

SPATIAL PRICE ADJUSTMENT WITH AND WITHOUT TRADE

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Abstract

In this paper we introduce a switching error correction model (SECM) estimator that allows for the possibility that price transmission between markets might vary during periods with and without physical trade flows. Applying this new approach to semi-weekly data on tomato markets in Zimbabwe, we find that intermarket price adjustment occurs quickly and as much when there is no trade as when product flows from one market to another. This finding underscores the importance of information flow for market performance.

JEL Codes: Q13, R12, C32, P42

I. Introduction

A large literature explores the functioning over time of distinct markets that are linked together in a network. This network can be spatial, as in markets for a commodity within a given region or country, or it may represent other kinds of integration, perhaps through vertical marketing channels as product is transformed or through intertemporal arbitrage via storage (Deaton and Laroque, 1996; Williams and Wright, 1991). The primary purpose of such research is often to determine how quickly markets respond to temporary shocks and how these shocks transmit through the network via price adjustment. The dominant analytical approach has exploited spatial market equilibrium conditions, described in detail by Takayama and Judge (1971). Deviations from these equilibrium conditions yield key information on over-

all market efficiency. Understanding these dynamics with respect to food markets may be of particular importance for policy makers in developing countries (Fackler and Goodwin, 2002), where large subpopulations are employed in the agricultural sector and where the considerable budget shares devoted to food expenditures leave many poor households vulnerable to price spikes commonly associated with market disequilibrium.

The underlying theory of spatial market equilibrium suggests particular patterns of price behavior under competitive arbitrage, based on the transactions costs associated with movement of goods between markets and observed trade flows. More specifically, if physical trade flows occur between markets, these markets are said to be in competitive spatial equilibrium if and only if the price differential exactly equals the costs of moving goods between them, such that excess returns to trade are completely exhausted. Further, with constant per unit costs of commerce, any price change in one market due to a local demand or supply shock should generate an equal price change in the other market. This strong spatial price transmission is the familiar Law of One Price.

The absence of trade may also imply that markets are in spatial equilibrium. This can occur when price differentials exactly equal transactions costs, leaving traders indifferent between trading and not trading, or when the intermarket price differentials are insufficient to cover the costs of arbitrage between the markets. Where competitive spatial equilibrium with trade implies strong spatial price transmission, however, this latter, segmented spatial equilibria is consistent with uncorrelated price series as well

as with the Law of One Price. Thus spatial price transmission dynamics may be markedly different in periods with and without trade even when markets are always in competitive spatial equilibrium.

Markets may also be out of equilibrium, with either apparent missed arbitrage opportunities (i.e., no trade in spite of intermarket price differentials in excess of the costs of arbitrage) or positive trade in the face of negative returns to arbitrage. The different possible combinations of trade flows and returns to trade are examined in detail in the switching regime branch of the spatial price analysis literature, which finds empirically that markets are frequently out of spatial equilibrium (Barrett and Li, 2002; Baulch, 1997). However, this literature is limited in its ability to comment on the actual process of transition between equilibrium and non-equilibrium regimes, as the approach is inherently static and does not make explicit use of the time series nature of the data at hand.¹

There is, however, a large body of work that performs spatial price analysis in a fully dynamic sense. But one of the main, latent assumptions of these models is the primacy of trade flows in bringing about spatial equilibrium. This assumption has been largely unexamined thus far in the literature. For the most part, lack of available complementary price, trade flow and transaction cost data has hampered analysts' ability to test empirically whether or not trade flows are the main mechanisms behind spatial equilibrium patterns.^{2,3} Further, until recently, appropriate methods in cointegration analysis in the presence of multiple regimes did not exist.

We overcome the difficulties of both of these literatures by introducing a

method for simultaneously incorporating price, trade flow and transactions costs time series data in order to study the nature of spatial price adjustment dynamics both with and without physical trade flows. We make use of recent, detailed semi-weekly data on tomato markets in Zimbabwe and recent work on threshold cointegration by Gonzalo and Pitarakis (2006) to test for the presence of non-linearities in long run equilibrium relationships and potentially different price transmission patterns under different trading regimes. Our method allows for useful characterization of market performance with respect to price adjustment while relaxing some strong, and typically indefensible, assumptions on which existing techniques depend. This method thereby provides different, more complete information about spatial price adjustment dynamics. In particular, we are able to test empirically for differences in these dynamics in periods with and without observed trade flows. The results implicitly demonstrate the importance of mechanisms other than physical trade flows – such as information flows – in linking spatially distinct markets and thereby influencing spatial price adjustment. This reinforces recent findings, such as Jensen (2007), that more directly demonstrate the impact of new information flows on spatial price and trade patterns. Our application to Zimbabwean tomato markets demonstrates that failure to allow for such structural differences in intermarket price transmission can lead to serious errors of inference with respect to market efficiency.

II. Models of Cointegration and the Switching Error Correction Model

A dynamic study of spatial price adjustment involves analysis of time series data on prices, transactions costs and trade flows between markets. Cointegration models have been used to great effect for this purpose in many spatial analysis studies.⁴ These studies make use of the fact that it is possible to use competitive spatial equilibrium conditions to find an error correction representation of the relationship between prices and transactions costs in two different markets, as we explain below. Based on this model, one can then estimate parameters that characterize how market prices adjust to random shocks that temporarily move connected markets out of long run equilibrium.

Error correction models have the attractive property that they allow for analysis of both long run and short run dynamics in the presence of a cointegrating relationship. Short run and long run price adjustment dynamics may be quite different, especially for markets with significant transactions costs, like those for perishable commodities in developing countries. Underlying error correction models is the idea that price time series may display long run equilibrium relationships, but short run deviations from equilibrium may be (at least partly) ‘corrected’ in subsequent time periods through the particular mechanisms that control price adjustment.

We use a variant of the error correction model to examine the nature of this adjustment in periods with and without trade flows. We are particularly interested in isolating price adjustment in periods without trade flows,

in order to establish whether price adjustment is attributable primarily to physical arbitrage associated with trade, or whether it is perhaps equally attributable to non-material flows, presumably of information.⁵ This possibility of a distinction between the mechanism behind price adjustment and trade flows is the general reason for the importance of separating spatial market equilibrium from market integration concepts (Barrett, 2001). Thus, if dynamic spatial price analysis is to be used to identify and understand the consequences of poorly functioning market systems, parsing out relative differences in adjustment due to direct linkages via physical trade flows versus more indirect connections that exist without them is a useful and novel exercise.

We study spatial equilibrium and integration by making use of data on prices, transactions costs and trade flows in a Switching Error Correction Model (SECM) that can estimate distinct error correction parameters for periods with and without observed trade flows. This new method provides estimates of the speed of price adjustment to temporary disequilibria when linkages between markets are in part due to the behavior of traders who operate in both markets and take advantage of arbitrage opportunities, as well as the relationship between prices when commodities do not move between markets, which may be attributable to other, more indirect mechanisms than physical trade.

The model's theoretical foundation is the standard competitive equilibrium relationship between prices in spatially distinct markets. The equilibrium conditions are a function of both the returns to trade and the observed

trade flows. With positive trade flows, two markets (source market i and destination market j) are said to be in competitive equilibrium if the price margin ($P_{jt} - P_{it}$) is exactly equal to the cost to transfer goods between the markets, τ_{ijt} .⁶ At this point, traders are indifferent between moving and not moving goods between the two markets. Trade flow reversals can occur if the price differential from market j to market i exceeds the cost of transferring goods in the opposite direction s periods later (τ_{jit+s}). Note that these costs need not be symmetric. Including non-trading periods into the definition, the generalized conditions for efficient spatial arbitrage (Barrett, 2001; Takayama and Judge, 1971) are:

$$P_{jt} \begin{cases} \leq P_{it} + \tau_{ijt} & \text{if } q_{ij} = 0 & \text{(a)} \\ = P_{it} + \tau_{ijt} & \text{if } q \in (0, \bar{q}_{ij}) & \text{(b)} \end{cases} \quad (1)$$

where q_{ij} represents trade flows from market i to market j and \bar{q}_{ij} represents a trade flow ceiling, (either due to a quota or some other imposed restriction). Note that in equation (1), the relationship that prevails between prices in different markets depends upon the observed trade flows, q_{ij} . However, as we show below, it is possible for other mechanisms to affect this relationship.

When the equilibrium relationship between P_{jt} and P_{it} binds with equality (as in 1(b)), this equality can be used to develop an error correction representation (Engle and Granger, 1987) of the dynamic relationship between market prices and transactions costs over time, with (1(b)) characterizing the long run equilibrium (i.e., the cointegrating relationship) between markets. However, in the short run, shocks to prices and/or transactions costs may

cause temporary deviations from this equilibrium. In a dynamic context, the long run difference between prices and transactions costs, $e_t \equiv P_{jt} - P_{it} - \tau_{ijt}$, should be a stationary process, in that any temporary deviation from long run spatial market equilibrium is expected to disappear over time. For market prices and transactions costs, this process can be expressed quite generally as the residual from the linear estimated relationship in (1b) (Engle and Granger, 1987):

$$P_{jt} - (\hat{\beta}_0 + \hat{\beta}_1 P_{it} + \hat{\beta}_2 \tau_{ijt}) \equiv \hat{e}_t \quad (2)$$

with \hat{e}_t thus representing an $I(0)$, white noise random variable.⁷ Analysis of this residual allows one to establish exactly how long it takes for intermarket price adjustment to return markets to their long run equilibrium state.

If e_t truly represents a long run, stationary process, then market prices and transactions costs are said to be cointegrated time series. In the spatial market analysis literature, cointegrated prices and transactions costs are often (if controversially) taken as indicators of the degree of market efficiency in a given network.⁸

A. The Switching Error Correction Model

In the most basic scenario, an error correction representation of the relationship between price margins, $(P_{jt} - P_{it} \equiv m_{ijt})$ and transactions costs (τ_t) can be written as:

$$\begin{pmatrix} \Delta m_{ijt} \\ \Delta \tau_{ijt} \end{pmatrix} = A \hat{e}_{t-1}(B) + \sum_d \Gamma_d \begin{pmatrix} \Delta m_{ijt-d} \\ \Delta \tau_{ijt-d} \end{pmatrix} + u_t, \quad u_t \sim N(0, \sum_{2 \times 2}) \quad (3)$$

In equation (3), the parameters in A (a 2x1 matrix) govern the speed of adjustment of the price margin and transactions costs from short-term shocks back to the long term equilibrium.⁹ The Γ_d matrices (2x2) provide estimates of the autocorrelation in the system between the price margin and the transactions costs series, with d indicating the lag length(s) included in the estimation. The lagged error correction term, \hat{e}_{t-1} , is used as an instrument for the cointegrating vector that describes the long-term relationship, as shown below:¹⁰

$$m_{ijt} - B_0 - B_1\tau_{ijt} \equiv e_t(B) \quad (4)$$

The model in equation (3) is appropriate only under the assumption that trade flows do not matter to price adjustment dynamics, as it specifies that only one set of parameters govern behavior for the entire length of the time series, instead of distinguishing between periods with and without trade flows.

Recognizing that the model in equation (3) may be too restrictive to represent market relationships with multiple regimes, threshold cointegration models (TAR), initially proposed by Balke and Fomby (1997), have been used to test spatial market equilibrium in the presence of unobserved constant transactions costs (Dercon and Van Campenhout, 1999; Goodwin and Piggott, 2001; Hansen and Seo, 2002). These transactions costs divide spatial market data into trade and non-trade regimes, recognizing the fact that within the band of prices defined by the transactions costs (described by equation (5) below):

$$|P_{jt} - P_{it}| \leq \tau_{ijt} \quad (5)$$

arbitrage will not be profitable and trade flows should not occur.¹¹ Therefore estimated transactions costs are often used to define a hypothesized ‘band of inaction,’ within which spatial price adjustment dynamics are expected to be quite different than outside the band.

Hansen and Seo (2002) present the following, more general model of threshold error correction and divide observations into regimes based on the size of the error correction term in relation to an unobserved threshold, γ . In terms of spatial price analysis, thresholds of this type may arise when price margins greatly exceed transactions costs, leading to different speeds of adjustment close to and far from the price band. Substituting our price margin and transactions cost data into this framework:

$$\begin{pmatrix} \Delta m_{ijt} \\ \Delta \tau_{ijt} \end{pmatrix} = \begin{pmatrix} A_1 * \hat{e}_{t-1}(B) + \sum_d \Gamma_{1d} \begin{pmatrix} \Delta m_{ijt-d} \\ \Delta \tau_{ijt-d} \end{pmatrix} \end{pmatrix} I_{1t} + \begin{pmatrix} A_2 * \hat{e}_{t-1}(B) + \sum_d \Gamma_{2d} \begin{pmatrix} \Delta m_{ijt-d} \\ \Delta \tau_{ijt-d} \end{pmatrix} \end{pmatrix} I_{2t} + u_t \quad (6)$$

where the estimated long run relationships is $\hat{e}_{t-1}(B) = m_{jt-1} - \hat{B}_0 - \hat{B}_1 \tau_{it-1}$, $I_{1t} = I(\hat{e}_{t-1}(B) \leq \gamma)$ and $I_{2t} = I(\hat{e}_{t-1}(B) > \gamma)$.¹² As can be seen above, in Hansen and Seo’s formulation, all parameters can potentially vary across regimes with the exception of B , the cointegrating vector. This is an assumption common to all work in the threshold cointegration literature, as asymptotic theory and tools for testing for threshold effects in the cointegration vector itself have not been available until Gonzalo and Pitarakis (2006).

However, markets linked by trade flows are potentially different than those not linked by trade flows, as the conditions in relation (1) based on spatial

equilibrium theory suggest. Not only might the speed of adjustment and short run parameters differ between trade and no trade periods, but there may also be different mechanisms at play effectively linking market prices in periods with and without trade.

This is precisely the effect we wish to explore, in order to better understand the role physical trade flows play in bringing about spatial competitive equilibrium via price adjustment. Evidence of cointegration between markets in non-trade periods suggests that the role of physical trade flows may be overstated in the literature and that information flows that may impact market function and efficiency independent of trading activity may be underappreciated. Allowing for complete variation in parameters across trading regimes is therefore critical to our analysis.

Gonzalo and Pitarakis (2006) present a method to test for these prospective non-linearities that enables us to specify and estimate the following model (the switching error correction model, SECM):

$$\begin{aligned} \begin{pmatrix} \Delta m_{ijt} \\ \Delta \tau_{ijt} \end{pmatrix} = & \left(A^{\text{trade}} * \hat{e}_{t-1}(B^{\text{trade}}) + \sum_d \Gamma_d^{\text{trade}} \begin{pmatrix} \Delta m_{ijt-d} \\ \Delta \tau_{ijt-d} \end{pmatrix} \right) I_t^{\text{trade}} + \\ & \left(A^{\text{no trade}} * \hat{e}_{t-1}(B^{\text{no trade}}) + \sum_d \Gamma_d^{\text{no trade}} \begin{pmatrix} \Delta m_{ijt-d} \\ \Delta \tau_{ijt-d} \end{pmatrix} \right) I_t^{\text{no trade}} + u_t \end{aligned} \quad (7)$$

where $\hat{e}_{t-1}(B^k) = (m_{ijt-1} - \hat{B}_0^k - \hat{B}_1^k \tau_{ijt-1})$, $k \in \{\text{trade, no trade}\}$ and I_t^{trade} and $I_t^{\text{no trade}}$ are indicator functions for the specific trade regime into which each time period, t , falls.

The specification in (7) allows for potential differences in both long run

price relationships between markets under different trading regimes (the B^k parameters), as well as how quickly the markets respond to shocks in each regime (the A^k parameters). With this model and necessary data on trade flows and transactions costs, as well as standard price time series, we are able to examine empirically a key assumption in the literature: that the $A^{\text{no trade}}$ parameters equal zero when there are no trade flows because physical arbitrage is commonly assumed to be the mechanism that returns markets to equilibrium.

Therefore, our null hypothesis is that $A^{\text{no trade}} = 0$ and all the action in spatial price adjustment occurs only during trading periods. Also under the null, the cointegrating vector is the same in both regimes (i.e., $B_{\text{trade}} = B_{\text{no trade}}$). However, in order to conduct this test, we need a method that accounts for the possibility of regime-specific cointegrating relationships. This is because, under the alternative hypothesis, if adjustment *is* taking place in non-trade periods, then a cointegrating relationship must be present. However, as it is clearly not due to the effect of trade flows, it could be distinct from the relationship that prevails during trading periods and should therefore be estimated separately.¹³

Note that, with this definition of the null, we are assuming that a cointegration vector is defined in non-trade periods. Although many of the studies in the spatial price adjustment literature specifically model prices within the price band as a random walk, we are unable to include this possibility in our analysis, given the specification of the threshold cointegration test statistic we plan to use. However, it has been observed that periods without

trade may still be consistent with a long run equilibrium relationship, (for example, if all arbitrage opportunities are exhausted such that traders are indifferent between trading and not (Barrett and Li, 2002; Dercon and Van Campenhout, 1999). Our model generalizes this possibility by allowing the equilibrium relationship in non-trade periods to be distinct from that in the periods with trade.

III. Data

The SECM specified in (7) is estimated with semi-weekly data between January and December 2001 on prices, transactions costs and trade flows for tomatoes in three important spot markets in Zimbabwe. The geographical distribution of these markets is shown in Figure 1. The data collected include unit prices for tomatoes (in Zimbabwean dollars (\$Z) per crate), transport costs (\$Z/crate), estimated from fuel prices and bus fares, and a binary indicator of trade flows between markets. The data were collected through direct semi-weekly interviews with tomato traders and transporters over 52 weeks in 2001, as well as through monthly surveys of bus operators. During this period in Zimbabwe, tomatoes were primarily transported as excess cargo on busses, the pricing of which was administratively imposed by government, resolving what might otherwise be a potential problem of endogenous transport costs. These data also have the attractive feature that they are available even when there are no tomato trade flows, allowing estimation of the error correction term in the non-trade periods in our model. Full details on data

collection can be found in Mabaya (2003).

The primary players in these spot markets are traders who have purchased produce from local smallholder farmers and then sell the tomatoes in the market mostly to low- or middle-income urban consumers. This constitutes a relatively informal marketing structure, with more formal contract farming transactions occurring directly between private wholesalers or other large buyers (such as supermarkets or public institutions like schools) and larger commercial farmers in other venues. Tomato prices are more volatile in these spot markets than in the formal sector, due to the absence of formal contracts and produce perishability.

We study price transmission between the following three directional market pairs:¹⁴ Harare to Gweru, Gweru to Bulawayo, and Harare to Bulawayo.¹⁵ Figures 2-4 plot out the price, transactions costs and trade flow data for the three markets. These three market pairs display the key characteristics necessary to test the SECM, in that the relevant price margins and transfer costs for each pair were both non-stationary and integrated of order one, and trade and non-trade periods were observed for each pair.¹⁶

IV. Estimation Strategy

Estimation of the SECM presents an econometric challenge. Under the null hypothesis, the speed of adjustment parameters in the non-trading periods ($A^{\text{no trade}}$) should equal zero and prices and transactions costs in non-trade periods should not show any tendency towards long-run adjustment. This

requires that the error correction mechanism describing the long-run relationship, e_t , be a stationary process that applies in all time periods, irrespective of trade flows. The alternative hypothesis is that the trade and no trade regimes have different speeds of adjustment and/or different long-run relationships. Given our desire to test the relative strength of the price adjustment impact of the physical flow of goods between markets against that of other forces that operate in non-trading periods, we need to test the linear cointegration model (shown in (6)) against one where the alternative is non-linear cointegration in the sense that the long run relationship may differ across regimes (7). We need this test to identify whether two distinct stationary long-run relationships in fact exist. Otherwise, we cannot use the tools of cointegration analysis for the SECM, as the error correction term for at least one of the regimes would be misspecified, leading to possibly spurious results.

Fortunately, Gonzalo and Pitarakis (2006) provide an appropriate test of linear versus non-linear cointegration. The test, described in the Appendix, calculates the supremum of a Lagrange Multiplier statistic that compares the linear model to the non-linear alternative in a model with two underlying regimes. The supremum is estimated over the range of a stationary process variable that determines which elements of the sample are in each regime.¹⁷ However, in our case, the regimes are determined precisely by the presence or absence of trade flows, so a unique Lagrange Multiplier statistic can be estimated directly from the data.

Our estimation strategy is as follows. First, we compute Gonzalo and Pitarakis' test statistic for the three market pairs. Then, we compare the

value of the test statistic to critical values derived in Andrews (1993) to determine whether there are distinct long-run equilibrium relationships in the trade and no trade regimes and thus whether the SECM can be estimated consistently. Then, for market pairs with regime-dependent error correction mechanisms, we estimate the residuals of the regime-by-regime long run relationships, $e_t(\hat{B}^{\text{trade}})$ and $e_t(\hat{B}^{\text{no trade}})$. Finally, we adapt the two stage procedure of Engle and Granger (1987) and use the regime-specific residuals as instruments in the final estimation of the SECM model in equation (7).

V. Results

In this section we present the final estimates of the switching error correction model in equation (7).

A. Gonzalo-Pitarakis test results

We calculated the GP test statistics (and their associated approximate p-values from Hansen (1997)) for each market pair under consideration, with results shown Table 1. We also report the corresponding Johansen trace statistics of linear cointegration for comparison were one to impose the assumption of a linear model.¹⁸ As can be seen, all three markets show strong evidence of non-linear cointegration, uniformly significant at the 1% level. Interestingly, the null of zero cointegration cannot be rejected by the Johansen test statistics for two of the markets in question, even at the 10% level. Thus, under maintained hypothesis of a linear model, cointegration between these

markets would ordinarily be rejected, suggesting significant market inefficiencies. However, by examining the trade and non-trade regimes separately, we find that spatially distinct Zimbabwean tomato markets appear to have the ability to self-correct via two distinct long-run equilibrium relationships, apparently using different mechanisms in trade and no trade regimes.

B. Switching error correction model estimates

Since the GP test confirmed the desirability of allowing for threshold effects in the cointegrating vector, we next estimated the parameters of equation (7) and report those results in Tables 2-4. We also looked at the statistical difference between the parameters across trade regimes. Focusing first on the B parameter estimates associated with the regime-specific long-run relationships, we can see that the equilibria that prevail with and without trade are quite different. For the most part, the B_0 estimates reflecting the unobserved, fixed costs of spatial arbitrage are either indistinguishable from zero or are large and negative, while the B_1 estimates reflecting the ad valorem coefficient on observed transport costs are positive (with the exception of the no trade regime for the Harare to Gweru market pair).

The relative magnitudes of the B point estimates suggest that the error correction mechanism is dominated by some unobserved factors and costs to spatial arbitrage. In the case of a positive B_0 (as can be seen in the non-trade periods between Harare and Gweru), it is possible that unobserved transactions costs such as search and other costs of information might be part

of the mechanism itself and might correct for changes in observed transport costs. For example, if market participants in two separated markets not currently trading reacted to shared information about an impending bad harvest, this might serve to link prices in the markets, even without trade flows, and would appear in the unobserved transactions costs term, B_0 . For the market pairs with negative B_0 estimates, this suggests that although threshold cointegration is present, some destination market prices appear to be systematically lower than what observed transactions cost might suggest. However, we cannot examine this relationship more fully without additional data.

As for the A parameter estimates, recall that they represent the speed of adjustment, indicating how quickly the price margin and transactions costs return to long-run equilibrium after a shock. The estimates from all three market pairs indicate that speeds of adjustment in trade and non-trade periods are quite similar in magnitude and statistical significance, although most of the estimated parameters are significantly different from each other across regimes.

Examining these parameters more closely, it can be seen that adjustment parameters for the price margin equation are typically significantly different from zero, while those in the transport costs equations are not. During the study period, transport costs were often set administratively by the government. Given that, the lack of adjustment of transport costs to shocks makes perfect sense; none of the adjustment in intermarket prices occurs through changes in the observed transport costs, only through corrections to inter-

market price margins. Looking jointly at the A and B parameter estimates, they suggest that unobserved costs drive the error correction process, with corrections occurring entirely through product price adjustment.

The magnitudes of the A parameters also indicate that price margins respond quite quickly to deviations from equilibrium in both regimes, showing a high degree of market efficiency in general for the Zimbabwean tomato markets in question. Table 5 summarizes the implied half-lives for these adjustment parameters (λ_T and λ_{NT} for the trade and no trade regimes, respectively), in terms of the average number of days it takes for a shock out of the long-run equilibrium to be halved. The interesting feature of these estimates is that there appears to be qualitatively similar adjustment towards the regime specific long-run equilibrium (at least for the price margins) in both the trade and non-trade periods, in contrast to the oft-assumed dynamic of limited or no adjustment without trade and all the corrections occur thanks to physical arbitrage. The relative swiftness of the adjustment (the longest half life is only about 23 days) may also help to explain the limited amount of autocorrelation in the data, which leads to little explanatory power in the Γ estimates in the model.¹⁹

In addition to relatively fast spatial price adjustment overall, the hypothesis that no adjustment occurs in the periods without trade is strongly rejected. Price margins and transport costs return to their (trade regime-specific) long run equilibrium within a few weeks in periods both with and without trade. Given that no produce physically moves between markets in the no-trade regime, clearly price adjustment must instead be due to disem-

bodied information flows between markets, whether it is via price speculation by traders, producers' rational expectations about future prices, or producers' unobserved decisions of which market to supply directly. Even trader decisions on where and when to participate in markets serve to effectively link prices in all of the markets in which they operate, even when the decision is not to transport, as their decisions affect local demand and supply conditions in each market. In any case, it seems that information flows lead to swift correction of potential deviations from competitive spatial equilibrium pricing such that price transmission in periods without trade flows is no less effective than when it is mediated by physical arbitrage, even though these regimes appear governed by significantly different mechanisms. Further examination of the specific mechanisms that regulate price transmission is beyond the scope of this paper; but clear, indirect evidence of their existence is perhaps a useful jumping off place for future research.

VI. Conclusions

Using a newly developed test for non-linear cointegration analysis, we specify and estimate a novel Switching Error Correction Model and analyze the similarities and differences between spatial price adjustment dynamics in tomato markets in Zimbabwe in periods with and without physical trade flows. It appears that error correction between price margins and transactions costs occurs both with and without trade. This provides evidence that the mechanisms governing spatial price adjustment dynamics extend

well beyond the physical arbitrage activities of traders, and thus that analysis of market functioning and efficiency must allow for the multiple price transmission mechanisms that may be at work in a given network. In particular, in this instance, by ignoring the possibility of multiple spatial pricing equilibria, time series analysis based on linear cointegration would have suggested that tomato markets in Zimbabwe were not cointegrated and thus highly inefficient. Our more general method, by accounting for the trade and non-trade regime dynamics separately, leads to the conclusion that these markets are actually very efficient in transmitting market signals across space through price adjustment dynamics. Given the very different policy implications of each of these analyses, it seems clear that testing and accounting for non-linearities in long run equilibrium states characterized by trade flows is important. It also opens up questions as to the precise nature of spatial price adjustment in non-trade periods, which has been given very little attention in the spatial price analysis literature, despite the acknowledged importance of trade flows on adjustment (Barrett and Li, 2002).

For market studies with the full complement of prices, transactions costs and trade flow time series, our method should provide a useful means to characterize the time series behavior of these variables and avoid the possible mistaken inference likely to result from spatial price analysis with trade and non-trade regime data mixed together. This should serve as an additional tool for researchers and policy makers working to understand spatial price transmission.

Figure 1: Location of sample spot markets in Zimbabwe



Figure 2: Semi-weekly tomato prices in Gweru, Harare and Bulawayo

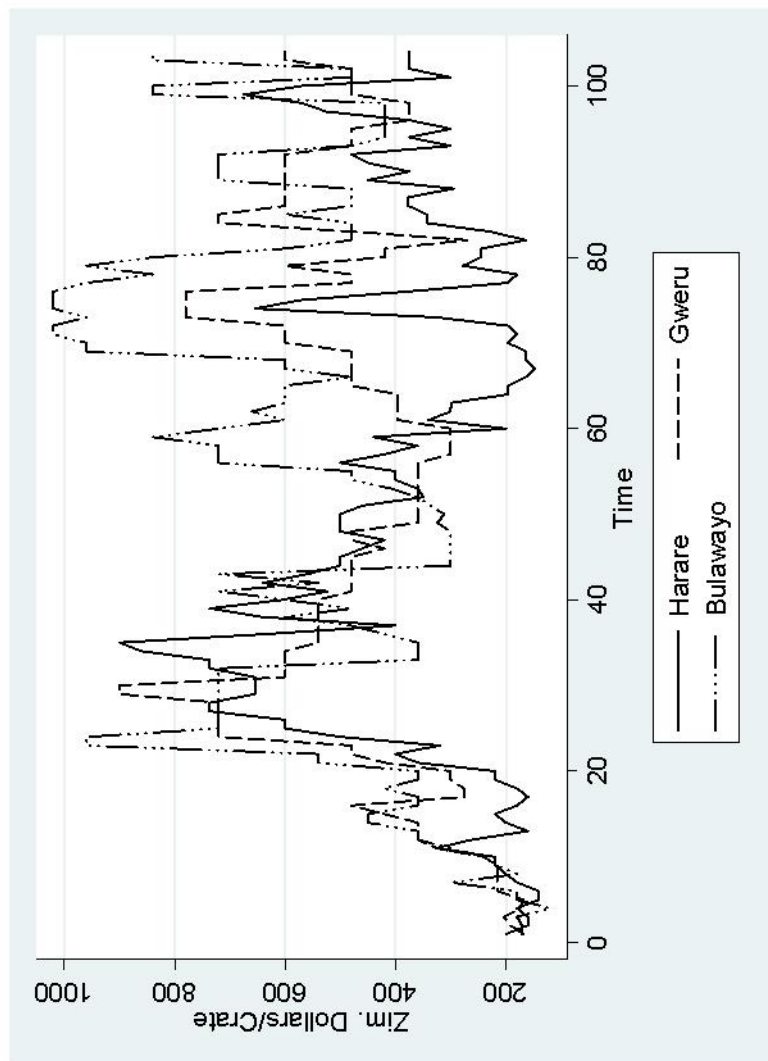


Figure 3: Transport costs between the three markets

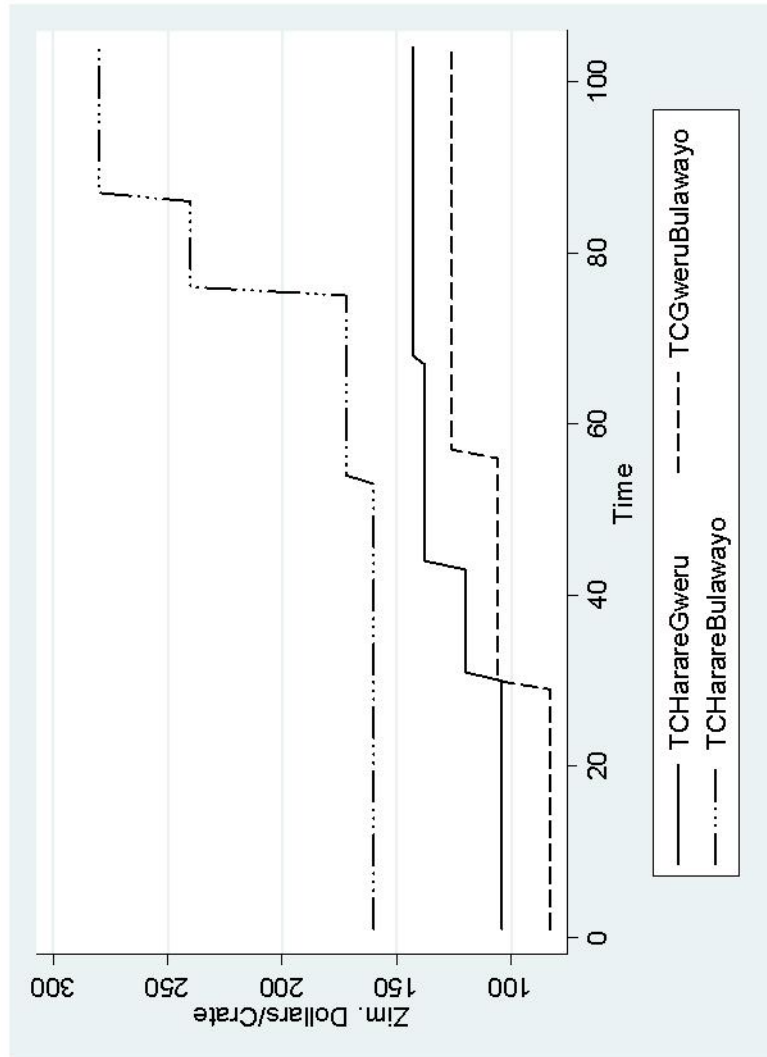


Figure 4: Trade flows observed between the three markets

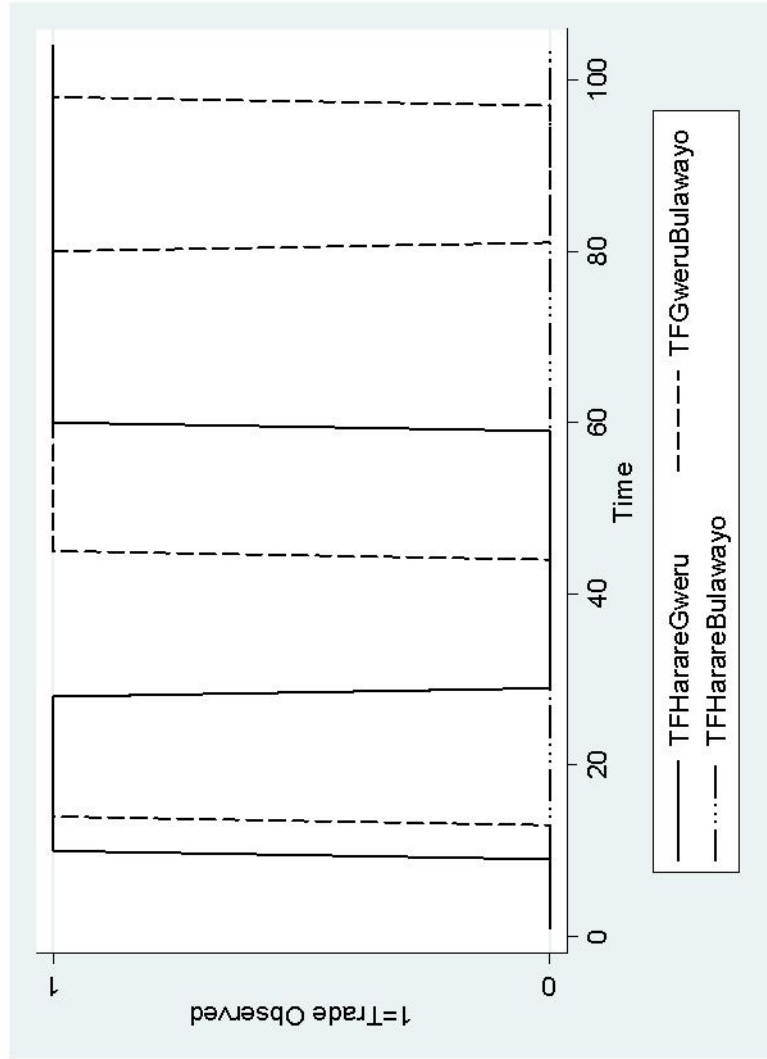


Table 1: Gonzalo-Pitarakis (GP) test statistics, Johansen trace statistics and critical values

Market Pair	GP Test Statistic^a	Johansen Trace Statistic
Harare-Gweru	41.62 (0.00)	15.55
Gweru-Bulawayo	26.27 (0.05)	21.99
Harare-Bulawayo	27.48 (0.03)	9.06
Critical Values	GP Critical Value^b	Johansen Critical Value^c
10%	10.50	17.85
5%	12.27	19.96
1%	16.04	24.60

^a p-values are reported in brackets.

^b The critical values quoted here are from Andrews (1993, Table 1), for a two-parameter model under the null (i.e., $p = 2$) and with a 5% (symmetric) trimming parameter (π_0). GP demonstrate that the limiting distribution of their test is equivalent to that used by Andrews to calculate the above critical values.

^c These critical values have been calculated to test for a model of cointegration that includes an intercept term in the cointegration vector, without drift.

Table 2: Parameter estimates of equation (7) - Harare to Gweru market pair

Parameter	Trade Regime			No Trade Regime			Wald test of $H_0 : \theta^T = \theta^{NT}$
	Coefficient ^a (θ^T)	Std. Err.	Coefficient (θ^{NT})	Std. Err.	Std. of Err.		
$e_{t-1}(B)$	B_0	-130.562	121.098	320.130	180.950*		**
	B_1	2.304	0.918**	-2.978	1.464**		***
m_{ijt}	a_m	-0.298	0.089***	-0.787	0.168***		***
	$\Gamma(\Delta m)$	-0.004	0.123	0.428	0.163***		**
	$\Gamma(\Delta \tau)$	6.292	19.354	2.103	4.259		
τ_{ijt}	a_τ	0.001	0.002	0.007	0.004*		
	$\Gamma(\Delta m)$	-0.000	0.003	-0.001	0.004		
	$\Gamma(\Delta \tau)$	-0.033	0.492	-0.075	0.108		

^a Note: *, **, *** indicate significant at 10%, 5%, and 1% respectively. Intercept terms in the final VAR have been omitted for clarity.

Table 3: Parameter estimates of equation (7) - Gweru to Bulawayo market pair

Parameter	Trade Regime		No Trade Regime		Wald test of $H_0 : \theta^T = \theta^{NT}$
	Coefficient	Std. Err.	Coefficient	Std. Err.	
$e_{t-1}(B)$					
B_0	-389.457	122.685***	-78.540	136.490	*
B_1	5.013	1.093***	0.633	1.266	**
m_{ijt}					
a_m	-0.167	0.074**	-0.554	0.156***	
$\Gamma(\Delta m)$	-0.052	0.118	0.017	0.169	
$\Gamma(\Delta \tau)$	2.397	6.647	9.411	5.833*	
τ_{ijt}					
a_τ	0.000	0.001	-0.004	0.003	
$\Gamma(\Delta m)$	0.003	0.003	-0.004	0.004	
$\Gamma(\Delta \tau)$	-0.035	0.155	-0.055	0.136	

Table 4: Parameter estimates of equation (7) - Harare to Bulawayo market pair

Parameter	Trade Regime				No Trade Regime				Wald test of $H_0 : \theta^T = \theta^{NT}$
	Coefficient	Std.	Err.	(θ^T)	Coefficient	Std.	Err.	(θ^{NT})	
$e_{t-1}(B)$	B_0	-909.581	243.099***		-406.560	107.361***			**
	B_1	7.085	1.401***		2.233	0.497***			***
m_{ijt}	a_m	-0.099	0.062		-0.141	0.067**			*
	$\Gamma(\Delta m)$	-0.094	0.169		-0.000	0.128			
	$\Gamma(\Delta \tau)$	2.835	2.326		2.989	3.762			
τ_{ijt}	a_τ	0.001	0.005		0.001	0.004			
	$\Gamma(\Delta m)$	0.005	0.009		-0.004	0.007			
	$\Gamma(\Delta \tau)$	-0.057	0.126		-0.024	0.205			

Table 5: Implied Half-Lives (in days) for Trade vs. Non-Trade Regimes

Market Pair	Par. (Eq.)	Trade Regime		No Trade Regime	
		$(T_{half} = \lambda^T)$		$(T_{half} = \lambda^{NT})$	
		Coeff.	Std. Err.	Coeff.	Std. Err.
Hre-Gwr	$T_{half}(a_m)$	6.857	2.457***	1.569	0.800***
Hre-Gwr	$T_{half}(a_\tau)$	<i>undef</i>	-	<i>undef</i>	-
Gwr-Byo	$T_{half}(a_m)$	13.277	6.455***	3.005	1.302***
Gwr-Byo	$T_{half}(a_\tau)$	<i>undef</i>	-	605.290	454.878
Hre-Byo	$T_{half}(a_m)$	23.271	15.361**	15.962	8.192**
Hre-Byo	$T_{half}(a_\tau)$	<i>undef</i>	-	<i>undef</i>	-

Notes

¹Negassa and Myers (2007) offer a dynamic extension to the parity bounds model (Baulch, 1997), but like the rest of the switching regime literature, their approach relies heavily on strong, atheoretical distributional assumptions.

²See Barrett (1996) for a break down of the types of market analysis methods by data classification.

³Several studies use various threshold cointegration models to better characterize price dynamics in hypothesized trade and no trade regimes (e.g., Goodwin and Piggott (2001)) and the possibility of differences between short run and long run equilibrium dynamics (e.g., Dercon (1995); Ravallion (1986)).

⁴See Fackler and Goodwin (2002) for a detailed summary.

⁵Information flows may, for example, be due to the effect of elaborate networks of traders operating in several markets simultaneously or the overall complexity of spatial market networks (Fackler and Tasthan, 2008).

⁶Subscripts indicate the direction of trade flows. For example, $m_{ijt} = P_{jt} - P_{it}$, indicates the intermarket price differential for goods flowing from market i to market j in period t . Similarly, transactions costs to move commodities from market i to market j are listed as τ_{ijt} .

⁷As has been pointed out by Dercon (1995) and others (Goodwin and Piggott, 2001), the long-run equilibrium relationship between prices and transactions costs may involve price movements that are proportional to one another,

rather one-for-one, net of transactions costs. Hence the inclusion of the β parameters in equation (2).

⁸Barrett (1996), Fackler and Goodwin (2002) and others have noted that cointegration is neither necessary nor sufficient for market efficiency, and that violations of some common assumptions underlying cointegration models, like stationary transport costs and continuous trade flows, may be more to blame for the frequent rejection of efficiency found in the literature than an absence of efficiency itself. We attempt to address some of these issues in this work.

⁹The speed of adjustment parameters can be more easily expressed as a half-life, T_{half} , which indicates how long it takes for half of the deviation from long run equilibrium to be corrected. $T_{half} = \ln(0.5)/\ln(1 + a_k)$, $k = \{m, \tau\}$. a_k is the parameter estimate from the matrix A for the price margin ($k = m$) and the transactions costs ($k = \tau$) equation, respectively (Dercon and Van Campenhout (1999)). In all of our estimates, since our time observations are semi-weekly, T_{half} has been multiplied by 3.5 (days/semi-week) to convert the half-life into units of days, rather than ‘semi-weeks.’

¹⁰Note that the cointegrating vector β in equation (2) has been normalized such that $\beta_0/\beta_1 = B_0$ and $\beta_2/\beta_1 = B_1$. This simplifies our subsequent work by eliminating any concerns about the existence of multiple cointegrating vectors.

¹¹Equation (5) is just a reformulation of the efficient spatial arbitrage condition shown in (1a) that prevails when trade flows do not occur due to excessively high transactions costs.

¹² I_{1t} and I_{2t} represent indicator functions that divide the observations into

two groups based on the location of the error correction term relative to the unknown threshold. Given the absence of transactions cost data in many market network price datasets, their effects are often modeled similarly modeled like such an unobserved threshold that divides observations into periods where trade is positive and efficient and into periods where transactions costs exceed the price margin between two potential markets.

¹³Also, assuming linearity in the case of nonlinear long-run equilibrium relationships results in inconsistent estimation of the (misspecified) cointegration vector (Gonzalo and Pitarakis, 2006).

¹⁴Only market dyads are considered in our analysis and the SECM does not take into explicit account the possible higher order effects of trade in a network with multiple linkages. See Fackler and Tastan (2008) on this issue.

¹⁵Harare is the capital of Zimbabwe and is close to major tomato production areas, which may explain the fact that there are no trade flow reversals observed during the sample year.

¹⁶Augmented Dickey-Fuller test statistics were used to determine the integration order of the different time series. Details are available from the authors by request.

¹⁷Note that this threshold is not determined by the size of the error correction term, as elsewhere in the threshold error-correction literature (e.g., Hansen and Seo (2002)).

¹⁸The Johansen (1988) trace test is a method of testing for cointegration that is essentially a multivariate version of the Dickey Fuller unit root test. The trace test looks for non-stationarity in a system of time series variables

by examining the rank of the parameter matrix that describes system relationships.

¹⁹Lag length tests using VAR appropriate portmanteau statistics (Brüggeman et al., 2004) show that the single lag structure is appropriate for all market pairs.

VII. Appendix: The Gonzalo-Pitarakis test for non-linear cointegration

Gonzalo and Pitarakis (2006) (hereafter GP) develop a test for possible non-linearities in a cointegrating regression of the following form:

$$\begin{aligned} y_t &= (\beta_0 + \beta_1 x_t) + (\lambda_0 + \lambda_1 x_t)I(q_{t-d} > \gamma) + u_t \\ x_t &= x_{t-1} + v_t \end{aligned} \tag{A1}$$

where u_t and v_t are scalar and p-vector valued stationary disturbance terms, respectively, q_{t-d} (with $d \geq 1$) is a stationary threshold variable and $I(q_{t-d} > \gamma)$ is an indicator function that equals one when $q_{t-d} > \gamma$ and is zero otherwise. p represents the number of explanatory variables, x_t , in the model.

The specification in (A1) assumes a single long-run relation exists between y_t and x_t . Alternatively, there might be two distinct long-run relationships present between the non-stationary variables y_t and x_t :

$$y_t = \begin{cases} \beta_0 + \beta_1 x_t + e_t^{\text{No Trade}} & \text{if } q_{t-d} \leq \gamma \\ (\beta_0 + \lambda_0) + (\beta_1 + \lambda_1)x_t + e_t^{\text{Trade}} & \text{if } q_{t-d} > \gamma \end{cases} \tag{A2}$$

To test for such a non-linearity in (A2), GP propose the following test statistic:

$$SupLM = \sup_{\gamma \in \Gamma} LM_T(\gamma) \quad (A3)$$

for $LM_T(\gamma) = \frac{1}{\hat{\sigma}_0^2} u' M X_\gamma (X_\gamma' M X_\gamma)^{-1} X_\gamma' M u$. Note that M is the projection matrix $I - X(X'X)^{-1}X'$ over all observations of X in the sample of length T , u is the residual vector under the null hypothesis of linear cointegration (i.e., $\lambda_0 = 0$ and $\lambda_1 = 0$) and $\hat{\sigma}_0^2$ is the residual variance estimated under the null. The supremum statistic is estimated over the statistical distribution of γ given by the range of the stationary threshold variable, q_{t-d} .

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