SPATIAL PRICE TRANSMISSION ANALYSIS IN GHANAIAN AGRICULTURAL MARKETS: DOES THE DATA FREQUENCY IMPROVE OUR ESTIMATION?

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January 2011

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. Analysing price dynamics, especially in agricultural markets, 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 usually operate daily or weekly, not monthly, as implied by the market analysts who use low frequency data. This paper investigates the relevance of data frequency in price transmission analysis by using a standard and a threshold vector error correction model to estimate and compare price adjustment parameters for high frequency semi-weekly data and low frequency monthly data obtained from five major fresh tomato markets in Ghana. 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. There is reason to suspect that using low frequency data, as confirmed in some literature, leads to an overestimation of the price adjustment parameters. More research involving a large number of observations is however needed to enhance our knowledge about the usefulness of high frequency data in price transmission analysis.

Keywords

Price transmission, high frequency data, low frequency data, vector error correction model, Ghana

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1. INTRODUCTION

Spatial price transmission or market integration (MI) measures the degree to which markets in geographically separated locations share common long-run price or trade information on a homogeneous 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; Engle & Granger, 1987) 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 include asymmetrical and switching effects in trading mechanisms between markets (McNew, 1996; von Cramon-Taubadel, Loy & Musfeldt, 1995; Baulch, 1997; Goodwin & Piggott, 2001; Barrett & Li, 2002; Mabaya, 2003; Belcombe, Bailey & Brooks, 2007).

Currently, techniques for analysing market integration are quite sophisticated, but most empirical studies that use sophisticated techniques to analyse spatial price transmission in agricultural markets suffer from 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 using low frequency quarterly or monthly data to investigate market performance. The unavailability of reliable high frequency and complete (daily or weekly) data from secondary sources is often the excuse for not using this form of data for investigating price integration in the agricultural markets of developing countries. Furthermore, agricultural markets in developing countries are usually widely dispersed, implying exorbitant associated costs in collecting high frequency data (HFD) and thus compelling researchers to collect and use low frequency, quarterly or monthly market data.

The issue of data frequency should however be given added importance when market performance (Goodhart and O'Hara, 1997) is examined. 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 information and communication technology (ICT) service improvements between geographical markets, more frequent trading patterns and increasingly rapid rates of transmission of trade information between markets, even in developing countries, is possible (Aker, 2008; Jensen, 2007). Ihle, Amikuzuno and von Cramon-Taubadel (2010) found that in Ghana, it takes just 1.5 market weeks (about five days) for half the deviations of prices of tomato from their market equilibrium values following 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 lapses in operational and structural market mechanisms, market efficiency and temporal market dependencies are revealed when HFD is used. Using HFD also increases the power of the tests of significance for estimated parameters and helps overcome potential data-related limitations of market analyses (Choi 1992, in Choi & Chung, 1995). Lutz, Van Tilburg and Van der Kamp (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)(Choi & Chung, 1995).

This paper investigates the issue of data frequency in price transmission analysis in agricultural markets. This is done 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 five major fresh tomato markets in Ghana. The high frequency series consists of 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, in the face of lack of storage and processing facilities, is affected by trading risks and quality effects. Where markets exhibit, as is the case in Ghana's fresh tomato markets, rapid dynamics due to supply source changes, and extremities in surplus and lean seasons, then HFD should be able to handle the resulting rapid price adjustment mechanisms better than LFD. By accounting for data frequency in this analysis, therefore, we expect to learn from the usefulness of HFD and gain more insight into the question of data frequency in price transmission analysis as addressed for instance in Von Cramon-Taubadel, Loy and Musfeldt (1995) and Von Cramon-Taubadel, Loy and Meyer (2006).

In the following section, the market setting, the nature of both HFD and LFD, and the processes and tests on both datasets prior to using them in the analysis is described. Then the standard and threshold VECMs used for the analysis are specified and the reasons for adapting the two techniques as relevant analytical methods for our data are justified in section three. This sets the stage for section four, where the results are presented and discussed. The final section concludes the paper and outlines suggestions for policy and further research.

2. STUDY SETTING AND DATA

Five major tomato markets in Ghana constitute the study area (**Appendix A**). 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 entirely 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 being the main source of tomato supply in the dry season (December – May), and Techiman supplying the marketing system with tomato in the alternate 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 due to lack of adequate market stalls and the scorching sun. The tomato market of Ghana as the target of this study is therefore characterized by sharp seasonal variations in output, commodity sources, transfer costs and price volatility.

Two types of datasets are used for the analysis in this paper. The first is a high frequency, semi-weekly price series (**Figure 1**). This HFD was generated through self-conducted wholesale level market surveys administered continuously in the five markets between March 2007 and May 2009. **Figure 1** shows the normal patterns of variability pertaining particularly to prices of perishable agricultural commodities, but it can be seen that the individual price series are related in terms of their co-movement over time.

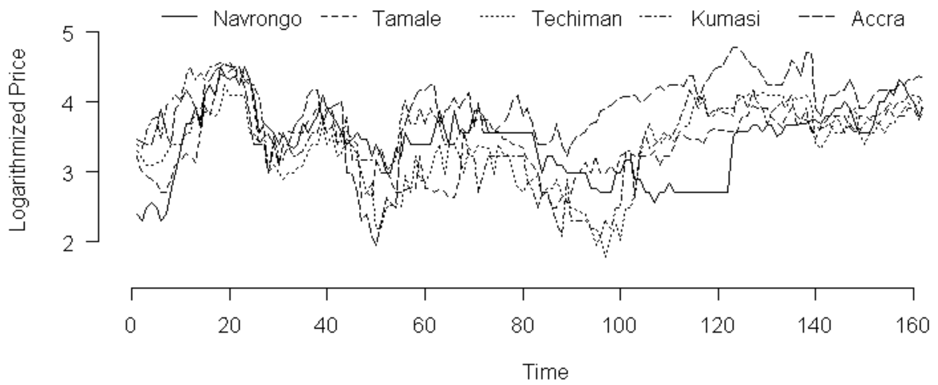

FIGURE 1: High Frequency, Semi-weekly Price Data (in Ghana Cedi)

Source: *Author's own plots*

The second dataset is a low frequency monthly wholesale price series of fresh tomato obtained from Ghana's Ministry of Food and Agriculture (MoFA) offices in the five markets (**Figure 2**). This dataset covers a period of 10 years – January 1998 to April 2008. As observed in the high frequency series plotted in Fig.1, the low frequency series also exhibit common characteristics by being closely interrelated over the entire period of study. These series suggest, however, that prices in the tomato markets under study are more volatile than illustrated in Fig 1.

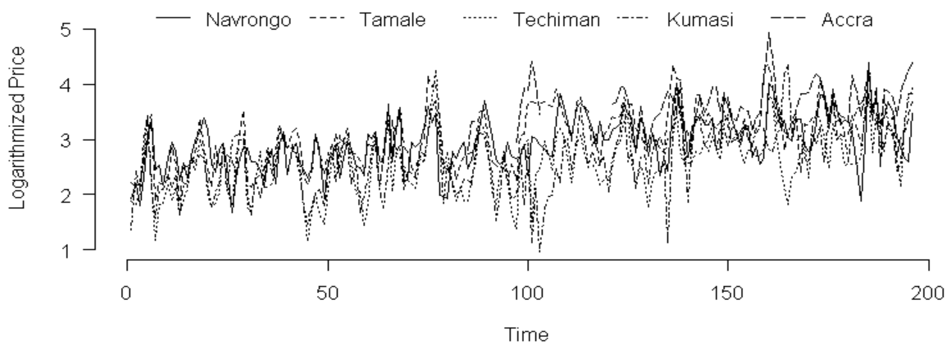

FIGURE 2: Low Frequency, Monthly Price Data (constant January 1997 in Ghana Cedi)

Source: *Author's own plots*

Our use of only the monthly series generated from 1998 to 2008, though there is data dating back to 1992, is to ensure homogeneity in the policy and market settings under which both the HFD and LFD were generated. Anticipated limitations due to the disparity in the lengths of the two datasets are avoided by converting the secondary, nominal price data to real prices by deflating the series using monthly consumer price indices for food with January 1997 as the base month. In addition, the analysis focuses solely on the dynamics of the price adjustment parameters, which should be comparable across the datasets, and not on the long-run price relationships, which may differ across both datasets.

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. Note that the main analysis with the LFD excludes Accra, because a complete series for this market from the MoFA was no available. 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: *Author's own computations*

Table 1 shows 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 observed data frequency-dependent differences in the computed CVs and in the patterns of volatility in the prices series identified by the graphical plots of the series is a priori evidence that using LFD and HFD to estimate price adjustment parameters will not yield similar results for the same system of markets.

3. METHODOLOGY

Conventional analytical techniques of price transmission 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 (Barrett & Li, 2002 in Rashid, 2004), or when the techniques use time series data for the analysis (Goodwin & Piggott, 2001), ignoring non-linearity in the price adjustment processes, as do the conventional techniques, is an empirical flaw. This flaw is avoided by applying an error correction model (ECM) to our two datasets.

Two variants of the error correction model are applied. First, under the conventional assumption of no threshold, a standard linear VECM (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 datasets 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 when thresholds are ignored. The standard and threshold VECMs are specified respectively .

The equilibrium relationship between the net consumer market prices series P_t^c and the net producer market price series P_t^s is denoted 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:

$$P_t^c - \beta P_t^s = \alpha v_{t-1} + \varepsilon_t \tag{1}$$

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 specification v_{t-1} represents lagged deviations from equilibrium and is fundamentally called the error correction term (ECT), while α, which measures the response of P_t^c and P_t^s to deviation from equilibrium following shocks to market equilibrium, is known as speed of price adjustment.

In the first technique, a standard VECM form of equation (**1**) is estimated. The VECM specifies changes in each of the contemporaneous prices, ΔP_t^c and ΔP_t^s and, 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:

$$\begin{aligned} \Delta P_t^c &= \delta_1 + \alpha^c[ECT_{t-1}] + \sum \beta_k^c \Delta P_{t-k}^c + \sum \beta_k^{cs} \Delta P_{t-1}^s + \varepsilon_t^c \\ \Delta P_t^s &= \delta_2 + \alpha^s[ECT_{t-1}] + \sum \beta_k^{sc} \Delta P_{t-k}^c + \sum \beta_k^s \Delta P_{t-1}^s + \varepsilon_t^s \end{aligned} \tag{2}$$

Equition (**2**) can be reformulated in vector representation as:

$$\boldsymbol{\Delta P_t} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 ECT_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\Gamma_i \Delta P_{t-1}} + \varepsilon_t \tag{3}$$

where $\boldsymbol{\Delta P_t} = (\boldsymbol{\Delta P_t^s \Delta P_t^c})'$ is a vector of first differences of prices in the consumer and producer markets respectively; Γ_i, i = 1,...,k, is a k × k matrix of short-run coefficients which quantify the short-term response of the contemporaneous price differences to their lagged values, and the lagged value of the error correction term, ECT_{t-1}, is a continuous and linear function of the deviation of $\boldsymbol{P_t}$ from the long-run equilibrium relationship in equation (**1**) following random shocks either to P_t^c or P_t^s. In other words, it measures the deviation of P_t^c or P_t^s from the long-run equilibrium relationship specified in (**1**): $P_t^c - \beta P_t^s = v_t$. Finally, as in the linear model, the coefficient $\boldsymbol{\alpha_1} = (\alpha^s \alpha^c)'$ denotes the speed of adjustment by the net producer and net consumer market prices respectively to correct deviations from the long-run equilibrium. The closer the value of $\boldsymbol{\alpha_1}$ is to 1, the faster the deviations from equilibrium become corrected.

In the TVECM, the adjustment of the commodity's prices to deviations from equilibrium depends on whether the magnitude of the deviations or the lagged error correction term (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. Where deviations occur the threshold ϕ is known as regime I, but when deviations surpass the threshold, then regime II occurs. Using the specification from equation (**3**), the TVECM estimated is expressed as:

Regime I:

$$\boldsymbol{\Delta P_t = \alpha_0 + \alpha_1 ECT_{t-1}} + \sum_{i=1}^{k} \boldsymbol{\Gamma_i \Delta P_{t-1}} + \varepsilon_t, \text{ if } |ECT_{t-1}| \leq \phi \qquad \textbf{(4)}$$

Regime II:

$$\boldsymbol{\Delta P_t = \alpha_0 + \alpha_1 ECT_{t-1}} + \sum_{i=1}^{k} \boldsymbol{\Gamma_i \Delta P_{t-1}} + \varepsilon_t, \text{ if } |ECT_{t-1}| > \phi \qquad \textbf{(5)}$$

All variables are as already defined. As in the standard VECM, the price adjustments in the TVECM depend on both long- and short-run price dynamics (ECT_{t-1} and $\boldsymbol{\Delta P_{t-1}}$), but the TVECM allows a display of different price dynamics depending on the magnitude of $\boldsymbol{\phi}$. The threshold value in our model represents the price differentials or transfer costs between net producer and consumer market pairs. For the sake of estimation convenience, a stationary threshold variable over the periods in which both datasets were obtained is assumed.

Before presenting the results of the analysis, a note on the empirical strengths and weaknesses of the VECM and its extended variant – TVECM – may be useful. An assumption of competitive market equilibrium and a proof of cointegration between market pairs are often prerequisites for using the two models. However, competitive equilibrium hardly obtains in agricultural markets in developing countries, while the existence of potential inter-market cointegration relations between market pairs may at times be due to simultaneity between prices rather than their stable long-run relations. As noted earlier, however, transaction costs and trade flow reversal are the two most important determinants of price dynamics in Ghana's tomato markets, and the applied models, being capable of accounting for these underlying variables via error correction and threshold processes, are ideal for analysing price transmission in the selected markets.

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 the graphical plots presented in section 2 reveals a drift but no time trend in the data generation process (DGP). The ADF unit roots test and Johansen's cointegration test are thus specified with a drift but without a time trend. The ADF results (see **Appendix B**) indicate that all series in both the HFD and LFD are unit root, i.e. I(1) in their levels but stationary i.e. I(0) in their first differences. Therefore, the generation process for both datasets is, as expected, purely stochastic.

The Johansen's maximum likelihood (ML) cointegration test was used to determine the number of cointegrating vectors (relations) between the 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. two 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**.

TABLE 2: Johansen's cointegration test statistics and long-run 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: *Author's own computation*

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 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% (*). The null hypothesis of the existence of at least 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, cannot however be rejected at the 5%. When tested at the 1%, only the market pairs Navrongo–Tamale and Techiman–Tamale under the LFD show significance for both null hypotheses 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 one (r = N-1 = 1) cointegrating vector for each market pair, since N = 2 variables (pair-wise markets).

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).

From the above preliminary findings, it can be concluded that there is at least one stationary cointegration vector (r = 1) between pairs of net producer and net consumer tomato markets using the semi-weekly HFD and the monthly LFD. A cursory observation of the test statistics indicates that the LFD with about 125 observations yields larger estimated 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 that dates back to 1998 than with the HFD gathered between 2007 and 2009 – the hub of the global food price crises.

The findings also suggest that a common stochastic process, possibly the effective flow of the commodity and/or trade information, seems to determine price linkages between the markets under study. This would mean that tomato prices between the markets do not drift apart in the long run, but always converge towards long-run equilibrium following random, short-run shocks on market equilibrium. The estimated, cointegration coefficients (β_1) range from 0.23 to 0.84. This suggests varying, but largely high, degrees of price transmission and market integration between fresh tomato markets in Ghana. Against expectations, note again that these coefficients indicate stronger price linkages for the analysis with the LFD than with the HFD.

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

Table 3: Results of the Standard Vector Error Correction Model

MarketPair	*Results of HFD (Semi-Weekly)*				*Results of LFD (Monthly)*			
	$\hat{\alpha}^s$	$\hat{\lambda}^s$	$\hat{\alpha}^c$	$\hat{\lambda}^c$	$\hat{\alpha}^s$	$\hat{\lambda}^s$	$\hat{\alpha}^c$	$\hat{\lambda}^c$
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	-0.082	8.7	0.089	7.8	-0.297	2.1	0.332	1.8

Source: *Author's own computation*

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. 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 – 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 significant price adjustment parameters of the net producer markets, $\hat{\alpha}^s$, range from about 5.6 semi-weeks (or 9 days) to about 10.5 semi-weeks (31 days) with an average of about 8.7 semi-weeks (26 days) 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 (17days) to 10 semi-weeks (30 days) averaging about 7.8 semi-weeks (23 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 both higher price adjustment parameters and half-lives (in days) when applied to the monthly LFD than is the case when applied to the semi-weekly HFD. With respect to the improvement in the quality of market, transportation and information exchange facilities, it would be expected that market performance between 2007 and 2009 when the HFD was collected would be more effective than between 1998 and 2008, the duration of the LFD. It is therefore likely that the LFD overestimates the adjustment parameters. In this case, our findings would be consistent with the earlier observation that prices adjust more quickly in agricultural markets, and such adjustments are usually not adequately captured in monthly observations. The tomato markets under study exhibit particularly highly rapid price volatility due to the perishable nature of tomato under tropical weather, and the inadequate storage and processing facilities in Ghana. This rapid volatility may increase the likelihood of many key episodes of price dynamics in monthly observations being omitted.

It should 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. Highly 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. (2010) that the net consumer markets are so weakly exogenous that only the net producer markets adjust to attain market equilibrium following market shocks.

Finally, the TVECM that allows the price adjustment parameters and half-lives of the two datasets to vary under different regimes is estimated. A simple one threshold and two-regime model is specified and estimated 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 a statistically adequate number of observations under both regimes to give empirically interpretable price 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 also presented.

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 when the model is applied to the LFD than to 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^crespectively. These values, -0.170 and 0.090 respectively for α^s and α^cunder 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 possible stronger reaction of the markets to shocks when the TVECM is estimated using 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%).

TABLE 4: Results of the threshold vector error correction model

Data	Market Pair	Regime I α^s	Regime I α^c	Regime II α^s	Regime II α^c	Threshold 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	-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	-0.170	0.090	-0.092	0.104	

Source: *Author's own computation*

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. It is probable that factors influencing price transmission such as 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, estimated adjustment parameters from the LFD in both models to a data limitation such as missing episodes in the DGP. It also implies that the differences in the statistical properties revealed in **Table 1** are not just noise but real, and that data frequency does make a difference when price dynamics are estimated.

If, as it is, the estimated thresholds are considered to be akin to proportional transaction costs, then the estimated threshold values 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 geographical 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 thresholds for the Navrongo–Accra and Techiman–Accra pairs are the lowest under the HFD. This means that price difference between Accra and Navrongo needs to be just 0.143 (14.3%) to kick-start the price adjustment process towards equilibrium, while just 0.080 (8%) of a price difference between Accra and Techiman is needed to make adjustment by arbitrageurs necessary.

4. SUMMARY AND CONCLUSION

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, the issue of data frequency in analysing the performance of agricultural markets in developing countries, with Ghana as a case, was addressed. Our goal was to explore the question of what constitutes a suitable data frequency for price transmission analysis by empirically comparing the estimation results of cointegration test and price adjustment parameters computed using two sets of fresh tomato prices with different frequencies. 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 in Ghanaian tomato markets. 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 estimates of price adjustment coefficients and adjustment half-lives with greater magnitudes than with the semi-weekly HFD. Perhaps 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 parameters, and thus confirms findings in the literature that HFD reveals more limitations to the effectiveness of market performance than does LFD.

The paper makes two contributions. First, it uses 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, the importance of data periodicity in estimating price dynamics in agricultural markets is assessed. In this case, it is acknowledged that estimating the threshold as a constant may make economic sense in the short period (e.g. 20 months) covered by the HFD, but is practically impossible over the 10 year period of the LFD.

The evidence seems to suggest that accessing and using HFD to analyse price transmission and market integration has 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. Efforts are already under way to pursue the matter of gathering high frequency data of prices, transfer costs and trade flow information. It is hoped that future research will lead to the development of techniques that could make use of this relevant market data.

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APPENDIX A

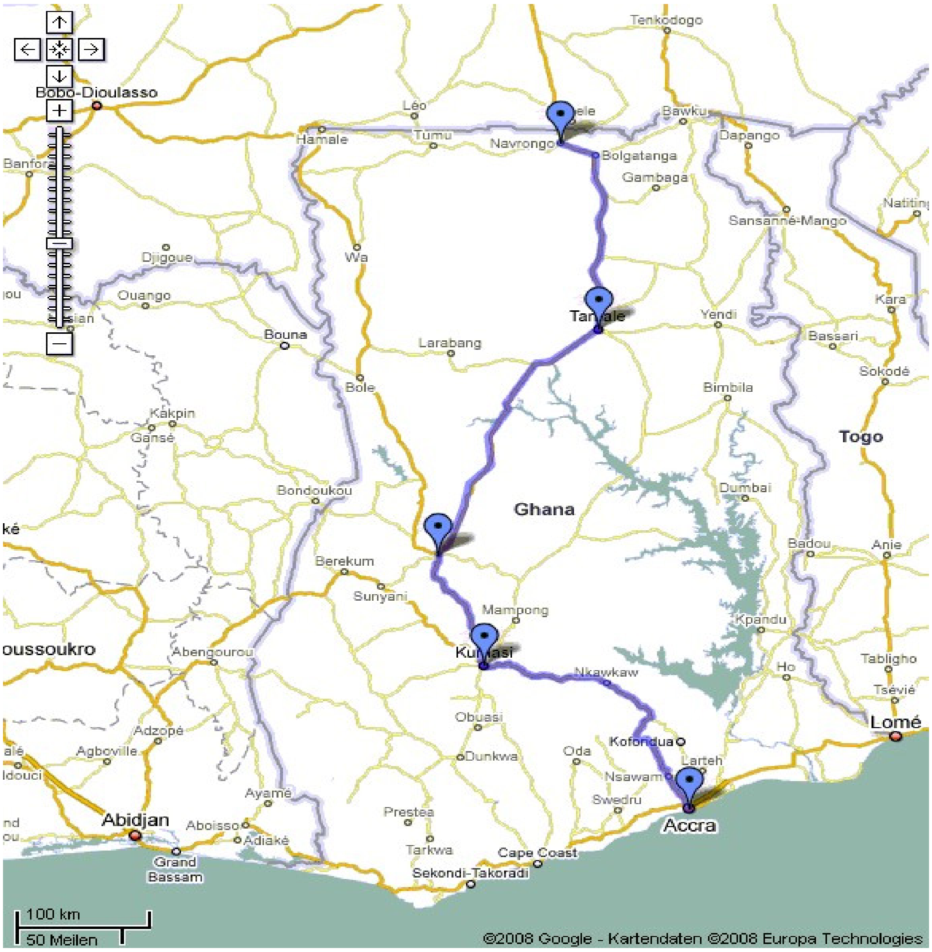

FIGURE A1: Map of Ghana showing the markets under study

Source: *Google Maps*

APPENDIX B

ADF Tests of unit roots in the price series

ADF Results of Low Frequency Data				
Price Series	*Lags at * Levels*	*ADF Statistic at Log Levels*	*ADF Statistic at First Difference*	*5% Critical Value*
Navrongo	10 (10)	-1.02	-8.86**	
Tamale	10 (8)	-1.43	-8.98**	-2.86
Techiman	11 (10)	-0.26	-8.44**	
Kumasi	10 (9)	-0.52	-8.12**	

ADF Results of High Frequency Data				
Price Series	*Lags at * Levels*	*ADF Statistic at Log Levels*	*ADF Statistic at First Difference*	*5% Critical Value*
Navrongo	0 (0)	-2.62	-12.65**	
Tamale	1 (0)	-2.51	-13.81**	
Techiman	0 (0)	-2.19	-13.81**	-2.86
Kumasi	2 (1)	-1.69	-10.47**	
Accra	12 (11)	-2.02	-4.99**	

Source: *Author's own computation*

*The lag values in brackets are the recommended AIC lag lengths for the ADF equation when the first differences of the series are used.

NB: The null hypothesis of unit roots is typically not rejected at the 1% and 5% significance levels when the ADF test is applied to the price series at their levels, but is rejected at the selected significance levels when the test is applied to the first differences of the price series. This provides evidence favouring unit roots of the order one in both datasets.