Asymmetric Price Transmission in the U.S. Beef Market: New Evidence from New Data

by

Veronica F. Pozo, Ted C. Schroeder,
and Lance J. Bachmeier

Asymmetric Price Transmission in the U.S. Beef Market: New Evidence from New Data

Veronica F. Pozo,

Ted C. Schroeder

and

Lance J. Bachmeier*

Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 22-23, 2013.

* Veronica F. Pozo is a Ph.D. student, Ted C. Schroeder is a Professor in the Department of Agricultural Economics, and Lance J. Bachmeier is an Associate Professor in the Department of Economics at Kansas State University. Email: vpozo@k-state.edu for correspondence.

Asymmetric Price Transmission in the U.S. Beef Market: New Evidence from New Data

We examine price transmissions among farm, wholesale and retail U.S. beef markets using two types of retail level price data, one collected by the Bureau of Labor Statistics (BLS) and the other one collected at the point of sale using electronic scanners. Although some evidence suggests that BLS prices are bias (do not account for volume sales and discounted prices), we find no evidence of asymmetric price transmissions in the response of retail prices to changes in upstream prices. Our findings have important implications for the U.S. beef market efficiency. Since retailer price adjustments to farm and wholesale price changes are symmetric, the U.S. beef market is not as inefficient as found in previous studies.

Key words: price transmissions, asymmetry, BLS prices, scanner prices, impulse response functions, beef market, threshold vector error correction model.

Introduction

Farm, wholesale and retail meat price relationships have been the source of contested debate for a long time in the U.S. Since the 1970s, numerous congressional hearings and commissions have addressed price transmissions among vertically coordinated markets (Mathews et al., 1999). An often noted concern is that retail prices respond asymmetrically to farm price changes. That is, responses to price increases may differ from responses to price decreases. The literature largely supports the claim that retail meat prices are rigid or slow to respond to farm price declines, but responsive to farm price increases suggesting potential market failure (Goodwin and Holt, 1999). Consequently, cost increases are transferred on to consumers more promptly than are costs savings (Abdulai, 2002).

Several potential explanations have been offered for asymmetric price responses in vertically linked markets, including market power and concentration at processing and retail levels (e.g., Bailey and Brorsen, 1989; Azzam, 1999; Peltzman, 2000; Xia, 2009); adjustment and menu costs (e.g., Bailey and Brorsen, 1989; Levy, 1997); inventory adjustment practices (e.g., Blinder, 1982); government intervention (e.g., Kinnucan and Forker, 1987; Mohanty et al., 1995); consumption inertia (Xia and Li, 2010); and the empirical methodology employed in testing for asymmetry (Miller and Hayenga, 2001). However, a necessary condition for assessing market failure is that the data used to test for asymmetry are adequate (Bailey and Brorsen, 1989; von Cramon-Taubadel, 1998).

The objective of this study is to determine the sensitivity of specific retail price series employed in testing for nonlinear price adjustments. In particular, we compare price transmission in the U.S. beef market chain using two distinct sources of retail prices that differ according to the collection procedure. The first source is a retail price series used widely in a large body of published research – retail prices collected by the Bureau of Labor Statistics (BLS), which is ultimately compiled for computation of the Consumer Price Index. We contrast results of the BLS retail price data to scanner quantity-weighted retail price data collected by Freshlook, using a threshold cointegration approach.

Evidence suggests that the BLS retail price data may be biased. Hausman (2003) showed that the methodology BLS uses to calculate the food Consumer Price Index (CPI) may overestimate the price of food. The omission of random-weight food items (BLS collects only price data, but does not collect quantity data) and supercenter purchases (reflecting shifts in shopping patterns to lower-priced stores) may cause a significant upward bias on price estimates. In addition, BLS data do not account for large volumes sold at discounted prices during retail specials (Rojas et al., 2008; Lensing and Purcell, 2006). Therefore, this issue raises the question of whether findings from previous studies that have used BLS retail price data are reliable.

The use of BLS retail price data in economic analysis has long been criticized. In 1978, Geithman and Marion published a critique of the use of BLS data for market structure-price analysis. They argued that bias in the BLS price data confounded true market structure-price relationships and adjustments in sampling and reporting procedures are needed to make the data more useful. Despite frequent revisions in price data collection and measurement methodologies, the BLS has not developed a methodology to correct for potential bias in reported food prices. Recent work by Hausman and Leibtag (2009) showed that the consumer price index (CPI) for food at home, calculated using price data collected by BLS, overstates food price inflation. During 1998 to 2001 about a 15 percent upward bias was present in the CPI for food-at-home, which Hausman and Leibtag attributed to the increasing share of food purchases made at alternative (non-traditional) retail stores such as supercenters, mass merchandisers and club stores.

The Livestock Mandatory Reporting Act of 1999 mandated collection of farm and wholesale meat prices to facilitate open, transparent price discovery and provide market participants with comparable levels of market information for cattle, swine, sheep, beef, and lamb meat. The Act also required U.S. Department of Agriculture (USDA) to investigate the use of an alternative source of retail meat prices that would provide retail price data more reflective of actual consumer purchases than BLS data. The purpose of this provision was to address concerns regarding the quality of BLS retail meat price data (Hahn, Perry and Southard, 2009). As an alternative to BLS retail meat price data, scanner based quantity-weighted retail price data was considered. These data are collected at the point of sale by supermarkets using electronic scanners in check-out lines. Unlike BLS price data, scanner data enables accounting for volume of sales and discounted prices in summarizing prices each period. In addition, it also allows collecting data from a larger number of food items.

Results from this study provide relevant implications for U.S. beef market efficiency. Particularly, since retailer adjustments to farm and wholesale price changes might differ according to the type of data used, conclusions from previous studies that used BLS price data could be misleading. This information is valuable to all producers, processors, packers and retailers involved in the U.S. meat industry, as well as consumers and policy makers.

Previous Work

The widening gap between retail, farm and wholesale prices has motivated many empirical analyses of vertical price transmission in various markets. Meyer and Cramon-Taubadel (2004) and Frey and Manera (2007) surveyed empirical literature on price asymmetry in commodities, classifying and comparing heterogeneous studies in terms of econometric models, type of asymmetries and findings. A popular technique used to test for asymmetry, especially in the agricultural economics and energy economics literature, has been threshold cointegration. This method captures price asymmetries by splitting the price series of interest according to deviations of prices from equilibrium, permitting different speeds of adjustment depending on whether a particular variable is above or below the threshold.

In addition to the application of threshold cointegration in single equation models, this approach has also been implemented in systems of equations to account for potential interdependences among input and output prices and other exogenous variables (e.g., Goodwin and Holt, 1999; Balcombe, Bailey and Brooks, 2007; Ben-Kaabia and Gil, 2007). Goodwin and Holt (1999) used threshold vector error correction models (TVECM) to investigate price transmission asymmetries in U.S. beef prices using weekly data. They found asymmetric price transmission with unidirectional causal flow from farm to wholesale to retail markets, but they concluded that the magnitude of the asymmetry was not economically significant.

Few studies have compared the advantages and shortcomings of using scanner price data versus BLS retail price data. Hahn, Perry and Southard (2009), used dynamic-adjustment, state-space models to assess the relative value of the two data series in representing the national average retail price and forecasting near-term meat market conditions. Using monthly data from January 2001 to August 2005 (56 observations), they also analyzed wholesale-retail price relationships (including speed of adjustment) in beef, pork, broiler, whole chickens and whole frozen turkeys. Scanner data contributed little to the price analysis for four of the five meat products, particularly attributed to timing issues –scanner data was available with a 7-8 week lag, whereas BLS data were generally available 12-20 days after the end of the month of interest. Lensing and Purcell (2006) analyzed differences between the means and variances of BLS and scanner quantity-weighted monthly average prices for beef and estimated elasticities using a single equation quantity-dependent demand function. Scanner quantity-weighted monthly average retail prices for five of six beef items were lower than BLS prices. In addition, scanner quantity-weighted prices also had a higher variance for five of six retail items. More importantly, BLS prices were greater than scanner prices and resulted in more elastic own-price elasticity estimates.

Rojas et al., (2008) estimated an asymmetric vector error correction model using farm, wholesale and the two types of retail price data: BLS and scanner. They used monthly price data for farm, wholesale and retail levels, corresponding the 2001-2005 period (56 observations). Their findings indicated that retail scanner data was more responsive (significantly larger and quicker) to changes in wholesale beef prices than BLS data. In addition, the authors argued that previous assertions about retailers not responding to decreases in wholesale prices might be incorrect because they are based on flawed retail price data. Rojas et al. cautioned that their analysis was subject to a notable limitation of a small sample especially given the importance of sample size in the time series techniques they used. There are important differences between Rojas et al. and the approach developed here. First, instead of allowing for symmetric adjustment dynamics when conducting cointegration tests, deviations from the equilibrium are modeled to follow a threshold autoregressive process. Second, the procedure described in this study allows us to model asymmetric price transmissions not only in the long run, but also in the short run. Therefore, asymmetric responses can be captured before the variables reach their long run equilibrium. Third, our model includes threshold effects not only in farm or wholesale variables, but also in lagged retail price variables. Thus, it allows accounting for lagged effects of retail variables. Fourth, we incorporate a different methodology to test for asymmetry.

Econometric Methodology

This study follows a vector error correction approach. This modeling technique is particularly suitable for analysis of agricultural markets because in addition to taking into account the long run stationary equilibria relationship between prices (i.e., cointegration), such models allow for the analysis of potential asymmetries and nonlinearities in the price adjustment process (Awokuse and Wang, 2009). We are particularly interested in understanding how changes in farm and wholesale prices affect retail prices and vice versa. Thus, we use a system of equations or a threshold vector error correction (TVEC) model.

In the implementation of the TVEC model, we employ Enders and Siklos' (2001) test for threshold cointegration, which extends Engle and Granger's (1987) two-step estimation approach to include possible asymmetric adjustment to disequilibrium. The cointegration relationship between two price variables, assumed to be integrated of order one, takes the form:

(1) $$Y_t = \gamma_0 + \gamma_1 X_t + \varepsilon_t$$

where Y_t represents the downstream price variable (i.e., retail price), X_t represents the upstream price variable (i.e., farm or wholesale price) and ε_t is the error term. Here, ε_t measures the deviation from the equilibrium relationship between Y_t and X_t. In the first step, consistent estimates of γ_0 and γ_1 can be obtained using ordinary least squares. For the two variables to be cointegrated, ε_t should be stationary. In the second step, the residuals from equation (1) are used to estimate the following autoregressive process:

$$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \mu_t \tag{2}$$

where the variables Y_t and X_t are cointegrated if the null hypothesis $\rho = 0$ is rejected indicating that the residuals in equation (1) are stationary. However, while the previous estimation approach is appropriate for evaluating symmetric long-run adjustment, it is unsuitable for evaluating asymmetric price relationships because it assumes a symmetric adjustment process (Awokuse and Wang, 2009; Meyer and von Cramon-Taubadel, 2004). Enders and Siklos (2001) proposed instead to test for cointegration by modifying (2) to allow for asymmetric adjustment dynamics. Thus, deviations from equilibrium are modeled to follow a threshold autoregressive process:

$$\Delta\varepsilon_t = I_t\rho_1\varepsilon_{t-1} + (1 - I_t)\rho_2\varepsilon_{t-1} + \sum_{k=1}^{P}\delta_k\Delta\varepsilon_{t-k} + \mu_t \tag{3}$$

where, Δ is the difference operator, ρ_1 and ρ_2 are the speed of adjustment of $\Delta\varepsilon_t$ and I_t is the indicator function restricted as follows:

$$I_t = \begin{cases} 1 \;\; if \; \varepsilon_{t-1} \geq \tau \\ 0 \;\; if \; \varepsilon_{t-1} < \tau \end{cases} \tag{4}$$

where τ represents the threshold value. Note that higher order processes are included to account for serially correlated residuals. Here, cointegration exists if $\rho_1 < 0$ and $\rho_2 < 0$ and the test for cointegration can be performed based on the t_{Max} and Φ tests proposed by Enders and Siklos (2001). The t_{Max} statistic is given by the largest t-statistics of ρ_1 and ρ_2. The Φ test is an F-test examining the joint hypothesis $\rho_1 = \rho_1 = 0$. Since this test does not follow a standard distribution, the simulated critical values reported in Enders and Siklos (2001) are used. The value of the critical threshold is usually unknown to the researcher and needs to be estimated. Chan (1993) proposed a search method for obtaining a consistent estimate of the threshold value. The best threshold is determined by fitting (3) for possible threshold values, sorting the residuals by sum of squared errors (SSE) and selecting the one with the lowest SSE within the middle 70% of the sorted values.

Having confirmed the existence of an asymmetric cointegrating relationship, the next step in modeling asymmetric price transmissions is to estimate the TVEC model that incorporates threshold effects of the price variables and their cointegration relationship in order to account for positive and negative price changes. Hence, the TVEC model is expressed as:

(5)
$$\Delta Y_t = a_{10} + I_t b_{11}^{+} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{+} \Delta Y_{t-k} + \sum_{k=0}^{p} c_{13,k}^{+} \Delta X_{t-k} + (1 - I_t)\, b_{11}^{-} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{-} \Delta Y_{t-k} + \sum_{k=0}^{p} c_{13,k}^{-} \Delta X_{t-k} + e_{1,t}$$

$$\Delta X_t = a_{20} + I_t b_{21}^{+} ECT_{t-1} + \sum_{k=1}^{p} c_{22,k}^{+} \Delta Y_{t-k} + \sum_{k=1}^{p} c_{23,k}^{+} \Delta X_{t-k} + (1 - I_t)\, b_{21}^{-} ECT_{t-1} + \sum_{k=1}^{p} c_{22,k}^{-} \Delta Y_{t-k} + \sum_{k=1}^{p} c_{23,k}^{-} \Delta X_{t-k} + e_{2,t}$$

where, $ECT_{t-1} = Y_{t-1} - \gamma_0 - \gamma_1 X_{t-1}$ is the one-period lagged error correction term, $c_{12,k}^{+}$ and $c_{22,k}^{+}$ apply when $\Delta Y_{t-k} \geq 0$ and $c_{12,k}^{-}$ and $c_{22,k}^{-}$ apply when $\Delta Y_{t-k} < 0$, and similarly for $c_{13,k}^{+}$ and $c_{23,k}^{-}$. The indicator function I_t has the same specification as indicated in equation (4). However, the threshold value is different for each equation. In addition, the TVEC model also distinguishes between long- and short-run price adjustments. The long-run adjustment is determined by b_{i1}^{+} and b_{i1}^{-} and the short-run adjustment is determined by $c_{i2,k}^{+}$, $c_{i2,k}^{-}$, $c_{i3,k}^{+}$ and $c_{i3,k}^{-}$ for equation $i = 1, 2$ and all $k = 1, 2, \dots, p$.

Tests for Asymmetric Price Transmissions

We test for asymmetric price transmissions using two different approaches. The first approach consists of testing the difference between parameter estimates among each equation in the TVEC model (slope-based tests). The test for long-run symmetry examines the null hypothesis $H_0\colon b_{i1}^{+} = b_{i1}^{-}$ and the test for short-run symmetry examines the null hypothesis $H_0\colon c_{i2,k}^{+} = c_{i2,k}^{-}$ and $c_{i3,k}^{+} = c_{i3,k}^{-}$, for equation $i = 1, 2$ and all k. A rejection of either hypothesis indicates asymmetry in price adjustment. One drawback of the slope-based test is that it does not indicate the speed of adjustment. This adjustment could be faster or slower after a positive (or negative) shock, but the test is silent about which is the case. Further, it is possible to reject the null hypothesis of equal slope coefficients, yet have a symmetric response at horizons greater than one. The reason is that asymmetry in the coefficients at one horizon can offset asymmetry in the coefficients at a different horizon. To address this issue, the second approach involves the analysis of nonlinear impulse response functions. This test is built on the observation that under the null hypothesis of a symmetric response function, the vector of impulse responses to a positive price shock should be equal to the vector of impulse responses to a negative price shock except for its sign, such that the sum of these vectors is equal to a vector of zeros (Kilian and Vigfusson, 2011).

In linear models, impulse response functions are calculated by simulating the effects of a one unit shock at time t, where the marginal effect of a shock is constant. The same does not hold in a nonlinear model because the effect of a particular price shock will depend on the magnitude of the shock, the values of the upstream and downstream prices prior to the shock, and the future shocks to the upstream and downstream prices. In this study, we compute impulse response functions by Monte Carlo integration as described in Kilian and Vigfusson (2011). The algorithm followed is:

1. Define U_k to be a vector holding a draw of a block of k consecutive values of the upstream prices and D_k to be a vector holding a draw of a block of k consecutive values of the downstream prices, where k is the lag length of the TVEC model.
2. Define e_0 to be the shock to the price that is of interest.
3. Define e_U to be a vector holding a draw of H values of the identified shocks to the upstream price. Here, H is the number of periods forward or horizon specified in the simulation.
4. Define e_D to be a vector holding a draw of $H + 1$ values of the identified shocks to the downstream price.
5. Predict the values of the upstream and downstream prices for periods t through $t + H$, conditional on U_k, D_k, $(e_0, e_U)'$, e_D, where e_0 is defined to be either positive or negative.
6. Predict the values of the upstream and downstream prices for periods t through $t + H$, conditional on U_k, D_k, $(e_0, e_U)'$, e_D, where $e_0 = 0$.
7. Calculate the difference in predicted values of the two variables from steps 5 and 6.
8. Steps 1-7 are repeated 1,000 times, and the conditional impulse response function is the average of the output from step 7 across the 1,000 simulations. This is a conditional impulse response function because it depends on the draw of the initial values and shocks.
9. Conduct a wild bootstrap (1,000 simulations) to calculate confidence intervals.

Symmetry implies that:

(6) $$I_Y(h, e_0^+) = -I_Y(h, e_0^-) \quad for\ h = 1, .., H,$$

or equivalently,

(7) $$I_Y(h, e_0^+) + I_Y(h, e_0^-) = 0 \quad for\ h = 1, .., H,$$

where I_Y is the unconditional impulse response function of variable ΔY_t from step 8, which in turn depends on the value of e_0. Then, the test of symmetry is constructed using cumulative impulse responses. Here, we test the following hypothesis:

(8) $$Ho\colon CI_Y\,(h, e_0^+) + CI_Y\,(h, e_0^-) = 0 \quad for\ h = 1, .., H.$$

Confidence intervals for the difference in cumulative impulse response functions are given by the wild bootstrap simulation results.

Results

Data and Time Series Properties

The data used in this analysis are monthly price series for beef corresponding to farm, wholesale and two sources of retail price series (i.e., Bureau of Labor Statistics and retail scanner data) covering the period from January 2001 to December 2012 (144 observations).[1] Farm (live cattle) and wholesale (boxed beef) price series were obtained from the Agricultural Marketing Service (USDA-AMS). *Farm* price is the weighted–five-area average Texas-Oklahoma, Kansas, Nebraska, Colorado, and Iowa-Minnesota live steer and heifer price for all grades. *Wholesale* price is the weighted-average of Choice and Select boxed beef cutout value for 600–900 lbs. carcasses. The Economics Research Service (USDA-ERS) has available retail beef prices reported by the Bureau of Labor Statistics. The *BLS* retail price used is the traditional simple-average retail price for all grades beef. Retail *scanner* quantity-weighted retail prices are compiled by USDA-ERS and Freshlook and were obtained from the National Cattlemen's Beef Association (NCBA). These prices also correspond to all grades beef. All prices are in dollars per pound. Figures 1 and 2 contain plots of the U.S. beef price series. Differences between the two retail price series are apparent. Scanner prices are generally lower than BLS prices and have greater variance.

[1] Scanner price data was only available from January 2001, thus limiting the period considered in this analysis.

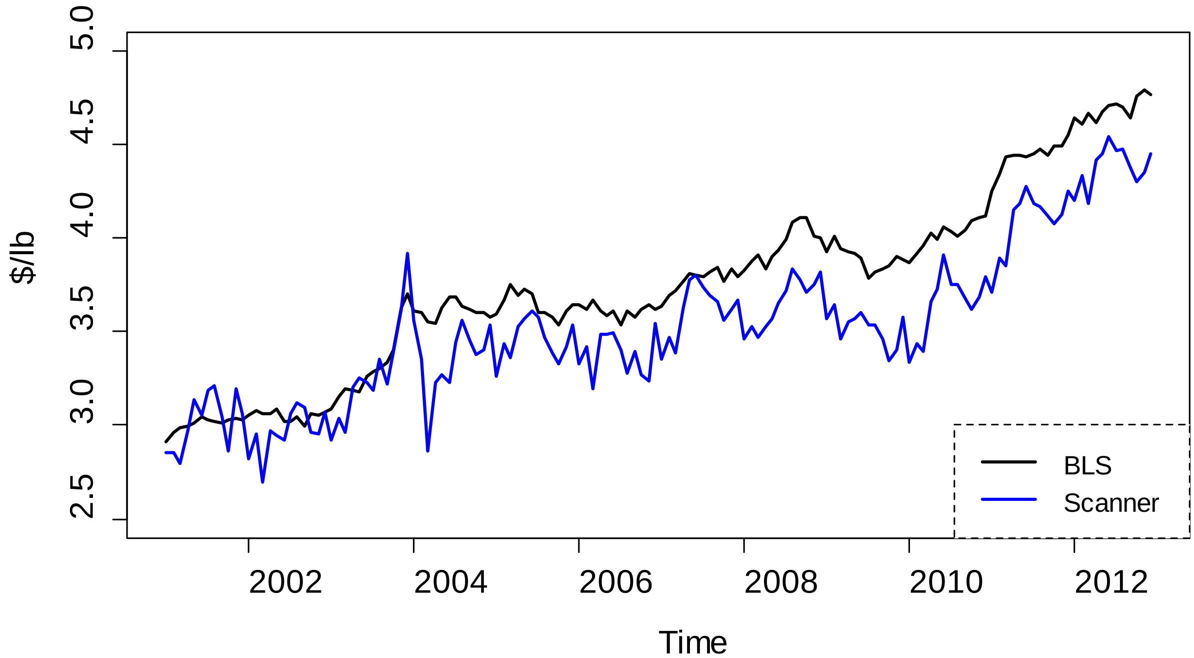

Figure 1. Monthly Retail BLS and Scanner Beef Prices, January 2001- December 2012.

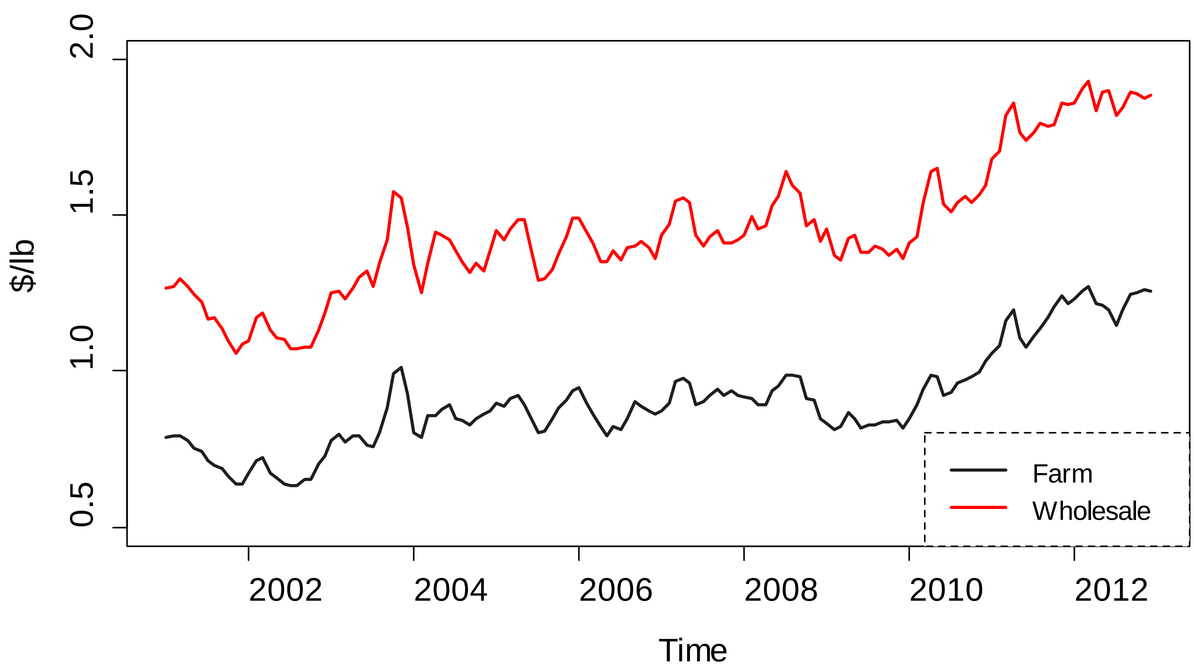

Figure 2. Monthly Feed Cattle and Wholesale Beef Prices, January 2001- December 2012.

Table 1 presents the results of the evaluation of the univariate time series properties of the four beef price series. We conducted two tests to verify the presence of a unit root in individual price series, a DF-GLS test proposed by Elliott et al. (1996), and a Kwiatkowski et al. (1992) KPSS test. In the DF-GLS test the null hypothesis is nonstationarity, whereas in the KPSS test the null hypothesis is stationarity. Both tests were conducted including different deterministic parts (i.e., constant but not trend and constant and trend). Results from these tests are mixed. We reject the null hypothesis of nonstationarity according to the DF-GLS (trend) test for *farm*, *wholesale* and *scanner* price series; on the contrary, the DF-GLS (constant) test and the KPSS test indicates that all price series contain a unit root. Schwert (1989) argues that commonly used unit root tests might over-reject the null hypothesis of nonstationarity in cases where the time series present a unit root in the MA (moving average) process, because such tests rely on the assumption that the time series is generated by a pure autoregressive process. Thus, we estimated an MA(1) model for each price series to check whether the coefficient is close to unity. The MA(1) coefficients ranged from 0.84 to 1.00, indicating that a DF-GLS unit root test is likely to reject the null even when the data are nonstationary. Therefore, we conclude that the four price series are nonstationary.

In this study we are interested in analyzing price the transmission of price shocks from the following price pairs: *Farm* and *BLS*, *Farm* and *Scanner*, *Wholesale* and *BLS* and *Wholesale* and *Scanner*.[2] Before estimating the TVEC models, we tested for cointegration. Table 2 contains the results of the t_{Max} and Φ tests for cointegration which accounts for the possibility of asymmetry in price transmissions in the cointegrating term. This test was performed in two steps. First, equation (1) was estimated by OLS for each pair of price variables. Then, equation (3) was estimated using the residuals from equation (1) and the specification of equation (4) where the value of τ was set equal to zero (*TAR 1*) and different from zero (*TAR 2*). The optimal threshold value was found using the search method proposed by Chan (1993). In both cases, the results strongly support the existence of long-run equilibrium relationship for all pairs of variables, confirming the appropriateness of a TVEC model.

Threshold Vector Error Correction Models and Asymmetry Tests

The TVEC models were estimated using equation (5) and the specification in equation (4), where the value of τ was set equal to zero and different from zero.[3] Based on the AIC, the TVEC models estimated with a value of τ different from zero are preferred to those models estimated with a value of τ equal to zero. Table 3 presents the parameter estimates for TVEC models that follow an upstream–downstream direction, where the dependent variable is either *BLS* (PB) or *Scanner* (PS) retail price and the independent variables are either *Farm* (PF) or *Wholesale*

[2] The *Farm* and *Wholesale* pair is also included to maintain consistency.
[3] In the estimation using a value of τ different from zero, we allowed the threshold to vary in each equation.

prices(PW).[4] The coefficients of the cointegrating term have the expected signs and are statistically significant in all models. In addition, the magnitude of response (markup) of retail price to a farm price increase is higher compared to a wholesale price increase. Further, the coefficients of the error correction terms are statistically significant in all models. These coefficients, which measure the deviation from equilibrium, are negative and range between 0 and 1 in absolute value as expected. Thus, indicating what percent of the disequilibrium is corrected from one period to the next. Note that the magnitude of adjustment to disequilibrium in the models using scanner data is at least six times larger than the models that use BLS data.

Table 4 presents the results from the slope-based test of symmetry applied to the parameter estimates of the TVEC models. Our findings indicate that there is no long-run asymmetric price transmission in any of the models, except for the model analyzing the price transmission from *Farm* to *Scanner* market levels. Regarding the short run price adjustment, we fail to reject the null hypothesis of symmetry at the 0.05 significance level in all models. These results are not consistent with Goodwin and Holt (1999), who found price asymmetry in the beef market. Although Goodwin and Holt (1999) did not use BLS data in their study, they found asymmetric price transmissions using weekly average prices collected in a similar fashion as the BLS data. For consistency purposes, we tested for symmetric price transmissions at the *Farm-Wholesale* market levels. Results of this test indicate that farm prices are symmetrically transmitted to wholesale prices in both, the long run and the short run equilibrium.

Although the sloped-based tests provide evidence of asymmetric price transmissions in the beef market chain, results from the impulse response based tests of symmetry are not consistent with these findings. That is, we fail to reject the null hypothesis of symmetry (equation 8) at the 0.05 significance level in all models. Thus, suggesting that asymmetry in the coefficients at one horizon offset asymmetry in the coefficients at a different horizon. Figures 3 and 4 illustrate the results from the impulse response based test of symmetry applied to TVEC models following an upstream-downstream direction.[5] Cumulative responses represent the summation of the cumulative impulse responses to two standard deviation positive and negative shocks (equation 8). Each figure presents cumulative responses of the corresponding retail price to a shock in the *Farm* price (left plot) and to a shock in the *Wholesale* price (right plot). Note that cumulative responses are represented by the solid black line and 95% confidence intervals are represented by the dashed red lines. In general, *Scanner* prices are more responsive to *Wholesale* price shocks compared to *BLS* prices. Additionally, the direction of the cumulative responses is consistent with previous findings. That is, both retail prices respond quicker and faster to an increase in upstream prices increases than to a decrease in upstream prices (except in the case of the

[4] Results from the downstream-upstream direction models are not presented but are available upon request.
[5] Results from the impulse response based test of symmetry corresponding to TVEC models following a downstream-upstream direction are not presented but are available upon request.

response of *Scanner* price to a shock in *Farm* price). However, these cumulative responses are not statistically significant.

Since our findings differ from those found in the current literature, an important question that rises is whether it is because of the use of a different methodology or the use of newer data. To address this question, we applied our model to the data used in Goodwin and Holt (1999). Results show evidence of asymmetric price transmissions. Particularly, retail prices responded asymmetrically to shocks on farm prices. However, as noted in Goodwin and Holt, asymmetric responses are modest and might not be economically significant. This assessment indicates that our results might not differ from those found in previous studies because of the implementation of a different methodology. Thus, the results we obtained are mostly influenced by the use of newer data.

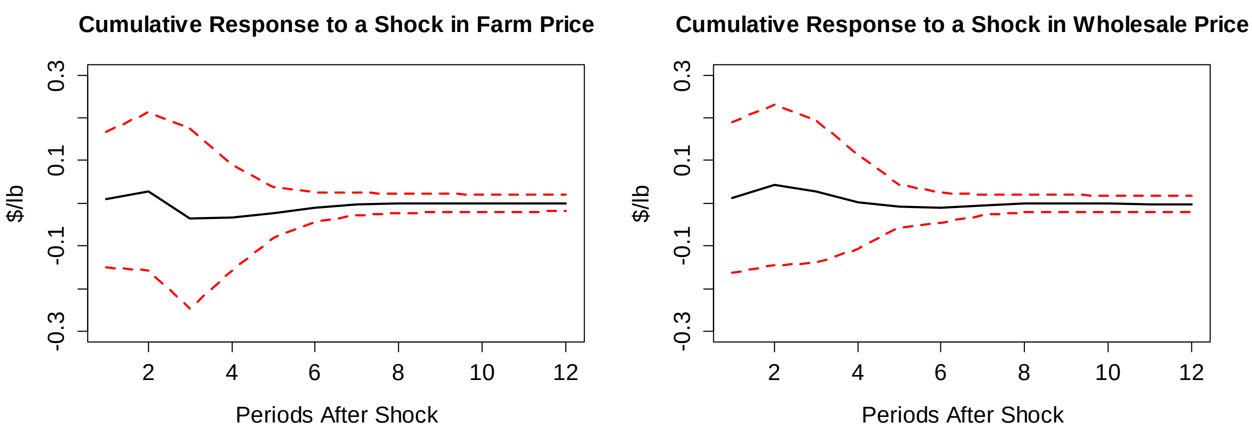

Figure 3. Cumulative Responses of *BLS* Retail Price to a Shock in Upstream Prices.

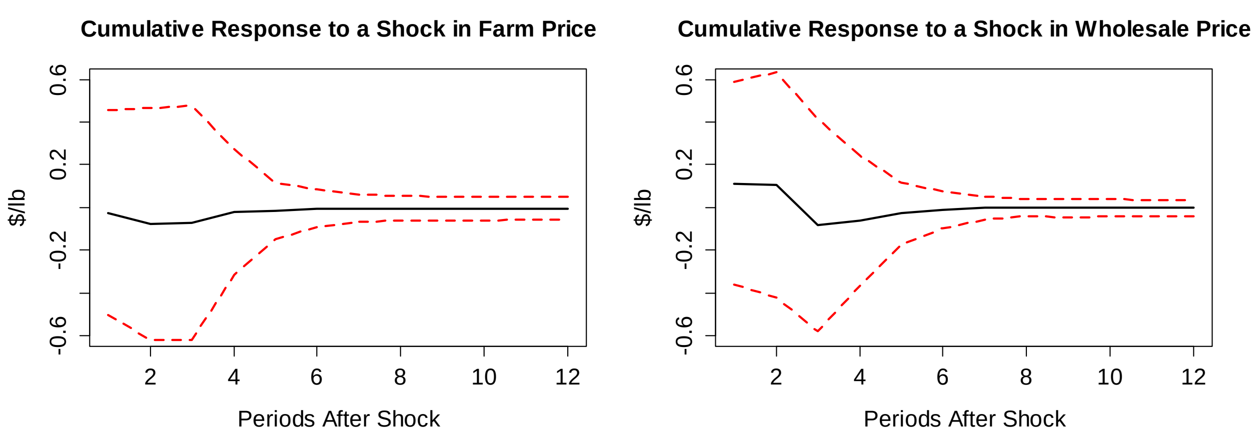

Figure 4. Cumulative Responses of *Scanner* Retail Price to a Shock in Upstream Prices.

Conclusions and Implications

In this study, we examine price transmissions among farm, wholesale and retail U.S. beef markets using two types of retail level price data, one collected by the Bureau of Labor Statistics (BLS) and the other one collected at the point of sale using electronic scanners. In particular, we compare BLS and scanner price adjustments to changes in upstream prices (i.e., farm and wholesale prices). Although these two retail price series differ in the way they are constructed (e.g., data collecting methods, volume sales and discounted price considerations), we find no evidence of asymmetry in the response of retail prices to shocks in upstream prices.

Our results have important implications for the U.S. beef market efficiency. Particularly, since retailer adjustments to farm and wholesale price changes are symmetric, the U.S. beef market is not as inefficient as found in previous studies (e.g., Goodwin and Holt, 1999). Finally, our analysis suggests that the U.S. beef market has become more efficient in recent years. That is, information is transmitted more efficiently along vertically coordinated beef markets.

References

Abdulai, A. (2002). “Using Threshold Cointegration to Estimate Asymmetric Price Transmissions in the Swiss Pork Market.” *Applied Economics*, 34: 679–687.

Awokuse, T.O. and X. Wang (2009). “Threshold Effects and Asymmetric Price Adjustments in U.S. Dairy Markets.” *Canadian Journal of Agricultural Economics,* 57: 269–286.

Azzam, A. (1999). “Asymmetry and Rigidity in Retail-Price Transmission: A Theoretical Analysis.” *American Journal of Agricultural Economics*, 81: 52–533.

Bailey, D and B.W. Brorsen (1989). “Price Asymmetry in Spatial Fed Cattle Markets.” *Western Journal of Agricultural Economics,* 14: 246–252.

Balcombe, K., A. Bailey and J. Brooks (2007). “Threshold Effects in Price Transmission: The Case of Brazilian Wheat, Maize, and Soya Prices.” *American Journal of Agricultural Economics*, 89: 308–323.

Ben-Kaabia, M. and J.M. Gil (2007). “Asymmetric Price Transmission in the Spanish Lamb Sector.” *European Review of Agricultural Economics*, 34: 53–80.

Blinder, A.S. (1982). “Inventories and Sticky Prices: More on the Microfoundation of Macroeconomics.” *American Economic Review* 72(3): 334–348.

Chan, K.S. (1993). “Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model.” *The Annals of Statistics,* 21(1): 520–533.

Elliott, G., Rothenberg, T. and Stock, J. (1996). “Efficient Tests for an Autoregressive Unit Root.” *Econometrica*, 64 (4): 813–836

Enders, W. and P. L. Siklos (2001). **“**Cointegration and Threshold Adjustment.” *Journal of Business and Economic Statistics,* 19: 166–67.

Engle, R. F. and C. W. Granger (1987). **“**Co-integration and Error Correction: Representation. Estimation and Testing.” *Econometrica,* 55: 251–76.

Frey, J. and M. Manera (2007). “Econometric Models of Asymmetric Price Transmission.” *Journal of Economic Surveys*, 21: 449–415.

Geithman, F. and B. Marion (1978). “A Critique of the Use of BLS Data for Market Structure-Price Analysis.” *American Journal of Agricultural Economics*, 60: 701–705.

Goodwin, B. K. and M. T. Holt (1999). **“**Asymmetric Adjustment and Price Transmission in the U.S. Beef Sector.” *American Journal of Agricultural Economics,* 81: 630–37.

Hahn, W. (1990). "Price transmission asymmetry in pork and beef markets." *Journal of Agricultural Economics*, 42: 21–30.

Hahn, W., J. Perry and L. Southard (2009). "Comparing Two Sources of Retail Meat Price Data." Economic Research Report Number 88. Available at: http://ageconsearch.umn.edu/bitstream/55958/2/err88.pdf. Last accessed: April 14, 2012.

Hausman, J. (2003). "Sources of Bias and Solutions to Bias in the Consumer Price Index." *The Journal of Economic Perspectives*, 17(1): 23–44.

Hausman, J. and E. Leibtag (2009). "CPI Bias from Supercenters: Does the BLS Know that Wal-Mart Exists?" NBER Chapters, in: Price Index Concepts and Measurement, pp. 203–231 National Bureau of Economic Research, Inc.

Kilian, L. and R. Vigfusson (2011). "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?" *Quantitative Economics*, 2: 419–453

Kinnucan, H.W. and Forker, O. D. (1987). "Asymmetry in Farm-Retail Price Transmission for Major Dairy Products." *American Journal of Agricultural Economics,* 69(2): 285–292.

Kwiatkowski, D., Phillips, P., Schmidt, P. and Shin, Y. (1992). "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?" *Journal of Econometrics*, 54: 159–178

Lensing C. and W. Purcell (2006). "Impact of Mandatory Price Reporting Requirements on Level, Variability, and Elasticity Parameter Estimations for Retail Beef Prices." *Review of Agricultural Economics*, 28: 229–239.

Mathews, K., W. Hahn, K. Nelson, L. Duewer, and R. Gustafson. (1999). "U.S. Beef Industry: Cattle Cyles, Price Spreads, and Packer Concentration." United States Department of Agriculture, Economic Research Service, Technical Bulletin No. 1874. April. Available at: http://www.ers.usda.gov/media/487899/tb1874_1_.pdf. Accessed May 22, 2012.

Meyer, J. and S.von Cramon-Taubadel. (2004). "Asymmetric Price Transmission: A Survey." *Journal of Agricultural Economics* 55(3): 581–611.

Miller, D.J. and M.L. Hayenga. (2001). "Price Cycles and Asymmetric Price Transmission in the U.S. Pork Market." *American Journal of Agricultural Economics* 83(3): 551–562.

Mohanty, S., Peterson, E.W.F. and Kruse, N.C. (1995). "Price Asymmetry in the International Wheat Market." *Canadian Journal of Agricultural Economics,* 43: 355–365.

Peltzman, S. (2000). "Prices Rise Faster than they Fall." *Journal of Political Economy*, 108(3): 466–502.

Rojas, C., A. Andino and W. Purcell (2008). "Retailers' Response to Wholesale Price Changes: New Evidence from Scanner-Based Quantity-Weighted Beef Prices." *Agribusiness*, 24:1–15.

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

Xia, T. and X. Li (2010). "Consumption Inertia and Asymmetric Price Transmission." *Journal of Agricultural and Resource Economics*, 35 (2): 209–227.

Table 1. Results from Unit Root Tests

Test	**Test-statistics**	
DF-GLS	*Constant*	*Trend*
Farm	-0.9455	-3.1198**
Wholesale	-0.8130	-3.2710**
BLS	2.0964	-1.9984
Scanner	0.0103	-3.3733**
KPSS	*Constant*	*Trend*
Farm	2.0754**	0.2571**
Wholesale	2.2304**	0.2263**
BLS	2.6722**	0.2245**
Scanner	2.3430**	0.2147**

Notes: AIC was used to determine appropriate lag lengths. The null hypothesis under the DF-GLS test is nonstationary. The critical values are -1.94 and -2.93 for the 0.05 significance level, corresponding to the specifications using a constant (but not trend) and a trend, respectively. By contrast, the null hypothesis under KPSS test is stationary. The critical values are 0.463 and 0.146 for the 0.05 significance level, corresponding to the specifications using a constant and a trend, respectively. ** indicates rejection of the null hypothesis at the 0.05 significance level.

Table 2. Results from the Enders–Siklos Test for Threshold Cointegration

Relationship	**Cointegration Test-statistics**								
Dependent and	***TAR 1***				***TAR 2***				
Independent variables:	t_{Max}	C.V.	Φ	C.V.	t_{Max}	C.V.	Φ	C.V.	*threshold*
BLS and *Farm*	-2.62**	-2.14	11.05**	6.01	-2.35**	-1.90	11.47**	7.08	0.09
BLS and *Wholesale*	-3.22**	-2.14	12.52**	6.01	-3.05**	-1.90	12.80**	7.08	-0.12
Scanner and *Farm*	-4.84**	-1.98	29.35**	6.28	-3.96**	-1.92	31.13**	7.41	0.15
Scanner and *Wholesale*	-5.17**	-1.98	28.28**	6.28	-5.04**	-1.92	28.67**	7.41	-0.07
Wholesale and *Farm*	-3.38**	-2.11	12.87**	5.98	-3.46**	-1.85	13.26**	6.95	-0.03
Farm and BLS	-2.77**	-2.14	12.41**	6.01	-2.24**	-1.90	13.09**	7.08	-0.05
Wholesale and *BLS*	-3.17**	-2.14	14.19**	6.01	-2.90**	-1.90	15.23**	7.08	0.05
Farm and *Scanner*	-3.73**	-2.11	18.14**	5.98	-3.55**	-1.85	19.54**	6.95	0.07
Wholesale and *Scanner*	-4.15**	-2.11	20.81**	5.98	-3.73**	-1.85	22.56**	6.95	0.08
Farm and *Wholesale*	-3.20**	-2.11	14.45**	5.98	-2.55**	-1.85	12.67**	6.95	0.02

Note: The lag used for each test is determined using the BIC, with a maximum lag order of 8 allowed. The null hypothesis under test is no cointegration. Approximate critical values for the t_{Max} and Φ tests are tabulated by Enders and Siklos (2001). The critical values (C.V.) reported correspond to the 0.05 significance level. ** indicates the rejection of the null hypothesis at the 0.05 significance level.

Table 3. Estimation Results for Threshold Vector Error Correction Models (upstream-downstream direction)

	BLS & Farm		**BLS & Wholesale**		**Scanner & Farm**		**Scanner & Wholesale**	
Regressor	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*	*Coeff.*	*Std. Error*
Constant	0.0078	0.0086	0.0045	0.0087	0.0360	0.0232	0.0417 *	0.0233
ECT_{t-1}^{+}	-0.0622 *	0.0323	-0.0837 **	0.0366	-0.2869 **	0.1247	-0.5850 ***	0.1269
ECT_{t-1}^{-}	-0.0891 **	0.0349	-0.1143 ***	0.0378	-0.6498 ***	0.0975	-0.7184 ***	0.1196
ΔPF_{t}^{+}	0.1916	0.2011			-0.6132	0.5591		
ΔPF_{t}^{-}	0.5942 ***	0.2101			-0.3752	0.5614		
ΔPF_{t-1}^{+}	-0.0590	0.2126			-0.0501	0.6115		
ΔPF_{t-1}^{-}	0.3307 *	0.1897			0.2224	0.6207		
ΔPF_{t-2}^{+}	0.7454 ***	0.2180			-0.0099	0.6035		
ΔPF_{t-2}^{-}	0.2938	0.1991			0.0545	0.5950		
ΔPW_{t}^{+}			0.1432	0.1262			-0.1024	0.3573
ΔPW_{t}^{-}			0.2858 **	0.1384			-0.2248	0.3903
ΔPW_{t-1}^{+}			0.2242 *	0.1333			-0.2390	0.4055
ΔPW_{t-1}^{-}			0.2578 *	0.1317			-0.3495	0.4322
ΔPW_{t-2}^{+}			0.2877 **	0.1427			-0.0815	0.3947
ΔPW_{t-2}^{-}			0.2006	0.1396			-0.5227	0.4212
ΔPB_{t-1}^{+}	0.0867	0.1136	0.1048 ***	0.1171				
ΔPB_{t-1}^{-}	-0.5873	0.1716	-0.6833	0.1688				
ΔPB_{t-2}^{+}	-0.1324 **	0.1202	-0.1696	0.1126				
ΔPB_{t-2}^{-}	0.1344	0.1685	0.1089	0.1661				
ΔPS_{t-1}^{+}					-0.2148	0.1440	-0.1824	0.1422
ΔPS_{t-1}^{-}					0.0343	0.1532	0.1134	0.1571
ΔPS_{t-2}^{+}					-0.0655	0.1313	-0.1892	0.1298
ΔPS_{t-2}^{-}					0.2513 *	0.1456	0.3155 **	0.1439
R-squared		0.4186		0.4422		0.4602		0.4779
Cointegrating Term (ECT_{t-1})								
Constant		1.163***		0.677***		1.408***		1.026***
PF_{t-1}		2.867***				2.348***		
PW_{t-1}				2.120***				1.725***

Note: ***, ** and * indicate statistically significance at the 0.01, 0.05 and 0.10 level, respectively. The lag length was determined using the AIC.

Table 4. Results from the Slop-Based Test of Symmetry in Beef Price Adjustments

Causal Direction	**Short Run Adjustment**	**Long Run Adjustment**
	H_0: $All\ c^{+}_{i2,k} = c^{-}_{i2,k}\ and\ c^{+}_{i3,k} = c^{-}_{i3,k}$	H_0: $b^{+}_{i1} = b^{-}_{i1}$
From *Farm* to *BLS*	0.0153 [0.9017]	0.2907 [0.5907]
From *Wholesale* to *BLS*	1.0043 [0.3182]	0.3418 [0.5598]
From *Farm* to *Scanner*	0.6493 [0.4219]	5.8343 [0.0173]
From *Wholesale* to *Scanner*	0.0154 [0.9013]	0.5639 [0.4541]
From *Farm* to *Wholesale*	0.0247 [0.8752]	1.7213 [0.1919]
From *BLS* to *Farm*	0.0014 [0.9699]	1.3512 [0.2472]
From *BLS* to *Wholesale*	0.1140 [0.7362]	0.3764 [0.5406]
From *Scanner* to *Farm*	0.4867 [0.4867]	1.3988 [0.2391]
From *Scanner* to *Wholesale*	0.0183 [0.8927]	0.1651 [0.6852]
From *Wholesale* to *Farm*	0.0002 [0.9892]	1.0382 [0.3101]

Note: H_0 describes the respective null hypotheses under test. For short-run adjustment, both $c^{+}_{i2,k} = c^{-}_{i2,k}\ and\ c^{+}_{i3,k} = c^{-}_{i3,k}$ for $i = 1, 2$ are restrictions applying to all individual lags (k =1, 2,…, p) of the estimated TVEC model. Corresponding p-values for F-tests are given in brackets.