TESTING SYMMETRY IN PRICE TRANSMISSION MODELS

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ABSTRACT

This paper evaluates traditional data segmentation approaches used to study asymmetric price transmission. This segmentation procedure creates artificial collinearity that renders symmetry tests fragile. Supporting evidence comes from a Monte Carlo experiment that is buttressed by empirical findings. The simulation finds asymmetry in its absence and low rates of rejection of symmetry in some asymmetric time series models. Findings suggest that multicollinearity increases with sample size regardless of model structure that includes a bivariate threshold model. Recent literature on momentum threshold modeling offers promising alternatives for assessing asymmetry.

INTRODUCTION

Asymmetric adjustment in the transmission of prices at various levels of the food marketing system has been of considerable empirical interest to agricultural economists for decades. By definition, asymmetry is an unreciprocal relationship between rises and falls in prices between the commodity, retail and intermediate levels in the market for a product. Asymmetric price responses are of concern to producers of agricultural commodities who often claim that retail prices rise faster and fuller than farm price increases, but that retail price declines are not likely to be either as full or transmitted as fast as declines in farm prices. The implication is that retailers possess and exercise greater market power as evidenced by asymmetric price responses. Typical studies use farm-retail prices to test asymmetry by segmenting prices into increasing and decreasing time series sequences. A common assertion with respect to agricultural commodities is that the initial price response at retail to a reduction in prices at the farm lags the response to an increase in producer prices. This assertion justifies research to assess the gains and losses to producers and consumers from changes in marketing margins and to enhance understanding of the welfare effects of changes in government policies impacting prices.

To what extent these findings are vulnerable to the method used to measure asymmetric behavior is an important research question. An extensive review of the empirical literature reveals that the most frequently used approach to evaluating price transmission is a segmentation procedure that divides prices into one series of accumulating price increases and into a second series of accumulating price decreases (Houck). It was recognized early in the literature that existing segmentation procedures introduced a trend effect into the model. In some works, multicollinearity was reported [Houck]. The adverse effects of multicollinearity on the stability of parameter estimates and the accuracy of the standard errors for estimated coefficients is well documented in the econometrics literature. As a result, tests of hypotheses, such as those for the equality of coefficients in price transmission models, may be indirectly affected.

Over the years, independent studies of the price segmentation procedure have addressed questions regarding the seriousness of multicollinearity introduced through segmentation of the price data [Vande Kamp and Kaiser]. The extent to which collinearity may affect asymmetry findings using data segmentation procedures and how such findings vary with sample size is unknown. One purpose of this paper is to revisit a typical price segmentation procedure used in applied work and evaluate the nature of multicollinearity introduced by the segmentation procedure as the sample size increases. A Monte Carlo simulation experiment is used to define models representative of various types of asymmetric behavior. The simulation results are accompanied by empirical results on a cross-sectional sample of agricultural commodity farm and retail prices often used in applied work.

BACKGROUND

Measuring Asymmetry

As a historical note, the literature on asymmetric analyses tends to cluster around the end and beginning of decades. The first attempt at estimating asymmetric adjustment documented in the American Journal of Agricultural Economics appeared in the late 1960s [Tweeten and Quance], followed by Wolffram in 1971. These works were followed with perhaps the most widely cited paper by Houck in the late 1970s. He developed a more rigorous approach to specifying and testing nonreversible linear functions in economic research. Houck's paper stimulated considerable interest in the study of price linkages and dynamics in the food marketing industry [Heien; Ward; Kinnucan and Forker; Carman; Reed and Clark; Cramon-Taubadel; Vande Kamp and Kaiser].

A recurrent observation in the literature has been the presence of a high linear correlation among the variables generated from the segmentation introduced in Houck's approach. In fact, in the initial paper Houck wrote that *"....intercorrelations among explanatory variables might be intensified. When a variable is segmented into increasing and decreasing components, it is possible that the two segments will be highly correlated with each other ..."*. Most researchers have proceeded as if multicollinearity is benign or that it is a problem only for certain data sets [Houck; Vande Kamp and Kaiser]. Recent studies in irreversible functions have improved the initial segmentation procedure [Heien; Vande Kamp and Kaiser]. Other studies have been motivated by new developments in time series analysis and their implications for estimation and hypothesis testing in price transmission models [Reed and Clark; Cramon-Taubadel]. But, even in these new approaches, limited diagnostic results are provided on the nature of the linear dependence in the segmented series. One exception is Vande Kamp and Kaiser, where certain restrictions are imposed to deal with multicollinearity.

Concurrent with Houck's introduction of this ingenious segmentation procedure for analyzing symmetry in time series data, nonstationary and unit-root tests were being formulated [Fuller; Granger and Newbold]. As discussed in a later section, these formulations have specific implications for modeling asymmetric behavior.

Margin Models

Marketing margins are the differences between retail and farm prices. An alternative definition is that farm prices and retail prices differ by the cost of providing marketing services in transforming raw agricultural commodities into finished consumer goods [Tomek and Robinson, p. 108]. The condition of asymmetry occurs between different levels of a market and finds expression in not only the magnitudes of price movements between market levels, but also in the lead and lag relationships between market levels. The difference in prices between market levels is commonly referred to as the margin. The implications of changes in the margin on the dependent variable vary depending upon whether a price change is due to a shift in the primary (retail) demand, in the primary (farm) supply, or in the supply function of marketing services [Gardner].

Thompson and Lyon (see also Lyon and Thompson) provided a concise review and justification of the conceptual base for the derivation of four marketing margin models that often appear in applied work. Of these, the markup (MU) model provides the simplest explanation of margin behavior,

$$M = f\,(PR, Z),\ \ M = PR - PF \qquad (1)$$

where M is the farm-to-retail marketing margin, PR is the retail price, and Z is a vector representing marketing input costs, trends, or other deterministic components.[1] The farm price, PF, is linked to the retail price through M. The MU model dates back to the work by Waugh and the extensive empirical investigation by George and King. The simplicity of this mark-up model makes it ideal for simulating asymmetric properties of farm and retail prices and is the basis for the various models used for the simulation experiments introduced in this paper.[2]

THE ECONOMETRIC PRICE TRANSMISSION MODEL

Houck suggested a rather simple approach for testing asymmetry, which can be explained as follows. Let X and Y be two related time series. The test of symmetry, which requires first differencing of X, implies that one-unit increases in X from period to period have a different absolute impact on Y than do one-unit decreases in X. This relationship Houck wrote as:

$$\Delta Y_t = a_0 + a_1 \Delta X_t^{'} + a_2 \Delta X_t^{''},\ \ t = 1,2,\ldots,t, \qquad (2)$$

where ΔY are the first differences of Y, $\Delta X'$ and $\Delta X''$ are the positive and negative differences in X from period-to-period, respectively. Houck argued that this segmentation must be tied to the initial observation on Y, and accounted for this first value of Y through the model:[3]

$$P_d = a_0 t + a_1 H^+ + a_2 H^- + u_t \qquad (3)$$

where P_d is the deviation in Y_t from the initial observation (Y_t-Y_0), H^+ is the sum of all period-to-period increases in X from its initial value up to period t, H^- is the sum of all period-to-period decreases in X from its initial value up to period t. H is used to distinguish Houck=s segmented series from series generated from other similar transformations and a_0 is a trend coefficient if its value is not zero [Houck. p. 570].[4] This is the econometric price transmission model typically found in the empirical literature, ignoring more complex terms that capture dynamics.

Multicollinearity

Houck recognized that the segmentation of farm prices into H^+ and H^- could result in near collinearity between the two series and/or with the trend variable. No analysis in Houck=s initial work, or in the work that it spawned, has identified the importance of the degree of linear correlation between the increasing and decreasing series and its consequences for estimation and hypothesis testing. As the Monte Carlo experiment below finds, in time series data, whether the series are integrated or not, the period-to-period accumulated deviations (H^+ and H^-) constitute almost perfectly correlated trends giving rise to multicollinearity. A condition index [Belsley, Kuth and Welsch] can be used to diagnose the severity of multicollinearity in equation (3). This condition index number is estimated as the square root of the quotient between the largest eigenvalue and each of the eigenvalues of the cross-products of the independent variables. Near collinearity is assumed whenever the condition index is 20 or higher [Greene].

The symmetry hypothesis is tested by comparing the equality of coefficients a_1=a_2 in equation (3). The implicit assumption in Houck=s model is that retail and farm prices have the same stochastic behavior. The effect of the segmentation upon the size of the test as the sample size increases also is unknown. From a multicollinearity perspective, the linear restriction in the null hypothesis implies that the covariance coefficient between a_1 and a_2 must be calculated to obtain the standard error at the hypothesis value. Thus, the standard error for this linear restriction would be higher than expected.

THE SIMULATION EXPERIMENT

A Monte Carlo experiment was designed to simulate asymmetric responses for various price transmission models. The simulated model is the classical markup (MU)[5] given in equation

$$M_t = a + b * PR_t \tag{4.a}$$

where M_t is the marketing margin at time t and (a,b) are coefficients whose respective magnitude and sign define the relationship between the marketing margin and the retail price at that same time t.[6]

The simulation is started by generating farm prices as independent draws from a normal distribution with a constant mean and a variance of one. Houck=s segmentation technique is then applied to farm prices to obtain H^+ and H^-. Assessing how well the testing procedure identifies asymmetric behavior requires the introduction of various degrees of asymmetry through the coefficients of H^+ and H^- (see Table 1) in equation (3). Retail prices are then obtained by adding a constant margin to farm prices.

Table 1
Monte Carlo Simulation Models of Price Asymmetry

Model	a_1	a_2	b
A	1.0	1.0	1.0
B	2.0	0.5	1.25
C	2.0	1.0	1.5
D	3.0	1.0	2.0
E	0.3^*t_1	-0.0001^*t_2	
TAR	NA	NA	NA

Note: Coefficients a_1 and a_2 correspond to those in equation (3). The b coefficient is for the margin model in equation (4.a). Model A is symmetric and models B-D are asymmetric, with asymmetry four times as large for the price increases than price decreases in model B, twice as large in model C and three times as large in model D. These relative values of a_1 and a_2 should allow for power of test comparisons. Coefficients for the implied margin equation are shown in the b column. E is an autoregressive model of order 1 (AR1) with a middle fifth of the sample with a positive trend and the last two-fifth of the sample with a downtrend. The TAR is a bivariate threshold autoregressive model of order one with retail prices as a threshold variable. NA stands for not applicable.

The experiment is expanded by simulating a second model that generates retail and farm prices from simple autoregressive (AR) models with asymmetries defined by (referred to as model E in Table 1):

$$\begin{aligned} PR_t &= c_1 + 0.7 * PR_{t-1} + 0.3 * t_1 - 0.001 * t_2 + e_1 \\ PF_t &= c_2 + 0.2 * PR_t + 0.1 * t_1 - 0.001 * t_2 + e_2 \end{aligned} \tag{4.b}$$

This model simulates farm prices as a function of retail prices and adds an up-trend to retail prices (t_1) that increases retail prices faster than farm prices, but under conditions of retail price declines, the model has retail and farm prices declining at the same rate (0.001). Thus, the model simulates the assertion that when retail prices increase, farm prices increase, but they do not increase as fast, and when retail prices decline, farm prices decline at the same rate creating the asymmetric price response. In the simulation, the jump function is added after the AR process has been generated.

The time series literature on estimation of nonlinear models to capture asymmetries, limit cycles and jump phenomena has recently grown. One model that has gained popularity is the threshold autoregression [Enders and Granger; Tsay] known more commonly as TAR. This experiment simulated a two dimensional threshold autoregressive model (referred to as TAR) given by [Tsay]:

$$y_t = \begin{cases} \phi_1^{(1)} y_{t-1} + \varepsilon_t^{(1)} & \text{if } y_{1,t-1} < 0 \\ \phi_1^{(2)} y_{t-1} + \varepsilon_t^{(2)} & \text{if } y_{1,t-1} \geq 0 \end{cases} \tag{4.c}$$

where y_t contains two variables, namely retail (y_1) and farm prices (y_2), and the coefficient matrices are chosen as in Tsay:

$$\phi_1^{(1)} = \begin{bmatrix} .7 & 0 \\ .3 & .7 \end{bmatrix}, \ \ \phi_1^{(2)} = \begin{bmatrix} -.7 & 0 \\ -.3 & -.7 \end{bmatrix}, \ \ \Sigma_1 = \begin{bmatrix} 1.0 & .2 \\ .2 & 1.0 \end{bmatrix}, \ \ \Sigma_2 = \begin{bmatrix} 1.0 & -.3 \\ -.3 & 1.0 \end{bmatrix}.$$

The error terms in the model are generated from a bivariate normal distribution with covariances given by Σ_1 and Σ_2. It is well documented in the literature (e.g.,Tong; Tsay) that TAR is a reasonable approximation for asymmetric processes. The objective in this simulation is to identify how well previous segmentation procedures would detect asymmetries in price transmission if those asymmetries were built with a TAR structure. Rejections rates of symmetry approximating 1 would lead to the conclusion that segmenting a price series into increasing and decreasing series (as done in equation 3) is a reasonable approximation.

The simulation proceeds as if farm and retail prices have been obtained from some public source, as is done in practice, and the segmentation approach is applied to the simulated data. The first 50 observations of each series are deleted to minimize the impact of starting values as pre-testing suggested that the parameters in the experiment could be replicated with the expected accuracy. Random samples of size 25, 75, 100, and 200 are generated so that the results resemble the size of samples that commonly appear in applied work (small and large samples usually correspond to annual and monthly series, respectively).The experiment is repeated 1,000 times, and the number of rejections of the null hypothesis of symmetry is recorded. For models E and TAR, the experiment is run 5,000 times because their model structures are more complex. Model A in Table 1 is symmetric and is used as the control in the simulation experiment. Note that the rejection rates of symmetry for model A should be around 0.05 for the desired level of statistical significance. The results also include real world data often used in the study of pricing asymmetry in agriculture. Monthly price data for beef, pork, milk, rice, apples and tomatoes are used for the period 1982:01 – 1998:12.

RESULTS

Simulation

The first question investigated in this experiment is the degree of collinearity introduced by segmenting farm prices into H^+ and H^- series. The first block in Table 2 shows the collinearity diagnostic results for alternative sample sizes (25, 75, 100, 200).

Condition numbers (cn2 and cn3) higher than 20 suggest the presence of high collinearity. For model A, the values ranged from cn2=16.91 and cn3=28.34 for 25 observations, to cn2=68.27 and cn3=151.16 for 200 observations. Note that the larger the sample size, the stronger the collinearity in the independent variables of the model.

No direct linkage can be established between correlation coefficients and collinearity. The observation that the average correlation coefficient increased to 1 with increasing sample size, however, lends support to the increase in condition index values reported in Table 2. Reports of mild levels of collinearity has been cited in previous work [Houck]. However, this study provides first hand evidence that high collinearity between H^+ and H^- and between the two-segmented series and a time trend is much stronger than initially suspected and this result applies to all models included in the experiment.[7]

Table 2
Collinearity Diagnostics and Rejection Rates for the Symmetry Test, Simulated and Empirical Data[a]

	Sample Size								Sample Size[d]			
	25		75		100		200		25	75	100	200
	Condition Numbers[c]											
	cn2	cn3	cn2	cn3	cn2	cn3	cn2	cn3				
Model(a_1,a_2)[b]									Symmetry Hypothesis: a_1=a_2			
	Simulated Data								---------- Rejection Rates -------------			
A(1,1)	16.91	28.34							0.17	0.29	0.35	0.44
B(2,.5)			39.46	60.90					0.91	1.00*	1.00*	1.00*
C(2,1)					46.99	77.94			0.76	1.00*	1.00*	1.00*
D(3,1)							8.27	151.16	0.97*	1.00*	1.00*	1.00*
E	4.08	20.11	4.01	54.62	3.99	69.53	3.97	133.38	0.24	0.49	0.58	0.67
TAR	4.05	71.10	4.03	46.65	4.02	61.50	4.00	180.63	0.16	0.21	0.21	0.24
	Empirical Data (1982:01-1998:12)											
	cn2	cn3	cn2	cn3	cn2	cn3	cn2	cn3	p-values			
BEEF	8.58	37.47	24.52	81.74	27.72	93.49	38.26	66.32	0.00*	0.22	0.00*	0.00*
PORK	5.52	32.46	21.01	42.68	28.55	57.68	30.76	80.01	0.05	0.00*	0.00*	0.00*
MILK	6.38	37.18	17.29	26.12	10.82	30.17	17.10	43.27	0.00*	0.00*	0.00*	0.00*
RICE	6.53	33.36	7.44	18.15	9.34	23.96	17.87	46.97	0.17	0.03*	0.00*	0.00*
APPLES	13.62	25.49	16.09	25.39	15.97	29.73	28.84	58.16	0.04*	0.04*	0.22	0.02*
TOMATOES	12.76	30.58	41.57	52.55	4.67	39.85	23.12	95.24	0.15	0.03*	0.00*	0.00*

a) The margin model M=a+b*PR_t was estimated 1000 times for models A-D and 5000 times for model E and TAR. Average values of b were (1.01,1.26,1.51,2.01) for models A-D at 25 observations. The true values of b which can be obtained from the (a_1, a_2) coefficients of models A-D in column 1 are (1,1.25,1.5,2.0) which are close to the true values. Models E and TAR are autoregressive with a jump function and a threshold regressive model, respectively.
b) Model A is symmetric but models B-D are asymmetric, a_1 is the coefficient on H^+ and a_2 is the coefficient on H^- in equation (3).
c) Condition numbers for each model at the same sample size are not shown because farm prices are generated from the same seed. A condition number of 20 or higher is considered an indication of near collinearity.
d) This block reports the rejection rates for the symmetry tests. For the empirical data section, the results of the symmetry test are reported as calculated p-values. When these p-values are less than 0.05, symmetry is rejected. A "*" on the upper right-hand side block for the simulated data indicates an expected rejection rate even at the .01 level of significance, and it indicates the rejection of symmetry for the empirical data for the "p-values" block.

The performance of the symmetry test can be assessed from the right-hand-side block in Table 2. Rejection rates of the null hypothesis of symmetry for each of models A-D at the four sample sizes (25, 75, 100, 200) are reported in the first four rows. For instance, 0.17 implies that Ho: $a_1=a_2$ is rejected 17% percent of the time for model A at 25 observations. Model A is built with symmetry and carries an expected rejection rate of 0.05. The difference between the reported rejection rates (0.17) and the expected rejection rate (0.05) constitutes an unexpected discrepancy. This is not an isolated result and is part of a pattern common to both the symmetric model (A) and the asymmetric models (B-D). As the sample size increases to 75, 100, and 200 observations, the empirical nominal size of the test increases to 0.29, 0.35, and 0.44, respectively. Since models B-D are asymmetric (the size of the a_1 and a_2 coefficients is different), the expectation is that the rejection rates of the symmetry hypothesis approach 1 as the sample size increases. For model B, where the influence of the sum of positive price changes (H^+) is simulated to be four times as strong as the sum of negative prices changes (H^-), symmetry is rejected 91% of the time at 25 observations and increases to 100% at a sample size of 75. The same pattern of rejecting symmetry applies to models C and D.

Model E is a simple autoregressive process with jump functions that allow for retail prices to increase at a faster rate than farm prices while allowing both price series to decline at the same rate. Because these are more complex model structures, the experiment was replicated 5000 times for model E and TAR and their rejection rates (nominal size of test) are recorded in Table 2. It was found that as the sample size increases, the rejection rate for the symmetry test in Model E increases from 24.3% at 25 observations to 66.6% at 200 observations. While it is desirable for the rejection rates of symmetry to approach 1with increases in the sample size, it is not encouraging to observe that a nominal size of about 0.34 would be needed to reject symmetry in this type of asymmetric model (model E). In the case of a TAR process with two regimes, it is found that rejection rates increase from 16.1% at 25 observations to 23.8% at 200 observations. Clearly, the use of price segmentation procedures is suspect even when TAR asymmetry is present.

In summary, the detection of asymmetry at very small sample sizes is encouraging, but the test for symmetry based on segmentation procedures has trouble identifying symmetry when it exists (model A) as evidenced by rejection rates that increase with increases in sample size. Neither symmetry nor asymmetry is known a priori. The use of segmentation procedures reported in applied work often led to the erroneous conclusion that some degree of market power, or other type of market imperfection, was present when, in fact, it was not.[8]

Empirical Analysis

Are the simulation results consistent with empirical findings? Ordinary least squares regression **r**esults for monthly retail and farm prices for beef, pork, milk, rice, apples, and tomatoes for the January 1982 through December 1998 period (204 observations) are reported in the empirical data section of Table 2. The data were segmented by samples of size 25, 75, 100, and 204 so as to maintain consistency with the Monte Carlo experiment. Regarding multicollinearity, the conditions number (cn3) tends to be higher than 20 at the various sample sizes, suggesting that there is at least one linear dependency. Application of Houck=s procedure based on cumulative sums of price increases and decreases (equation (3)) results in rejection of symmetry for almost all commodities and sample sizes.

DISCUSSION

Various price transmission studies in the food marketing system have long argued that output prices tend to respond faster to input price increases than to decreases. This asymmetric response to price shocks is substantial and enduring in producer and consumer goods markets because of its implications for market effectiveness and efficiency. Recent contributions to the econometrics literature in nonlinear modeling offer a variety of models for analyzing asymmetric price behaviors and adjustments. The simulation experiment conducted in this study simulated a TAR structure. Prices for the same good at different levels of the market tend to move up and down in a synchronized manner [Tomek and Robinson]. This co-movement is often referred to as cointegration in the time series literature [Engle and Granger; Granger]. The observation is of increases (decreases) in producer prices resulting in reductions (increases) in marketing margins tending to be transmitted faster (slower) and into higher (lower) prices at retail [Abdulai]. The economic phenomenon that underlies this observation fits a more generalized structure than the TAR model and is called a momentum threshold autoregressive (M-TAR) model [Enders and Granger, Enders and Siklos]. The M-TAR model is a more general specification of the error-correction models (ECM) found in the cointegration literature. It encompasses the ECM when the adjustment is symmetric. Using Engle-Granger two-step approach [Engle and Granger] to error-correction modeling, the M-TAR approach first estimates an OLS regression of the long-run equilibrium between retail (PR) and farm (PF) prices:

$$PR_t = c + b * PF_t + u_t . \tag{5}$$

In the classical cointegration analysis, OLS would be used to estimate ρ in the following equation:

$$\Delta u_t = \rho u_{t-1} + \varepsilon_t \tag{6}$$

where ε_t is a white noise process. If the residuals in (5) are stationary with mean zero then cointegration is found. When there is asymmetric adjustment, Enders and Granger propose to use the M-TAR framework, which is represented by

$$\Delta u_t = \begin{cases} \rho_1 u_{t-1} + \varepsilon_t \text{ if } \Delta \mathrm{u}_{\mathrm{t-1}} \geq 0 \\ \rho_2 u_{t-1} + \varepsilon_t \text{ if } \Delta \mathrm{u}_{\mathrm{t-1}} < 0 \end{cases} \tag{7}$$

If the above sequence is stationary, the least squares estimates of ρ_1 and ρ_2 have an asymptotic multivariate normal distribution. The process is formally specified as:

$$\Delta u_t = I_t \rho_1 u_{t-1} + (1 - I_t)\rho_2 u_{t-1} + \varepsilon_t \tag{8}$$

where I_t is referred to as the Heaviside indicator function such that

$$I_t = \begin{cases} 1 \ \text{if} \ u_{t-1} \ \geq \ 0 \\ 0 \ \text{if} \ u_{t-1} \ < 0 \end{cases} \tag{9}$$

where 0 represents a critical threshold value. Equations (8) and (9) are referred to as M-TAR. Note that when the values of ρ_1 and ρ_2 are the same, then M-TAR reduces to equation (6), the traditional symmetric ECM specification. Thus, an asymmetric ECM specification is needed to capture M-TAR properties, referred to as M-TAR$_{ECM}$, which for retail prices may be written as

$$\Delta PR_t = \rho_{1,1} I_t u_{t-1} + \rho_{2,1}(1 - I_t)u_{t-1} + \sum lagged(\Delta PR_t, \Delta PF_t) + v_t \tag{10}$$

where the "lagged ( )" term on the right-hand side denotes the sum of the lagged period-to-period changes in retail and farm prices and in practice, the number of lags are identified through the use of statistical selection such as the Akaike information criterion (AIC).

This M-TAR$_{ECM}$ model has properties consistent with the asymmetric momentum in producer-retail price movements. For example, if $|\rho_2| < |\rho_1|$, this model exhibits little decay for negative changes in Δu_{t-1} but substantial decay for positive changes, a property consistent with observed asymmetries in retail and farm prices. An application to pork prices in the Swiss market is found in Abdulai. Much remains to be learned about properties of this model in multivariate settings. The specification in equation (10), however, provides a useful first approach to econometric modeling of asymmetric price behavior consistent with non-stationary time series properties of commodity prices and with the argument that there is more momentum in price changes in one direction than another. One appealing feature of these models is that asymmetric behavior is identified through the data itself rather than through segmentation procedures; thus, the model structure more naturally follows the nature of the data generation process. Additionally, M-TAR structures allow for price series (e.g., farm and retail prices) to return to a normal equilibrium, thus maintaining comovement as implied by market fundamentals.

SUMMARY AND IMPLICATIONS

This paper studied multicollinearity and nonstationarity in econometric irreversible functions that are based on the segmentation procedures often found in the study of price transmission. A Monte Carlo simulation was carried out, using price transmission models, to simulate farm and retail prices based on margin models that have often appeared in the literature. The simulation models included various degrees of asymmetry so that the nominal size of test could be calculated under symmetry and asymmetry. Samples of size 25, 75, 100, and 200 observations were generated, and the experiment was replicated 1,000 times for the margin models and 5,000 times for the autoregressive models.

The simulation and empirical findings carry considerable practical relevance. First, segmentation procedures for increasing and decreasing price series generate deterministic trends for both series; the larger the sample size, the stronger the trend behavior of the segmented series (test results not shown in paper). Second, condition numbers for collinearity diagnostics suggested that the larger the sample size, the stronger the multicollinearity in the independent variables, resulting from the segmentation, in price transmission models. Third, the test for the null hypothesis of symmetry detects asymmetry when it exists but at low rates, and finds asymmetry too often (compared to the nominal size of 0.05) when it does not exist at any sample size. Fourth, although not reported in the paper, the finding suggests that often the regression equation for price transmission models is unbalanced and that cointegration and error-correction modeling is only one specific case of many possible model specifications that are consistent with the time series properties of the data. Future research should seek to develop a nonlinear model to capture asymmetric behavior in time series when dependent and independent variables in the model used to test the null hypothesis of symmetry contain mixed unit-roots.

In summary, the results in this experiment caution that the conclusions generated from some previous applications with asymmetric price-transmission models may be fragile. It is possible to find asymmetry even in its absence or to not detect asymmetry when it exists. This study underscores the admonition to exercise care and caution in the choice of tools used to create facts about economic phenomena. The Monte Carlo findings suggest that previous findings with the use of price segmentation techniques to study asymmetry should be revisited and compared to findings generated from more general asymmetric process such as M-TAR. Recent developments in threshold modeling [Balke and Fomby; Tsay; and Hansen and Seo] are shedding light on promising procedures for modeling multivariate adjustment mechanisms which should enhance our analyses and understanding of asymmetric market price transmission phenomena.

ENDNOTES

[1] Three other popular margin models are the relative (RL), marketing cost (MC), and rational expectations hypothesis (REH), which are specified as M=f(PR, PR*Q, IC), M=f(Q, IC), and M=f(PF_t, $E_t(PF_{t+1})$;r,g), respectively, where IC is the marketing input costs, Q is total quantity marketed, PF_t is the farm price, E_t is the expectation of the farm price at time t for the following period (t+1) based on past and current information, $E_t(PF_{t+1})$ is a rational expectation of the farm price, and (r,g) are parameters for the discount rate and the inventory-to-sales ratio. The RL model, which represents linear homogeneity in input and output prices, and the MC model, which represents margins solely as a function of farm output and the firm=s cost function, were derived by Wohlgenant and Mullen. Wohlgenant also derived the REH model from the first-order conditions of a competitive firm maximizing present value of expected net revenues from inventory holdings.
[2] As pointed out by Gardner, this model is too simplistic for capturing various properties of margin behavior. However, it provides an ideal scenario for assessing the reliability of the symmetry test implied by Houck=s segmentation procedure. Failure of the testing procedure to confirm expected results in this model would make testing under more complex margin models unnecessary.
[3] Houck wrote this equation as $y_t=a_0t+a_1R_t+a_2D_t$ with obvious substitutions. An error term has been added to conform to the model used in econometric analysis.
[4] Wolffram used W^+ and W^- to refer to positive and negative changes, respectively.
[5] Other margin models also were simulated and the results are available from the authors upon request. Although the MU model is very simplistic, the results arising from this model hold for more complex models.
[6] George and King estimated simple regression equations between farm and retail prices for 32 commodities. In their work, the intercept and slope coefficients were significant for 19 commodities (beef, pork, lamb, beef, etc.). It follows that the "a and b" coefficients in model (4.a) were significant for those commodities. For 11 other commodities (wheat flour, corn meal, tomatoes, etc.), the intercept was not significant (a=0 in model (4.a)), but the slopes were significant, implying that margins were a fixed proportion of retail prices.
[7] The simulated H^+ and H^- series versus H^+ and H^- for monthly U.S. beef prices were plotted against time. The pattern for H^+ was exactly the same as the pattern for H^-. This pattern holds for all sample sizes as in the simulation results.
[8] One common solution to the multicollinearity problem is to estimate the model in first differences. However, as pointed out by Houck, a model in differences is not consistent with the data generation process implied by the segmentation procedure. Although not reported in this paper, a test on first differences was also calculated and the results suggested significant biases in testing for symmetry.
[9] Various margin models were simulated for stationary (I(0)) and nonstationary (I(1)) series. The results on collinearity and rejection rates were consistent with those reported in Table 2 for the Wolffram-Houck (WH) procedure. This finding is consistent with that in Reed and Clark, where the effect of stochastic trends is studied in a more complex model.
[10] A comparison of the simulation results against real-world data is illustrated through the correlation matrix. For the simulated data, the correlation matrix had ones in all entries at any sample size. The calculated correlation matrix for monthly U.S. retail and farm beef prices from January 1982 to December 1998 (204 observations) corroborated the

expected close correlation suggested by the condition index values reported in table 2. The estimated correlation coefficients were approximately 1 in absolute values. This suggests that the independent variables in the model were identical trends (with opposite signs). A priori, one would expect not to reject symmetry. However, the test of symmetry using 204 observations resulted in a t-value of -10.50, which clearly rejects symmetry in monthly U.S. retail-farm beef prices.

REFERENCES

Abdulai, A. “Using Threshold Cointegration to Estimate Asymmetric Price Transmission in the Swiss Pork Market,” *Applied Economics* (2002): 679-87.

Balke, N. S. and T. B. Fomby. “Threshold Cointegration,” *International Economic Review*, 38 (1997): 627-45.

Belsley, D.A., E. Kuth, and R.E. Welsch. “Identifying Influential Data and Sources of Collinearity.” *Regression Diagnostics.* New York: John Wiley & Sons, 1980.

Carman, Hoy F. ACalifornia Milk Marketing Margins.@ *Journal of Food Distribution Research.* 29(November 1998):1-6.

Cramon-Taubadel, S. von AEstimating Asymmetric Price Transmission with the Error Correction Representation: An Application to the German Pork Market.@ *European Review of Agricultural Economics.* 25(1998):1-18.

Enders, W. and C. W. J. Granger. “Unit-Root Tests and Asymmetric Adjustment with an Example Using the Term Structure of Interest Rates,” *Journal of Business and Economic Statistics*, 16(1998):304-11.

Enders, W. and P. L. Siklos. “Cointegration and Threshold Adjustment,” *American Statistical Association Journal of Business & Economic Statistics*, 19(2001):166-76.

Engle, R.F. and C.W.J. Granger. ACointegration and Error Correction: Representation, Estimation and Testing.@ *Econometrica.* 55(March 1987): 251-76.

Fuller, W.A. *Introduction to Statistical Time Series.* New York: John Wiley & Sons, 1976.

Gardner, Bruce L. AThe Farm-Retail Price Spread in a Competitive Food Industry.@ *American Journal of Agricultural Economics* 64(1975):399-409.

George, P.S. and G.A. King. *Consumer Demand for Food Commodities in the United States with Projections for 1980*. Giannini Foundation Monograph 26, University of California Division of Agricultural Sciences, 1971.

Granger, C.W.J.. *Modeling Economic Series: Readings in Econometric Methodology*. New York: Oxford University Press, 1990.

Granger, C. and P. Newbold. “Spurious Regressions in Econometrics”. *Journal of Econometrics* 2(1974):111-20.

Greene, W.H. *Econometric Analysis.* 4th ed. Upper Saddle River, New Jersey: Prentice-Hall, Inc. 2000.

Hansen, B. E. and B. Seo. “Testing for Two-Regime Threshold Cointegration in Vector Error Correction Models.” *Journal of Econometrics*. 110(2002):293-318.

Heien, D.M. AMarkup Pricing in a Dynamic Model of the Food Industry.@ *American Journal of Agricultural Economics.* 62(February1980):10-18.

Houck, J.P. AAn Approach to Specifying and Estimating Nonreversible Functions.@ *American Journal of Agricultural Economics* 59(August 1977):570-72.

Kinnucan, H.W. and O.D. Forker. AAsymmetry in Farm-Retail Price Transmission for Major Dairy Products.@ *American Journal of Agricultural Economics* 69(May 1987):285-92.

Lyon, C.C. and Thompson, G.D. ATemporal and Spatial Aggregation: Alternative Marketing Margin Models.@ *American Journal of Agricultural Economics* 75(August 1993):523-36.

Reed, A.J. and Clark, J.S. AThe Transmission of Trends in Retail Food and Farm

Prices.@ *American Journal of Agricultural Economics* 80 (December 1998):1139-43.

Thompson, G.D. and C.C. Lyon. AMarketing Order Impacts on Farm-Retail Price Spreads: The Suspension of Prorates on California-Arizona Navel Oranges.@ *American Journal of Agricultural Economics* 71(August 1989):647-60.

Tomek, W.G. and K.L. Robinson. 3rd ed. *Agricultural Product Prices*. Ithaca, NY: Cornell.1990.

Tong, H. *Threshold Models in Nonlinear Time Series Analysis, Lecture Notes in Statistics, No. 21*. Heidelberg: Springer-Verlag 1983.

Tong, H. *Non-Linear Time Series: A Dynamic System Approach*, Oxford: Oxford University Press, 1990.

Tsay, R. S. "Testing and Modeling Multivariate Threshold Models," *Journal of the American Statistical Association*, 93 (1998):1188-1202.

Tweeten, Luther and Leroy Quance. APositivistic Measures of Aggregate Supply Elasticities: Some New Approaches.@ *American Journal of Agricultural Economics* 51(May 1969):342-52.

Vande Kamp, P.R. and H. M. Kaiser. AIrreversibility in Advertising-Demand Response Functions: An Application to Milk.@ *American Journal of Agricultural Economics* 81(May 1999):385-96.

Ward, R.W. AAsymmetry in Retail, Wholesale and Shipping Point Pricing for Fresh Vegetables.@ *American Journal of Agricultural Economics* 64(May1982):205-12.

Waugh, F.V. *Demand and Price Analysis: Some Examples from Agriculture.* Washington DC: U.S. Department of Agriculture, Economic Research Service, Technical Bulletin No. 1316, 1964.

Wolffram, R. APositivistic Measures of Aggregate Supply Elasticities: Some New Approaches B Some Critical Notes.@ *American Journal of Agricultural Economics* 53(May1971):356-59.

Wohlgenant, M. K. ACompetitive Storage, Rational Expectations, and Short-Run Food Price Determination.@ *American Journal of Agricultural Economics* 67(November1985):739-48.

Wohlgenant, M.K. and Mullen, J.D. "Modeling the Farm-Retail Price Spread for Beef." *Western Journal of Agricultural Economics* 12(1987):119-25.