Are There Price Asymmetries in the U.S. Beef Market?

1 Introduction

Farm, wholesale and retail meat price relationships have been ardently debated for a long time in the U.S. Since the 1970s, numerous heated congressional hearings and commissions have addressed price transmissions among vertically linked meat markets (Koontz and Ward, 2011).[1] The focus of this debate has been on economic and agricultural policy issues related to market concentration, welfare distribution, and market efficiency. An often noted concern raised by both producers and consumers is the growing gap between farm and retail meat prices. Claims persist that producers do not benefit from downstream price increases, in the same magnitude or speed, as downstream price decreases. For instance, a decrease in retail beef price due to a decrease in beef demand passes to farm prices faster than a retail price increase (U.S. Department of Justice, 2012). From a consumer perspective, there are concerns that retail and wholesale meat prices are rigid or slow to respond to farm price declines, but responsive to farm price increases. Consequently, cost increases are transferred on to consumers more rapidly than costs savings (Abdulai, 2002). This study examines whether there is asymmetry in price transmissions and adjustments across U.S. beef markets.

Economic theory provides several mechanisms by which there could be asymmetric price responses in vertically linked markets. The most commonly cited is market power and concentration at the processing and retail levels (Azzam, 1999; Bailey and Brorsen, 1989;

[1] The interest of policymakers can at least partially be explained by the size of the U.S. beef industry, which had a retail equivalent value of $105 billion as of 2015 (U.S. Department of Agriculture, Economic Research Service, 2016).

Peltzman, 2000; Xia, 2009).[2] Beef cattle producers attribute the increase in farm-to-retail price spreads, and consequently the decline in the farmer's share of the dollar consumers spend on food, as evidence of a lack of competitiveness among middlemen along the beef supply chain. This claim is based on the high levels of market concentration among meat packing firms and large retailers, which enables them to potentially exercise market power (Crespi, Saitone and Sexton, 2012). As documented by the U.S. Department of Agriculture (USDA), the national four-firm concentration ratio for steer and heifer slaughter increased from 25% in 1976 to 85% in 2012 (USDA Grain Inspection, Packers and Stockyards Administration, 2013).

Concerns about industry concentration motivated the U.S. federal government to pass legislation providing market participants with better information. In 1999, the U.S. Congress passed the Livestock Mandatory Price Reporting (LMPR) Act, which required meat packers that slaughter 125,000 cattle per year to report transaction data to USDA, including average prices paid to cattle producers. The purpose of this provision, which was reauthorized in September 2015, was to facilitate open and transparent price discovery, and provide market participants with comparable levels of market information for cattle, swine, sheep, beef, pork and lamb meat. Therefore, by increasing transparency, price asymmetry concerns could be mitigated.

The LMPR Act of 1999 also required the 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 traditional series collected by the Bureau of Labor Statistics (BLS), widely used in a large body of published research. The purpose of this provision was to address concerns regarding the quality of BLS retail meat price data (Hahn, Perry and Southard, 2009). Evidence suggests that these data are biased and do not fully capture

[2] Other explanations for asymmetric price transmissions include menu costs (Bailey and Brorsen, 1989; Levy et al., 1997); inventory adjustment practices (Blinder, 1982; Miller and Hayenga, 2001); government intervention (Kinnucan and Forker, 1987; Mohanty, Peterson and Kruse, 1995); and consumption inertia (Xia and Li, 2010).

retail price variability over time (Hausman, 2003). In response to the request of the LMPR Act, USDA acquired scanner based quantity-weighted retail price data as an alternative to BLS data. Scanner data are collected at the point of sale by supermarkets using electronic scanners in check-out lines. Unlike BLS price data, scanner data accounts for volume of sales and discounted prices in summarizing prices each period.

The objective of this study is to evaluate and quantify asymmetric price transmissions in U.S. beef markets. We focus on two possible forms of asymmetry: from farm to retail, and from retail to farm, with potentially large welfare implications if responses to price increases and decreases are not symmetric. We estimate a nonlinear structural vector autoregressive (SVAR) model that allows for asymmetric responses of retail, wholesale, and farm prices to shocks to any of these series. To compare responses between retail price data from different sources, nonlinear SVAR models are estimated using either BLS or scanner data. We compute impulse response functions by simulation following the extension of Koop, Pesaran and Potter (1996) proposed by Kilian and Vigfusson (2011). We use this information to calculate the degree of asymmetry following shocks to each of the price series. Finally, we conduct a counterfactual analysis to check whether our results are due to an uninformative dataset that causes the test for asymmetric responses to have low power.

Interestingly, we find evidence that the results are sensitive to the choice of retail beef price series. We do not reject the null hypothesis of symmetric responses to shocks at other points in the distribution chain when models are estimated using scanner retail price data. On the other hand, when the scanner data is replaced with the widely-used BLS retail price series, we do find evidence of asymmetric price responses in some cases. What can account for the difference in results when changing the retail beef price series? The USDA began collecting scanner data in response to concerns about the quality of BLS retail meat price data (Hahn, Perry and Southard, 2009). There is evidence that the BLS data are biased and do not fully capture retail price variability over time (Hausman, 2003). The quantity-weighted retail scanner price data should better reflect the price that consumers actually pay for beef, and our results do support that notion, as we find that scanner retail prices are much more responsive than BLS prices to upstream price changes.

Our results have important implications for the U.S. beef market. First, since price is the primary link between vertically integrated markets, the analysis of price transmissions is fundamental to understand how markets operate (e.g., marketing margins, spreads and pricing practices). Second, this analysis has implications for policy makers because the presence of asymmetry implies a different distribution of welfare than under symmetry. Therefore, depending on the degree of asymmetry, certain policies may not be as beneficial to producers as expected, which in turn could also carry adverse effects for consumers (Awokuse and Wang, 2009). Lastly, the impact of government intervention targeting potential inefficiencies in the U.S. beef market could have unexpected welfare and income distribution effects depending on the presence or absence of asymmetry.

2 Related Literature

This is not the first paper to test for asymmetric adjustment in the U.S. beef market.[3] The closest to the present, Goodwin and Holt (1999, hereafter GH), investigated price transmission asymmetries using weekly data. They concluded that there was asymmetric price transmission, with unidirectional causal flow from farm to wholesale to retail markets, but the magnitude of asymmetry following a particular shock was not economically significant.

The primary difference between the present study and GH is the methodology. The generalized impulse response function analysis in GH can be used to make forecasts, identify deviations from linearity in a system of equations, and characterize persistence in the data, but it was not designed to do impulse response function analysis, at least not in the sense that the term is commonly used in the structural VAR literature.[4] We apply the methodology

[3] Related studies that we do not discuss here include von Cramon-Taubadel (1998), and Peltzman (2000).

[4] As Kilian and Vigfusson (2011) explain, "Such responses may be useful in characterizing the persistence of the data, but they are devoid of any economic interpretation."

in Kilian and Vigfussion (2011), which builds on the generalized impulse response function analysis in Koop, Pesaran and Potter (1996), to estimate the responses of retail, wholesale, and farm beef prices to shocks to upstream and downstream beef prices. The impulse response functions we report are not conditioned on an assumption of a particular choice for recent price behavior or a particular set of future shocks.[5] See Kilian and Vigfusson (2011) for further discussion of this point.

Our methodology also differs from GH along two other dimensions. First, we present confidence intervals on the estimated impulse response functions. Second, we allow for asymmetry in the response to deviations from the long-run relationship between the variables, using a threshold cointegration model as in GH, but also in the short run response to price changes, as in the literatures on gasoline pricing (see e.g., Borenstein, Cameron and Gilber, 1997), the effects of oil shocks on the macroeconomy (see e.g., Hamilton, 2011; Kilian, 2008; Kilian and Vigfusson, 2011), and other markets (Peltzman, 2000). The threshold cointegration model is intuitively appealing - a price series might return to equilibrium at a different speed depending on the sign and magnitude of its deviation from its long run equilibrium value. It is nonetheless difficult to justify the assumption that this is the only type of asymmetry in the system. Among other things, the requirement that asymmetries have to take a threshold cointegration form rules out asymmetries when the price series are stationary, or when they are nonstationary but not cointegrated. The theoretical justification for such a restrictive assumption is unclear.

A final difference between this paper and GH is that our dataset is taken entirely from the post-Livestock Mandatory Reporting Act regime. GH was published in 1999, and as a result, they used much older data in their analysis. In addition to the differences in methodology described above, a reassessment of their results using recent data is warranted.

Other studies dealing with asymmetric price transmission in the U.S. beef supply

[5] As Kilian and Vigfusson explain, "Thus, nonlinear impulse response functions must be computed for a given shock as the average of impulse response functions obtained using alternative initial conditions. This point is well known (see, e.g., Gallant et al., 1993; Koop et al., 1996) . . . "

chain are Boetel and Liu (2010), and Emmanouilides and Fousekis (2015). Boetel and Liu (2010) examined wholesale and retail price relationships by accounting for possible structural breaks in the data. Their results revealed the presence of asymmetric price responses in the beef market distribution chain. However, they worked with a reduced-form model, restricted the analysis to a threshold cointegration model, and conditioned on a specific history and set of future shocks when computing impulse response functions. Therefore, their findings are subject to the criticisms of Kilian and Vigfusson (2011). Emmanouilides and Fousekis (2015) used a statistical copula approach to assess the degree of price dependency along farm and wholesale, and wholesale and retail beef prices using data from 2000 to 2013. Their results provide evidence of positive asymmetric price transmissions, mainly between farm and wholesale prices, but they do not provide information about the magnitude of asymmetry, nor the speed of adjustment in the price transmission process, and their study was limited to performing hypothesis tests.

Frey and Manera (2007) and Meyer and von Cramon-Taubadel (2004) provide comprehensive surveys of the empirical literature on agricultural commodity price asymmetry, classifying and comparing heterogeneous studies in terms of econometric models employed, type of asymmetries tested and findings.

3 Methods

Our baseline model is a threshold vector error correction (TVEC) model. Let R_t, W_t and F_t be respectively the retail, wholesale, and farm prices of beef at time t. The structural form of our TVEC model can be written as:

$$
\begin{aligned}
\Delta R_t = a_{10} + I_t b_{11}^{+} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{+} \Delta R_{t-k} + \sum_{k=0}^{p} c_{13,k}^{+} \Delta W_{t-k} + \sum_{k=0}^{p} c_{14,k}^{+} \Delta F_{t-k} \\
+ (1 - I_t) b_{11}^{-} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{-} \Delta R_{t-k} + \sum_{k=0}^{p} c_{13,k}^{-} \Delta W_{t-k} + \sum_{k=0}^{p} c_{14,k}^{+} \Delta F_{t-k} + e_{1,t}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
\Delta W_t = a_{20} + I_t b_{21}^{+} ECT_{t-1} + \sum_{k=0}^{p} c_{22,k}^{+} \Delta R_{t-k} + \sum_{k=1}^{p} c_{23,k}^{+} \Delta W_{t-k} + \sum_{k=0}^{p} c_{24,k}^{+} \Delta F_{t-k} \\
+ (1 - I_t) b_{21}^{-} ECT_{t-1} + \sum_{k=0}^{p} c_{22,k}^{-} \Delta R_{t-k} + \sum_{k=1}^{p} c_{23,k}^{-} \Delta W_{t-k} + \sum_{k=0}^{p} c_{24,k}^{+} \Delta F_{t-k} + e_{2,t}
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
\Delta F_t = a_{30} + I_t b_{31}^{+} ECT_{t-1} + \sum_{k=0}^{p} c_{32,k}^{+} \Delta R_{t-k} + \sum_{k=0}^{p} c_{33,k}^{+} \Delta W_{t-k} + \sum_{k=1}^{p} c_{34,k}^{+} \Delta F_{t-k} + \\
(1 - I_t) b_{31}^{-} ECT_{t-1} + \sum_{k=0}^{p} c_{32,k}^{-} \Delta R_{t-k} + \sum_{k=0}^{p} c_{33,k}^{-} \Delta W_{t-k} + \sum_{k=1}^{p} c_{34,k}^{+} \Delta F_{t-k} + e_{3,t}
\end{aligned} \tag{3}
$$

where Δ is the difference operator; $ECT_{t-1} = R_{t-1} - \gamma_0 - \gamma_1 W_{t-1} - \gamma_2 F_{t-1}$ is the one-period lagged error correction term; the $c_{ij,k}^{+}$ apply when the corresponding variable is positive and the $c_{ij,k}^{-}$ apply when the corresponding variable is negative or less than zero, for equation $i = 1, 2, 3$, variable $j = 2, 3, 4$ and all $k = 0, \ldots, p$, where p is the chosen lag length of the VEC model.

$e_{1,t}$, $e_{2,t}$ and $e_{3,t}$ are uncorrelated structural shocks to the retail, wholesale, and farm beef markets, respectively. The structural TVEC model distinguishes between long-run 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 $c_{ij,k}^{+}$ and $c_{ij,k}^{-}$. The indicator function I_t is restricted as follows:

$$I_t = \begin{cases} 1 \text{ if } ECT_{t-1} > \tau \\ 0 \text{ if } ECT_{t-1} \leq \tau \end{cases} \tag{4}$$

where τ represents the threshold value estimated for the deviation from the long-run equilibrium, which is selected by minimizing the sum of squared errors, with a minimum of 15 percent of the observations in each regime.

We employ the Enders and Siklos (2001) test for threshold cointegration, which extends Engle and Granger's (1987) two-step estimation approach to include possibly asymmetric adjustment to equilibrium. The cointegration relationship between the three price series, each assumed to be integrated of order one, takes the form:

$$R_t = \gamma_0 + \gamma_1 W_t + \gamma_2 F_t + \varepsilon_t, \tag{5}$$

where ε_t measures the deviation from the equilibrium relationship between R_t, W_t and F_t. To allow for asymmetric adjustment dynamics, deviations from equilibrium are allowed to follow a threshold autoregressive process:

$$\varepsilon_t = I_{\varepsilon,t}\rho_1\varepsilon_{t-1} + (1 - I_{\varepsilon,t})\,\rho_2\varepsilon_{t-1} + \sum_{k=1}^{P} \delta_k \Delta\varepsilon_{t-k} + \mu_t, \tag{6}$$

where ρ_1 and ρ_2 are the speed of adjustment of $\Delta\varepsilon_t$, and the indicator function $I_{\varepsilon,t}$ has a similar specification as equation (4). Cointegration exists if $\rho_1 < 0$ and/or $\rho_2 < 0$, but as the test statistic has a nonstandard distribution due to the data-determined selection of τ, we use the t_{Max} and Φ tests. The t_{Max} statistic is the largest t-statistic associated with the estimated coefficients ρ_1 and ρ_2, and the Φ test is an F-test of the joint hypothesis $\rho_1 = \rho_2 = 0$. Simulated critical values for both test statistics are provided by Enders and Siklos (2001).

The presence of time t variables as regressors in the system (1)-(3) means there is an identification problem. One way to achieve identification would be to impose the assumption that the system is recursive, for example, that $c^{+}_{22,0} = c^{-}_{22,0} = c^{+}_{32,0} = c^{-}_{32,0} = c^{+}_{33,0} = c^{-}_{33,0} = 0$. That would be equivalent to identifying the system by imposing the assumption that the system is recursive. Unfortunately, it is hard to justify such an assumption *a priori*, given the frequency of our data and the information available to market participants.

To identify the system, we apply the heteroskedasticity-based estimator proposed in Rigobon (2003) and subsequently applied to gasoline markets in Bachmeier (2013). If there are at least two regimes for the variances of the structural shocks, the system is identified (Rigobon, 2003), and all parameters can be estimated by the generalized method of moments (GMM). The question is how to divide the data into regimes of high and low structural shock variances. We use historical volatilities corresponding to each price series to identify periods of low and high volatility.[6] Alternatively, we can rely on major market events such as the first case of bovine spongiform encephalopathy (BSE), also known as mad cow disease, reported in the U.S. in December 2003, to identify the regimes. The validity of the regime classification can be formally tested given the estimated structural shock variances.

Given estimates of the system (1)-(3), we test for symmetric responses to the structural shocks in two ways. The first approach is to test for equality of the coefficients in the two regimes using an F-test. A test for symmetric adjustment to deviations from the long run equilibrium is a test of $b^{+}_{i1} = b^{-}_{i1}$, while a test for symmetric short-run responses to price shocks is a test of $\sum_{k=k_0}^{p} c^{+}_{ij,k} = \sum_{k=k_0}^{p} c^{-}_{ij,k}$, where $k_0 = 0$ or 1, for each equation $i = 1, 2, 3$ and variable $j = 2, 3, 4$. A rejection of either hypothesis indicates asymmetry in price adjustment. The downside of testing for equality of coefficients is that a rejection of the null hypothesis of linearity does not provide any information about the speed of adjustment or the direction of asymmetry. The adjustment could be faster or slower after any particular shock. Further, it is possible to reject the null hypothesis of equal slope coefficients, yet still have a symmetric response to shocks at long horizons. That is, asymmetry in the coefficients

[6] Monthly historical volatility series are calculated using weekly prices.

at one horizon can offset asymmetry in the coefficients at a different horizon. Due to this limitation of coefficient tests, and to directly address the question of symmetry of responses to different price shocks, our second test for symmetry is to calculate impulse response functions by simulation following the approach outlined in Kilian and Vigfusson (2011).

The impulse response-based test is built on the observation that under the null hypothesis of a symmetric response function, the vector of responses to a positive price shock should be opposite in sign but of the same magnitude as the vector of responses to a negative price shock of the same size. Hence, we can test that all elements of the sum of these two vectors are zero. We compute impulse response functions by simulation using an algorithm similar to that in Kilian and Vigfusson (2011). For example, the algorithm used to estimate the response of the beef retail price to a farm price shock is:

1. Take a block of p consecutive values of ΔR_t, ΔW_t and ΔF_t, where p is the lag length of the structural TVEC model. This defines a history Ω^i.

2. Define e_0 to be the shock to the price that is of interest (in this case the shock to ΔF_t).

3. Define $e_{1,H}$ and $e_{2,H}$ to be vectors holding a draw of $H + 1$ values of the identified shocks to ΔR and ΔW, respectively, where H is the longest horizon for which impulse response functions are calculated.

4. Define $e_{3,H}$ to be a vector holding a draw of H values of the identified shocks to ΔF_t.

5. Predict the values of ΔR_{t+h}, ΔW_{t+h} and ΔF_{t+h} for periods $h = 0, \ldots, H$, conditional on Ω^i, e_{1H}, e_{2H} and $(e_0, e_{3H})'$, where e_0 is defined to be either a positive or negative one standard deviation shock to ΔF_t.

6. Predict the values of ΔR_{t+h}, ΔW_{t+h} and ΔF_{t+h} for periods $h = 0, \ldots, H$, conditional on Ω^i, e_{1H}, e_{2H}, and $(e_0, e_{3,H})'$, where $e_0 = 0$.

7. Calculate the difference in predicted values of the two variables from steps 5 and 6. This difference is the impulse response of retail price to a farm price shock of size e_0, conditional on Ω^i.

8. Steps 1-7 are repeated 1,000 times. The unconditional impulse response function is the average of the output from step 7 across the 1,000 simulations.

9. Perform a fixed-design wild bootstrap (Goncalves and Kilian, 2004) with 500 replications to calculate confidence intervals.[7] We use the Rademacher pick distribution as suggested by Godfrey (2009).

4 Data

Our empirical analysis utilizes monthly beef prices observed from January 2001 through December 2012 (144 observations), and to test for robustness, weekly beef prices observed from January 2007 through December 2012 (312 observations). Monthly and weekly 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 Economic Research Service (USDA-ERS) has available monthly retail beef prices reported by the BLS.[8] The BLS retail price used is the traditional simple-average retail price for all grades beef. All prices are in cents per pound.

A necessary condition for accurately assessing vertical market price asymmetry is that the data being analyzed are adequate (Bailey and Brorsen, 1989; von Cramon-Taubadel, 1998). For retail meat prices, concerns exist regarding the accuracy of traditional BLS data series (Lensing and Purcell, 2006). The omission of random-weight food items (BLS collects

[7]The wild bootstrap accounts for possible conditional heteroskedasticity of the error term.
[8]The BLS retail price for beef is only available on a monthly frequency.

only price data, but does not collect quantity data) and supercenter purchases, reflecting shifts in shopping patterns to lower-priced stores, causes a significant upward bias in price estimates. In addition, BLS data do not account for large volumes sold at discounted prices during retail specials (Lensing and Purcell, 2006). As a robustness check and to test whether the results are sensitive to the type of data used in the analysis of asymmetric price transmissions, we also estimate our structural TVEC model (system (1)-(3)) using scanner quantity-weighted retail prices. Scanner data are compiled by USDA-ERS and Freshlook and were obtained from the National Cattlemen's Beef Association. These prices are in both monthly and weekly frequency and also correspond to all grades of beef.[9] In total, three (trivariate) structural TVEC models are estimated using: monthly BLS, wholesale and farm prices; monthly scanner, wholesale and farm prices; and weekly scanner, wholesale and farm prices.

Figure 1 contains the plot of monthly BLS and scanner beef retail price series. There are apparent differences between the two price series. The mean of scanner prices for all grades of beef is 352.9 cents/lb. and the mean of BLS prices for all grades of beef is 375.2 cents/lb. According to the difference in means test, BLS prices are on average 6% higher than scanner prices (p-value < 0.01). In addition, a test of equality of variances indicates that the variance of detrended scanner prices (20.5) is larger than the variance of detrended BLS prices (14.4) (p-value < 0.01).

Unit root tests did not reject nonstationarity of any of the price series.[10] In addition, we conducted the Enders and Siklos's (2001) t_{Max} and Φ tests for threshold cointegration on each structural TVEC model to account for possible asymmetric adjustments to deviations from the long-run equilibrium (Table 1). This test was performed in two steps. First, equation (5) was estimated by OLS for each model. Then, equation (6) was estimated using the residuals from equation (5) and the specification of equation (4) where the value of τ was

[9] The scanner price data is only available beginning in January 2001 (monthly data) and January 2007 (weekly data), and was consistently collected until December 2012, thus limiting the period considered in this analysis.

[10] We used an ADF test with lag length chosen by the AIC.

set equal to zero ($TC1$) and different from zero ($TC2$), in which case the threshold value was estimated by grid search method as described in Chan (1993). Looking at the results in Table 1, we reject the null hypothesis of no cointegration at the 0.05 significance level in all cases, whether or not the threshold value is assumed to be zero. We conclude that there is a long-run equilibrium relationship characterized by asymmetric adjustment, and proceed with a structural TVEC model.

5 Results and Discussion

5.1 *Baseline Model*

Our baseline model is estimated using the natural logarithms of monthly retail BLS, wholesale and farm prices in first differences (*Monthly BLS*). We then check the robustness of our results by estimating two additional structural TVEC models, one using monthly scanner, wholesale and farm prices (*Monthly Scanner*), and the other using weekly scanner, wholesale and farm prices (*Weekly Scanner*). The data in both models are also expressed in natural logarithms and first differences.

Estimation of structural TVEC models using monthly data requires identification of contemporaneous effects.[11] We used the method proposed by Rigobon (2003), which exploits the heteroskedasticity of structural shocks. Two regimes, one of high volatility and one of low volatility, were identified using historical volatilities derived from each price series. First, a structural break test was conducted in the historical volatility series to find significant breaks and define the regime windows more precisely. We applied the Bai and Perron (2003) test because it allows us to identify multiple breaks. We allowed up to 5 breaks and used a trimming of at least 0.15, so each segment has a minimum of 15 observations. The best number of breaks was selected based on the Bayesian Information Criterion (BIC). Results from this

[11] Causality from farm to wholesale and retail markets using weekly data has been discussed in previous research (Goodwin and Holt, 1999).

test indicate the presence of one high volatility regime from February 2003 to June 2004, most likely caused by the BSE discovery. Thus, we define this period as the high volatility regime, and the remaining as the low volatility regime. Coefficients of contemporaneous effects and variances of structural shocks were estimated by GMM, with standard errors and confidence intervals computed using a fixed-design wild bootstrap (Goncalves and Kilian, 2004).

We reject the null hypothesis that the system is recursive with a causal direction from farm to wholesale to retail prices, as previously assumed in models estimated using weekly data.[12] Wholesale and farm prices affect retail prices contemporaneously, but not vice versa. Therefore, we set $c^{+}_{22,0} = c^{-}_{22,0} = 0$ and $c^{+}_{32,0} = c^{-}_{32,0} = 0$. We also find that farm and wholesale prices affect each other at time t. Because this is a bi-directional effect, the system cannot be estimated without further assumptions. Here, we assume that the contemporaneous effects of farm and wholesale prices on each other are symmetric by imposing the estimated values delivered by GMM, so that $c^{+}_{24,0} = c^{-}_{24,0} = 0.30$ and $c^{+}_{33,0} = c^{-}_{33,0} = 0.76$

The final step in the model specification stage is to impose thresholds. For the short run responses, we set the threshold to zero, so that price increases and decreases have different effects. For the long-run responses, we used two different specifications of equation (4), one where $\tau = 0$ and one where τ was estimated by grid search. Based on the Akaike information criterion (AIC), models estimated with a non-zero τ are preferred over models estimated with a value of τ equal to zero. Therefore, we based our analysis on models where the threshold value in equation (4) is different from zero. Furthermore, based on AIC and the evaluation of autocorrelation patterns, the models *Monthly BLS* and *Monthly Scanner* were estimated using four lags, and the model *Weekly Scanner* was estimated using six lags.

Table 2 presents parameter estimates of the equation for retail beef price series, given by (1), for both *Monthly BLS* and *Monthly Scanner* models.[13] T-values were calculated using Newey and West's (1987) HAC consistent standard errors when serial correlation was present

[12] GMM and wild bootstrap estimates are available upon request.

[13] Results from farm and wholesale models (equations 2 and 3), and those estimated using weekly data, are not presented but are available upon request.

in model residuals (i.e., *Monthly Scanner* model), and the cointegrating vector parameters were estimated using the Engle and Granger (1987) method to maintain consistency with the Enders and Siklos test.

The coefficients on the error correction term (ECT), which measure the immediate adjustment to the deviation from equilibrium, are negative and statistically significant in both equations. The coefficients on ECT indicate what portion of the disequilibrium is corrected from one period to the next. The adjustment to disequilibrium is several times larger in the *Monthly Scanner* model than in the *Monthly BLS* model. For example, b_{11}^{+}, which captures the response of retail price in the high deviation regime, is -0.162 for *Monthly BLS* and -0.558 for *Monthly Scanner*. This indicates that the immediate adjustment of scanner retail prices is almost 3.5 times faster than BLS retail prices after a given shock. In other words, retail beef scanner prices are much more responsive to deviations from equilibrium than are BLS retail prices. This is consistent with the notion that scanner prices are more reflective of the prices actually being paid at retail. Any further interpretation of the relationships at alternative market levels is best done by calculating impulse response functions rather than examining individual coefficient estimates.

5.2 *Slope-Based Tests for Asymmetry*

Table 3 presents the results from the slope-based test of symmetry applied to the parameter estimates of each equation in structural TVEC models estimated using the two types of data at different frequencies. The first column identifies the type of data used, followed below by the equation that is being tested. The second and third columns present results from the tests conducted on the short-run and long-run adjustments, respectively. There is evidence of long-run asymmetric price adjustment for only the *Monthly Scanner* retail price equation. These results indicate that beef prices along the vertical market chain adjust equally to positive and negative changes away from the long-run equilibrium, with one exception.

Regarding the short-run price adjustment, we fail to reject the null hypothesis of symmetry at the 0.05 significance level in the *Monthly Scanner* retail price equation. As noted above, while this test finds evidence of nonlinearity in one of the estimated equations, it does not provide information about the source of asymmetry (e.g., whether asymmetry is due to the farm or wholesale price adjustments, to its own shocks, or to more than one shock), the form that the asymmetry takes, or the speed of adjustment following positive and negative shocks to one of the variables in the model. The nonlinear impulse response function analysis proposed by Kilian and Vigfusson (2011) is able to provide a more meaningful summary of the estimated models.

5.3 *Impulse Response Functions*

The computed nonlinear impulse response functions are plotted in Figures 2-4. Each figure depicts cumulative responses to a one-standard deviation shock in farm, wholesale, or retail (BLS or scanner) prices. For example, in figure 2, the size of the initial farm price shock is 2.4% in the model estimated using BLS retail price data. Each row in figures 2-4 corresponds to one of the three structural TVEC models estimated. Since variables in each TVEC model are in log-differences, the "*pos-IRF*" and "*neg-IRF*" lines capture their percentage change after a positive and negative shock to a particular variable, respectively. In addition, the "*diff-IRF*" line is the summation of positive and negative *IRF*. The null hypothesis of symmetry is rejected if confidence intervals of "*diff-IRF*" do not contain 0. Therefore, our impulse response based test is based on the statistical significance of the "*diff-IRF*" line depicted in each plot. Confidence intervals are computed using the fixed-design wild bootstrap estimates, and are represented by the dashed lines.

From figures 2-4 we can obtain information related to both speed of adjustment and magnitude of price transmissions. Regarding speed of adjustment, plots in each figure indicate that price responses adjust as fast following positive or negative shocks, providing evidence that the speed of adjustment in price transmissions is fairly symmetric. However, it takes longer for the system to adjust to farm and wholesale price shocks, compared to shocks on retail prices. For example, it can take up to 10 months for wholesale and retail prices to adjust to farm price shocks (figure 2), whereas responses to retail market shocks are generally complete after 7 months (figure 4), suggesting that farm and wholesale price shocks have a longer effect in the beef supply chain.

Regarding the magnitude of price adjustments, we first focus on figure 2. We reject the null hypothesis of symmetry at the 0.05 significance level in one case. This case shows a negative asymmetric response in BLS retail prices during the first and second month after a shock to farm prices (first row, third plot). That is, after a 2.4% positive and negative shock to farm price, the net result is a decrease of 0.16% in BLS retail prices, two months after the shock. Economically, the magnitude of asymmetry is small compared to the size of the farm shock. Also, this result is not robust to other type or frequency of data. That is, both structural TVEC models estimated using monthly and weekly scanner data fail to reject the hypothesis of symmetry. This result shows evidence of how different types of data can lead to different conclusions about asymmetric price transmissions.

Figure 3 shows results from the impulse response based test following shocks to wholesale price. Farm, wholesale and retail prices show a statistically significant and positive asymmetric response to wholesale price shocks in the model using BLS retail price data (first row plots). Following a 2.7% increase and decrease in wholesale price, the net result is a 0.94% increase in wholesale prices, and a 1% increase in farm prices, three months after the shock. Contrary to previous research, this finding suggests that prices received by beef cattle producers adjust more fully to wholesale price increases than decreases. Moreover, four months after a wholesale shock, the net result is an increase of 0.42% in retail beef prices. This indicates that price increases at the retail level, caused by increases in wholesale prices, are transmitted more fully to consumers than price decreases. It also signals a relative advantage of retailers over meat packers and processors, because their gross margin tends to remain the same after a wholesale price increase, whereas it expands after a wholesale price decrease. It is not clear, however, whether the asymmetric behavior from wholesale to farm and from wholesale to retail markets is caused by inefficiencies in the price transmission process, or because of nonlinear price adjustments in the wholesale market. We will address this issue in the next section. Moreover, these results are not robust to either type or frequency of data.

Looking at price responses following shocks to retail price (figure 4), we fail to reject the null hypothesis of symmetry in all cases, except one. BLS retail prices react asymmetrically to own price shocks. That is, following a 0.9% positive and negative own-price shock, the net result is a 0.13% increase BLS retail price. This results, however, is not robust to either type or frequency of data.

Figures 2 and 3 also provide information regarding the responsiveness of scanner and BLS retail beef prices to changes in upstream prices. These figures show that monthly retail scanner prices are more responsive to farm and wholesale prices changes than monthly retail BLS prices. For example, figure 3 shows that after a 2.7% shock to wholesale prices, the maximum reaction in BLS retail prices is 1.3% increase or decrease depending on the sign of the shock (first row). However, scanner retail prices have a reaction of as large as 2% increase or decrease after the same shock (second row). This result provides more evidence in favor of scanner prices because it shows that they are more reflective of reality.

Table 4 summarizes the results from the impulse response-based test of symmetry in structural TVEC models. Interestingly, asymmetric responses along the beef market chain are only found in models that use BLS retail price data. In particular, retail prices respond asymmetrically to shocks in farm and wholesale prices, as well as own-price shocks. In addition, results obtained from models that use scanner retail price data are robust to the use of different data frequency (i.e., monthly and weekly). However, they are not consistent with results found using the slope-based test of symmetry (table 3). This finding corroborates Kilian and Vigfusson's (2011) argument suggesting that slope-based tests are misleading when the quantity of interest is the degree to which impulse response functions are asymmetric.

Since our findings differ from those found in the existing literature, an important question is whether it is because of the use of different methodologies, newer data, or a different type of data (scanner prices). To address this question, we applied our weekly model to the data set used by GH. GH found statistically significant, positive asymmetry in the wholesale market after a shock in farm prices using data from 1981 to 1998.[14] However, the magnitude of this asymmetry was economically small. Results of applying our model to their data reveal asymmetric price transmissions, consistent with their findings. Particularly, wholesale prices responded asymmetrically to shocks in farm prices in all horizons (up to 18 weeks after the shock).[15] However, the asymmetric responses we found were not as modest. Following a 2% positive and negative shocks to farm price, the net result is an average increase of 0.56% in wholesale prices. This assessment suggests that our results do not differ from GH because of methodology differences. Instead our differences in results rest on the use of more recent and/or different data. It is possible that the passage of the LMPR Act has improved the efficiency of beef markets in the U.S. However, a more detailed assessment would be needed to support such a claim. A more plausible explanation is that the scanner price data better reflect the prices consumers actually pay for beef.

5.4 *Counterfactual Analysis*

One objection to our failure to reject symmetry with the impulse response function-based tests is that those tests might have low power.[16] We have evaluated the relevance of this concern via a series of counterfactual exercises. Because our analysis reveals that scanner prices are likely to be more reflective of purchases at the retail level, we focus on the models

[14] Although GH did not use BLS data in their study, they found asymmetric price transmissions using weekly average retail prices collected by a private news service that were collected in a similar fashion to how the BLS data are collected (i.e., they were simple averages of listed prices, not volume-weighted prices).

[15] The null hypothesis of symmetry was rejected at the 0.1 significance level.

[16] We are not aware of any evidence to support that assertion, but test power is always a concern when one fails to reject the null hypothesis.

with scanner price data. The first counterfactual asks how the retail beef price would have behaved over our sample period if the retail price had responded symmetrically to all shocks. Specifically, we modified the estimated equation (1) to be symmetric:

$$\Delta R_t = a_{10} + b_{11} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k} \Delta R_{t-k} + \sum_{k=0}^{p} c_{13,k} \Delta W_{t-k} + \sum_{k=0}^{p} c_{14,k} \Delta F_{t-k} + e_{1,t}$$

We did this by transforming (1) in two ways:

- Case 1: Impose $b_{11} = \widehat{b}_{11}^{+}$, $c_{12,k} = \widehat{c}_{12,k}^{+}$, $c_{13,k} = \widehat{c}_{13,k}^{+}$, and $c_{14,k} = \widehat{c}_{14}^{+}$.
- Case 2: Impose $b_{11} = \widehat{b}_{11}^{-}$, $c_{12,k} = \widehat{c}_{12,k}^{-}$, $c_{13,k} = \widehat{c}_{13,k}^{-}$, and $c_{14,k} = \widehat{c}_{14}^{-}$.

The simulation was performed using the identified structural shocks together with the initial values of the retail, wholesale, and farm beef prices at the beginning of our sample. If price asymmetry hurts consumers, the simulated retail price series (which imposes symmetric responses) will be below the historical retail price series. The two price series can be seen in Figure 5. Although there are some differences in the two simulated price series, the general pattern is the same - the retail beef price would have been *higher* under symmetry. This indicates that to the extent that our tests are unable to detect asymmetry, any asymmetry that does exist has benefited consumers.

We repeated the exercise to see if farmers might be hurt by asymmetry. We imposed symmetry on equation (3), which has been identified by imposing $c_{33,0} = 0.76$:

$$\Delta F_t = a_{30} + b_{31} ECT_{t-1} + \sum_{k=1}^{p} c_{32,k} \Delta R_{t-k} + \sum_{k=0}^{p} c_{33,k} \Delta W_{t-k} + \sum_{k=1}^{p} c_{34,k} \Delta F_{t-k} + e_{3,t}$$

and symmetry is imposed as:

- Case 1: $b_{31} = \widehat{b}_{31}^{+}$, $c_{32,k} = \widehat{c}_{32,k}^{+}$, $c_{33,k} = \widehat{c}_{33,k}^{+}$, and $c_{34,k} = \widehat{c}_{34}^{+}$.
- Case 2: $b_{31} = \widehat{b}_{31}^{-}$, $c_{32,k} = \widehat{c}_{32,k}^{-}$, $c_{33,k} = \widehat{c}_{33,k}^{-}$, and $c_{34,k} = \widehat{c}_{34}^{-}$.

Similar to the retail case, the simulation was performed using the identified structural shocks together with the initial values of the retail, wholesale, and farm beef prices at the beginning of our sample. If price asymmetry hurts farmers, the simulated farm price series (which imposes symmetric responses) will be above the historical farm price series. Both simulated and actual price series can be seen in Figure 6. Here, we observe two different outcomes - the farm beef price would have been *lower* under case 1, which benefits farmers, and *higher* under case 2, which harms farmers. It is possible (based on the case 2 results) that there is a harmful form of asymmetry that the impulse-response based test is simply not able to detect.

To understand whether the observed nonlinearities in the wholesale price adjustment influence the behavior of farm prices, we treated the coefficients involving ΔW separately, resulting in four cases:

- Case 3: $c_{33,k} = \widehat{c}^{+}_{33,k}$.
- Case 4: $c_{33,k} = \widehat{c}^{-}_{33,k}$.
- Case 5: $b_{31} = \widehat{b}^{+}_{31}$, $c_{32,k} = \widehat{c}^{+}_{32,k}$, and $c_{34,k} = \widehat{c}^{+}_{34}$.
- Case 6: $b_{31} = \widehat{b}^{-}_{31}$, $c_{32,k} = \widehat{c}^{-}_{32,k}$, and $c_{34,k} = \widehat{c}^{-}_{34}$.

Figure 7 shows that the simulated farm price under symmetry is below the historical farm price when the wholesale price change coefficients are restricted to be symmetric (cases 3 and 4). However, when only the responses to retail and farm shocks are restricted to be symmetric, the simulated farm price is above the historical farm price (cases 5 and 6). Because this counterfactual analysis allows us to disentangle the total effect of each shock, we are able to confirm that positive asymmetry in the farm market is most likely caused by a nonlinear price adjustment at the wholesale market level. The impulse response-based test failed to show this result most likely because it accounts for the total effect when testing for asymmetry, and does not consider cases 1 and 2 separately, which appear to offset each other.

6 Conclusions

Price transmissions among farm, wholesale and retail U.S. beef markets have been a hotly debated topic for a long time. A sizable body of past research has found asymmetric price responses from upstream to downstream markets. A host of potential explanations including market power, information flows, inventory adjustments, menu costs, and empirical methodology employed have been suggested in the literature. We provide new results that update previous studies using more recent data, we add newly available and more appropriate scanner data to the retail price series evaluated, and we employ a methodology that is designed to allow analysis of this type of asymmetry. Using this novel approach based on the simulation of nonlinear impulse response functions, we test for asymmetric price transmissions in the U.S. beef supply chain.

In general, farm, wholesale, and retail vertical market prices respond symmetrically to price changes at each market level in models estimated using scanner retail price data. This result reveals an efficient market where price signals transmit vertically in a symmetric fashion up and down the beef value chain. This indicates that farm prices generally respond similarly to downstream market price increases and decreases, and consumer beef prices respond similarly symmetric to upstream price changes. However, we find evidence of asymmetry when models are estimated using BLS retail price series. By the way BLS retail price data are collected, they do not accurately reflect volume-weighted sales of beef products. Instead, BLS price data simply reflect posted shelf prices on beef products with limited adjustment for actual volumes of beef that is sold at each price level. In contrast, scanner data reflect volume-weighted prices paid for beef sold across retail UPC scanners. As such, scanner data reflect what consumers actually paid for retail beef products including feature prices which generate larger volume of store sales. Consistent with this is that scanner data beef prices are much more responsive than BLS prices to wholesale beef price changes. The implication is that farm-to-retail margins or the farmer's share of the retail beef dollar calculated using standard BLS retail beef prices are biased and unreliable barometers of farm-to-retail price relationships. This weakness strongly suggests that the use of scanner data for such comparisons would be more reflective of prices actually being paid at retail.

When we disentangle the total effect of a shock to each price series using counterfactual exercises, we find that farm prices tend to respond asymmetrically to wholesale price changes. Interestingly, the type of asymmetry found is positive, indicating that contrary to popular claims, feedlot owners benefit from price changes at the wholesale level. However, this effect is negligible, or cannot be captured by our impulse response-based test, because it is offset by farm price responses at retail and farm levels. Our preferred interpretation is simpler, with the relationship being symmetric, consistent with the hypothesis tests. The counterfactual analysis also suggests that the source of positive asymmetry at the farm level is caused by nonlinearities in the price adjustment of wholesale prices. Beef packers have flexibility to store beef in their coolers when short run wholesale prices decline and as such they can buffer wholesale beef price changes through adjustments to beef inventories. The inventory flexibility beef packers have is a probable explanation of the asymmetry observed in wholesale beef price responses to own price shocks.

Our results showing symmetric price responses in the U.S. beef market, contrast those obtained when applying our methodology to a period prior the passage of the LMPR Act. Perhaps the increased intensity of price reporting under the Act contributed to enhanced vertical market price transmission. However, a more profound assessment is needed to establish the level of causality of the Act on price transmissions, so this remains a question for future research.

The implication of our findings is that concerns voiced over the years about price asymmetry in the U.S. beef market and associated hypotheses regarding potential causes of previously found asymmetry appear less acute when the retail price data used in the empirical analysis is more reflective of actual consumer purchases.

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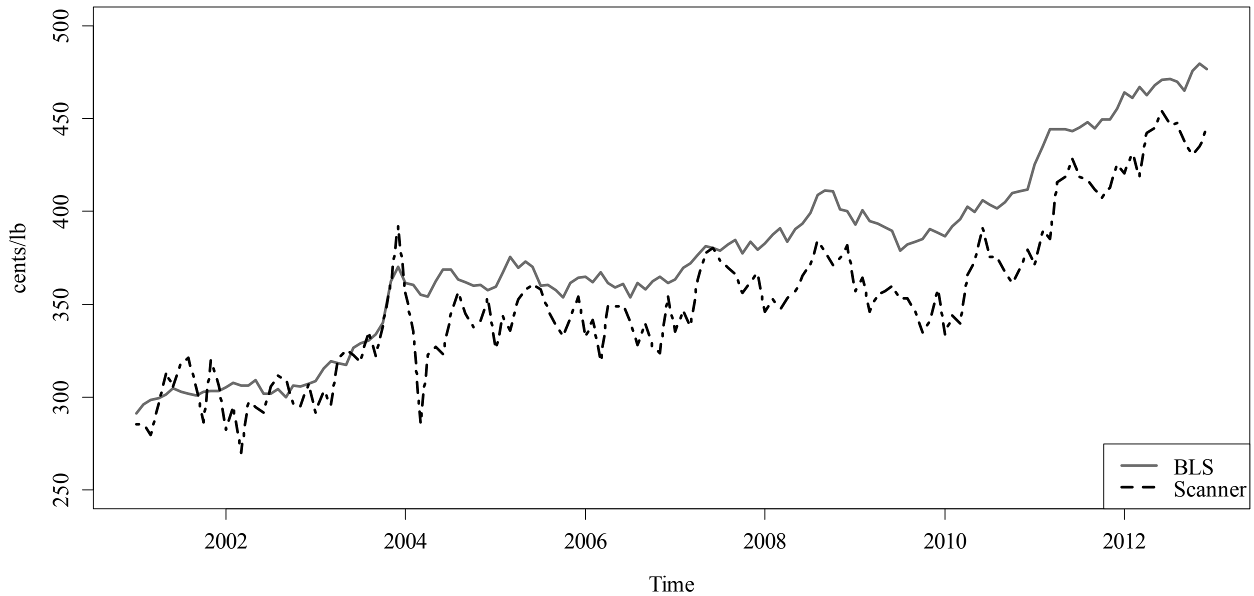


Figure 1. Monthly Retail BLS and Scanner Beef Prices, January 2001- December 2012

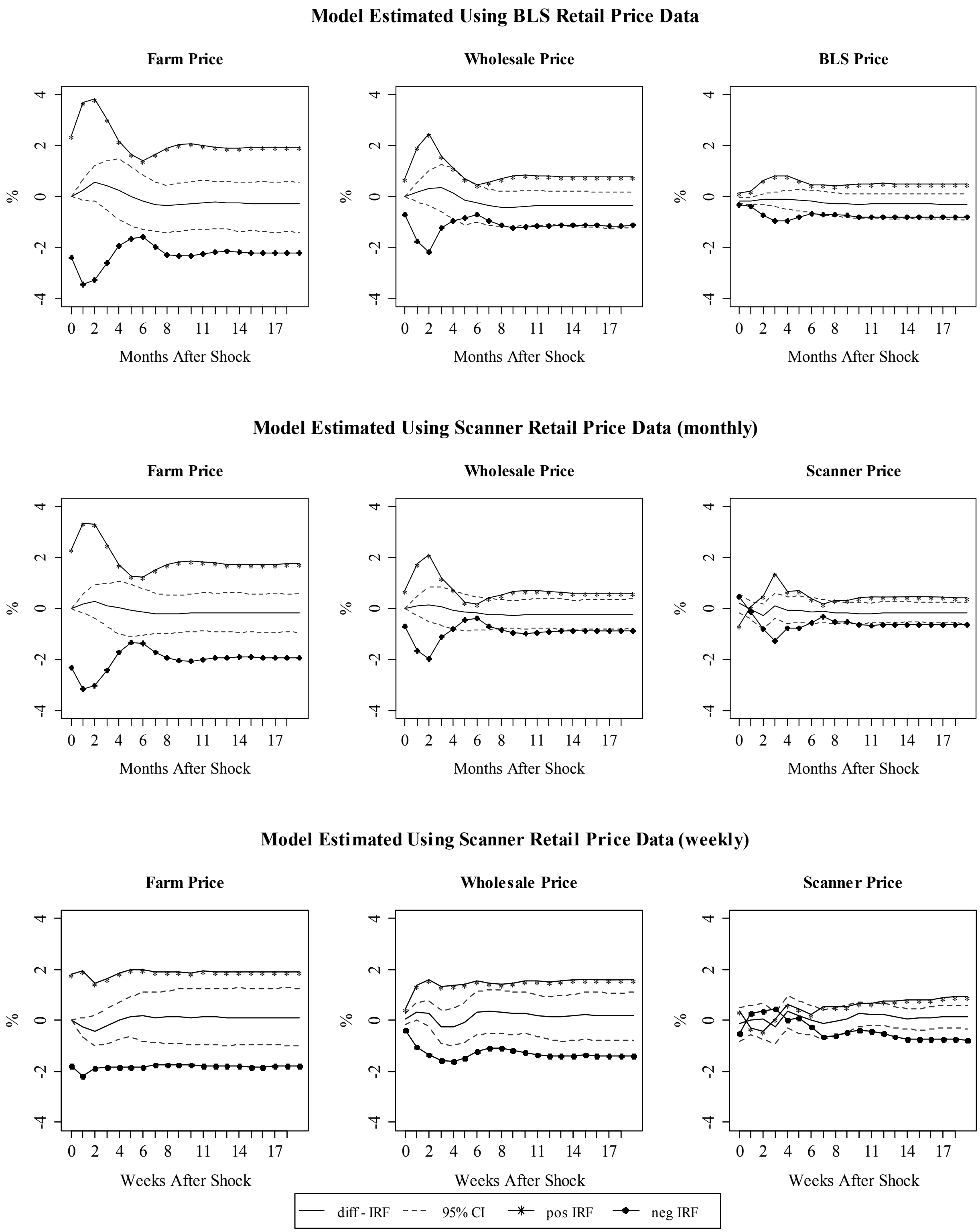


Figure 2. Cumulative Nonlinear Impulse Responses to Shock in Farm Price

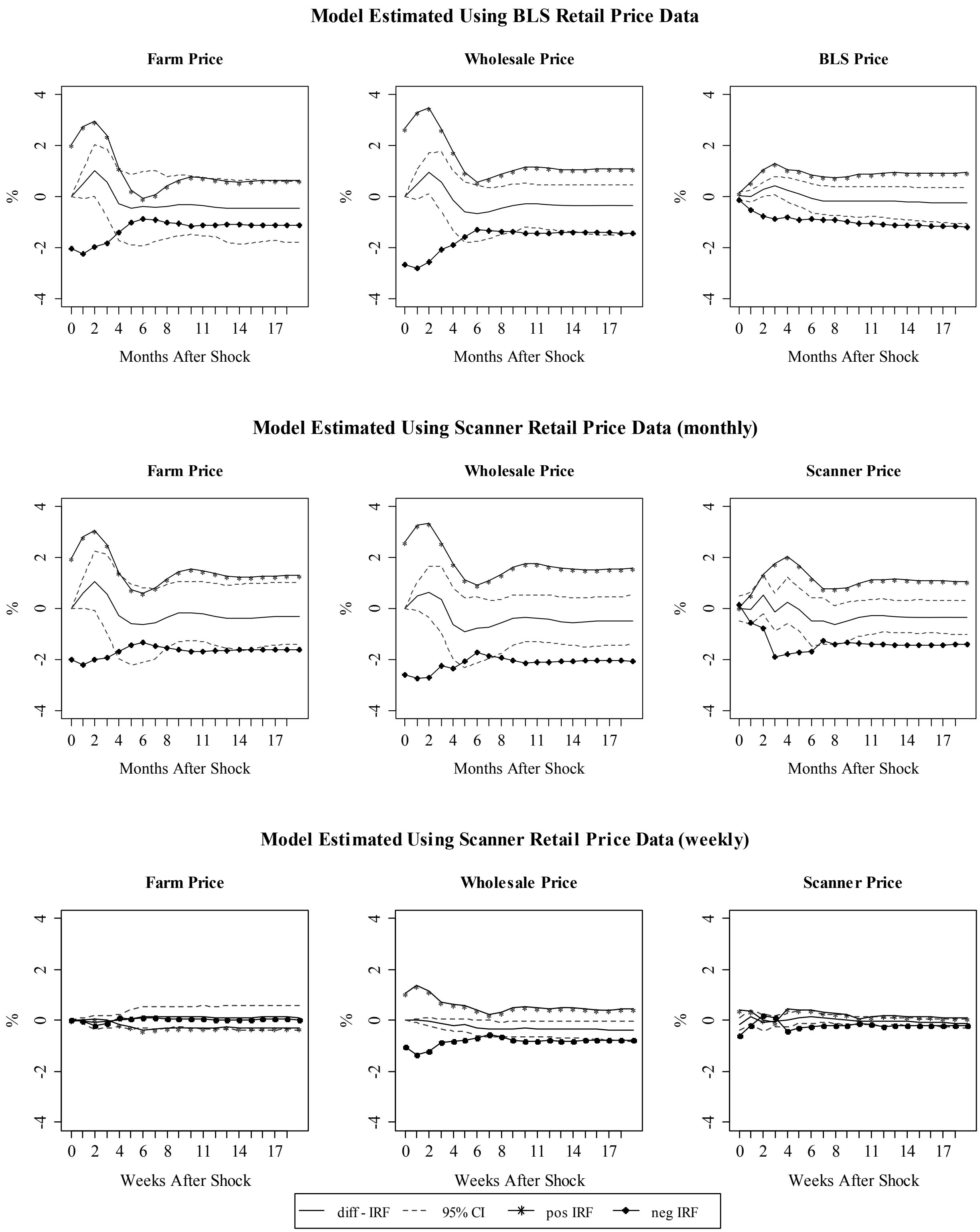


Figure 3. Cumulative Nonlinear Impulse Responses to Shock in Wholesale Price

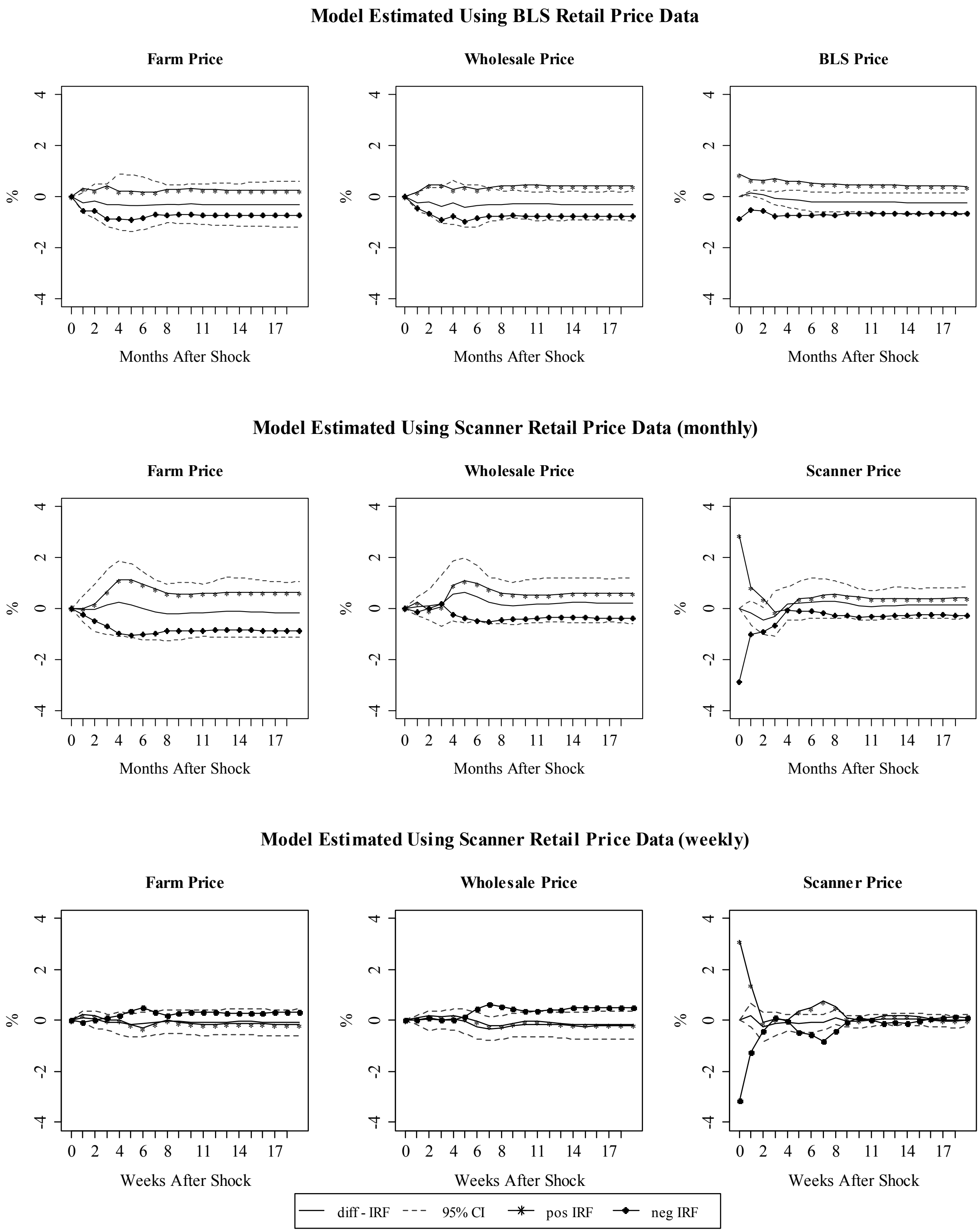
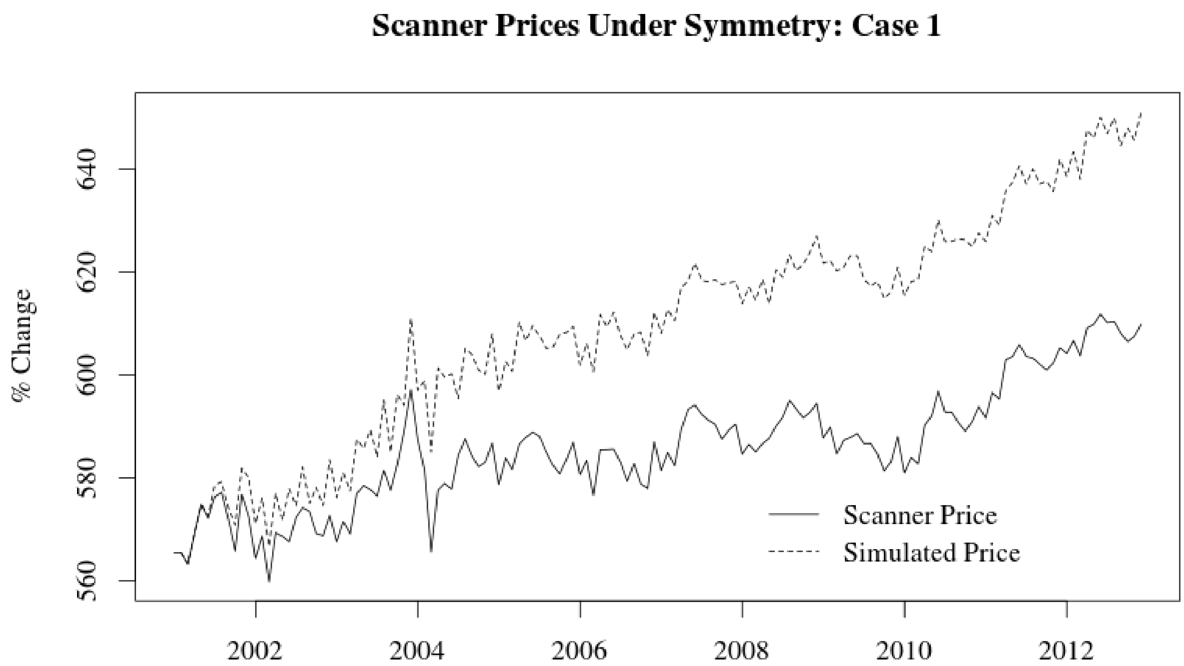


Figure 4. Cumulative Nonlinear Impulse Responses to Shock in Retail Price



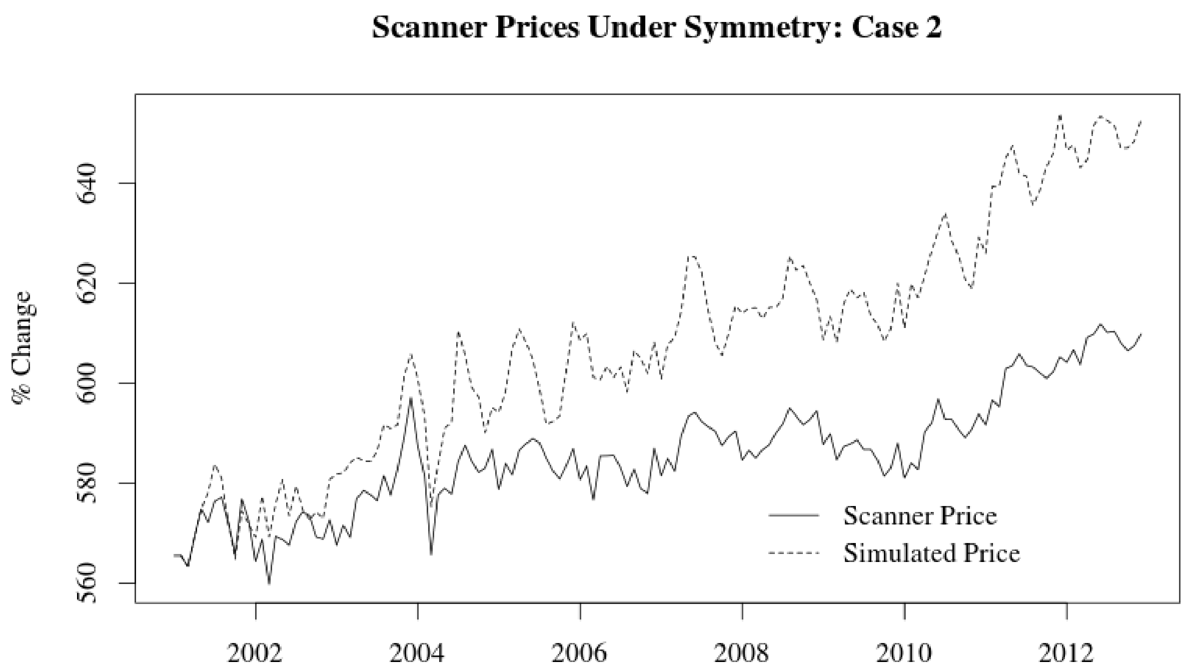


Figure 5. Scanner Prices Counterfactual Analysis

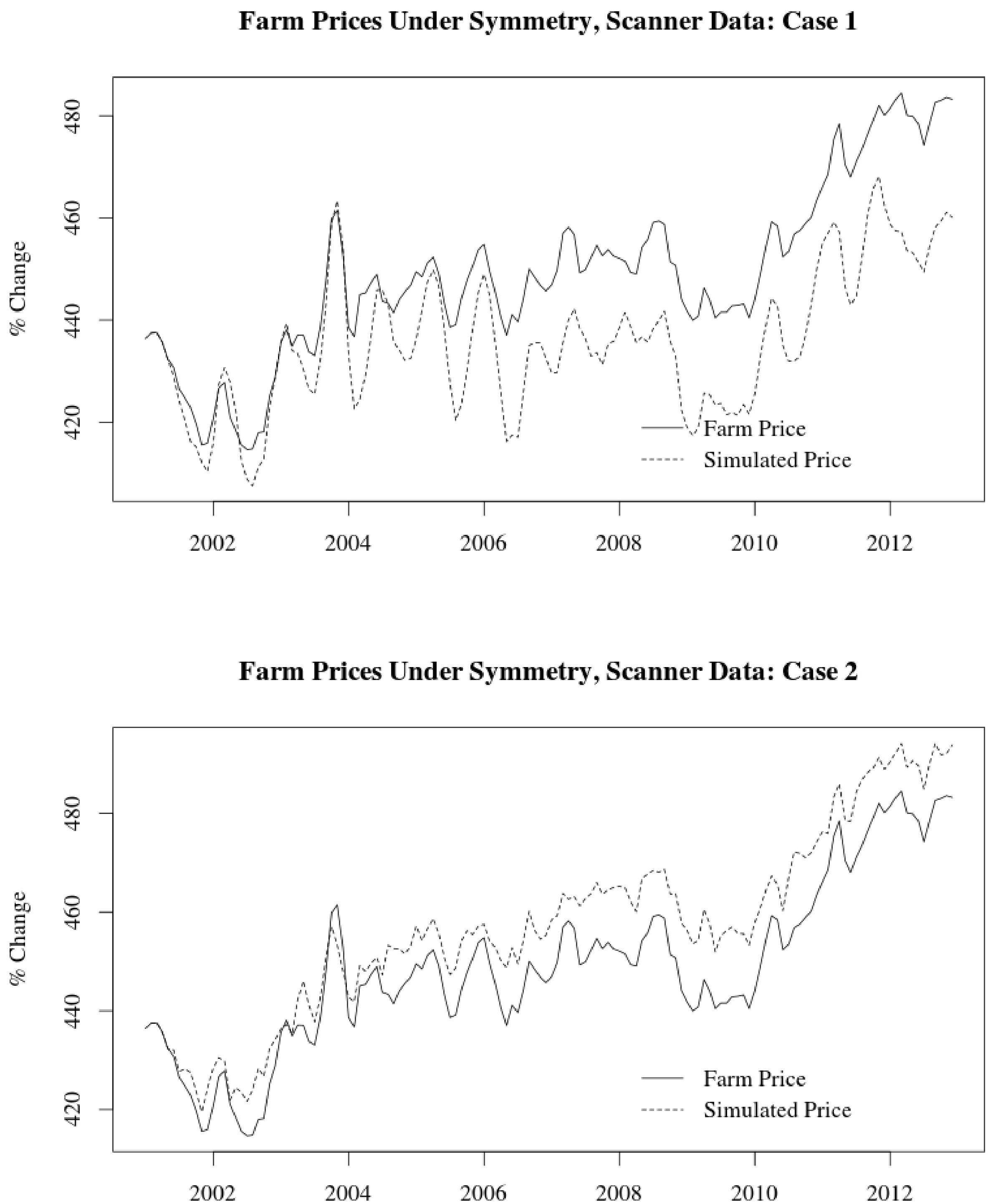


Figure 6. Farm Price Counterfactual Analysis – Symmetric Response to Farm, Retail and Wholesale Price Changes

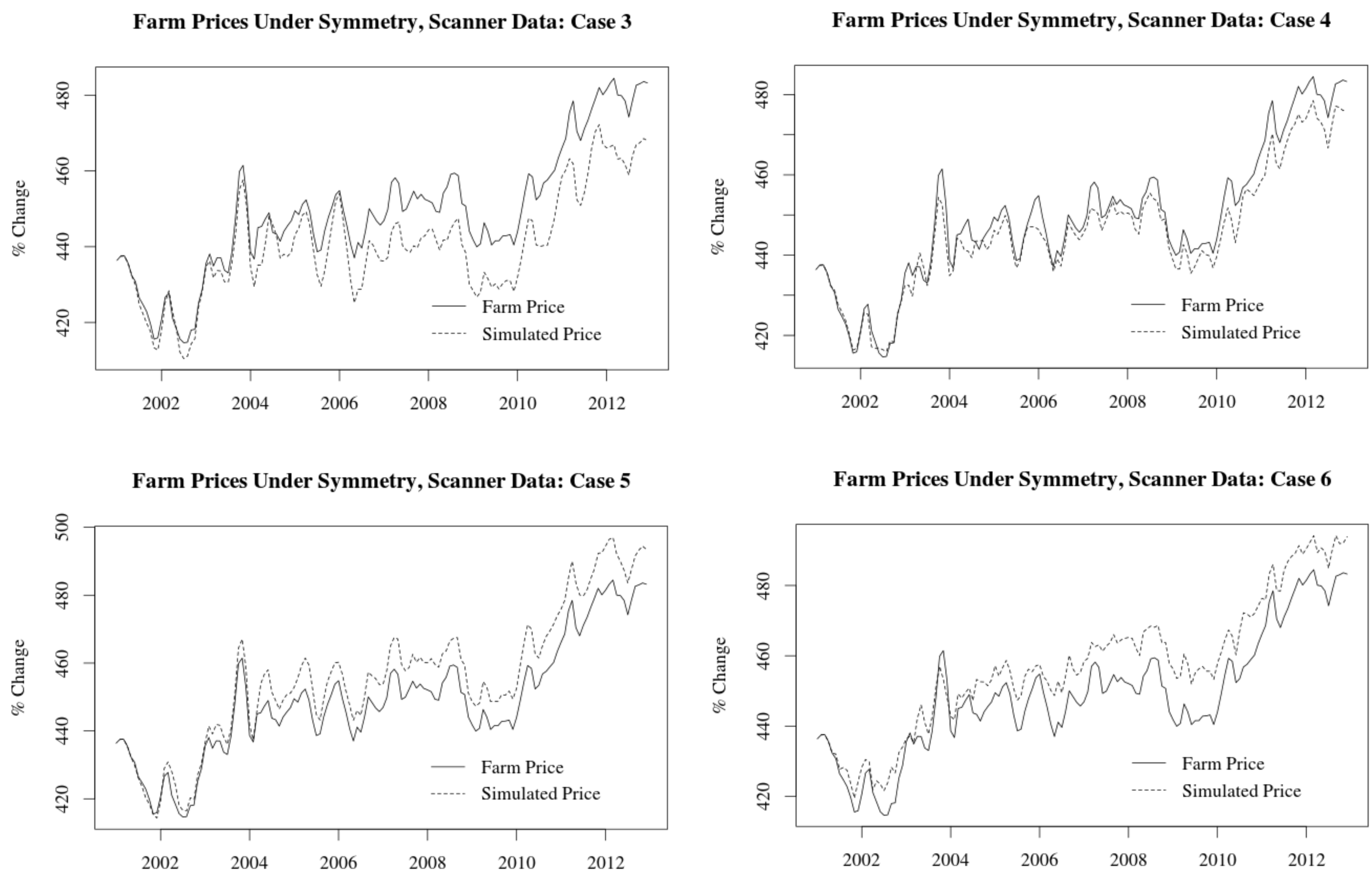


Figure 7. Farm Price Counterfactual Analysis

Table 1. Results from the Enders–Siklos (2001) Test for Threshold Cointegration (TC)

Relationship	**Cointegration Test-Statistics**				
	tMax	*C.V.*	Φ	*C.V.*	*threshold*
TC 1					
BLS-Wholesale-Farm	-3.62**	-2.14	14.57**	6.01	0
Scanner-Wholesale-Farm^a	-4.11**	-1.98	13.33**	6.28	0
Scanner-Wholesale-Farm^b	-3.19**	-1.91	9.83**	6.35	0
TC 2					
BLS-Wholesale-Farm	-3.89**	-1.90	14.96**	7.08	3.85
Scanner-Wholesale-Farm^a	-4.24**	-1.92	13.67**	7.41	-6.19
Scanner-Wholesale-Farm^b	-3.10**	-1.73	10.50**	7.56	4.05

Notes: The null hypothesis under test is no cointegration. Approximate critical values for the $tMax$ 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. (a) refers to monthly data, and (b) refers to weekly data.

Table 2. Estimation Results from Structural TVEC Models using Monthly Data (Retail Equation)

	Monthly BLS		**Monthly Scanner**	
Regressor	*Coefficient*	*T-Value*	*Coefficient*	*T-Value*
Constant	0.559**	2.036	2.332***	3.256
ECT^{+}_{t-1}	-0.162***	-3.461	-0.558***	-5.590
ECT^{-}_{t-1}	-0.114***	-3.008	-0.860***	-10.261
$\triangle PB^{+}_{t-1}$	0.005	0.036	-	-
$\triangle PB^{-}_{t-1}$	-0.612***	-3.450	-	-
$\triangle PB^{+}_{t-2}$	-0.016	-0.117	-	-
$\triangle PB^{-}_{t-2}$	-0.072	-0.380	-	-
$\triangle PB^{+}_{t-3}$	-0.081	-0.631	-	-
$\triangle PB^{-}_{t-3}$	0.266	1.456	-	-
$\triangle PB^{+}_{t-4}$	0.035	0.270	-	-
$\triangle PB^{-}_{t-4}$	-0.020	-0.115	-	-
$\triangle PS^{+}_{t-1}$	-	-	-0.239**	-2.064
$\triangle PS^{-}_{t-1}$	-	-	0.202*	1.697
$\triangle PS^{+}_{t-2}$	-	-	-0.037	-0.516
$\triangle PS^{-}_{t-2}$	-	-	0.228	1.300
$\triangle PS^{+}_{t-3}$	-	-	-0.178*	-1.920
$\triangle PS^{-}_{t-3}$	-	-	0.339***	2.626
$\triangle PS^{+}_{t-4}$	-	-	0.145	1.222
$\triangle PS^{-}_{t-4}$	-	-	-0.210*	-1.700
$\triangle PW^{+}_{t}$	0.036	0.512	0.367*	1.908
$\triangle PW^{-}_{t}$	-0.091	-1.010	0.051	0.194
$\triangle PW^{+}_{t-1}$	0.069	0.968	-0.340	-1.165
$\triangle PW^{-}_{t-1}$	0.014	0.148	-0.211	-0.869
$\triangle PW^{+}_{t-2}$	0.048	0.656	0.071	0.297
$\triangle PW^{-}_{t-2}$	-0.120	-1.268	-0.572**	-2.153
$\triangle PW^{+}_{t-3}$	0.060	0.841	-0.356*	-1.672
$\triangle PW^{-}_{t-3}$	-0.092	-1.022	0.303	1.210
$\triangle PW^{+}_{t-4}$	-0.139***	-1.988	0.224	1.504
$\triangle PW^{-}_{t-4}$	-0.108	-1.239	0.213	1.183
$\triangle PF^{+}_{t}$	-0.012	-0.176	-0.489***	-3.014
$\triangle PF^{-}_{t}$	0.241***	3.016	-0.110	-0.538
$\triangle PF^{+}_{t-1}$	-0.064	-0.933	0.144	0.730
$\triangle PF^{-}_{t-1}$	0.076	0.908	0.047	0.232
$\triangle PF^{+}_{t-2}$	0.117*	1.698	-0.134	-0.455
$\triangle PF^{-}_{t-2}$	0.141*	1.699	0.347	1.440
$\triangle PF^{+}_{t-3}$	-0.049	-0.730	0.270	1.568
$\triangle PF^{-}_{t-3}$	0.086	1.082	0.069	0.374
$\triangle PF^{+}_{t-4}$	0.049	0.722	-0.380***	-2.639
$\triangle PF^{-}_{t-4}$	0.169**	2.083	-0.331**	-2.156
Adj. R-squared	0.434		0.436	
Cointegrating Term (ECT_{t-1})				
Constant	167.890		241.345	
$\triangle PW_{t-1}$	0.970		0.686	
$\triangle PF_{t-1}$	-0.129		0.009	

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

Table 3. Results from the Slope-Based Test of Symmetry in Structural TVEC Models

Dependent Variable	Long Run Adjustment	Short Run Adjustment
	$H_0 : b_{i1}^{+} = b_{i1}^{-}$	H_0: $\sum_{k=1}^{p} c_{ij,k}^{+} = \sum_{k=1}^{p} c_{ij,k}^{-}$
Monthly BLS		
BLS	0.776 [0.380]	0.157 [0.693]
Wholesale	0.001 [0.992]	1.240 [0.268]
Farm	0.433 [0.512]	0.755 [0.387]
Monthly Scanner		
Scanner	12.754 [0.000]	7.918 [0.005]
Wholesale	0.979 [0.325]	0.450 [0.504]
Farm	0.074 [0.787]	0.006 [0.938]
Weekly Scanner		
Scanner	0.408 [0.523]	2.102 [0.148]
Wholesale	0.111 [0.739]	0.198 [0.656]
Farm	0.001 [0.983]	0.182 [0.669]

Notes: H_0 describes the respective null hypotheses under test. For the short-run adjustment, the null hypothesis corresponds to equation $i = 1, 2, 3$, variable $j = 2, 3, 4$, and all $k = 1, ..., p$, where p is the number of lags in the estimated structural TVEC model. Corresponding p-values for F tests are given in brackets.

Table 4. Descriptive Results from the Impulse Response Based Test of Symmetry in Structural TVEC Models

TVEC Model	**Asymmetric Price Response**		
Shock to Farm	***Farm***	***Wholesale***	***Retail***
Monthly BLS	none	none	negative
Monthly Scanner	none	none	none
Weekly Scanner	none	none	none
Shock to Wholesale	***Farm***	***Wholesale***	***Retail***
Monthly BLS	positive	positive	positive
Monthly Scanner	none	none	none
Weekly Scanner	none	none	none
Shock to Retail	***Farm***	***Wholesale***	***Retail***
Monthly BLS	none	none	positive
Monthly Scanner	none	none	none
Weekly Scanner	none	none	none