Spatial Price Transmission Analysis in Agricultural Markets: Does the Data Frequency Improve our Estimation?

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Contributed Paper prepared for presentation at the 3rd AAAE International Conference, Cape Town, South Africa, 19 - 23 September, 2010

Abstract

Unavailability of high frequency, weekly or daily data compels most studies of price transmission in developing countries to use low frequency, monthly data for their analyses. Analyzing price dynamics with monthly data may however yield imprecise price adjustment parameters and lead to wrong inferences on price dynamics. This is because agricultural markets in developing countries operate daily or weekly. In this paper, we investigate the relevance of data frequency in price transmission analysis. We use a standard- and a threshold vector error model to estimate and compare price adjustment parameters for a high frequency, semi-weekly, data and a low frequency, monthly data. The results reveal that adjustment parameters estimated from the low frequency data are higher in all cases than those estimated from the high frequency data. We suspect that using low frequency data leads to an overestimation of price adjustment parameters. The findings therefore confirm observations in the literature that high frequency data is capable of estimating price adjustment parameters more precisely than low frequency data. More research involving a large number of observations is however needed to enhance our learning from the usefulness of high frequency data in price transmission analysis.

Keywords— **Ghana, tomato, market integration, physical trade**
JEL: Q13

1. Introduction

Spatial price transmission or market integration (MI) measures the degree to which markets at geographically separated locations share common long-run price or trade information on a homogenous commodity. The study of market integration has attracted a lot of empirical research interests since the 1970s. Premier studies (JONES, 1968; LELE 1971 in PRAKASH, 1997; RAVALLION, 1986; TIMMER, 1987; ENGEL and GRANGER 1989, etc.) applied correlation coefficient, regression, cointegration and causality techniques to investigate spatial price transmission and market integration. In the last decade, evidence of non-linearity in price series, the role of market power, transactions costs and trade flow information in price transmission led to extensions of the premier analytical techniques to permit asymmetric and switching effects in trading mechanisms between markets (Mcnew, 1996; von CRAMON-TAUBADEL, 1996; BAULCH, 1997, and GOODWIN and PIGGOT, 2001; BARRETT and LI 2002; MEYER, 2003, and BALCOMBE et al, 2007).

Currently, techniques for analyzing market integration are quite sophisticated, but most empirical studies of spatial price transmission in agricultural markets using the sophisticated techniques suffer a common drawback – the failure to use data of relevant frequency for their analyses. The agricultural market integration literature on developing countries indicates a common trend by a majority of studies in using low frequency, quarterly or monthly data to investigate market behaviour. Unavailability of reliable, high frequency (daily or weekly) data from secondary sources is often the excuse for not using this form of data for investigating price integration in agricultural markets of developing countries. Furthermore, agricultural markets are usually dispersed, implying exorbitant associated costs in collecting high frequency data (HFD) and compelling researchers to collect and use quarterly or monthly market data.

The issue of data frequency should however be given added importance in examining market behaviour (GOODHART and O'HARA, 1997). Our knowledge of real trading patterns in agricultural markets in most developing countries is that markets usually have a three or six day periodicity. With infrastructural and ICT service improvements between geographical markets, more frequent trading patterns and rapid transmission of trade information between markets, even in developing countries, is possible (AKER, 2007). IHLE et al. (2008) found that in Ghana, it takes just 1.5 market weeks (about 5 days) for half of the deviations of prices

of tomato from market equilibrium due to price shocks to be corrected. Thus, in practice, agricultural markets exhibit high frequency trading structures and more rapid arbitrage processes than can be captured in the monthly or quarterly data used for most price transmission analyses.

Some empirical evidence of the benefits of using HFD for price transmission and market integration analysis has been reported in the literature. GOODHART and O'HARA, (1997) who used high frequency, daily data to investigate price and interest rate dynamics note that, more limitations to price dynamics, as well as operational and structural market mechanisms, market efficiency and temporal market dependencies are revealed as a result. Using HFD also increases the power of tests of significance for estimated parameters and helps overcome potential, data-related limitations of analyses (CHOI 1992, in CHOI and CHUNG, 1995). LUTZ et al 1994 prove that time series data of lower frequencies is limited in capturing some relevant market dynamics that occur in the wide interval between one observation and the next. Moreover, the reactions of prices to market shocks i.e. their speed of adjustments towards equilibrium, are more precisely estimated using HFD than with low frequency data (LFD) (ibid).

In this paper, we investigate the issue of data frequency in price transmission analysis in agricultural markets. We do this by statistically comparing estimated price adjustment parameters and deviation half-lives of a high frequency price series with those of a low frequency price series obtained from fresh tomato markets in Ghana. The high frequency series is a semi-weekly, wholesale price data generated by self-conducted tomato market surveys in Ghana, whereas the low frequency, monthly, wholesale tomato prices are collected from Ghana's ministry of agriculture (MoFA). Our application is to a standard vector error correction model (VECM) and its extension as a threshold vector error correction model (TVECM).

Tomato is the commodity of interest because, unlike grains on which most previous agricultural market integration studies in developing countries are based, tomato is a perishable product and its marketing is affected by trading risks and quality effects. Where markets exhibit, as it is in Ghana's fresh tomato markets, rapid dynamics due to supply source changes, extremities in surplus and lean seasons, and trading risks, then HFD should be able to handle the resulting price adjustment mechanisms better than LFD. In this way, we expect

to learn from the usefulness of HFD and create more insights on the question of data frequency in price transmission analysis as addressed for instance in von CRAMON-TAUBADEL et al. (1995) or von CRAMON-TAUBADEL et al. (2006).

In the following section, we describe the market setting, the nature of both the HFD and LFD and the processes and tests on both datasets prior to using them in the analysis. Then we specify the standard and threshold VECMs used for the analysis and justify why the two techniques are relevant for our data in section three. This sets the stage for section four where we present and discuss the results of the analysis. The final section concludes the paper and outlines suggestions for policy and further research.

2.   Study Setting and Data

The HFD and LFD data used for estimating the models is wholesale price data of fresh tomato from Ghana. The tomato market of Ghana as the target of this study is characterized by sharp, seasonal variation in output, commodity sources, transfer costs and price signals.

Five major tomato markets in Ghana are targeted by the study (Figure 1). These include two net producer markets - Navrongo and Techiman; and three net consumer markets namely Tamale, Kumasi and Accra. In a season, all tomato markets across Ghana are almost connected by a single source of supply from Navrongo and its satellite producing areas or Techiman and its satellite producing areas. These two sources switch seasonally, with Navrongo (and surrounding areas) as the main source of tomato supply in the dry season (December - May), while Techiman (and surrounding areas) supplies the marketing system with tomato in the rainy season (June-November). During peak supply seasons, intra-market price volatility can be as high as 100%, with daily price variations dependent on the quality of tomato, which deteriorates from morning to evening.

Two types of data sets are used for the analysis in this paper. The first is a high frequency, semi-weekly price series. This HFD was generated through a self-conducted wholesale level market surveys administered continuously in the five markets over five tomato production seasons between March 2007 and May 2009. The second dataset is a low frequency, monthly wholesale price series of fresh tomato obtained from Ghana's MoFA offices in the five markets. This data covers a period of 10 years; starting from January 1998 to April 2008. The analysis with the LFD excludes Accra because a complete series for this market from the MoFA was no available.

Fig.1: A Map of Ghana showing the Target Markets under the Study
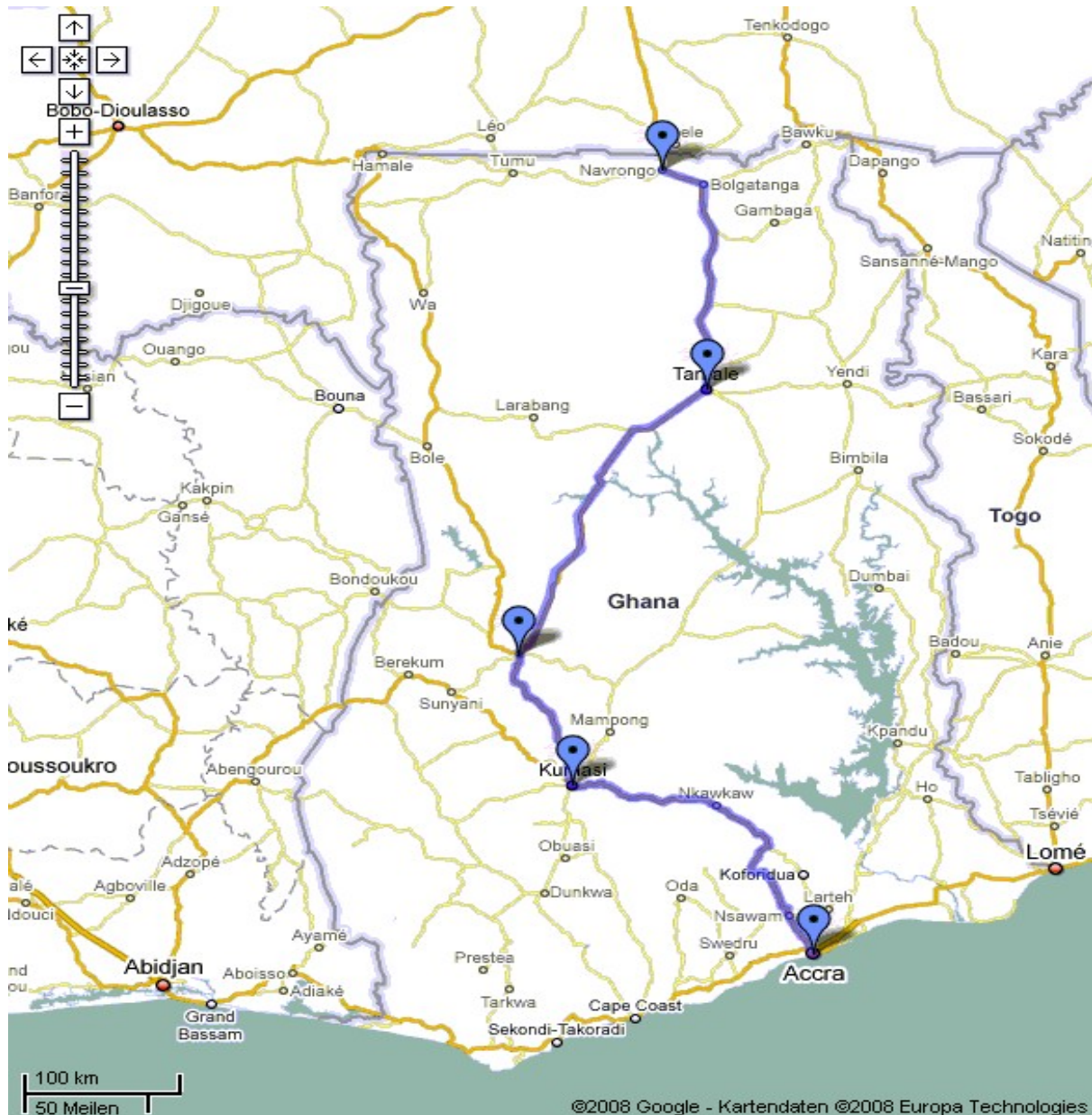
Our use of only the monthly series generated from 1998 to 2008, though we have data dating back to 1992, is to ensure homogeneity in the policy and market settings under which both the HFD and LFD were generated. The secondary data was converted to real prices by deflation using monthly, food consumer price indices from Ghana. The price per crate of fresh tomato for both series is in the new Ghana Cedi (GH¢). All analysis is done in the logarithmic values of the prices. The analysis is pair-wise in nature – examining price adjustment processes between net producer and

consumer markets in each case. Table 1 shows two statistical properties of the data viz. mean price values of the series and their corresponding coefficients of variation.

Table 1: Statistical Properties of the High and Low Frequency Data

Market	*High Frequency Semi-Weekly Data* (N = 192)		*Low Frequency Monthly Data* (N = 125)	
	Mean Price (GH¢/Crate)	Coefficient of Price Variation (%)	Mean Price (GH¢/Crate)	Coefficient of Price Variation (%)
Navrongo	37.56	47.02	19.25	61.06
Tamale	34.20	42.27	21.86	60.05
Techiman	31.71	49.10	13.82	78.32
Kumasi	41.32	46.12	17.30	78.64
Accra	55.33	41.38	-	-

Source: Own

It can be seen that the two datasets do not have similar values for the two statistical properties examined. The mean price per crate of tomato (in GH¢) for the HFD data is higher than that of the LFD, while the coefficients of price variation (CVs) of the monthly, LFD exceed those of semi-weekly, HFD in all cases. The average differences, about 25%, in the coefficient of price variation between the two datasets is similar to the about 30% differences in the coefficients of variation observed between daily and monthly prices of grain in Benin by LUTZ et al (1994). The disparity in the CVs may imply differences in the ability of the LFD and HFD in estimating the price adjustments parameters with precision. We expect the HFD with lower CVs to be more ideal in estimating price adjustment coefficients and deviations half-lives than the LFD.

3.   Methodology

Conventional analytical techniques of PT are limited in demonstrating long run market equilibrium. This limitation represents a major weakness in market research. When the markets under study are characterized by significant inter-market transfer costs and trade flow reversal (BARRETTE and LI, 2002 in RASHID, 2004), or when the techniques use time series data for the analysis (GOODWIN and PIGGOTT, 2001), ignoring non-linearity in the

price adjustment process, as do the conventional techniques, is an empirical flaw. We avoid this flaw by applying an error correction model (ECM) to our two datasets.

Two variants of the ECM are applied. First, under the conventional assumption of no threshold, a standard LVECM is used to estimate the speed of price adjustments between the net producer and net consumer market pairs. This is done separately for the high frequency and low frequency data. Then a threshold VECM (TVECM) is applied separately to both data for a similar purpose. Both models capture non-linear adjustment (in terms of direction and magnitude) of the commodity prices to long run, inter-market equilibrium following price shocks. In particular, the TVECM incorporates information on commodity transfer costs considered relevant for price dynamics. As noted by GOODWIN and PIGGOTT, (2001), thresholds imply faster adjustments to deviations from equilibrium conditions than it is when thresholds are ignored. The standard and threshold VECM are specified respectively below.

We denote the equilibrium relationship between the net consumer prices series P_t^c and net producer price series P_t^s as: $P_t^c - \beta P_t^s = v_t$. If v_t, the error term, is assumed to follow an autoregressive (AR) process, then $v_t = \alpha v_{t-1} + \varepsilon_t$, and the equilibrium relationship between P_t^C and P_t^S can be expressed as:

$$(1)\ P_t^c - \beta P_t^s = \alpha v_{t-1} + \varepsilon$$

The equation (1) implies that the relationship or cointegration between P_t^c and P_t^s is a function of the autoregressive process of v_t. In the above linear representation, v_{t-1} represents deviations from equilibrium and is called the error correction term (ECT), while α measures the response of P_t^c and P_t^s to deviation from equilibrium following shocks to market equilibrium.

In the first technique, we estimate a standard VECM form of equation (1). This form specifies changes in each of the contemporaneous prices, ΔP_t^c and ΔP_t^s, as a function of the lagged short term reactions of both prices, ΔP_{t-k}^c and ΔP_{t-k}^s, and their deviations from equilibrium at period $t-1$ (i.e. ECT_{t-1}) as follows:

$$(2)\ \Delta P_t^c = \delta_1 + \alpha^c \left[ECT_{t-1} \right] + \sum \beta_k^c \Delta P_{t-k}^c + \sum \beta_k^{cs} \Delta P_{t-l}^s + \varepsilon_t^c$$
$$\Delta P_t^s = \delta_2 + \alpha^s \left[ECT_{t-1} \right] + \sum \beta_k^{sc} \Delta P_{t-k}^c + \sum \beta_k^s \Delta P_{t-l}^s + \varepsilon_t^s$$

The model (2) can be reformulated in vector representation as:

$$(3)\ \Delta \mathbf{P}_t = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1 \mathbf{ECM}_{t-1} + \sum_{i=1}^{k} \boldsymbol{\Gamma}_i \Delta \mathbf{P}_{t-1} + \varepsilon_t$$

Where $\Delta \mathbf{P}_t = (\Delta \mathbf{P}_t^s \Delta \mathbf{P}_t^c)'$ is a vector of first differences of prices in the consumer and source markets respectively; $\boldsymbol{\Gamma}_i$, i = 1,…,k, is a k x k matrix of short run coefficients which quantify the short term response of the contemporaneous price differences to their lagged values. The error correction term, ECT_{t-1} is a continuous and linear function of the deviation of $\mathbf{P}_t$ from the long-run equilibrium relationship in equation (1) following a random shock to P_t^S or P_t^c. The coefficient $\boldsymbol{\alpha}_1 = (\alpha^s \alpha^c)'$ denotes the speed of adjustment of the net producer and net consumer market prices respectively to deviations from the long-run equilibrium where $\varepsilon_t = 0$. The closer the value of $\boldsymbol{\alpha}_1$ approaches one; the faster the deviations from equilibrium become corrected. The ε_t is assumed to be a white noise process.

In the TVECM, the adjustment of the commodity's prices to deviations from equilibrium depends on whether the magnitude of the deviations or the error correction variable ECT_{t-1} exceeds or is less than a given threshold ϕ. The number of thresholds specified separates the price adjustment processes into $\phi+1$ trade regimes.   In our specification, one threshold ϕ is used to divide the adjustments into two separate regimes - regimes I and II. For deviations below the threshold ϕ, we have regime I and when deviations surpass the threshold, we have regime II. Using the specification from model (3), the TVECM we estimate is expressed as:

$$(4)\ \Delta \mathbf{P}_t = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1 \mathbf{ECM}_{t-1} + \sum_{i=1}^{k} \boldsymbol{\Gamma}_i \Delta \mathbf{P}_{t-1} + \varepsilon_t, \ \text{if } |EMT_{t-1}| \le \phi$$ …… Regime I &

$$(5)\ \Delta \mathbf{P}_t = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1 \mathbf{ECM}_{t-1} + \sum_{i=1}^{k} \boldsymbol{\Gamma}_i \Delta \mathbf{P}_{t-1} + \varepsilon_t \ \text{if } |EMT_{t-1}| > \phi$$ ………… Regime II

All variables are as already defined. Like in the standard VECM, the price adjustments in the TVECM depend on both short and long run price dynamics (EMT_{t-1} and $\Delta \mathbf{P}_t$), but allows a display of different dynamics depending on the magnitude of ϕ. The threshold value in our model represents the price differentials or transfer costs between net producer and consumer

market pairs. We assume, for the sake of estimation convenience, a stationary threshold variable over the periods in which both datasets were sampled.

4.   Results

The usual prior tests of unit root and cointegration were conducted to establish the time series properties of both the high and low frequency price series. A visual inspection of the basic characteristics of the data in graphical plots reveals a drift but no time trend. We thus specify the models for the ADF unit roots test and the Johansen's cointegration test with a drift and without a time trend. The ADF results (not presented for lack of space) indicate that all series in both the HFD and LFD are I(1) in their levels but I(0) in their first differences. Therefore, the generation process for both datasets is purely stochastic.

The Johansen's maximum likelihood (ML) cointegration test was used to determine the number of cointegrating vectors (relations) between market pairs. In theory, a system of N time series should have at most N-1 significant, linearly dependent cointegrating vectors or relations contained in the matrix of parameters; where N is the number of markets in a cointegration relationship (i.e. 2 in our pair-wise analysis). The results of this cointegration test and OLS estimates of the magnitude of the long run cointegration relation ($\hat{\beta}_1$) for both the HFD and LFD are presented in Table 2.

The null hypothesis of r = 0, implying an absence of a cointegrating vector is rejected for all the market pairs under both data series at the 1% significance level. The exception is the Navrongo-Techiman pair for the HFD, which can be rejected at the 5%. We cannot however reject the null hypothesis of one cointegrating relation, i.e. r = 1 between seven out of the eight market pairs for the HFD and two out of the six pairs for the LFD at the 5% (*). When tested at the 1% (**), only the market pairs Navrongo - Tamale and Techiman - Tamale under the LFD, show significance for r = 0 and r = 1 even at the 1%. This result, suggesting the presence of two cointegrating relations between Navrongo-Tamale and Techiman–Tamale, is statistically unexplainable since there should be only N-1 (1) cointegrating vector for each market pair where N = 2 variables (markets).

Table 2: Johansen's Cointegration Test Statistics and Relations between Market Pairs

Market Pair	Results of HFD (Semi-Weekly)			Results of LFD (Monthly)		
	r0 = 0	r1 = 1	$\hat{\beta}_1$	r0 = 0	r1 = 1	$\hat{\beta}_1$
Navrongo –Accra	25.14**	9.70*	0.23^+	-	-	-
Navrongo - Kumasi	24.75**	8.09	0.44^+	50.48**	8.65	0.40^+
Navrongo - Techiman	19.27*	5.89	0.34^+	46.94**	12.33*	0.50^+
Navrongo - Tamale	23.19**	8.07	0.72^+	47.00**	19.41**	0.60^+
Techiman - Accra	21.67**	5.75	0.65^+	-	-	-
Techiman -Kumasi	23.76**	5.01	0.71^+	29.97**	4.37	0.54^+
Techiman - Tamale	19.27*	5.89	0.76^+	64.83**	15.42**	0.84^+
Techiman - Navrongo	28.17**	4.62	0.40^+	46.94**	12.33*	0.73^+
All Markets	82.99**	6.55	-	124.30**	12.12*	-

Source: Own

The asterisks * and ** denote rejection of the null hypothesis of no cointegration at the 5% and 1% levels respectively. The critical values for r = 0 and r = 1 respectively for the 5% and 1% are 20.16 and 9.14, and 24.69 and 12.53. $^+$ indicates significance of the value of the LR cointegration relation at the 5% level.

The last row of Table 2 presents the results of the multivariate Johansen's approach of determining the number of cointegrating vectors, for both the HFD and LFD, between all the markets in the system as a group. The results suggest a cointegrated or common marketing system at the 1% significance level for the HFD (with r = N-1 = 4 cointegrating vectors) and at the 5% level for the LFD (with r = N-1 = 3 cointegrating vectors). We therefore conclude that there exists at least one stationary cointegration vector (r = 1) between pairs of net producer and net consumer tomato markets using the semi-weekly, HFD or the monthly, LFD. A cursory observation of the test statistics indicates that the LFD with about 125 observations yields larger statistics for both r = 0 and r = 1 than the HFD with 192 observations. This seems to suggest, against realistic expectations, stronger market integration with the LFD than with the HFD.

Since the existence of a cointegrating relation between markets either in pairs or as a system, by Granger's representation theorem, implies error correction between them, we fit our high- and low frequency data to the standard and threshold VECM separately and estimate price adjustment parameters and the associated half-lives of price adjustments between net producer/net consumer pairs of markets. The results of this estimation by the standard VECM are presented in the Table 3.

Table 3: Results of the Standard Vector Error Correction Model

Market	Results of HFD (Semi-Weekly)				Results of LFD (Monthly)			
Pair	$\hat{\alpha}^s$	$\hat{\lambda}^s$	$\hat{\alpha}^c$	$\hat{\lambda}^c$	$\hat{\alpha}^s$	$\hat{\lambda}^s$	$\hat{\alpha}^c$	$\hat{\lambda}^c$
Navrongo –Accra	-0.022	-	0.068**	9.8	-	-	-	-
Navrongo - Kumasi	0.010	-	0.104**	6.3	-0.106	-	0.397**	1.4
Navrongo - Techiman	-0.012	-	0.067**	10	-0.293**	2	0.350**	1.6
Navrongo - Tamale	-0.064*	10.5	0.084**	7.9	-0.376**	1.5	0.262**	2.3
Techiman - Accra	-0.041	-	0.113**	5.8	-	-	-	-
Techiman -Kumasi	-0.019	-	0.111**	5.9	-0.285**	2.1	0.277**	2.1
Techiman - Tamale	-0.116**	5.6	0.076**	8.8	-0.179*	3.5	0.412**	1.3
Techiman - Navrongo	-0.067**	10	0.012	-	-0.350**	1.6	0.293**	2
Average[a]	**-0.082**	**8.7**	**0.089**	**7.8**	**-0.297**	**2.1**	**0.332**	**1.8**

Source Own

The half-lives $\hat{\lambda}^s$ and $\hat{\lambda}^c$ of the adjustment parameters $\hat{\alpha}^s$ and $\hat{\alpha}^c$ measure in semi-weeks (for the HFD) or months (for the LFD) the time taken for one-half of the deviation from equilibrium to be eliminated. A semi-week equals 3 days. Significant adjustments at the 5% and 10% levels are denoted by ** and * respectively. [a]The averages are calculated from only significant estimates.

A comparison of the results in Table 3 shows stark differences in the magnitude of the adjustment parameters and values of the half-lives across both the high- and low frequency price series. The inter-market adjustments parameters seem to be much larger when the standard VECM is estimated with the monthly data than with the semi-weekly data. Whereas the significant adjustment parameters (denoted $\hat{\alpha}^s$) of the net producer markets – Navrongo and Techiman to price shocks range from -0.064 to -0.116 with an average of -0.082 for the semi-weekly data, significant $\hat{\alpha}^s$ for the same market pairs range from -0.179 to -0.376, averaging -0.297, for the monthly price series. Similarly, significant adjustment parameters for shocks on the net consumer markets (denoted $\hat{\alpha}^c$) range from 0.067 to 0.113 with an average of 0.089 for the semi-weekly price series, as against a range of 0.262 to 0.412, averaging 0.332, for the monthly price series.

The estimated half-lives associated with the adjustment coefficients of the net producer markets, $\hat{\alpha}^s$, range from about 5.6 semi-weeks (or 9days) to about 10.5 semi-weeks (31.5days) with an average of about 8.7 semi-weeks (26days) for the HFD and from about 1.5 months (45 days) to 3.5 months (105 days) for the LFD. The half-lives estimated for

adjustment by net the consumer markets to random shocks, $\hat{\alpha}^c$, also range from 5.8 semi-weeks (17.4 days) to 10 semi-weeks (30 days) averaging about 7.8 semi-weeks (23.4 days) for the HFD and from about 1.3 months (39 days) to about 2.3 months (69 days), averaging 2 months (60 days) for the LFD.

Therefore, the standard VECM yields higher adjustment parameters and half-lives (in days) when applied to the monthly, LFD than is the case when applied to the semi-weekly, HFD. It is likely that the LFD overestimates the adjustment parameters. In this case, our findings would be consistent with the observation that prices adjust more quickly in agricultural markets and such adjustments may not be adequately captured in monthly observations. The tomato markets under study especially exhibit more frequent price volatility due to the perishable nature of tomato under tropical weather, and the inadequate storage and processing facilities in Ghana.

It can also be noted that the producer markets – Techiman and Navrongo in a majority of the cases involving the HFD do not exhibit significant adjustments to exogenous shocks. More significant and more rapid adjustments to deviations to equilibrium are made by the net consumer markets. This contrasts with the finding of IHLE et al (2008) that the net consumer markets are so weakly exogenous that only the net producer markets adjust to attain market equilibrium following market shocks.

Finally, we estimate the TVECM that allows the adjustment parameters and half-lives of the two datasets to vary under different regimes. We specify a simple one threshold and two-regime model and estimate it using the routine of HANSEN and SEO (2002). The results of this model are expected to improve upon the results of the standard VECM since the latter assumes perfect price adjustment and ignores the role of transfer costs in the adjustment process.

A limitation to note however is the need for the TVECM to have statistically adequate number of observations under both regimes to give statistically interpretable adjustment coefficients. The adjustment parameters of the TVECM for the HFD and LFD are presented in Tables 4. Adjustment parameters estimated with statistically inadequate number of observations are omitted and denoted in the table as NA. Estimated half-lives of adjustment are not presented for lack of space.

Table 4: Results of the Threshold Vector Error Correction Model

Data	Market Pair	Regime I		Regime II		Threshold
		α^s	α^c	α^s	α^c	ϕ
Low Frequency Data	Navrongo - Kumasi	-0.516**	-0.019			
	Navrongo - Techiman	-0.361**	0.291**	NA	NA	0.161
	Navrongo - Tamale	-0.273**	0.410**	NA	NA	0.571
	Techiman -Kumasi	-0.539**	-0.213	-0.182*	0.419**	-0.051
	Techiman - Tamale	0.048	0.374*	0.041	0.695**	0.537
	Techiman - Navrongo	NA	NA	-0.291**	0.361**	-0.172
	Average[a]	**-0.422**	**0.358**	**-0.237**	**0.492**	**0.104**
High Frequency Data	Navrongo –Accra	-0.080	0.139**	0.027	0.289	0.143
	Navrongo - Kumasi	NA	NA	0.010	0.098**	-0.652
	Navrongo - Techiman	-0.168*	0.012	0.046*	-0.001	-0.405
	Navrongo - Tamale	NA	NA	0.016	0.067*	-0.57
	Techiman - Accra	NA	NA	-0.037	0.099**	-0.080
	Techiman -Kumasi	NA	NA	0.011	0.089**	-0.328
	Techiman - Tamale	-0.171**	0.085*	0.137**	0.095	0.329
	Average[a]	**-0.170**	**0.090**	**-0.092**	**0.104**	

Source: Own

The results of the TVECM across the LFD and HFD fundamentally exhibit a similar pattern with those of the standard VECM. More rapid and significant adjustments occur with the LFD than do with the HFD. With the LFD, the average values of significant adjustment parameters under regime I are -0.422 and 0.358 for α^s and α^c respectively. These values, -0.170 and 0.090 respectively for α^s and α^c under the HFD, are smaller. Similarly, α^s and α^c under regime II for the LFD average -0.237 and 0.492 respectively, as against -0.092 and 0.104 for the HFD. This again shows a stronger reaction of the markets to shocks when the TVECM is estimated with the LFD than when it is estimated with the HFD. A comparison of the average values of the estimated adjustment parameters of the standard VECM and TVECM shows that the TVECM signifies faster adjustment across both LFD and HFD.

The estimated thresholds, a measure of the transaction costs between net producer and consumer pairs of tomato markets are expectedly lower under the LFD than in the HFD. Under the former dataset, the estimated thresholds range from 0.05 (5%) to 0.571 (57%), averaging 0.104 (10.4%) of the inter-market price difference between net producer/net

consumer market pairs. Under the latter dataset however, the estimated thresholds range from 0.08 (8%) to 0.652 (65.2%) averaging 0.358 (35.8%).

As noted under the cointegration results, accepting the finding that markets were more integrated and responded more rapidly to price shocks between 1998 and 2008, the period in which the LFD was collected, than between 2007 and 2009, the period of collecting the HFD, is a hard case to make. We suspect that factors influencing price transmission such trade policy, quality of market infrastructure, marketing margins and telecommunication services are unlikely to be more favourable between 1998 and 2008 than between 2007 and 2009. It is therefore reasonable to attribute the higher adjustment coefficient from the LFD in both models to a data limitation. It also implies that the differences in the statistical properties revealed in Table 1 are not just noise but real, and that data frequency makes a difference when estimating price dynamics.

If we consider, as it is, the estimated thresholds to be akin to transactions costs, then the estimated thresholds are as expected. The values of the estimated thresholds are an inverse function of distance between market pairs. Accra as a net consumer market is separated by the largest geographic distance from the net producer markets Techiman and Navrongo. Accra's price therefore needs to differ by a smaller margin from the net producer market prices to affect profitable arbitrage opportunities and initiate price adjustment towards equilibrium. For instance, the threshold for the Navrongo - Accra and Techiman - Accra pairs are the lowest under the HFD. This means price difference between Accra and Navrongo needs to be just 0.143 (14.3%) to kick-start the price adjustment process towards equilibrium; while 0.080 (8%) of a price difference between Accra and Techiman is needed to make adjustment by arbitragers necessary. As pointed out earlier, much of the adjustment towards long run equilibrium is performed by the net consumer markets.

5.   Summary and Conclusions

Informed trade paradigms and arbitrage processes in agricultural markets, even in developing countries, signify that markets occur daily or once in a market week of three or six days. This notwithstanding, most studies of agricultural price dynamics in developing countries are based on low frequency, monthly prices instead of high frequency, daily or weekly prices. However, monthly observations may not capture the dynamics of the arbitrage processes that occur daily or weekly. A possible consequence of not using the relevant data frequency to

estimate price dynamics in agricultural markets is imprecise results and misleading inferences from market studies.

In this paper, we address the issue of data frequency in analyzing agricultural markets in developing countries. Our goal is to explore the question of suitable data frequency for price transmission analysis by empirically comparing the estimation results of cointegration test statistics and price adjustment parameters estimated using two sets of fresh tomato prices of different periodicity from Ghana. The datasets include a high frequency, semi-weekly price series collected over a period of about two years, and a monthly series collected over a period of 10 years. Our application is to the Johansen maximum likelihood cointegration approach used to determine the existence of cointegration relations between market pairs, and to the standard and threshold VECMs for estimating inter-market price adjustment parameters and associated half-lives of price adjustment. The analysis is pair-wise, involving estimations of the cointegration test statistics and adjustment parameters and their half-lives between pairs of net producer and net consumer fresh tomato markets.

The results of both the cointegration test and the error correction models for the same market pairs clearly differ across the high frequency and low frequency datasets. The Johansen cointegration test revealed at least a single cointegrating vector between most of the market pairs under the HFD and LFD. However, the tests statistics estimated using the LFD in all cases are larger than those estimated with HFD. This suggests the unlikely case of stronger market integration with the LFD which dates back to 1998 than with the HFD collected from 2007 to 2009. The application to the standard VECM and TVECM also reveals that the monthly, LFD tends to give bigger estimates of price adjustment coefficients and adjustment half-lives than with the semi-weekly, HFD. We suspect that the monthly price series generally overestimate test statistics and adjustment parameters. If this is true, then the LFD may be imprecise in estimating price transmission elasticities, and confirm findings in the literature that HFD reveals more limitations to market efficiency than LFD.

The paper makes two contributions. First, it uses a high frequency, semi-weekly price data to estimate price transmission between fresh tomato markets in Ghana. This is a unique feature not widely considered in the price transmission literature on agricultural markets in developing countries. Most previous studies used monthly data and are based on grain markets. Second, we assess the importance of data periodicity in estimating price dynamics in

agricultural markets. In this case, we however acknowledge the limitation that, estimating the threshold as a constant makes economic sense for the short period (e.g. 20 months) HFD, but is practically impossible over the 10 year period of the LFD.

The evidence seems to suggest that accessing and using HFD to analyze price transmission and market integration will provide an enormous potential for furthering our understanding of agricultural price dynamics. The challenge however lies in getting adequate data that will permit the estimation of price adjustment parameters under different trade regimes and threshold variables. Approaches that could estimate error correction models using real transfer costs are within the realm of research possibility and could be a useful step towards understanding the significance of data frequency in commodity market analysis. We are already pursuing the matter of gathering high frequency data of prices, transfer costs and trade flow information. It is hoped that efforts in future research will lead to the development of techniques that could make use of this relevant market data.

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