imports from RSA into Zambia. The two thresholds define a lower regime where

[10] The bootstrapped p-values also provide some support for a threshold in *qdrc* and time as well, but since these variables provide higher p-values and negative GP BIC values, we only consider *qzam* and *qmal* as initial threshold variables.

[11] A relatively small amount of imports is also quite common in the data, with 58 months (about 30% of the sample) experiencing imports of between 0 and 20 metric tons.

Table 3. Unit Root and Cointegration Tests by Regime

	Model			
Statistic	Full Sample	Regime 1 $qzam \leq 20$	Regime 2 $20 < qzam \leq 6,934$	Regime 3 $qzam > 6,934$
T	185	86	70	29
DF p-value for p_t	0.013	0.103	0.001	0.909
PP p-value for p_t	0.014	0.068	0.003	0.922
DF p-value for s_t	0.248	0.921	0.450	0.441
PP p-value for s_t	0.307	0.935	0.572	0.634
EG p-value	0.002	0.032	0.000	0.899

$qzam \leq 20$ metric tons, a middle regime where $qzam$ is between 20 and 6,934 metric tons, and an upper regime where $qzam > 6,934$ metric tons.

The next step is to estimate the extent of price transmission in each regime. We begin by applying conventional unit root and cointegration tests to data sub-samples associated with each of the three identified regimes. Results are provided in table 3. As discussed previously, these test results need to be interpreted with caution because conventional p-values for the tests do not allow for the multiple regime environment. However, the first thing to notice in table 3 is that the evidence strongly supports the hypothesis that the RSA price is non-stationary in every regime, as well as over the full sample. Thus, even acknowledging the possible bias in the regime-specific unit root test results, it appears that non-stationarity of the RSA price is a reasonable assumption for all three regimes. However, results on non-stationarity of the Lusaka price, and on the existence of cointegration, are more mixed. Full sample results in the first column suggest that the Lusaka price is stationary, which implies no long-run equilibrium price relationship. Hence, ignoring the possibility of thresholds would lead to the conclusion that there is no long-run price transmission between these markets.

Under sample separation, test results for the first regime ($qzam \leq 20$) suggest the Lusaka price is non-stationary and cointegrated with the RSA price (i.e., long-run price transmission exists). Test results for the second regime ($20 < qzam \leq 6,934$) suggest the Lusaka price is stationary, and therefore not cointegrated with the RSA price (no long-run price transmission). Test results for the third regime ($qzam > 6934$) suggest the Lusaka price is non-stationary but *not* cointegrated with the RSA price (no long-run price transmission).

Given the potential bias problems with the regime-specific unit root and cointegration tests, we proceeded to estimate regime-specific long-run price transmission and speed of adjustment parameters under the conservative assumption that a long-run equilibrium price relationship exists in every regime. Results from estimating (3) for each regime are provided in table 4. Results for the low import regime ($qzam \leq 20$) are consistent with the previous conclusion that a long-run equilibrium relationship exists for this regime. The long-run price transmission parameter is estimated at 0.622, indicating a long-run increase of 62 ¢ in Zambian prices for every \$1 increase in RSA prices. The speed of adjustment parameter is estimated at -0.202, which provides a half-life of 3.1 months. The 95% confidence intervals for these parameters are given by $[0.289, 0.956]$ and $[-0.322, -0.083]$, which provides a half-life interval of $[1.8, 8.0]$ months.

Results for the intermediate import regime ($20 < qzam \leq 6,934$) are also consistent with the existence of a long-run equilibrium, even though regime-specific unit root and cointegration tests suggested no such long-run equilibrium occurs in this regime. The long-run price transmission parameter for this regime is estimated slightly higher, at 0.684, and the speed of adjustment slightly faster, at -0.428 (half-life of 1.2 months). These parameters also seem to be estimated fairly precisely, though we have to interpret these results with care because they are not valid if there really is no cointegration in this regime (as suggested by the regime-specific unit root and cointegration tests).

However, the results for the high import regime ($qzam > 6,934$) are not at all consistent with the existence of a long-run equilibrium in this regime. Both the long-run transmission parameter and the speed of adjustment are estimated very imprecisely, and the estimated

Table 4. Price Transmission Estimation Results by Regime

	Model		
Parameter	Regime 1 ($qzam \leq 20$)	Regime 2 ($20 < qzam \leq 6934$)	Regime 3 ($qzam > 6,934$)
$\hat{\beta}$	.622*	.684*	1.771
	(.167)	(.095)	(1.644)
$\hat{\lambda}$	−.202*	−.428*	−.085
	(.060)	(.061)	(.123)
Half-life	3.1 months	1.2 months	7.8 months
$\hat{\mu}$	1.625	17.719	−7.497
	(8.707)	(11.667)	(19.257)
$\hat{\rho}$	−.927*	−.192	−.699
	(.240)	(.166)	(1.630)
$\hat{a}_1$	.184	.243*	.373*
	(.102)	(.094)	(.174)
$\hat{b}_1$	.206	−.183	.446
	(.182)	(.179)	(.635)
T	86	70	29
R^2	0.883	0.850	0.911
$Q(1)$	0.888	0.529	0.744
$Q(5)$	0.322	0.922	0.914
$Q(10)$	0.336	0.897	0.999

Notes: * indicates statistically significantly different from zero at the 5% level; $Q(j)$ indicate Ljung-Box p-values for testing the null hypothesis of no residual autocorrelation against the alternative of jth degree autocorrelation.

speed of adjustment parameter is very close to zero, indicating infinite adjustment (no long-run equilibrium). So in this case, the previous conclusion of no cointegration in this regime is strongly supported.

Ignoring the possibility of thresholds in this data set leads to the conclusion of no long-run maize price transmission between the RSA and Zambia. However, multiple threshold analysis suggests price transmission does occur in the low import regime ($qzam \leq 20$) and may also occur in the intermediate import regime ($20 < qzam \leq 6,934$). However, the conclusion is that price transmission does not occur in the high import regime ($qzam > 6,934$). The latter result may seem counterintuitive since, *a priori*, we might expect better price transmission as the level of trade flow increases. However, there are two possible explanations for this result. First, it could be that transport capacity constraints disrupt price transmission at high import levels (see Coleman 2009b), leading to the result that long-run price transmission only occurs when imports are relatively low. But a second, and more likely, explanation is the role that the Government of Zambia plays in maize importation from RSA. Periods of no or low imports from RSA are typically associated with adequate domestic food supplies and moderate price levels in Zambia. Indeed, Ministry of Agriculture (2011) data indicate that the Government of Zambia was not involved in maize importation at these times. During these periods, regional weather patterns and production are usually good and informal cross-border trade, as well as information flows and the potential for commercial imports from RSA, help link Zambian prices with prices in other parts of the region, including RSA. In contrast, during periods of high imports from RSA to Zambia there are usually acute shortages and high prices in Zambia. The Government of Zambia usually responds to such crises by using the treasury to channel imports to local buyers at highly subsidized prices, with the explicit goal of putting downward pressure on domestic prices. In other words, the Zambian government actively seeks to prevent the transmission of prices during high-price (high import) periods to protect low-income consumers against food insecurity. The private sector cannot compete with subsidized government imports, and so almost all of the maize imported during these periods is imported by the government and sold at subsidized prices. These maize marketing policy activities then break the link between RSA and Zambian maize prices, which is reflected in our empirical finding of no long-run price transmission in the high import regime.

These conclusions can to some extent be seen graphically in figure 1, which shows

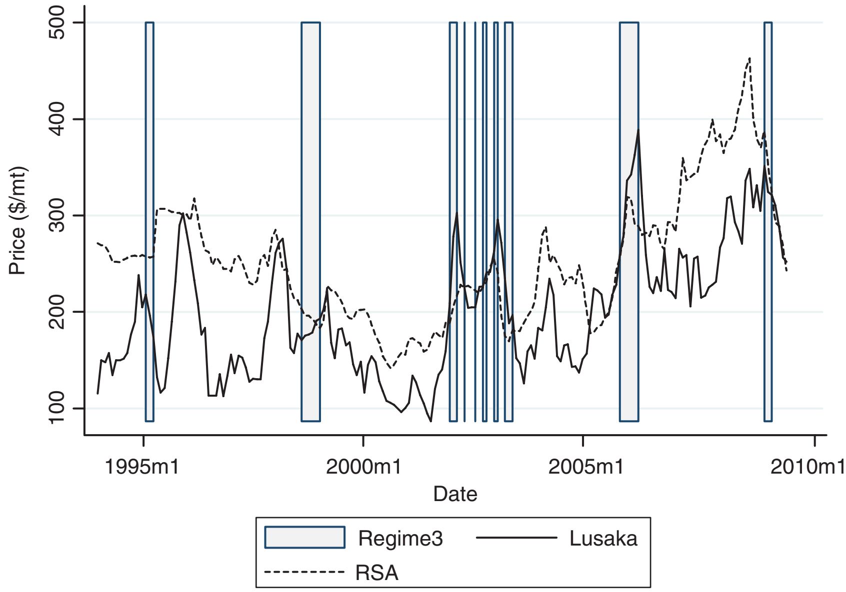

Figure 1. Zambia and RSA prices with high import regime periods (regime 3) shaded

Lusaka retail prices and the transport-adjusted RSA price over time, with the shaded periods indicating high import periods when $qzam > 6,934$. In periods of higher imports, Lusaka and RSA prices are often moving in opposite directions, even though the Lusaka price is generally much higher relative to the landed RSA price during these periods. Not surprisingly, most high import regime periods (e.g., 2002, 2003, and 2006) correspond to local food production shortfalls during poor growing season conditions in Zambia. During these periods the Zambian Government often announced early in the season that it would arrange imports from RSA to offset the shortfalls, and that these imports would be sold to local millers at prices below the landed cost of imports from RSA. This explains the disconnect between RSA and Zambia prices during these periods.

In 2008, high food prices associated with the global food crisis induced a similar response by the Zambian government, which inhibited the transmission of high international maize prices to the domestic market. These policy tools were never employed during the low import regime periods, during which time our results suggest price transmission did occur.

One important implication of these results is that, to the extent that government policy affects both the level of trade and the relationship between RSA and domestic prices, price transmission estimates may reveal more about the effects of government policy than the efficiency or performance of private sector markets *per se*. In principle, this implication could be tested directly by separating the sample into periods of high and low intervention (as opposed to periods with different levels of imports). However, separating the sample in this way would be somewhat arbitrary and might add very little in the current context because the periods of high imports are also the periods when the government is intervening the most, so these two issues are one and the same. Furthermore, we would argue that the import threshold approach is more general because it potentially allows one to pick up on other factors that may be influencing the nature of price transmission besides changes in government policies (such as limited physical trade flows).

Conclusions

A major purpose of price transmission analysis is to provide estimates of the link between world markets and a particular national market. However, it is clear that over a given sample period there may be major changes in transport capacity constraints, incentives for trade between world and national markets, and policy actions which alter these incentives. In turn, all of these factors influence the amount of trade and its composition (government or private sector). When these types of changes occur, a conventional full sample analysis may lead to overly-aggregated and potentially misleading estimates of international-to-domestic market adjustment dynamics. Allowing for multiple thresholds and regime changes may lead to quite different conclusions. For example, when government policies attempt to dampen world-to-domestic price transmission in some periods, and allow for a stronger role for the private sector in other periods, it is important that price transmission analysis accounts for these changes in regimes.

This article contributes to the price transmission literature by using trade flow data as a threshold variable to identify multiple thresholds and price transmission regimes, allowing price transmission performance to differ depending on the magnitude of trade flows between regions. Unlike in standard TAR and TIC models, we allow for the possibility of different long-run equilibrium relationships under different regimes, as well as different speeds of adjustment. Furthermore, we include an estimate of transfer costs directly into the model, which helps overcome the limitation of the usual (often implicit) assumption of constant transfer costs. These innovations add valuable flexibility that should provide better inferences on both the nature of long-run price transmission and the speed of adjustment under different market conditions.

We applied the empirical approach to estimate maize price transmission dynamics between South Africa and Zambia. A perhaps surprising feature of the results is that price transmission fails when imports are at their highest. We argue this is because high imports occur in periods of severe domestic shortage when the government is doing the importing, and these imports are sold in domestic markets at subsidized prices. During these periods the private sector has little incentive to import. In essence, the lack of price transmission is an implicit or explicit policy goal because the government wants to lower domestic prices relative to world prices and is willing to subsidize imports to do so. This breaks the link between South African and Zambian maize prices.

This interpretation suggests that price transmission estimates during a substantial portion of the sample period do not reflect the performance of private sector trade, but rather the impacts of government behavior in heavily-regulated markets. In some sub-periods, however, the Zambian Government did take a more unregulated approach to imports from RSA, and these sub-periods do provide an opportunity to measure the price transmission and adjustment dynamics of private sector markets in the region. In Zambia, these periods occurred during years when production was estimated to exceed, or only moderately fall short of, consumption requirements. Our empirical results suggest that during these periods there was a long-run equilibrium between RSA and Zambian maize prices, and the speed of adjustment was comparable to that estimated in many other price transmission studies.

This study underscores three main points for consideration in future price transmission analyses. First, the price transmission process between any two regions is likely to be sensitive to trade volume, that is, whether trade is occurring or not, and if so, by the quantity of trade relative to the size of the market and the existing transport capacity. For this reason, there may be multiple long-run equilibrium price relationships among markets depending on the level of imports. Ignoring the possibility of these multiple thresholds and regimes can lead to incorrect inferences about the extent and speed of spatial price transmission and the potential for deriving misleading implications for policy. Second, transfer costs can vary greatly across time, and treating them as a constant, or as if they follow a smooth trend limits the ability of price transmission analysis to provide meaningful policy conclusions. Third, in most if not all countries in the world, market prices are affected by governmental behavior. During the recent 2007/08 world food crisis, for example, many governments sought to limit the degree of price transmission between world and domestic markets. Under such conditions, the public and private sectors may strategically interact, making it difficult to draw conclusions from price transmission analyses about the performance of private sector trade or the spatial efficiency of private sector markets.

Funding

The authors acknowledge funding from the Bill and Melinda Gates Foundation under the Guiding Investments in Sustainable Agricultural Markets in Africa (GISAMA) program, and the African Agricultural Markets Program (AAMP) in association with the Common Market for Eastern and Southern Africa (COMESA) and the Alliance for Commodity Trade in Eastern and Southern Africa (ACTESA).

Acknowledgments

The authors thank three anonymous referees and seminar participants at Michigan State University and the University of Nevada, Reno, for their very helpful comments.

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Appendix

This appendix provides details of a simulation experiment evaluating the performance of standard unit root and cointegration tests applied to regime-specific data generated by a multiple regime threshold model. There is no known distribution theory for this testing environment, so we use simulation to evaluate how the tests will perform in a specific case.

The data-generating mechanism used for the simulations is a single threshold two-regime model:

$$\begin{aligned}
\Delta p_t &= \beta_1 \Delta s_t + \lambda_1 (p_{t-1} - 10 - \beta_1 s_{t-1}) \\
&\quad + \varepsilon_t \quad \text{if } q_t \le 100 \\
\Delta p_t &= \beta_2 \Delta s_t + \lambda_2 (p_{t-1} - 10 - \beta_2 s_{t-1}) \\
&\quad + \varepsilon_t \quad \text{if } q_t > 100 \\
\Delta s_t &= v_t \\
q_t &= 10 + 0.9 q_{t-1} + w_t
\end{aligned}$$

where ε_t, v_t, and w_t are independent draws from zero mean normal distributions. Each simulation is initiated at $s_0 = 150$ and $p_0 = 160$, which are approximate USD/metric ton prices for RSA and Zambia at the start of the sample period in our application. The threshold variable is initiated at the unconditional mean of the q process, $q_0 = 100$, which is also the threshold value. This ensures that approximately half of the observations from each simulation will be in either regime. By construction, s_t is integrated of order 1, denoted $I(1)$, in both regimes. But in each regime p_t is made either: (a) $I(1)$ and cointegrated with s_t, denoted as $CI(1,1)$, by setting $\beta_i = 0.6$ and $\lambda_i = -0.2$; (b) $I(1)$, and *not* cointegrated with s_t by setting $\beta_i = 0.6$ and $\lambda_i = 0$; or stationary, denoted $I(0)$, by setting $\beta_i = 0$ and $\lambda_i = -0.2$. The standard errors of ε_t, v_t, and w_t were set to 10, 80, and 10, respectively.

Each simulation of the model generated 200 observations which were subsequently used for unit root and cointegration testing. The simulation was then repeated 10,000 times to determine the performance of the tests in repeated samples. For each simulation the 5% critical values from standard Dickey-Fuller and Engle-Granger tests for unit roots and cointegration were used to determine whether the relevant null hypothesis could be rejected when true. The percentage of rejections was then recorded over the 10,000 simulations to evaluate the performance of the tests.

Results from the simulations are summarized in table A1. The first row provides a baseline by providing the percentage of rejections of the true model (unit roots and no cointegration) when the full sample is used and there is no regime separation. This is the standard unit root and cointegration testing environment and the percentage of rejections for each test is close to the expected value of 5%. The second row shows the percentage of rejections under the null when there is regime separation, the test is applied to the first regime subsample only ($q_t \le 100$) and data for the second regime is also generated from a model with $s_t \sim I(1)$, $p_t \sim I(1)$, and no *CI*. In this case the percentage of rejections for each test is about half that of the expected 5%. Evidently, regime separation changes the distribution of the unit root and *CI* test statistics even when both regimes feature unit roots and no *CI*. When the second regime features *CI* as well as unit roots, the bias in the test for CI in the first regime is even greater (see the third row of the table). When the second regime features $p_t \sim I(0)$, both the unit root test for p_t and the test for *CI* in the first regime are severely biased.

These results suggest that in this simulation environment the p-values from standard Dickey-Fuller unit root and Engle-Granger cointegration testing are biased upward when the tests are applied to regime-dependent subsamples, resulting in too few rejections of the null hypothesis of within-regime unit roots. Thus, in applications similar to the simulation environment we are more likely to find evidence of regime-specific unit roots and *no* cointegration than we would with bias-corrected p-values.

Table A1. Percentage of Rejections of the (True) Null Hypothesis of Unit Roots and No Cointegration under Different Scenarios using Conventional 5% Critical Values

	Null Hypothesis		
Model	$s_t \sim I(1)$	$p_t \sim I(1)$	No *CI*
No Regime Separation	4.77%	4.59%	4.98%
Regime Separation with Second Regime $s_t \sim I(1), p_t \sim I(1)$, No *CI*	2.82%	2.68%	2.39%
Regime Separation with Second Regime $s_t \sim I(1), p_t \sim I(1), s_t, p_t \sim CI(1,1)$	2.82%	2.6%	1.08%
Regime Separation with Second Regime $s_t \sim I(1), p_t \sim I(0)$,	2.82%	1.3%	0.44%