FORECASTING CATTLE PRICES IN THE PRESENCE OF STRUCTURAL CHANGE

Barry K. Goodwin

Abstract

Recent empirical research and developments in the cattle industry suggest several reasons to suspect structural change in economic relationships determining cattle prices. Standard forecasting models may ignore structural change and may produce biased and misleading forecasts. Vector autoregressive (VAR) models that allow parameters to vary with time are used to forecast quarterly cattle prices. The VAR procedures are flexible in that they allow the identification of structural change that begins at an *a priori* unknown point and occurs gradually. The results indicate that the lowest RMSE for out-of-sample forecasts of cattle prices is obtained using a gradually switching VAR model. However, differences between the gradually switching VAR model and a univariate ARIMA model are not strongly significant. Impulse response functions indicate that adjustments of cattle prices to new information have become faster in recent years.

Key words: cattle prices, multivariate gradual switching regressions, structural change, time-varying parameter models

A number of recent empirical investigations have used vector autoregression (VAR) models to forecast economic variables and furnish insights into dynamic relationships. A partial list of examples includes Sims, Featherstone and Baker, Orden, and Bessler and Babula. Vector autoregression models have been used to investigate livestock prices by several researchers, including Bessler, Bessler and Brandt, Brandt and Bessler, Bessler and Kling, and Babula, Bessler, and Schluter.

VAR models differ from standard econometric analyses of structural relationships in that they do not apply the usual exclusion restrictions to specify *a priori* which variables appear in which equations. Instead, a set of distributed lag equations is used to model each variable as a function of other variables in the structural system (Bessler). Such an approach reduces spurious *a priori* restrictions on the dynamic relationships (Sims). In the case of livestock prices, the implicit structural system should include variables that influence the interaction of livestock supply and demand conditions to yield an equilibrium price.

The assumption of structural stability in the unknown parameters of the underlying economic model is implicit in VAR models (Sims). In the event of a structural change in the underlying economic relationships, standard VAR models may produce biased forecasts and inaccurate inferences regarding dynamic relationships among the economic variables.

Recent empirical research and developments in the cattle industry suggest several reasons to suspect that there is structural change in economic relationships determining cattle prices. Significant changes in U.S. meat consumption patterns, geographic shifts in marketing patterns, changes in marketing practices, and structural changes in the beef packing and slaughter industry have occurred through the 1970s and 1980s, suggesting the potential for structural change in cattle price relationships.

The possibility of structural change, along with the finding that forecasting models have tended to systematically overpredict livestock prices during the 1980s (Conway et al.), has led researchers to consider less restrictive forecasting models that allow coefficients to vary over time. Conway et al. and Dixon and Martin made use of random coefficient models to provide flexible forecasts of prices and production and found an improvement in forecasting ability. However, this approach does not provide an explicit test, *per se*, for structural change and may provide limited insights into the exact nature of any such change.

The objective of this article was to forecast cattle prices and evaluate dynamic relationships in the cattle industry in the presence of structural change. A gradually switching VAR model that explicitly recognizes structural change was used to forecast cattle prices. Changes in dynamic relationships be-

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tween beef prices and relevant economic variables were considered, and implications for the precision of price forecasting were evaluated. The gradually switching VAR model offers advantages over standard tests for structural change (e.g., Chow tests) in that it does not require *a priori* specification of the timing of the change, and it allows the change to occur gradually.

ELEMENTS OF STRUCTURAL CHANGE IN THE BEEF INDUSTRY

The observation that significant changes have occurred in U.S. meat consumption patterns has led many researchers to consider the possibility of structural change in meat demand. A number of studies, including Choi and Sosin; Moschini and Meilke; Chavas; Nyankori and Miller; Thurman; Dahlgran; and Eales and Unnevehr, have concluded that significant structural changes have occurred in demand for meats.[1] Most studies finding structural change point to the mid-1970s as the period of demand shifts.

Figure 1 illustrates per-capita consumption patterns (boneless, trimmed equivalents) for beef, pork, and poultry and the poultry/beef price ratio. A decline in beef consumption is apparent from 1976 through 1990. Over the same period, poultry consumption rose at a fairly constant rate. The ratio of poultry to beef prices fell substantially between 1975 and 1980. This relative price effect may have contributed significantly to the observed consumption shifts as consumers substituted away from beef toward relatively less expensive poultry products. In 1990, poultry consumption was 63.6 pounds per capita and had nearly reached the level of beef consumption, 64.0 pounds per capita. Pork consumption has remained much more stable, realizing modest increases through the late 1970s and modest declines through the 1980s. Many point to increased health concerns regarding red meat consumption as a fundamental force affecting meat consumption changes.

In addition to the possibility of changes in beef demand relationships, significant changes in the structure of the cattle industry have occurred through the 1970s and 1980s. Paul has noted that the declining importance of terminal markets relative to direct markets has had significant effects on pricing relationships in the cattle industry. Regional shifts have also occurred in the cattle industry, with cattle marketing volumes rising significantly in the southwestern plains and falling substantially in the corn belt (USDA).[2] The expansion of electronic marketing systems in the 1980s (Bailey et al.) and increased use of cattle futures markets in the 1970s and 1980s (Paul) may also have altered cattle pricing relationships.[3] Finally, considerable changes have occurred in the structure of the livestock slaughter industry. Numerous buyouts and mergers significantly increased the concentration of the meatpacking industry through the 1970s and 1980s. Purcell (p. 1213) notes that demand changes provided an impetus for change and that previously profitable firms such as Wilson, Armour, and Swift became takeover targets for current industry giants such as IBP, Excel, and ConAgra. Figure 2 illustrates the four-firm concentration ratio for steer and heifer slaughter from 1972 to 1988. In 1976, the four largest firms accounted for 25.2 percent of steer and heifer slaughtering. By 1988, this figure had risen to almost 70 percent.

The effect of increased market concentration on the speed of price adjustment has received considerable attention in recent years. A number of papers, including Domberger (1979, 1982, 1983) and Kardasz and Stollery, have concluded that increased concentration of an industry causes faster price adjustments. The rationale for this effect was discussed by Stigler, who noted that firms in concentrated industries are more aware of the pricing practices of their rivals. However, a negative relationship between market concentration and the speed of price adjustment has been found in other research, including papers by Phlips; Dixon; and Bedrossian and Moschos. This negative relationship was justified on grounds that firms in highly concentrated industries have large irreversible investments that induce them to peg prices on long-term goals rather than respond to short-run market factors. In light of the conflicting conclusions offered by previous research, the effect of increased concentration of the meat industry on cattle price dynamics is uncertain.

In light of the observed changes in beef demand and supply relationships, it is important that the potential for structural change be recognized in forecasting models. It is of interest to consider whether

[1] Several studies have found structural stability in U.S. meat demands. A partial list includes Wohlgenant; Haidacher et al.; and Chalfant and Alston.

[2] For example, in 1970 Kansas accounted for 8.67 percent of the USDA's 13-State fed cattle marketings, while Iowa accounted for 20.74 percent. In 1989, Kansas' share had risen to 18.49 percent while Iowa's share had fallen to 7.73 percent (USDA).

[3] Paul (p. 62) noted that the number of month-end open poositions in futures contracts for choice steers rose from 18,000 contracts in 1971-1972 to over 79,000 contracts in 1986-1987.

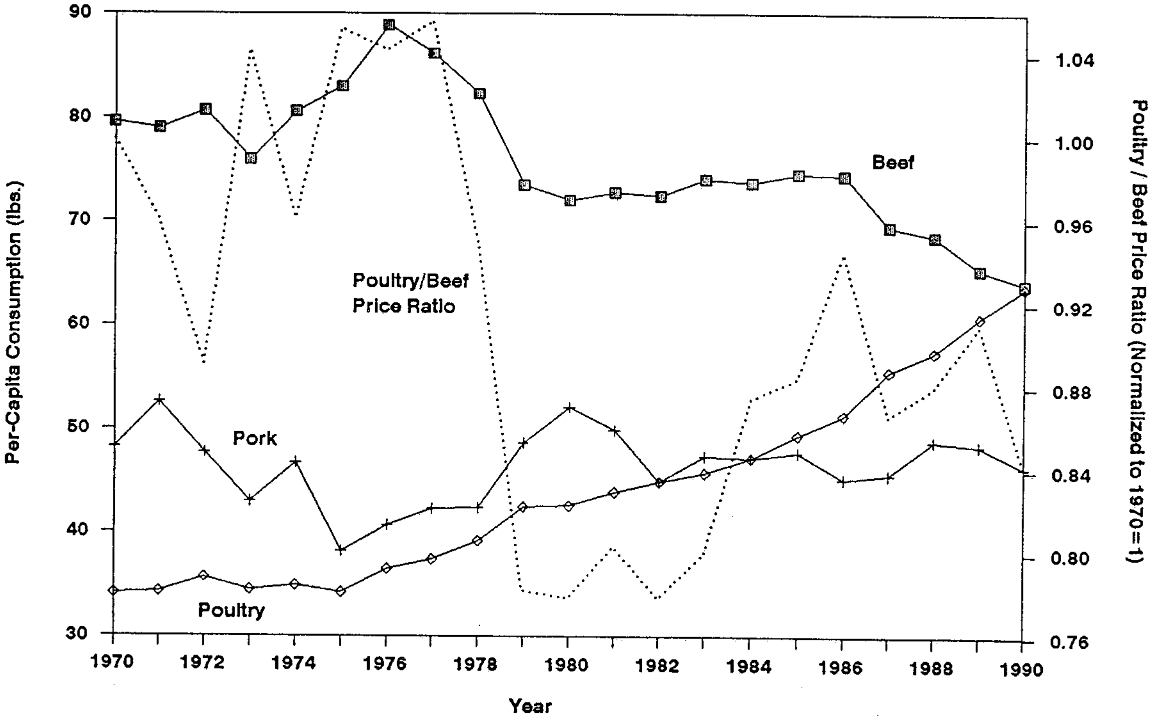

Figure 1. Per-Capita Meat Consumption and the Poultry/Beef Price Ratio (1970-1990)
Source: Putnam and Allshouse.

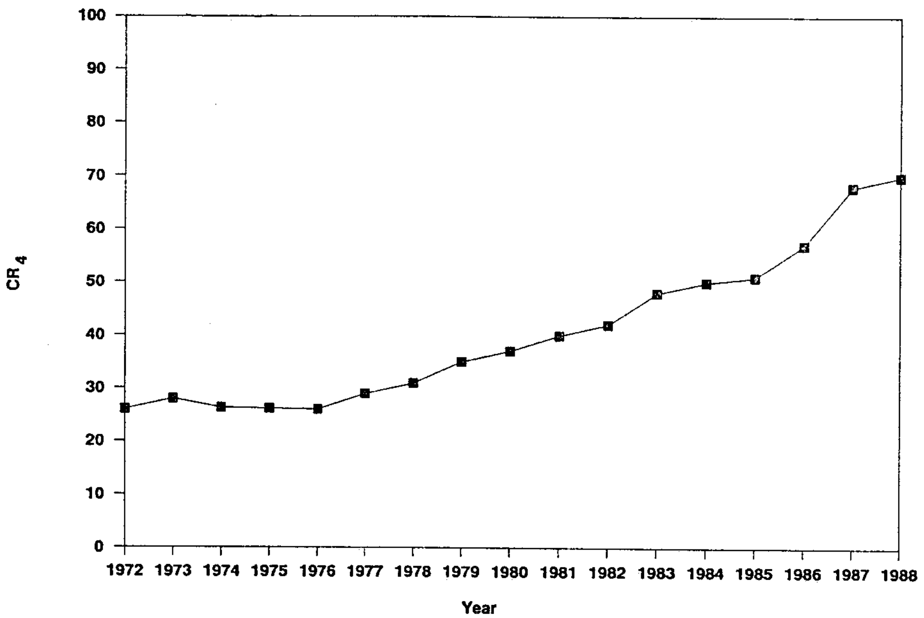

Figure 2. Four-Firm Concentration Ratio, Steer and Heifer Slaughter (1972-1988)
Source: Ward (1990).

market relationships relevant to the determination of the prices received by beef producers have undergone structural change. The speed of price adjustments and responsiveness to new market information are important factors characterizing the dynamic operation of a market that can be affected by structural change.

MODELS OF STRUCTURAL CHANGE

Many recent econometric studies of livestock markets have used vector autoregressions (VAR) to furnish insights into dynamic relationships and to provide forecasts of economic variables. This analysis modified the standard VAR modeling approach by considering two alternative VAR models that allow parameters to change in accordance with a changing economic environment. The first approach used the time-varying parameter VAR model of Wolff to allow parameters to drift according to a random walk. The time-varying parameter model has been used by Bessler and Kling in an evaluation of monthly slaughter and feeder cattle prices and by Kling and Bessler in a VAR model of money, prices, and output. Wolff; Bessler and Kling; and Kling and Bessler found that allowing time-variation in VAR parameters improved forecasting.

A second approach to modeling structural change in a VAR model was pursued in the context of multivariate gradual switching regressions. This approach detects and empirically incorporates gradual structural changes in a VAR system. This empirical approach offers advantages over standard tests for structural change in that it provides a flexible test for the presence of structural change in the underlying economic system while identifying the exact nature of the change in the parameters of the VAR model. Specifically, the procedures identify the timing of the change, while allowing the speed of adjustment between alternative regimes to be gradual. In contrast to the time-varying parameter approach, the gradual switching VAR model identifies an exact, structured path for parameter adjustment.

A VAR system for m time-ordered variables can be written as:

$$(1)\ Y(t) = \Phi\, Y(t\text{-}s) + \varepsilon(t)$$

where t refers to time (t = 1,...,T), Y(t) is an mT x 1 vector of economic variables, Φ, is an mk x mk matrix of parameters, and $\varepsilon(t)$ is a mT x 1 vector of random errors. The $\varepsilon(t)$ vector, representing white noise innovations, is assumed to obey the following conditions:

$$(2)\ E[\varepsilon(t)] = 0, \text{ and}$$

$$(3)\ E[\varepsilon(t)\varepsilon(s)'] = \begin{cases} 0 \text{ if } t \neq s \\ \Omega \text{ if } t = s. \end{cases}$$

In order to implement the VAR system, some technique for choosing the appropriate lag order (k) is required. A variety of techniques for choosing k is available. In the applications which follow, the minimum value of Schwartz's criterion is used to choose k (Lütkepohl).

Estimates of equation (1) can be used to provide out-of-sample forecasts. In addition, inferences regarding the dynamic adjustments to each of the variables in response to unexpected shocks to the series can be obtained by converting the system to an equivalent moving-average representation using Choleski decomposition:

$$(4)\ Y(t) = \varepsilon(t) + \Theta_1\, \varepsilon(t\text{-}1) + \Theta_2\, \varepsilon(t\text{-}2) + \ldots\ .$$

This conversion allows the VAR system to be used to forecast the time path responses to exogenous shocks to any one of the variables (Hakkio and Morris). These time path responses, referred to as impulse responses, may provide useful insights into dynamic relationships among interrelated economic variables.

In the event of structural change in the underlying structural model, the VAR forecasts and impulse responses may be biased and misleading. If such a change were suspected to be instantaneous, one might apply standard testing techniques, such as Chow tests, to determine the point of change and then confine the estimation to a period of stability. However, a more realistic consideration of structural change will not require that the point of change be specified *a priori* and will allow for gradual as well as instantaneous changes.

Wolff altered the basic VAR model to allow parameters to gradually drift according to a random walk through recursive estimation using the Kalman filter. Under Wolff's approach, the VAR model given by equation (1) is modified to allow for parameter drift:

$$(5)\ Y(t) = \Phi(t)\, Y(t\text{-}s) + \varepsilon(t),$$

where:

$$(6)\ \Phi(t+1) = \Phi(t) + v(t).$$

Under the time-varying parameter approach, it is assumed that $E_t[\Phi(t+1)] = \Phi(t)$, $E_t[\varepsilon(t)] = 0$, $E_t[v(t)] = 0$, $var[\varepsilon(t)] = R$, and $var[v(t)] = Q$. Error matrices $\varepsilon(t)$ and v(t) are assumed to be normally distributed. With prior knowledge of the values of $\Phi(t)$, R, and Q, the Kalman filter can be applied and the posterior mean and covariance matrix resursively computed for each observation, allowing the parameters to drift according to the prior distributions. However, prior knowledge of mean and covariance starting values for the Kalman filter is generally not available. Wolff recommended estimating the model over an early subset of the data and using the estimated parameters and covariance matrices from this sub-period as priors to start the Kalman filter. In this case, the period from 70.1 through 85.4 was used to obtain priors for the Kalman filter and for out-of-sample forecasts. The estimated parameter set from this sub-period and its estimated covariance matrix Σ, were used as priors. The squared standard errors of the estimates were used as inputs for R. A prior for the dispersion matrix Q was constructed from the covariance matrix Σ by assuming the proportionality relationship $Q = \lambda\Sigma$, where λ is a scalar.

An alternative approach for allowing parameter drift in a VAR model can be found in the gradual switching method developed by Tsurumi, Wago, and Ilmakunnas. The gradual switching method allows structural change to occur gradually. A structural change can be interpreted as a shift in the parameter matrices Φ, from one regime to another. In this application, this change was allowed to start at an unknown join point t^* and to occur at an unknown gradual rate of η.

The join point t^* and rate of adjustment η are treated as unknown parameters in a transition function, defined as $trn(s_t/\eta)$, where:

$$(7)\quad s_t = \begin{cases} 0 \text{ for } t \leq t^* \\ t - t^* \text{ otherwise}. \end{cases}$$

The use of transition functions to identify movements between alternative structural regimes was introduced by Bacon and Watts and has been applied recently by Tsurumi and Tsurumi, Wago, and Ilmakunnas. An appropriate transition function will satisfy the following conditions:

$$(8)\quad \lim_{s\to\infty} trn(s_t/\eta) = 1,$$

$$(9)\quad \lim_{\eta\to 0} trn(s_t/\eta) = 1, \text{ and}$$

$$(10)\quad trn(0) = 0.$$

Given an appropriate transition function, the gradually switching VAR system can be written as:

$$(11)\quad Y(t) = \Phi\, Y(t\text{-}s) + trn(s_t/\eta)\, \psi\, Y(t\text{-}s) + \varepsilon(t)$$

where ψ is an mk x mk matrix of parameters that transforms the Φ matrix to its post-shift values.[4] Equation (11) can be used to evaluate the stability of the VAR system. If the parameters of the transition function are found to be significant, structural change is implied, and the timing and the speed of the change are indicated by the transition function parameter values.[5]

EMPIRICAL PROCEDURES

The time-varying parameter VAR model requires an *a priori* choice for the factor used to scale the parameter covariance matrix in constructing a prior for the dispersion matrix Q. Following Wolff, a value of $\lambda = .01$ is used. As Kling and Bessler note, such an arbitrary choice is made under the assumption that the forecaster does not have future observations available for choosing an optimal value for λ.

Estimation of the gradual switching VAR model requires selecting a specific functional form for the transition function that satisfies the conditions given by equations (8) through (10). Many functional forms will satisfy these conditions, including probability distribution functions. In this analysis, the transition between alternative regimes was represented using the hyperbolic tangent function:[6]

$$(12)\quad trn(s_t/\eta) = (\exp(s_t/\eta) - \exp(-s_t/\eta)) / (\exp(s_t/\eta) + \exp(-s_t/\eta)).$$

Ashley, Granger, and Schmalensee (AGS) have developed formal procedures for testing the statistical significance of differences in out-of-sample forecasts from alternative models. To implement their procedure, e_t^1 is defined as the one-step ahead forecast error from the model with the lower RMSE and e_t^2 is defined as the one-step ahead forecast error from the alternative model. These variables are

[4] Note that it was assumed that the join point t* and the rate of adjustment η were the same for each equation in the VAR system. This assumption was followed on the grounds that the variables in the system were intimately related across equations through parametric restrictions that were implied by neoclassical demand and production theory. As an alternative, each of the m equations might be allowed to have a unique join point and rate of adjustment.

[5] As is the case with all parametric tests of structural change, the test is a joint test of structural change and the specification of the gradual switching VAR model. Stability might be implied in alternative dynamic structural models that incorporated specific elements of the changing structure of the cattle industry.

[6] Results contained in Tsurumi et al. indicated that empirical results obtained from the application of transition functions are not, in general, sensitive to the choice of functional form for the transition function.

combined to form the following linear combinations:

(13) $\Delta_t = e_t^2 - e_t^1$, for t = 1, ..., n, and

(14) $E_t = e_t^2 + e_t^1$, for t = 1, ..., n,

where n is the number of forecasts made to the end of the sample. The following regression is then estimated:

(15) $\Delta_t = \beta_0 + \beta_1[E_t - m(E_t)] + e_t$,

where $m(E_t)$ is the sample mean of E_t, for t = 1, ..., n, and e_t is a white noise residual. AGS showed that the parameter β_0 is the difference in the mean-square forecast errors between the two models and represents bias. Likewise, β_1 is proportional to the difference in forecast error variance between the two models (Bradshaw and Orden). A test for the significance of differences in mean-square forecast errors for the alternative models is based on the null hypothesis that $\beta_1 = \beta_2 = 0$, versus the alternative that $\beta_1 > 0$ and/or $\beta_2 > 0$. Rejection of the null hypothesis suggests a significant difference between the mean square errors of the two alternative forecasts.[7] In addition, the significance of differences in forecast bias and variance between alternative models may be considered by evaluating β_0 and β_1 independently.

RESULTS

The time varying parameter VAR model and the gradual switching VAR system were estimated with quarterly cattle market data covering the period from 1970 through 1990. Although attention was focused on cattle prices, five other variables were considered as relevant to the determination of cattle prices. These variables included prices for hogs and broilers, total cattle on feed, corn prices, and nominal disposable personal income. Cattle, hog, and poultry price variables were national average prices received by farmers. The cattle and hog prices and cattle on feed figures were collected from the USDA's *Livestock and Meat Statistics* series. The broiler prices were collected from the USDA's *U.S. Egg and Poultry Statistical Series.* Nominal disposable personal income was taken from selected issues of the U.S. Department of Commerce's *Business Conditions Digest.* Corn prices were collected from selected issues of the Commodity Research Bureau's *Commodity Yearbook* series.

The gradual switching VAR system of equations represented by (11) was estimated using iterative nonlinear regression.[8] The five year period, 1986 through 1990, was withheld for out-of-sample forecast evaluation of both models. A consideration of Schwartz's criterion for a standard VAR model revealed that a lag order of one was most appropriate for the cattle market data.[9]

The join point parameter t^* had an estimated value of 18.0152 with a corresponding t-ratio of 3.98. This corresponds to a significant structural change beginning in the first quarter of 1974. The speed of adjustment parameter η had an estimated value of 16.6477 with a corresponding t-ratio of 2.95, implying a rather gradual shift. In particular, this suggests that it took over 10 quarters, or until 1976.2, for 50 percent of the change to be complete. By the second quarter of 1980, the adjustment was 90 percent complete. The timing of the revealed structural change coincides with the results of Choi and Sosin, who found a gradual structural change in meat demands that began in 1974. The path of adjustment between alternative regimes implied by the estimated transition function parameters is illustrated in Figure 3.[10]

The significance of the estimated join point and speed of adjustment parameter confirm the presence of a gradually occurring structural change among

[7] Detailed applications of the AGS test were presented by Bessler and Brandt and Bradshaw and Orden. A usual F-test may be applied if both coefficients are positive. If either coefficient is significantly negative, it cannot be concluded that the lower RMSE model provides significantly superior forecasts. If one coefficient is negative, but not significant, a one-tailed t-test can be applied. Bessler and Brandt noted that the F-test is four-tailed because it does not take the signs of the coefficients into consideration. Finally, if the sample mean of any of the series is negative, the entire series must be multiplied by -1 before running the tests.

[8] Starting values for the VAR parameters were obtained by splitting the data into halves and running standard VAR models. Starting values for the join point were obtained from an iterative search for the discrete join point which minimized the VAR system's sum of squared errors. Estimation was accomplished using the Gauss-Newton algorithm of SYSNLIN procedure of SAS.

[9] Lutkepohl suggested that Schwartz's criterion chooses the correct lag order more often and produces better forecasts than other criteria and thus recommended its use. Schwartz's criterion had values of 44.23,34.00, 35.28., 36.03, 36.42, and 36.63 for lag orders of k = 0, ..., 5.

[10] Alternative procedures for the identification of structural shifts include the cumulative sum (CUMSUM) test of recursive residuals (Brown et al.) and Chow tests. An evaluation of the CUMSUM and Chow tests confirmed a very significant break between regimes for the cattle price equation at the first quarter of 1974. CUMSUM and Chow tests for structural change are subject to several weaknesses that were discussed by Swamy, Conway, and LeBlanc. Details regarding these tests are available on request.

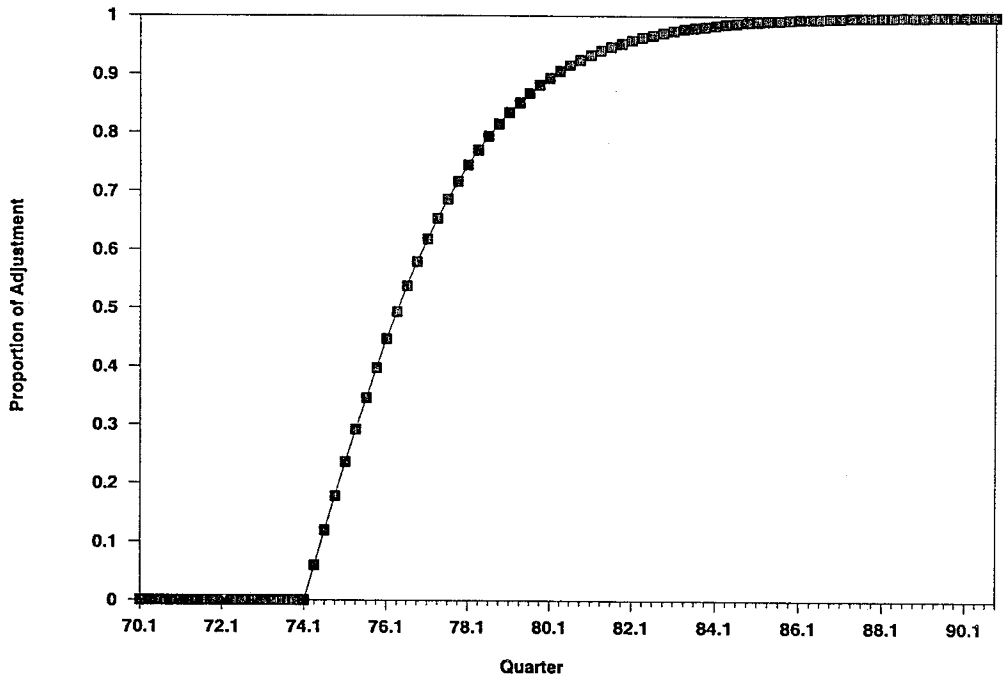

Figure 3. Adjustment Path Between Regimes

economic relationships in the beef industry. The presence of this change may have important implications for the suitability of standard VAR and univariate models for forecasting. The failure to recognize such change may induce important specification biases in the estimation of such forecasting models and thus may produce misleading forecasts and inferences.

The time-varying parameter VAR model was initially estimated using standard ordinary least squares regression techniques for data covering the period from 1970 to 1985. These estimates were used to calculate priors for the mean and covariance matrices. Kalman filtering techniques were then utilized to recursively calculate the posterior mean and covariance matrices and to provide out-of-sample forecasts.

In order to formally evaluate the forecasting performance of the time-varying parameter VAR and the gradual switching VAR, out-of-sample forecasts of cattle prices for the 20 quarters covering 1986 through 1990 were generated. Forecasts were also generated from a standard univariate ARIMA model for comparison. Brandt and Bessler and Nerlov et al. have concluded that univariate time series models produce forecasts which are superior to those obtained from multivariate VAR models. An evaluation of autocorrelation functions suggested that cattle prices could be modeled in a univariate context as a restricted sixth order moving average process, using first-differenced prices. The estimated model (asymptotic standard errors in parentheses) was:

$$(16)\ P_t = P_{t-1} + \underset{(.0615)}{.5687} + \underset{(.1141)}{.5674}\,\varepsilon_{t-5} + \underset{(.1193)}{.4326}\,\varepsilon_{t-6}$$

with a Ljung-Box Q(24) value of 24.17, which does not reject the null hypothesis of white noise residuals at the .01 level.

Table 1 contains actual cattle prices and forecasts and summary statistics for each of the alternative forecasting models. The one-period-ahead forecasts were generated using the Kalman filter, updating the models as each new observation was added. In general, the alternative forecasting models compare favorably in terms of out-of-sample RMSEs. The switching VAR model has the lowest out-of-sample forecast RMSE, followed by the univariate model, and finally by the time-varying parameter model. However, the RMSEs from the alternative models are quite close together and thus no estimation approach seems to clearly dominate the others. In general, the gradual switching VAR model tended to overpredict prices while the univariate and time-varying parameter models tended to underpredict prices.

Table 2 contains testing results for the significance of forecasting differences for the alternative models. In general, the significance of differences in forecasts are about .15. The univariate model's forecasts are significantly different from those obtained from

Table 1. Out-of-Sample Forecasts for Quarterly Cattle Prices (dollars per hundredweight)

Date	Actual Prices	Time Varying Parameter VAR Forecasts	Switching VAR Forecasts	Univariate ARIMA Forecasts
86.1	52.87	56.31	53.94	54.83
86.2	50.47	55.37	54.45	54.88
86.3	53.97	52.67	50.86	53.32
86.4	54.07	59.15	56.20	59.43
87.1	58.13	57.25	55.25	55.45
87.2	62.70	61.55	60.65	58.01
87.3	62.23	65.90	63.96	66.07
87.4	62.27	65.41	63.09	64.06
88.1	67.03	64.23	63.62	64.93
88.2	67.77	69.00	69.35	68.73
88.3	65.43	69.04	69.11	64.66
88.4	66.97	65.40	65.26	65.74
89.1	71.37	67.17	67.51	70.21
89.2	68.80	71.94	72.18	71.80
89.3	68.63	69.24	69.32	68.80
89.4	69.83	69.27	68.09	69.12
90.1	74.17	70.96	69.96	69.51
90.2	74.47	75.42	74.88	73.77
90.3	74.90	75.34	73.55	75.95
90.4	75.63	75.88	74.54	76.63
Root Mean Squared Error		2.7692	2.5600	2.6658

the time-varying parameter VAR model at the .1 level. The results also imply significantly lower forecast bias for the univariate model relative to the time-varying VAR model. In all, despite the observed differences in out-of-sample forecast RMSEs, formal testing does not suggest statistically different forecast RMSEs between the alternative models.

Figure 4 presents the cattle price impulse responses brought about by shocks of one standard deviation to each of the variables for the two structural regimes identified by the gradually switching VAR model.[11] Panel A contains the responses calculated in the pre-shift regime (1970.1 through 1973.4). Panel B contains the responses in the post-shift regime. In general, the direction of the shocks agrees with expectations. However, an exception exists for the negative effect of higher corn prices in both of the regimes. An analogous negative effect of higher corn prices on broiler prices was revealed by Babula, Bessler, and Schluter. Significant differences in dynamic relationships for cattle prices are apparent between the alternative regimes. Adjustments to shocks to the exogenous variables appear faster and of smaller magnitudes in the second regime. In the first regime, such adjustments appear to be spread over the 12 quarters that follow the shocks, and responses lie in the range of +/- $3 per hundredweight. However, in the second regime, with the exception of shocks to cattle prices themselves, the adjustments are of much smaller magnitudes and appear to be complete after just two or three quarters. This result suggests greater exogeneity and faster adjustment of cattle prices in the second regime.

Table 2. Ashley-Granger-Schmalensee (AGS) Tests for Significance of Forecast MSE Differences[a]

			Significance Levels[b]		
Comparison	β_0	β_1	H_0: $\beta_0 = \beta_1 = 0$	H_0: $\beta_0 = 0$	H_0: $\beta_1 = 0$
Gradual Switching VAR vs. Time-Varying VAR	.0950 (1.2533)[c]	.8735 (1.0696)	.1691	.2351	.1062
Gradual Switching VAR vs. Univariate ARIMA	-.1500 (1.1514)	.2297 (.3603)	.1807	—	.1807
Univariate ARIMA vs. Time-Varying VAR	.5308 (.3729)	.0028 (.0737)	.0955	.0428	.2425

[a]AGS tests are obtained from regression estimates of: $\Delta_t = \beta_0 + \beta_1 [E_t - \bar{E}_t] - e_t$, where Δ_t is the difference between forecast errors, E_t is the sum of the forecast errors, $\bar{E}_t$ is the sample mean of E_t, and e_t is a white noise residual.
[b]Significance levels are for the appropriate four-tailed F-test.
[c]Standard errors in parentheses.

[11]The impulse responses are not invariant with respect to the ordering of the variables in the VAR system. These responses were calculated from the following ordering of variables: income, cattle on feed, hog price, poultry price, corn price, and cattle price. This ordering was suggested by causal relationships implied by Granger-type causality tests. Very similar responses were yielded by alternative orderings. Causality testing results and responses for alternative orderings and for those variables that are not presented here are available from the author upon request.

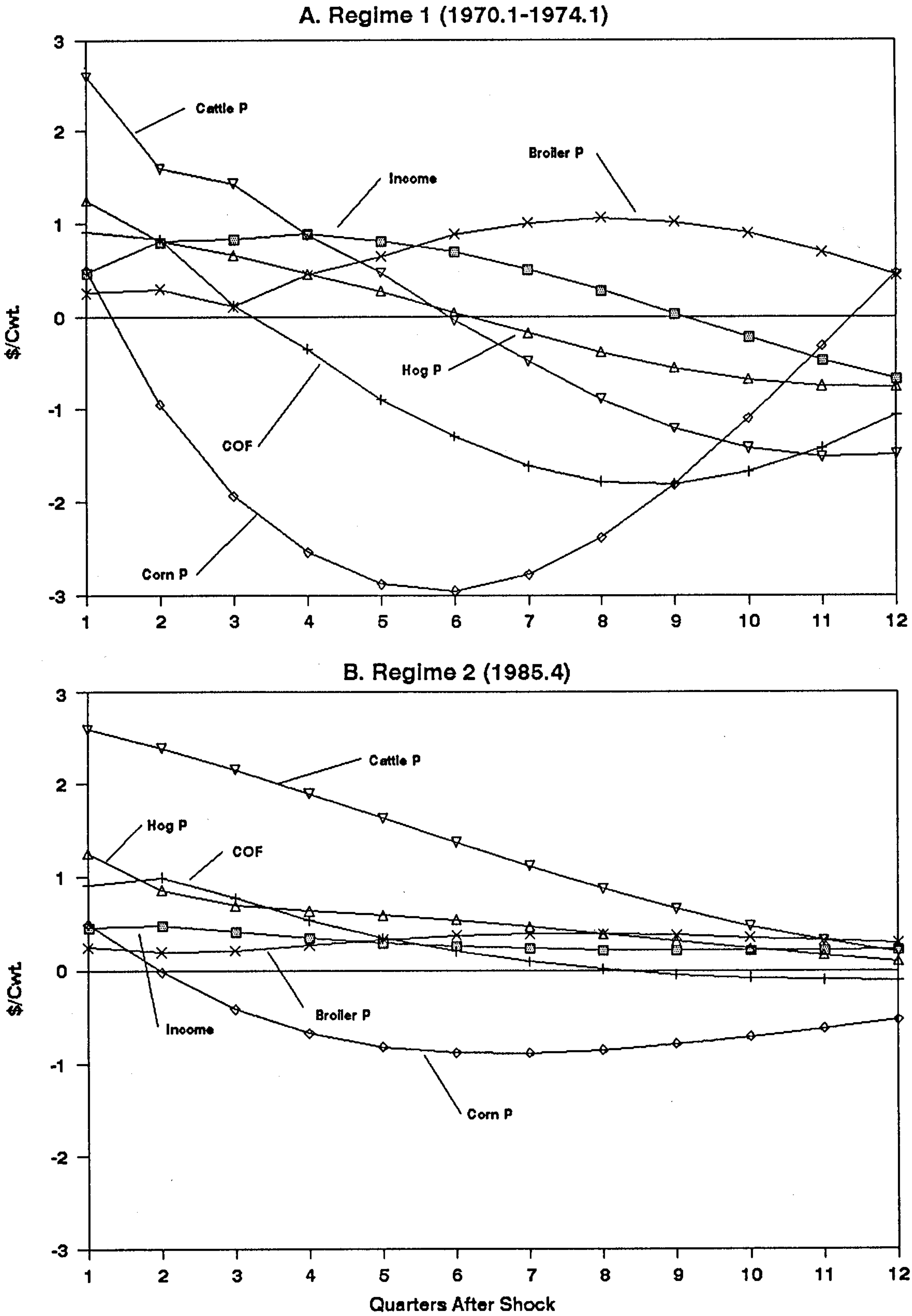

Figure 4. Impulse Response Functions from Gradually Switching VAR Model: Cattle Price Responses to a One-Standard-Deviation Shock to Each Series

Such a result is consistent with recent findings that cross-price elasticities between beef and poultry and income elasticities for beef have fallen in recent years (Goodwin; Chavas; Moschini and Meilke). The impulse responses indicating faster adjustment and lower volatility of beef prices in response to exogenous shocks coincides with the results of Goodwin and Schroeder that suggested that cattle price adjustments across regions have become significantly faster in recent years.

CONCLUDING REMARKS

This analysis utilized a time-varying parameter VAR model and a gradual switching VAR model to empirically incorporate gradual structural change in a forecasting model of cattle prices. The empirical results confirm the existence of a significant structural change. This structural change was of a gradual nature, beginning in 1974 and lasting through the early 1980s. Cattle prices became more exogenous and adjusted faster to shocks after the structural change. The timing of this change corresponds to the results of other studies that have found shifting demand relationships for beef in the mid-1970s. The change also parallels the gradually increasing concentration of the livestock industry and other changes in cattle production and marketing conditions.[12] In addition, significant macroeconomic shocks were realized in the U.S. in the 1970s. These shocks may have also affected cattle price adjustments.

An analysis of out-of-sample forecasting by the alternative models suggests that incorporating structural change in forecasting models may offer some advantages. The VAR models that allow for parameter drift provided forecasts that were similar to those obtained from a univariate model of cattle prices. Differences in forecasting ability of the alternative models were generally not statistically significant. Although the forecasting abilities of the models were quite similar, the gradual switching VAR model offered the lowest out-of-sample forecast RMSE.

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