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FORECASTING OF CANADIAN CATTLE PRICES: APPLICATION OF TIME SERIES AND REGRESSION MODELS

John D. Spriggs, Surenda N. Kulshreshtha, and Akinayo Akinfemiwa*

Uncertainty and instability, particularly price uncertainty, in the Canadian cattle economy, have been the source of problems over the last few years. Although this uncertainty cannot be controlled, its effect on the cattle economy could be mitigated by providing timely and accurate forecasts of future direction of changes in prices. In the past, several studies have focused upon short-run forecasting of the Canadian cattle sectors (e.g., Rosaasen et al., Agriculture Canada, and Haack, Martin, and MacAulay). All of these studies have used the regression approach, and forecasts were generated from a set of reduced form equations.

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It is hypothesized that, although such models may have been carefully specified to include the "correct" explanatory variables, they pay inadequate attention to the dynamic properties of the variables to be explained. This hypothesis has been tested in a number of recent studies in which traditional econometric models have been compared with univariate Box-Jenkins (ARIMA) models on the basis of predictive ability. Generally, the latter type of models have compared favorably (see for example, Nelson, Naylor et al., Narasimham et al., and Bhattacharyya). Furthermore, a number of other alternative methods, such as integration of regression and Box-Jenkins Method, multivariate Box-Jenkins models, and method of combined forecasts, can also be applied in forecasting Canadian cattle prices.

Objectives and scope of the study

One purpose of this paper is to explore the possibilities for generating forecasts by using methods which pay explicit attention to both the time series aspects and the causal aspects of economic time series. In particular, it is proposed to examine (a) the method of combined forecasts pioneered by Bates and Granger, (b) the method of mixed econometric-time series forecasting as outlined, for example, in Pindyck and Rubinfeld, and (c) the transfer function method of forecasting as outlined in Box and Jenkins. A second purpose is to compare the price forecasts based on these methods with those of the econometric model developed by Rosaasen et al., as well as with those of the univariate Box-Jenkins method.

The prices chosen to be forecast in this study are the finished steer price (basis Toronto) and feeder steer price (basis Winnipeg). The finished steer price was that for the choice (or equivalent) grade, and that for the feeder steers was for "good" (or equivalent) grade.

Monthly data for the January 1968 to December 1976 period were used. The 36-month post-sample period, January 1977 to December 1979, was used for evaluating the forecasting performance of various approaches.

In the next section the various methods used for generating forecasts are outlined. This is followed in subsequent sections by a presentation of the empirical results and a discussion of the forecast comparisons.

Methodology

Econometric method

The econometric model (Rosaasen et al.) used for the forecasts contained both the cattle and calves sectors, and specified demand, prices, and supply for both cattle and calves in a simultaneous equation framework. The underlying structural equations, from which reduced form equations are derived, were estimated using two-stage least squares. The forecasts were generated from the derived reduced form equations for feeder steer and finished steer prices.

Univariate Box-Jenkins method

In applying the univariate Box-Jenkins method, the three-stage process--identification, estimation, and diagnostic checking--was followed. For the two series, the ARIMA--autoregressive integrated moving average--method was selected as the one best explaining the past variation.

The identification process involves the tentative determination of the time series as an autoregressive and/or moving average process of a given order. Since the ARIMA method applies only to a stationary time series, a preliminary step in the identification stage is to transform the original series (if found to be non-stationary) into a stationary series by differencing the series one or more times. Once the tentative model is identified, its parameters are estimated over the historical sample using Marquardt's non-linear least squares algorithm. The third stage involves diagnostic checking of the residuals of the estimated process. By an examination of the sample autocorrelation function of the residuals, it is possible to test (e.g., using the Box-Pierce Q test) whether the original process identified is adequate. For the identified process to be considered adequate, the residuals must not be significantly different from a white noise process. Once the identified and estimated process is deemed adequate, forecasts are generated.

Combined forecasts method

The approach of combining individual forecasts was pioneered by Bates and Granger, and in the ensuing decade has been refined and applied in a number of research papers (e.g., Nelson, Brandt and Bessler). The method used in this study is somewhat similar to that of Nelson. Over the historical sample period for each price series the actual values (P_t) were regressed on the estimated values obtained from the econometric method (PF_t) and from the ARIMA method (PF_t).

(1)
$$P_t = a_0 + a_1 PFl_t + a_2 PF2_t + e_t$$

where, a_0 , a_1 and a_2 are OLS regression coefficients and e_t is a random disturbance term. In the forecast period the estimated coefficients along with the individual forecasts (PFl $_t$) and (PF2 $_t$) are used to generate composite forecasts.

Mixed method

In this method the estimated residuals for each price equation of the econometric model are analyzed for their time series properties using the univariate Box-Jenkins (ARIMA) methodology. The forecasts generated by the econometric method are then modified by the ARIMA forecasts of the errors.

Transfer function method

This method, like the ARIMA method, involves the development of a forecasting model through the three-stage process of identification, estimation, and diagnostic checking. The identification, however, is

complicated by the need to identify a process that includes an "input" series along with an output series. The selection of the "input" series is based upon identifying "leading indicators." One is obviously not interested in lagging indicators since these are of no value in an ex ante framework. Further, one should also minimize the use of those variables which have a feedback relationship with the output series. A further restriction on the selection of input series, particular to this study, is that only variables appearing in the right hand side (RHS) of the econometric reduced form equations for the cattle prices are eligible for inclusion.

The identification procedure used in this study is as follows:

- (i) All the stochastic RHS variables in the appropriate reduced form equation are pre-whitened using ARIMA filters. This becomes the pool of potential input series.
- (ii) Each pre-whitened potential input series is cross-correlated with the pre-whitened cattle price series. If there is no statistical evidence that the input series was led by the output series, then this input series becomes eligible for inclusion at the next step of identification.
- (iii) Each eligible input series is then cross-correlated with the output series using a common filter. The filter used on both series is the pre-whitening filter used on the input series. The cross-correlations from this step are used to suggest the form of the lag structure between the input and the output series (see Box and

Jenkins, p. 349 for some possible forms). The use of a common filter has been shown to be appropriate where no feedback relationships exist (e.g., see Granger and Newbold). Generally speaking, it will also result in a much simpler model (i.e., less parameters to estimate) as compared to a situation where separate pre-whitening filters were used.

(iv) The transfer function usually contains two parts: the lag relationship between the inputs and the output and the noise model. For example, in the two variable case one might have:

(2)
$$Y_{1t} = \frac{u(B)}{v(B)} Y_{2t} + \frac{\theta(B)}{\phi(B)} n_t$$

where

Y₁₊ = stationary output series,

Y_{2t} = stationary input series,

n₊ = random disturbance term,

u(B), v(B) = input and output lag parameters,

 θ (B), ϕ (B) = parameters of the noise model.

It is necessary to identify not only the input-to-output relationship, but also the noise model. Box and Jenkins suggest an initial estimation of the transfer function assuming a white noise model. Subsequently, the noise model may be developed by an examination of the sample autocorrelation function of the residuals. The estimation procedure is essentially the same as for the ARIMA method. At the diagnostic checking stage, the adequacy of the noise model can be examined by using the residual autocorrelations (e.g., using the Box-Pierce Q test).

In addition, the adequacy of the input-to-output relationship may be tested by an examination of the cross-correlations between the residuals and the pre-whitened input series (e.g., using Haugh's Q_1 , Q_2 , and Q_3 tests).

Results

For all methods, the estimation period was identical. Two alternative approaches were used in the generation of forecasts under each method: "regular forecasts" were generated on the assumption that information is available only to December, 1976, and "updated forecasts" are generated on the assumption that information is continually updated over the 36-month forecast period.

Econometric model

Monthly prediction models for the two price series were developed from the estimated structural form equations. The two (reduced-form) equations are as follows:

Farm price of finished steers (PC):

(3) PC = 2.36 + .856 SR - 7.96 BPC + 4482 DY - .012 WPP - 3.01 D1
- 5.21 D2 - 5.75 D3 - 2.97 D4 - 5.03 D5 - 2.84 D6
- 1.22 D7 - 1.00 D8 - .869 D9 + 2.27 D10 - 6.07 D11
+ .465 SIN9 + .681 COS9

Farm prices of feeder steers (PF):

(4) PF = 2.73 + .944 SR - 8.77 BPC + 4940 DY - .014 WPP - 2.18 D1
- 3.36 D2 - 4.20 D3 - 1.27 D4 - 3.69 D5 - 2.25 D6
- .281 D7 - .745 D8 - .663 D9 + 2.76 D10 - 6.53 D11
- .462 SIN9 + .453 COS9 + .074 CFB

where:

To generate the "regular forecasts" of PC and PF, RHS variables must be projected first. Non-stochastic RHS variables, such as Dl, were extrapolated in the natural way, while forecasts of the stochastic RHS variables, such as BPC, were generated from auxiliary regressions over the sample period of each such variable against a linear time trend and monthly dummy variables. The "updated forecasts" were computed by assuming perfect knowledge of all the RHS variables. This approach has been used elsewhere (e.g., Bourke), but it does tend to favor the econometric method over the other methods (e.g., ARIMA, transfer

function) which do not assume perfect forecasts. In contrast, the regular forecasts from the econometric model may be handicapped by the ad hoc procedure used to obtain the projection of RHS variables.

ARIMA method

With regard to the ARIMA method, the monthly prediction models for the two price series are as follows. For the farm price of finished steers (PC):

(5)
$$(1-.200B + .075B^2 + .162B^3)(1-B)PC_t = 1 + .167B^{11} + .229B^{12}$$

 $(.068)$ $(.070)$ $(.068)$ $(.065)$ $(.066)$
 $-.240B^{14} + .236B^{28})a_t$
 $(.066)$ $(.073)$

where B is the backshift operator and a_t is the normally and independently distributed error term. The equation was evaluated statistically using the Box and Pierce Q test on the autocorrelation of the residuals. For the above equation, Q=35.0, which may be compared with the chi-square statistic for 41 degrees of freedom at the 5 percent significance level (57.0). Therefore, the fitted ARIMA model was accepted as an adequate representation of the behavior of the PC time series.

For the farm price of feeder steers (PF), the estimated model was:

(6)
$$(1-B)PF_t = (1 - .157B^4 - .184B^7 - .206B^{20} + .250B^{37})a_t$$

(.067) (.070) (.073) (.082)

For this equation Q = 59.3, which may be compared with the chi-square statistic for 76 degrees of freedom. At the 5 percent significance level Q was less than the appropriate chi-square value (97.3), resulting in the acceptance of the fitted ARIMA model.

Combined forecasts method

The monthly prediction models are based on the OLS regression over the sample period of the actual cattle price series against the simulated econometric values and the estimated ARIMA values. The two OLS equations from which the composite forecasts are developed are as follows:

(7)
$$PC_t = -.377 + .149 PCl_t + .858 PC2_t + e_{1t}$$

 $R^2 = .977 N = 228$

(8)
$$PF_t = .028 + .062 PF1_t + .933 PF2_t + e_{2t}$$

 $R^2 = .965 N = 228$

where

 PCl_t , PFl_t = simulated econometric values of PC_t and PF_t $PC2_t$, $PF2_t$ = estimated ARIMA values of PC_t and PF_t

The composite forecasts were generated from the above equations by replacing PCl_t and PFl_t with the econometric forecasts and $PC2_t$ and $PF2_t$ with the ARIMA forecasts.

Mixed method

In this method the econometric forecasts are modified by an ARIMA model developed on the two sets of sample-period residuals $EC_{t} \text{ and } EF_{t} \text{ where } EC_{t} = PC_{t} - PC_{l} \text{ and } EF_{t} = PF_{t} - PFl_{t}.$ The estimated ARIMA models were:

(9)
$$EC_{t} = \frac{\begin{bmatrix} .05 \end{bmatrix} & [.06] \\ \frac{1 + .757B + .734B^{2})}{1 + .316B^{3} - .184B^{11})(1-B^{3})} a_{Ct}$$
[.07]

$$Q = 25.8$$
 (compare with $\chi^2_{20} = 31.4$)

(10)
$$\text{EF}_{t} = \frac{(1 - .751\text{B}^{3})}{(1 - .683\text{B})(1-\text{B}^{3})} \cdot a_{\text{Ft}}$$
[.06]

Q = 30.7 (compare with
$$\chi_2^2 = 33.9$$
)

All coefficients were greater than twice their standard errors and in both models the Q test statistic indicates model adequacy. The mixed method forecasts are then given by

(11)
$$PC_t = PCl_t + EC_t$$

(12)
$$PF_t = PFl_t + EF_t$$

Transfer function method

We outline the identification, estimation and diagnostic checking of the transfer functions for the cattle price series beginning with the transfer function for finished steer price (PC). The eligible input variables at the first step of the identification include the ratio of slaughter steers to slaughter heifers (SR), deflated income per capita (DY), beef supply per capita (BPC) and, the wholesale price of pork (WPP). Of these variables only SR gave some indication of being led by PC. The cross-correlations between each potential input

variable and PC using different pre-whitening filters are shown in Table 1. On these ground we decided to exclude SR from further analysis. In the second step, cross-correlations were calculated where a common (input filter is applied to both PC and the input series. Table 2 shows these cross-correlations. With regard to WPP there were significant cross-correlations only at fairly high order lags and the negative sign on these cross-correlations did not seem to be consistent with what might be expected on economic grounds. On the other hand, the significant cross-correlations for DY and BPC did appear to be consistent with economic theory. Tentatively the transfer function was modeled as

(13)
$$P_t^c = (u_1^B + u_2^B)D_t^4 + \frac{w_0(1-w_1^B)^2}{(1-x_1^B)}P_t^2C_t + e_t$$

where

$$\dot{PC}_{t} = (1-B)PC_{t}$$

$$\dot{DY}_{t} = (1-B)(1-B^{12})DY_{t}$$

$$\dot{BPC}_{t} = (1-B)(1-B^{12})BPC_{t}$$

This model was estimated initially on the assumption that e_t followed a white noise process. Following the initial estimation run, the sample autocorrelations for the generated noise series were calculated. Based on these sample autocorrelations, the noise function was modeled as $e_t = (1-\theta B^3) n_t$. The next estimation run produced insignificant coefficients for u_1 and u_2 and hence, DY was dropped from the equation. The model was reestimated and the noise model modified as a result of

Table 1. Cross-correlations between the Pre-whitened Slaughter Steer Price (PC) and the Pre-whitened Potential Input Variables

		Lag ^a			
WPP	BPC	DY	SR		
		.10	20*	- 12	
02	02		.03	-11	
09	01	.14	.19*	-10	
07	.03	10	.10	-9	
.05	.15	.03	.10	-8	
.07	05	10	.02	-7	
.10	07	04	05	-6	
.07	12	.03	.13	- 5	
.03	07	.04	.07	-4	
.02	.06	11	04	-3	
01	.12	07	03	-2	
.02	01	08	04	-1	
11	11	14	21*	0	
.27*	30*	.11	.07	1	
13	08	.17*		2	
10	03	11	06	3	
.04	14	00	.10	4	
12	.03	.22*	.13	5	
.00	.07	.01	.17*	6	
05	.12	01	04	7	
28*	.12	.02	.07	8	
.27*	.06	10	02	9	
.11	05	.08	06	.0	
.06	07	00	03	1	
.04	00	15	03	2	
16	.06	.06	.07		

 $^{^{\}mbox{\scriptsize a}}\mbox{\scriptsize A}$ negative lag is for cross-correlations where PC is the lag variable.

^{*} Suggests the correlation to be significant at five percent level.

Table 2. Cross-correlations between the Price of Slaughter Steers and Various Input Series Using Common Filters

		Input Series		
Lag	DY	BS	WPPK	
0	.11	25*	.13	
1	.17*	12	05	
2	11	03	05	
3	00	.11	05	
4	.22*	• 02	12	
5	.01	00	11	
6	00	02	08	
7	.02	.05	17*	
8	10	.08	.14	
9	.08	.08	.16	
10	00	.00	.12	
11	15	06	02	
12	.06	17*	17*	

^{*}Significant at five percent level.

dropping DY. The final estimated equation is as follows (with standard errors in square brackets):

(14)
$$PC_{t} = \frac{\begin{bmatrix} 1.07 \end{bmatrix} & \begin{bmatrix} .25 \end{bmatrix}_{12}}{(1 - .44B)} & BPC_{t} + \frac{(1 - .19B^{3} + .21B^{11} + .21B^{14} + .21B^{14})}{(1 - .34B^{12})} \\ & \begin{bmatrix} .23 \end{bmatrix} & \begin{bmatrix} .15 \end{bmatrix} & \begin{bmatrix} .15 \end{bmatrix}_{11} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{12} & \begin{bmatrix} .15 \end{bmatrix}_{13} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{13} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{14} & n_{t} \\ & \begin{bmatrix} .15 \end{bmatrix}_{14} & \begin{bmatrix} .15 \end{bmatrix}_{$$

The Box-Pierce test on the residual autocorrelations yielded a

Q value of 27.0 when 24 lag periods were considered. This is less than the critical (5 percent) chi-square value of 31.4, thus indicating the adequacy of the noise model. The adequacy of the whole transfer function may be tested using Haugh's Q_1 , Q_2 and Q_3 statistics. The Q_1 statistic tests that given the function is unidirectional in causality the model is adequate. The Q_2 statistic tests model adequacy making no assumptions about direction of causality. The Q_3 statistic tests the validity of using a unidirectional causality model rather than a feedback model. For the present model Q_1 = 33.2 (compare with χ_2^2 = 33.9)

$$Q_2 = 39.7$$
 (compare with $\chi_2^2 = 33.9$)

$$Q_3 = 59.4$$
 (compare with $\chi^2_{24} = 36.4$)

On the basis of these tests it appears that this model was perhaps not the final answer. There is reason to suspect that feedback is present when this has not been taken into account. This is, of course, not entirely unexpected since the presence of livestock cycles is widely suspected as being the result of a feedback relationship between price and output.

For the feeder steers price (PF), the procedure followed was essentially the same as that for finished steer price. The eligible input variables at the first step of the identification included SR, DY, BPC, WPP and the cost of feed barley (CFB). As in the case of slaughter steers price, SR gave some statistical indication of being led by PF and was excluded from further analysis. At the second step,

all four remaining potential input series exhibited significant cross-correlations with the (transformed) PF (see Table 3). Tentatively the transfer function was modelled as:

$$(15) \quad PF_{t} = \frac{u_{1}^{B}}{1 - v_{1}^{B}} \dot{Dy}_{t} + \frac{w_{1}}{1 - x_{1}^{B}} \dot{DP}_{t} + (y_{1} + y_{2}^{B}) \dot{WP}_{t} + z_{1}^{B} \dot{DP}_{t} + e_{t}$$

where

$$PF_{t} = (1-B)PF_{t}$$

$$DY_{t} = (1-B)(1-B^{12})DY_{t}$$

$$BPC_{t} = (1-B)(1-B^{12})BPC_{t}$$

$$WPP_{t} = (1-B)WPP_{t}$$

$$CFB_{t} = (1-B)CFB_{v}$$

Table 3. Cross-correlations between the Price of Feeder Steers and Various Input Series using Common Filters

_		Input Ser			
Lag	DY	BX	WPPK	СОВ	
	0.0	22*	22*	.09	
0	.02	23*	.22*		
1	.25*	12	11	03	
2	04	01	.02	.17*	
3	05	04	.06	14	
4	.20*	.03	05	.01	
5	08	05	11	.04	20 20
6	10	14	19*	11	
7	.08	.00	14	01	
8	10	.07	.08	.04	
9	04	.03	.15	.09	
10	.07	.04	.01	.06	
11	03	23*	04	05	
12	03	03	07	16	

^{*}Significant at five percent level.

Following some initial estimation runs and deleting insignificant coefficients, the final equation is as follows,

(16)
$$PF_{t} = \frac{\begin{bmatrix} .004 \end{bmatrix} \begin{bmatrix} .003 \end{bmatrix} \begin{bmatrix} .004 \end{bmatrix} 3}{(1 - .933B^{3})} DY_{t} - \frac{\begin{bmatrix} .523 \end{bmatrix}}{3.29} BPC_{t} + n_{t}$$

$$\begin{bmatrix} .004 \end{bmatrix} \begin{bmatrix} .003 \end{bmatrix} \begin{bmatrix} .004 \end{bmatrix} 3$$

There was no noise model in the final estimation run. The Box-Pierce test on the residual autocorrelations yielded a Q value of 29.4 when 24 lag periods were considered. This is less than the critical (5 percent) chi-square value of 31.4 implying that the noise model (or lack of it) is adequate. The Q_1 , Q_2 , and Q_3 tests of adequacy of the total model yielded the following values with comparable chi-square values (at 5 percent level) in parentheses.

- (a) on cross-correlations between pre-whitened DY and residuals $Q_1 = 28.4 \ (\chi^2_{21} = 32.7)$ $Q_2 = 27.8 \ (\chi^2_{21} = 32.7)$ $Q_3 = 28.8 \ (\chi^2_{24} = 36.4)$
- (b) on cross-correlations between pre-whitened BPC_t and residuals $Q_1 = 41.6 \ (\chi^2_{23} = 35.2)$ $Q_2 = 43.8 \ (\chi^2_{23} = 35.2)$ $Q_3 = 40.5 \ (\chi^2_{24} = 36.4)$

From these tests the DY component of the transfer function apparently is satisfactory while the BPC component is still open to question.

With regard to the latter, a high value for Q_1 is attributable to three significant cross-correlations (at periods 11, 18 and 21). One may argue that the model should be further specified to take account of these. The high values for Q_2 and Q_3 are attributable to a significant cross-correlation at lag -2 (i.e., with the residuals leading the pre-whitened BPC_t). As in the transfer function for PC, this may indicate the need for a more complex feedback model.

Comparison of the Forecasting Methods

The predictive abilities are measured using two criteria: mean square forecast error and a measure of directional accuracy. The former measure is widely known; the latter is the ratio of correct directional moves to total directional moves over the forecast period. Thus, for example, if a particular method correctly predicts the direction of change from one period to the next in 20 out of a total of 36 actual directional moves it receives a score of 20/36 or 0.56. The maximum score would be 1.0 and on average one would expect a random set of forecasts to achieve a score of 0.5.

As discussed above, forecasts are generated over the post-sample period in two ways. Three sets of "regular forecasts" are generated: 6, 12, and 36 months ahead. Forecasts of the causal variables in the econometric method are based on the auxiliary regressions already discussed. Forecasts of the input variables in the transfer function method are made on the basis of an ARIMA model for each such variable. The second or "updated" forecasts consist of 36 one-period-ahead

forecasts. It might be noted that the estimated coefficients are not themselves updated (i.e., re-estimated).

The mean square forecast errors of the two cattle price series using the five different forecast methods appear in Table 4. Also, for comparison, in that table are the mean square errors achieved with a naive (no-change) forecast. The measure of directional accuracy for the five methods appear in Table 5.

Table 4. Mean Square Errors of Forecasts Using the Box-Jenkins and Econometric Methods to Forecast Canadian Cattle Prices

Forecasts			ric circa	of Forecast		Transfer
				Combined		function
for:	Naive	Econometric	ARIMA	forecasts	Mixed	Tunector
Finished steers	price:					1
1/77-6/77	1.64	3.99	5.42	3.27	23.99	1.06
1/77-12/77	14.32	4.46	22.14	16.25	34.26	7.37
1/77-12/79	626.80	444.77	715.87	672.40	669.54	542.62
1/77-12/79:						
Updated	7.63	126.38	5.51	8.64	34.79	20.39
Feeder steers p	rice:					
1/77-6/77	9.30	28.19	1.40	.96	17.63	3.08
1/77-12/77	33.91	17.22	23.57	19.94	24.05	1.81
1/77-12/79	1151.70	638.35	998.21	970.55	890.02	666.09
1/77-12/79:						
Updated	14.0	195.48	17.19	19.72	50.48	29.32
- E						

Table 5. Measure of Directional Accuracy Using Various Forecasting Methods

Forecasts		Combined Tra				
for:	42	Econometric	ARIMA	forecasts	Mixed	function
Finished steers	s pri	ce:				
1/77-6/77		3/6	3/6	4/6	4/6	4/6
1/77-12/77		7/12	9/12	10/12	8/12	8/12
1/77-12/79		14/36	20/36	17/36	20/36	
1/77-12/79: updated		15/36	26/36	26/36	17/36	25/36
Feeder steers	price	•				
1/77-6/77		4/6	4/6	4/6	5/6	4/6
1/77-12/77		6/12	7/12	6/12	10/12	10/12
1/77-12/79		24/36	17/36	17/36	20/36	19/36
1/77-12/79: updated		16/36	24/36	24/36	20/36	25/36

In the regular forecasts (6, 12, and 36 months ahead), there is a tendency for the econometric method to produce smaller MSE forecasts for both price series than the ARIMA method (6 month forecast of PF is the exception). On the other hand, the ARIMA method was much superior in the one-month-ahead updated forecasts. Actual and predicted forecasts are compared in Figure 1 for the price of slaughter steers and in Figure 2 for the feeder steers price, for the period January, 1977, to December, 1979.

These results are somewhat consistent with previous studies which have found that in the case of short-run forecasts (1 to 3 months ahead) the ARIMA method tends to produce lower MSE forecasts than the traditional econometric method. A possible explanation for this

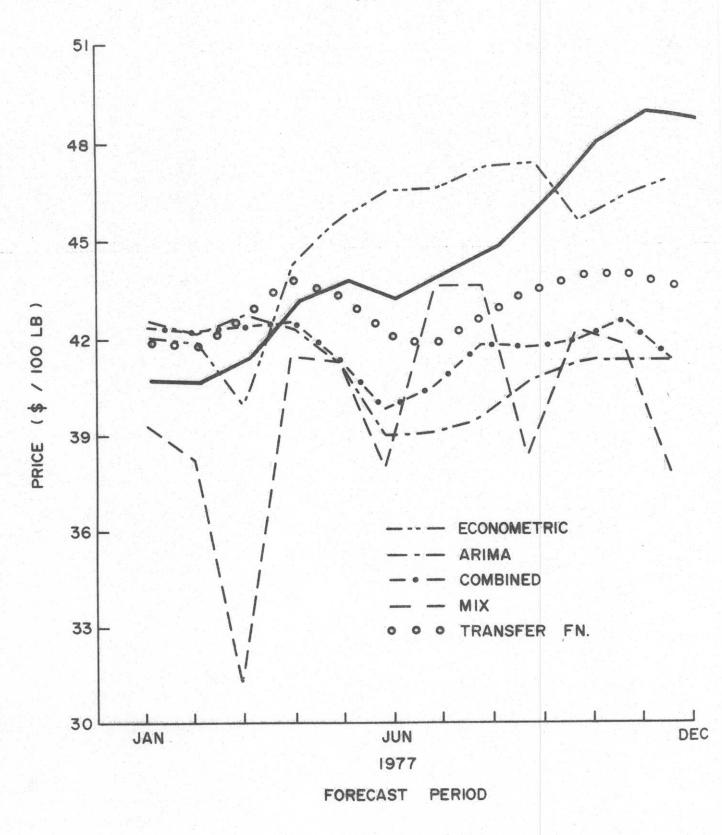
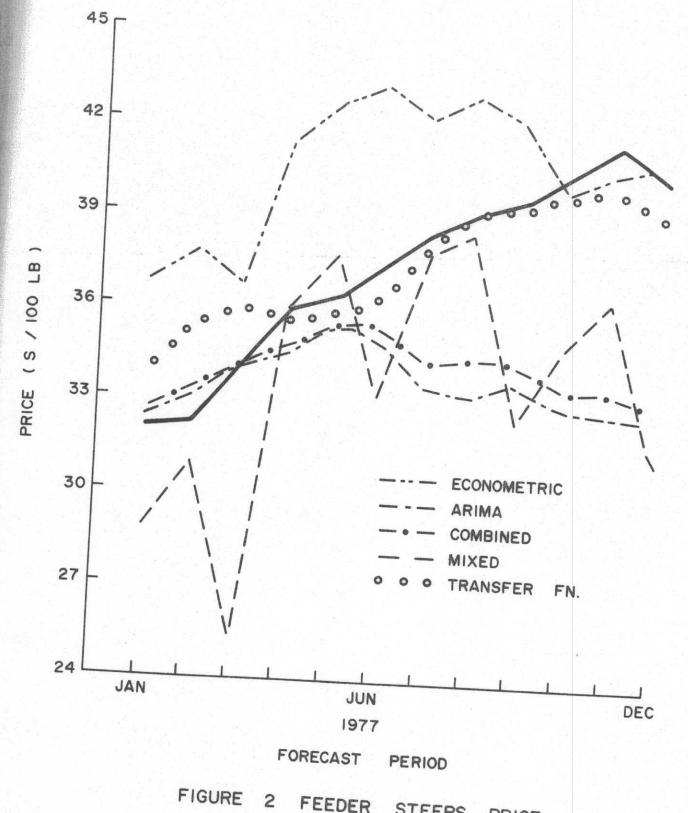


FIGURE I SLAUGHTER STEERS PRICE



2 FEEDER STEERS PRICE

phenomenon has been suggested by Zellner who argued that traditional econometric models tend to concentrate on obtaining the best specification of explanatory variables, but pay only limited attention to the time series behavior of the dependent variables. ARIMA models, on the other hand, concentrate on the time series aspects and exclude consideration of specific explanatory variables. In short-run forecasts, the time-series aspects may be relatively more important while in longer-run forecasts the effects of specific explanatory variables become relatively more important. These shortcomings in the individual forecasts are what has provided the main impetus for composite methods of forecasting.

With regard to the measure of directional accuracy (Table 5), neither the econometric nor the ARIMA method is clearly superior over the regular forecast time horizons. However, with respect to the updated forecasts, the ARIMA method does seem to be superior. This is of some significance, because one would expect this measure to receive greater attention by users of short-run forecasts.

Turning to the three composite methods of forecasting, some interesting results can be seen in Table 4. First, the mixed method consistently performed the poorest of the three methods. An examination of Figures 1 and 2 reveal that the mixed method forecasts are consistently below the econometric forecasts and the actual values. This is partly due to an unusually large error in the last simulated econometric value of the historical sample period. The econometric method over-predicted in this period by over 25 percent for both

cattle price series. This, together with third-order differencing in Equations (9) and (10), led to a strong negative bias in the ARIMA forecasts of the econometric errors with a particular three-month periodicity. Second, the combined forecasts method tended to perform similarly to the ARIMA method. This is due to the large weight accorded to the ARIMA forecasts in the combined forecasts weighting scheme. Hence, this method, like the ARIMA method, performed well in the updated forecasts and relatively poorer in the regular forecasts. The transfer function, on the other hand, performed relatively well in generating the regular forecasts and not so well in generating the updated forecasts.

With respect to Table 5, there is again little to choose between the composite methods over the regular forecast time horizons. Over the updated forecasts, the combined forecasts method and the transfer function method performed equally as well and considerably better than the mixed method.

In Canada, the feedlot operator would primarily be interested in six-month to 12-month ahead forecasts, and the cow-calf operator must run his operation with a two-year to three-year planning horizon. Hence, producers are more likely to be concerned with the longer-run forecasts than with the one-month-ahead forecasts. For such forecasts the results (meager as they are) would tend to favor the traditional econometric or transfer function method. Of these two methods, the transfer function method is preferable since (a) it does in a fairly

sophisticated way take account of the causal and time series aspects both of which seem to be important in determining livestock prices.

(b) In terms of the MSE results the transfer function method seems to do a better job overall than the econometric method, and (c) despite the terminology which is probably new to those unfamiliar with the time series literature the methodology is not very difficult.

Summary and Conclusions

In this study a number of forecasting approaches were applied to beef cattle prices in Canada. The price of finished steer and the price of feeder steer were the two key prices forecasted. The techniques of forecasting included the traditional econometric model, univariate Box-Jenkins, mixed econometric and Box-Jenkins approach, and the transfer function approach. In addition, a method that the Box-Jenkins and econometric forecasts was developed.

For short-run (within 6 months ahead) forecasts, the ARIMA method performed best. For the six-month to 12-month forecasts, the results suggest the transfer function or econometric method somewhat better than others.

In our opinion the transfer function method has significant potential to improve our ability to forecast in the short-run. It attempts to combine, at the same time, the causal relationships between economic variables and the time series aspects of those economic

variables. In our empirical study it performed well relative to some alternative composite methods. The principal limitations of the transfer function method are two-fold:

- (a) The number of input variables that one can readily incorporate in a single transfer function is small. In this respect
 it is no different than a single econometric estimating equation.

 However, when one compares the single transfer function with a multiple
 equation structural econometric model one advantage of the latter is
 its ability to incorporate many explanatory variables.
- (b) It is considerably more difficult to build feedback models than it is to build models involving unidirectional causality. In this study, we did not consider building models of the feedback type even though there was evidence to suggest this might have been appropriate.

One potential advantage of the mixed method is its ability to incorporate many explanatory variables (from a derived reduced form equation) and also to take account of the time series component of the dependent variable. Thus, we were particularly disappointed with the empirical results of this method. However, we do not reject the method yet, since the results may be a product of our particular data set. We would like to see further testing of this method with other data sets.

Footnotes

With the exception of the study by Rosaasen et al., these studies have used quarterly data.

This is done so that the information set (in terms of causal variables) is the same under all three composite forecasting methods. In practice, of course, no such restriction would be made and with an expanded information set it is reasonable to suppose other potentially useful leading indicators could become available. However, given that the econometric model has already such variables, the practice applied here would appear reasonable.

See Granger and Newbold (pp. 242-243) for further details.

⁴A commercial software package is readily available.

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