Price Transmission and Asymmetric Adjustment in the U.S. Beef Sector

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1 Introduction

The U.S. livestock sector has experienced numerous structural changes in recent years. For example, the meatpacking industry has experienced many mergers and acquisitions leading to significant increases in industry concentration. In particular, the four-firm concentration ratio for steer and heifer slaughter, an oft cited statistic and an important indicator of industry concentration, increased from 35.7% in 1980 to 79.8% in 1997 (US Packers and Stockyard Administration 1998). There have also been significant regional shifts in livestock production and changes in marketing practices, with decreased use of public markets in many areas. For some products, traditional markets have been largely replaced by contract production and sales. Cattle inventories have also trended downward over the last two decades. This has been accompanied by decreases in the number of producers and, in some cases, by significant increases in the scale of operations.

The vertical transmission of shocks among various levels of the market is an important characteristic describing the overall operation of the market. Price is the primary mechanism by which various levels of the market are linked. The extent of adjustment and speed with which shocks are transmitted among producer, wholesale, and retail market prices is an important factor reflecting the actions of market participants at alternative market levels. The nature, speed, and extent of adjustments to market shocks may also have important implications for marketing margins, spreads, and mark-up pricing practices.

An extensive literature has examined market linkages among farm, wholesale, and retail markets for meat and livestock products. Much of this research has established the existence of significant lags in the adjustment of prices at various levels in the marketing channel (see, for example, Boyd and Brorsen (1988), Schroeder(1988), and Hahn (1990)). These lags are generally attributed to adjustment costs which delay or otherwise inhibit market price adjustments. Recent research in this area has concentrated on the potential for asymmetric adjustments in prices at various market levels. In particular, conventional wisdom suggests that responses to price increases may differ from responses to price decreases. Most of these studies utilize some variation of a model originally introduced by Wolffram (1971) and later modified by Houck (1979) and Ward (1982). These various model specifications typically involve the regression of differenced price data on lagged price differences where allowances

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are made for differential effects of positive and negative lagged differences. Although a sweeping generalization of the results is somewhat difficult to make, most research has revealed the presence of asymmetries in price adjustments at the various market levels though the extent of asymmetry is generally small. In addition, most existing research has found that the direction of causality flows from the farm level to wholesale and retail markets. In particular, farm prices have generally been found to be relatively less responsive to shocks in wholesale and retail markets than is the case for wholesale and retail markets.

A number of institutional and theoretical reasons for asymmetries in price adjustments have been offered.[2] Ward (1982) noted that agents in possession of perishable goods may resist the temptation to increase prices for fear of being left with spoiled product. Bailey and Brorsen (1989) noted that asymmetries in adjustment costs may underlie asymmetric price adjustments. Imperfectly competitive markets characterized by price leadership roles by major buyers or sellers may also underlie asymmetric price adjustments. Finally, Kinnucan and Forker (1987) noted that, where applicable, government intervention through price supports and marketing quotas could lead to asymmetric price adjustments.

With a single exception, this literature has ignored important time series properties of the data. In particular, most research has not considered the potential for nonstationarity in individual prices or long-run stationary equilibria (i.e., cointegration) relationships among prices. The typical econometric specification used to evaluate asymmetric price adjustments is incompatible with long-run cointegration linkages. This is because the regressions of price differences on lagged price differences omit error correction terms which characterize the long-run relationship. This limitation of standard models of asymmetry was recently recognized by Cramon-Taubadel (1998) in an investigation of asymmetric price adjustment in German producer and wholesale hog markets. Cramon-Taubadel modified the standard Wolffram (1971) specification to include an error correction term and found that wholesale prices reacted more rapidly to positive shocks than to negative shocks originating at the farm level.

Although recent research on price transmission has focused on asymmetric adjustments, these models generally require the functional relationships which underlie the price transmission process to be fundamentally *linear*. Recent developments in time series analysis techniques have recognized the potential for nonlinear and threshold-type adjustments in error correction models. Threshold effects occur when larger shocks (i.e., shocks above some threshold) bring about a different response than do smaller shocks. The resulting dynamic responses may be of a nonlinear nature in that they may involve various combinations of adjustments from alternative regimes defined by the thresholds. Threshold models of dynamic economic equilibria are usually motivated by adjustment costs, which may inhibit or otherwise constrain adjustments to small shocks. Put another way, a shock may have to be of a particular size before a significant response is provoked.

[2]See Cramon-Taubadel (1998) for an extensive discussion of models of asymmetric price transmission.

The objective of this analysis is to evaluate price linkages among producer, wholesale, and retail marketing channels in U.S. beef markets. We utilize the threshold cointegration methods recently introduced by Balke and Fomby (1997). In particular, a threshold error correction model allowing asymmetric adjustments is estimated and used to evaluate the dynamic time paths of price adjustments to shocks at each level in the U.S. beef marketing channel.

2 Econometric Methods

The concept of nonlinear threshold time series models was introduced by Tong (1978). Tsay (1989) developed an approach to testing for threshold effects and modeling threshold autoregressive processes. Balke and Fomby (1997), noting the correspondence between error correction models representing cointegration relationships and autoregressive models of an error correction term, extended the threshold autoregressive models to a cointegration framework. Balke and Fomby (1997) also showed that standard methods for evaluating unit roots and cointegration work reasonably well when threshold cointegration is present.[3]

Consider a standard cointegration relationship representing an economic equilibrium

$$y_{1t} - \beta_1 y_{2t} - \beta_2 y_{3t} - \ldots \beta_k y_{kt} = \nu_t, \quad \text{where} \quad \nu_t = \rho \nu_{t-1} + e_t. \tag{1}$$

Cointegration of the y_{it} variables depends upon the nature of the autoregressive process for ν_t. As ρ approaches one, deviations from the equilibrium become nonstationary and thus the y_{it} variables are not cointegrated. Balke and Fomby (1997) extend this simple framework to the case where ν_t follows a threshold autoregression:

$$\rho = \begin{cases} \rho^{(1)} & \text{if} \quad |\nu_{t-1}| \leq c \\ \rho^{(2)} & \text{if} \quad |\nu_{t-1}| > c, \end{cases} \tag{2}$$

where c represents the threshold which delineates alternative regimes.[4] A common case is that of $\rho^{(1)} = 1$, which implies that the relationship for small deviations from equilibrium is characterized by a random walk (i.e., a lack of cointegration). Parity relationships among commodity prices and interest rates have been examined in such a context.[5]

An equivalent vector error correction representation of the threshold model can be written as:

$$\Delta y_t = \begin{cases} \sum_{i=1}^{p} \gamma_i^{(1)} \Delta y_{t-i} + \theta^{(1)} \nu_{t-1} & \text{if} \quad |\nu_{t-1}| \leq c \\ \sum_{i=1}^{q} \gamma_i^{(2)} \Delta y_{t-i} + \theta^{(2)} \nu_{t-1} & \text{if} \quad |\nu_{t-1}| > c. \end{cases} \tag{3}$$

[3] Balke and Fomby (1997) and Enders and Granger (1998) have also shown, however, that standard tests may lack power in the presence of asymmetric adjustment.

[4] More generally, thresholds pertain to some delay parameter d in adjustment to ν_t, such that $|\nu_{t-d}| \leq c$ defines the threshold. Although testing for d is discussed below, most applications assume a delay of $d = 1$.

[5] See Obstfeld and Taylor(1997) and Goodwin and Grennes (1998) for examples of the former and Siklos and Granger (1997) for an example of the latter.

Balke and Fomby (1997) note that this simple framework is easily extended to permit multiple thresholds, implying multiple parametric regimes and thus allowing asymmetric adjustment.[6] In our analysis, we follow Martens, Kofman, and Vorst (1998) and utilize two thresholds (c_1 and c_2) which allows three regimes and thus permits asymmetric adjustment.[7]

Testing for threshold effects presents a number of challenges. Tsay (1989) developed a general nonparametric test for the nonlinearity implied by thresholds in an autoregressive series. Consider a standard autoregressive model of the form:

$$\nu_t = \alpha + \gamma \nu_{t-1} + \epsilon_t. \tag{4}$$

In constructing Tsay's (1989) test, we denote each combination of ν_t and ν_{t-1} as a "case" of data. The individual cases of data are ordered according to the variable relevant to the threshold behavior, ν_{t-1} in this case. Recursive residuals are obtained by estimating the autoregressive model for an initial sample and then for sequentially updated samples obtained by adding a single observation. A test of nonlinearity is then given by the regression F-statistic obtained by regressing the recursive residuals on the explanatory variables (ν_{t-1}). Obstfeld and Taylor (1997) note that, as a practical matter, the test should be run with both increasing and decreasing ordering in the arranged autoregression.[8] Tsay's (1989) test is also useful in determining the "delay" parameter d which defines the threshold autoregression in equation (2). The test is typically run for alternative delays and the delay giving the largest F statistic is chosen as optimal.

Once the presence of threshold effects is confirmed, some parametric estimation strategy must be considered to estimate the threshold. Following the standard approach, we utilize a two-dimensional grid search to estimate the thresholds c_1 and c_2 which define the three regimes. Two alternative grid search techniques have been proposed. Obstfeld and Taylor (1997) use a grid search to find the threshold which maximizes a likelihood function. Alternatively, we follow Balke and Fomby (1997) and use a grid search which minimizes a sum of squared error criterion.

Our specific estimation strategy can be summarized as follows. First, standard Dickey-Fuller unit root tests and Johansen cointegration tests are used to evaluate the time-series properties of the data. We then follow the general two-step approach of Engle and Granger (1987) and utilize ordinary least squares estimates of a cointegrating relationship among the variables.[9] Lagged residuals from this regression are then used to define the error correction terms. A two-dimensional grid search is then

[6] In the case of k thresholds, $k+1$ different regimes are implied, each of which may imply its own set of dynamics for the system.

[7] The number of thresholds considered is typically constrained by the number of available observations, 897 in our case.

[8] The test is nonparametric in that it depends neither on the number of thresholds or their values. The alternative ordering of the data in the arranged regressions allows more power in discerning thresholds for which data are concentrated in a particular regime at either end of the arranged series. We report only the more significant of the two ordered tests.

[9] In cases of $p > 2$ variables, a finding of more than a single cointegrating relationship among the variables in the cointegration tests suggests that the OLS estimates of the cointegrating vector are not unique. Properties of the OLS estimates in such a case are discussed by Hamilton (p. 590, 1994). As always, the results may also be sensitive to the normalization rule.

conducted to define two thresholds. In particular, we search for the first threshold between 5% and 95% of the largest (in absolute value) negative residual. In like fashion, we search for the second threshold between 5% and 95% of the largest positive residual. The error correction model is then estimated conditional on the threshold parameters.

Some method of testing the statistical significance of the differences in parameters across alternative regimes is desirable. In the case of a single threshold, this amounts to a conventional Chow test of parameter differences. As is well known, this testing problem is complicated by the fact that the threshold parameter is not identified under the null hypothesis of no threshold effects and thus conventional test statistics have nonstandard distributions. Hansen (1997) has developed an approach to testing the statistical significance of threshold effects. After optimal thresholds have been identified, a conventional Chow-type test of the significance of threshold effects (i.e., the significance of the differences in parameters over alternative regimes) is conducted. Because the test statistic has a nonstandard distribution, simulation methods must be used to approximate the asymptotic distribution and identify appropriate critical values. Hansen (1997) recommends running a number of simulations whereby the dependent variables are replaced by standard normal random draws. For each simulated sample, the grid search is used to select optimal thresholds and the standard Chow-type test is used to test the significance of the threshold effects. From this simulated sample of test statistics, the asymptotic p-value is approximated by taking the percentage of test statistics for which the test taken from the estimation sample exceeds the observed test statistics.

3 Empirical Application

Our empirical analysis utilizes three series of weekly beef prices observed from January 1981 through the first week of March 1998, giving a total of 897 observations. Producer prices were taken from the Bridge database of live cattle prices.[10] Wholesale prices for boxed beef cutouts (550-700 lbs.) were collected from unpublished Agricultural Market Service and Economic Research Service databases. Retail prices were represented by the Bridge composite retail beef price series.

Standard unit-root tests confirmed a single unit root in each price series. Johansen cointegration tests (Table 1) indicated the existence of a single cointegrating relationship among the three prices.[11] Lag orders for the cointegration tests and threshold error correction models were chosen using Akaike and Schwartz-Bayesian criteria. The alternative criteria indicated lag orders ranging from 3 to 5. An evaluation of autocorrelation patterns for the residuals led us to adopt a specification with four lags in both the cointegration and error correction models. The equilibrium relationship was normalized on the retail price and ordinary least squares was used

[10]The Bridge data represent published *Wall Street Journal* quotes. From 1981 through mid 1987 these prices were for Choice Omaha. Subsequent prices were Texas-Oklahoma average prices.

[11]In that deterministic time trends did not appear to be present in the series, we restricted the intercept term to apply to the cointegration relationship only.

to obtain estimates of the cointegrating relationship. These estimates are presented in Table 1.

Tsay's (1989) test was conducted using the error correction terms implied by the OLS estimates. The test (Table 1) strongly rejected linearity and thus implied the presence of one or more thresholds. The largest rejections occurred for delays of a single week, suggesting a delay parameter of one. The two-dimensional grid search identified thresholds at -0.0646 and 0.0906. A standard likelihood ratio test of the significance of the differences in parameters across regimes was strongly rejected using conventional critical values. As noted above, however, the test statistic is likely to be nonstandard since a search for the thresholds preceded the testing. When Hansen's (1997) simulation approach was utilized to approximate asymptotic p-values for the test, the p-value of the test statistic was 0.09.[12] Thus, our results suggest that the threshold effects are statistically significant, though with a much larger p-value than would be implied by standard tests. The thresholds correspond to three regimes of 182, 605, and 110 observations, respectively.

An evaluation of the timing of shifts between the three alternative regimes is instructive. It is important to recognize that the price adjustment process at any point in time is unique in that it depends upon the values of the error correction term and lagged price differences at each observation. This is in contrast to standard vector autoregressive and error correction models, where responses to shocks are independent of the timing of the shock. Figure 1 illustrates the timing of jumps among the regimes. The figure suggests that jumps between Regimes I and II dominated in the earlier portion of the sample, a period characterized by less industry concentration. In contrast, jumps between Regimes II and III appear to be much more influential toward the end of the sample.

Parameter estimates (Table 2) indicate significant dynamic relationships among the price series. In general, dynamic interrelationships among the prices reflected relatively more interaction between wholesale and retail prices and lagged price differences than for farm prices and lags— a finding consistent with causality in the direction of farm to wholesale to retail levels. Error correction terms are especially significant in the first regime (corresponding to large negative deviations from equilibrium).

Interpretation of the dynamic interrelationships among prices at alternative market levels is best pursued through a consideration of impulse response functions. Again, in contrast to the linear model case, the response to a shock is dependent upon the history of the series. In addition, the possibly asymmetric nature of responses implies that the size and sign of the shock will influence the nature of the response. In this light, there are many different possible impulse response functions. We chose two observations representative of the early (observation 160) and late (observation 897) periods to evaluate responses to shocks.[13] We adopt the nonlinear impulse response

[12]Because of the long computing time required for the simulation, we used a coarser grid (5% increments) in simulating the test statistics. One-hundred replications were used in the simulation.

[13]It is important to again note that the impulse responses are observation-dependent. An examination of a broad range of impulses at various observations suggested that the results were not especially sensitive to the observation chosen for evaluation.

Table 1: Cointegration and Threshold Testing Results

Test	Test Statistic	Critical Value[a]
Maximum Eigenvalue Test Statistic		
r=0	45.25	21.28
r=1	13.64	14.59
r=2	4.13	8.08
Trace Test Statistic		
r=0	63.02	31.26
r=1	17.77	17.84
r=2	4.13	8.08
Tsay's Nonlinearity Test		
	8.443	[0.004][b]
Hansen's Threshold Test		
	157.474	[0.090][c]

OLS Estimates of Cointegrating Relationship

$$P_t^R = \underset{(0.1647)^d}{2.7507} + \underset{(0.0763)}{0.3034 * P_t^F} + \underset{(0.2958)}{0.2958 * P_t^W}$$

$R^2 = .3741$

Threshold / Regime Estimates

Regime I ($-\infty < \nu_{t-1} \leq -0.0646$))	$n = 182$
Regime II ($-0.0646 < \nu_{t-1} \leq 0.0906$)	$n = 605$
Regime III ($0.0906 < \nu_{t-1} < \infty$)	$n = 110$

[a]Critical values are at the $\alpha = .05$ level and are taken from Hamilton (1994).
[b]Numbers in brackets are approximate asymptotic p-values for test statistics.
[c]Empirical p-value based upon bootstrap simulation.
[d]Numbers in parentheses are standard errors .

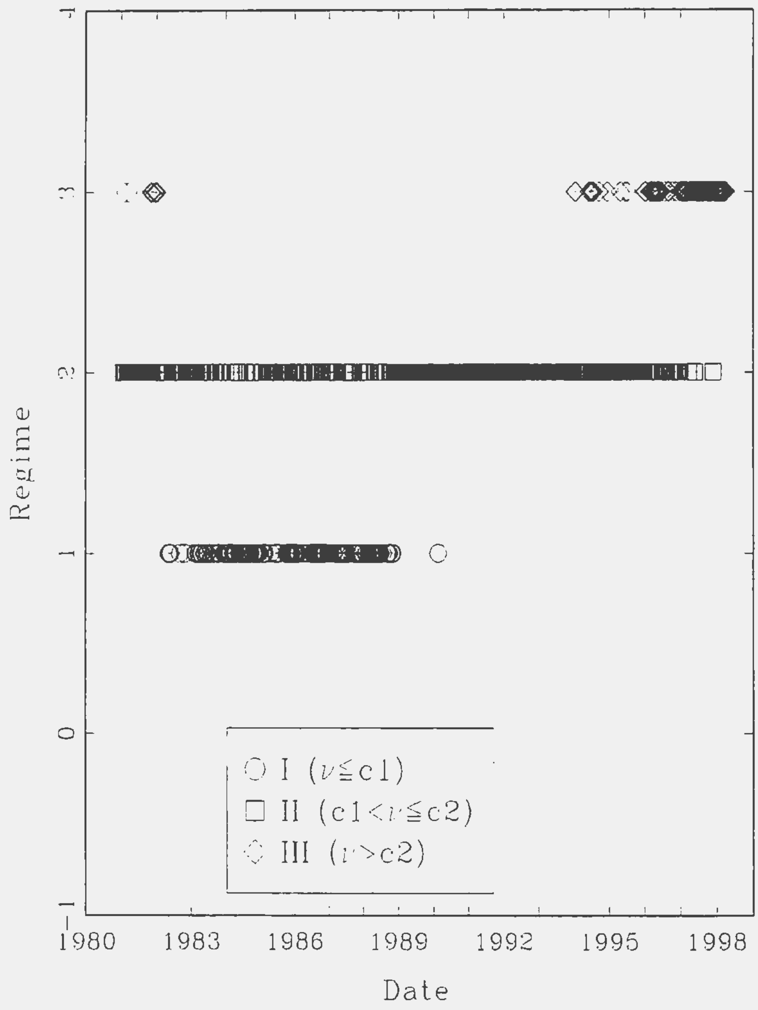

Figure 1: Timing of Regime Switching

Table 2: Threshold Error Correction Model: Parameter Estimates and Summary Statistics

Variable	Retail Parameter Estimate	Wholesale Parameter Estimate	Farm Parameter Estimate
$c_1 * \Delta R_{t-1}$	−0.4181	−0.0216	0.0182
	(0.0849)*	(0.0586)	(0.0752)
$c_1 * \Delta R_{t-2}$	−0.2831	−0.0438	−0.0515
	(0.0931)*	(0.0643)	(0.0825)
$c_1 * \Delta R_{t-3}$	−0.2163	−0.0324	−0.0754
	(0.0832)*	(0.0574)	(0.0737)
$c_1 * \Delta R_{t-4}$	−0.0155	0.0016	−0.0124
	(0.0821)	(0.0567)	(0.0727)
$c_2 * \Delta R_{t-1}$	−0.8174	−0.0067	−0.1444
	(0.0916)*	(0.0632)	(0.0811)*
$c_2 * \Delta R_{t-2}$	−0.7925	−0.0576	−0.0557
	(0.1049)*	(0.0724)	(0.0929)
$c_2 * \Delta R_{t-3}$	−0.5865	−0.0891	−0.1765
	(0.1157)*	(0.0799)	(0.1025)*
$c_2 * \Delta R_{t-4}$	−0.2682	0.0008	−0.0230
	(0.0948)*	(0.0655)	(0.0840)
$c_{12} * \Delta R_{t-1}$	−0.6312	−0.0257	0.0206
	(0.0402)*	(0.0277)	(0.0356)
$c_{12} * \Delta R_{t-2}$	−0.4599	−0.0174	0.0394
	(0.0452)*	(0.0312)	(0.0400)
$c_{12} * \Delta R_{t-3}$	−0.2351	−0.0159	0.0260
	(0.0449)*	(0.0310)	(0.0397)
$c_{12} * \Delta R_{t-4}$	−0.0906	−0.0087	0.0053
	(0.0382)*	(0.0264)	(0.0338)
$c_1 * \Delta W_{t-1}$	0.1306	−0.2336	0.0250
	(0.1198)	(0.0827)*	(0.1061)
$c_1 * \Delta W_{t-2}$	−0.0316	−0.3474	−0.0304
	(0.1172)	(0.0809)*	(0.1038)
$c_1 * \Delta W_{t-3}$	0.0082	−0.1048	0.0332
	(0.1215)	(0.0839)	(0.1076)
$c_1 * \Delta W_{t-4}$	0.2276	−0.0187	−0.0376
	(0.1203)*	(0.0831)	(0.1066)
$c_2 * \Delta W_{t-1}$	−0.1959	−0.2150	−0.3275
	(0.1770)	(0.1222)*	(0.1567)*
$c_2 * \Delta W_{t-2}$	−0.3951	−0.2925	0.0502
	(0.1642)*	(0.1133)*	(0.1454)
$c_2 * \Delta W_{t-3}$	0.0199	−0.0195	−0.2644
	(0.1700)	(0.1174)	(0.1505)*

[a]Numbers in parentheses are asymptotic standard errors. Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table 2: continued

Variable	Retail Parameter Estimate	Wholesale Parameter Estimate	Farm Parameter Estimate
$c_2 * \Delta W_{t-4}$	0.3155	−0.0462	−0.0124
	(0.1352)*	(0.0934)	(0.1197)
$c_{12} * \Delta W_{t-1}$	0.1586	−0.0369	−0.1776
	(0.0813)*	(0.0561)	(0.0720)*
$c_{12} * \Delta W_{t-2}$	0.0867	−0.2007	0.0571
	(0.0834)	(0.0576)*	(0.0739)
$c_{12} * \Delta W_{t-3}$	0.1379	−0.1760	−0.1357
	(0.0817)*	(0.0564)*	(0.0723)*
$c_{12} * \Delta W_{t-4}$	0.1002	0.0699	0.0830
	(0.0744)	(0.0514)	(0.0659)
$c_1 * \Delta F_{t-1}$	0.0382	0.3556	−0.0143
	(0.1105)	(0.0763)*	(0.0979)
$c_1 * \Delta F_{t-2}$	0.2279	0.4008	0.1468
	(0.1200)*	(0.0828)*	(0.1062)
$c_1 * \Delta F_{t-3}$	0.1297	0.2775	0.1631
	(0.1217)	(0.0840)*	(0.1078)
$c_1 * \Delta F_{t-4}$	−0.2512	0.2097	0.2080
	(0.1172)*	(0.0809)*	(0.1038)*
$c_2 * \Delta F_{t-1}$	0.1037	0.4724	−0.0550
	(0.1114)	(0.0769)*	(0.0986)
$c_2 * \Delta F_{t-2}$	0.3532	0.0783	−0.2250
	(0.1405)*	(0.0970)	(0.1244)*
$c_2 * \Delta F_{t-3}$	0.3553	0.0938	0.0476
	(0.1354)*	(0.0935)	(0.1199)
$c_2 * \Delta F_{t-4}$	−0.0818	0.0522	0.2319
	(0.1257)	(0.0868)	(0.1113)*
$c_{12} * \Delta F_{t-1}$	−0.0620	0.3226	0.1765
	(0.0620)	(0.0428)*	(0.0549)*
$c_{12} * \Delta F_{t-2}$	−0.0225	0.0727	−0.1011
	(0.0651)	(0.0449)	(0.0576)*
$c_{12} * \Delta F_{t-3}$	0.0360	0.1439	0.0366
	(0.0639)	(0.0441)*	(0.0566)
$c_{12} * \Delta F_{t-4}$	0.0624	0.0203	−0.0151
	(0.0634)	(0.0438)	(0.0561)
$c_1 * \nu_{t-1}$	−0.0523	0.0379	0.0307
	(0.0239)*	(0.0165)*	(0.0212)
$c_2 * \nu_{t-1}$	0.0038	−0.0056	−0.0074
	(0.0207)	(0.0143)	(0.0184)
$c_{12} * \nu_{t-1}$	−0.0287	−0.0085	0.0017
	(0.0221)	(0.0153)	(0.0196)

[a]Numbers in parentheses are asymptotic standard errors. Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

function approach of Potter (1995), which defines responses (denoted I_{t+k}) on the basis of observed data $(z_t, z_{t-1}, \ldots)$ and a shock (v) as:

$$\begin{aligned} I_{t+k}(v, Z_t, Z_{t-1}, \ldots) &= E[Z_{t+k}|Z_t = z_t + v, Z_{t-1} = z_{t-1}, \ldots] \\ &- \quad E[Z_{t+k}|Z_t = z_t, Z_{t-1} = z_{t-1}, \ldots]. \end{aligned} \tag{5}$$

It should also be noted that, in light of the nonstationary nature of the price data and the error correction properties of the system of equations, shocks may elicit either transitory or permanent responses. In particular, nonstationarity implies that shocks may permanently alter the time path of variables.

Figures 2 and 3 illustrate responses to one standard deviation positive and negative shocks. Figure 2 illustrates responses to positive and negative shocks, respectively, at observation 160 (January 20, 1984) while Figure 3 provides the corresponding responses at the last observation in the data (March 6, 1998). Several implications for price interrelationships emerge from the responses. First, with the exception of responses to positive farm price shocks in the early period, it appears that prices are more responsive to shocks in the later period. This may imply that changes in the structure of markets in the beef complex have enhanced price transmission. It is also apparent, however, that there is little feedback to farm and wholesale markets from shocks at the retail level regardless of the time period being analyzed. Retail price shocks bring about a short-lived response from retail prices in the first period and a permanent adjustment to retail prices in the second period. In both cases, however, no response is realized by wholesale and farm market prices. A second implication of the impulse responses is that, although parametric differences across the alternative regimes were statistically significant, price adjustments appear to be reasonably symmetric. This confirms the findings of Hall et al. (1981) for beef markets and Boyd and Brorsen (1988) for pork markets but contrasts with the findings of Hahn (1990) for beef. A small degree of asymmetry is apparent in the diagrams, particularly in the early period. The differences, however, would not appear to be economically significant. In most cases, shocks elicit permanent adjustments which are mostly complete after 6-8 weeks. Wholesale market price shocks elicit responses in wholesale and retail markets. These responses are considerably larger in the latter period, suggesting greater interaction between wholesale markets and retail and farm markets in the latter period. Farm price shocks elicit responses in all three markets. The response to farm price shocks does appear to be somewhat damped as one moves up the marketing chain— farm prices exhibit the largest response, followed by wholesale prices, and finally by modest retail market price adjustments.

In all, the impulse responses are generally in agreement with expectations and with previous research. Price transmission appears to occur mainly in one direction— from farm to wholesale to retail markets. Responses to market shocks are generally complete after 12 weeks. Responses are generally as one would expect, with positive shocks eliciting positive responses and negative shocks eliciting negative responses.

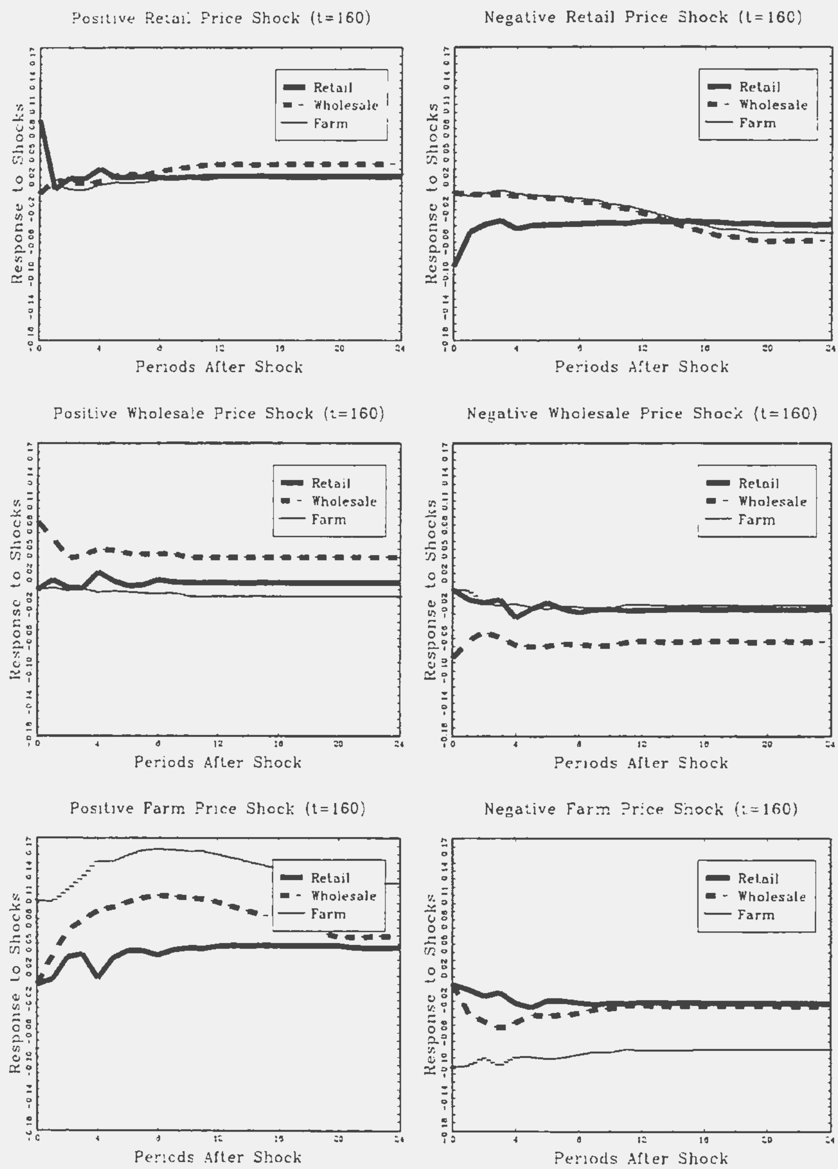

Figure 2: Nonlinear Impulse Response Functions at t=160

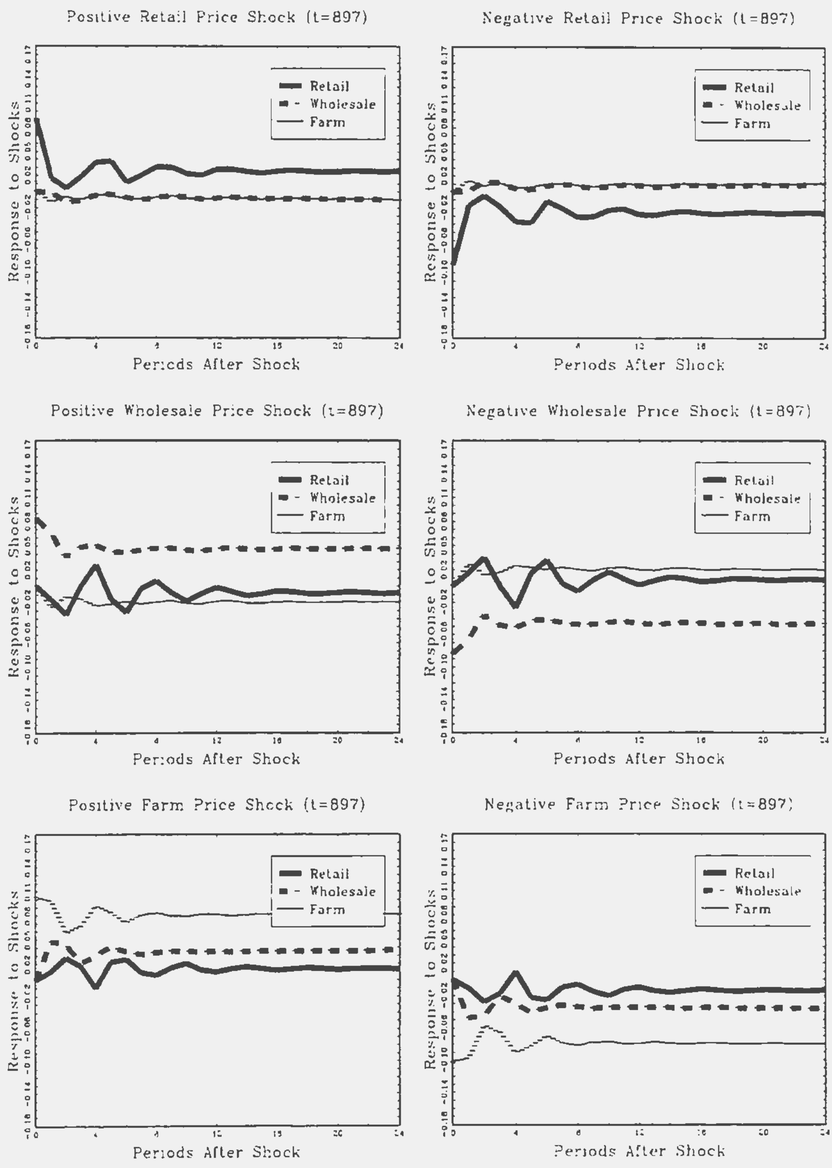

Figure 3: Nonlinear Impulse Response Functions at t=897

4 Concluding Remarks

We have examined price interrelationships and transmission among farm, wholesale, and retail beef markets. We give special attention to the time series properties of the price data. In particular, we estimate a threshold error correction model which recognizes the nonstationary nature of the price data and allows for asymmetric price responses.

Our results largely confirm the findings of other research. In particular, the transmission of shocks appears to be largely unidirectional with information flowing up the marketing channel from farm to wholesale to retail markets but not in the opposite direction. Farm markets do adjust to wholesale market shocks. The effects of retail market shocks, however, are largely confined to retail markets. Although formal testing confirms asymmetries in responses to new information, an evaluation of nonlinear impulse response functions suggests that these differences are modest and thus may not be economically significant. Finally, the results suggest that the responsiveness to price shocks has increased in recent years. This result may suggest that markets have become relatively more efficient in transmitting information through vertical marketing channels.

Our results have important implications for current concerns regarding the failure of retail meat prices to respond quickly to changes at live animal and wholesale levels. In particular, our results confirm the conventional wisdom prevalent in the large body of related research that retail markets do not effectively transmit shocks back to wholesale and, especially, to farm market levels. In contrast, farm level shocks do significantly influence prices at the retail and wholesale market levels. In most cases, it takes from 8-12 weeks for adjustments to new equilibria following market shocks. Conventional wisdom has also maintained that responses are asymmetric—with farm prices being lowered by negative price shocks at retail and wholesale market levels but not being raised by analogous positive price shocks. For the most part, our research does not reveal large asymmetries. It is the case, however, that positive shocks at the farm level evoke much larger retail and wholesale market price increases than is the case for the corresponding decreases in these markets brought about by negative shocks to farm prices. Thus, the results may indicate that a degree of "price-stickiness" exists in retail markets.

Prices appeared to be "sticky" at retail levels during 1998, for example. The April through December retail prices for Choice beef were essentially stable, with monthly average prices ranging from $2.74 to $2.80, about 2 percent in terms of change. Over the same period, Nebraska direct fed cattle prices ranged from monthly averages of $58.28 to $64.68, a change of some 11 percent. Daily or weekly fed cattle prices were even more volatile in the presence of largely stable retail prices. Since consumers react to retail prices, a failure of retail prices to promptly reflect significant declines in raw material (cattle) prices can be especially damaging. The immediate need, when cattle prices are pushed lower by a short-term surge in beef supplies, are lower retail prices to stimulate increased quantity consumed. When retail prices change slowly and with a time lag and then reflect only part of the change in the cattle and boxed beef markets, the market struggles in attempts to restore equilibrium.

Future research may benefit from the consideration of empirical models that are of a more structural nature; models that capture the possible implications of changes in industry concentration levels. In addition, an extension of this analysis to other commodities, pork in particular, may be beneficial. Such research is currently in process and may help to improve the efficiency of the marketplace in its price discovery efforts.[14]

[14] Results will be available in a future report by May 1999.

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