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Further Information on the Usefulness and Flexibility of Bayesian and Nonbayesian Vector Autoregressions: Forecasting Monthly U.S. Cattle Prices

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FURTHER INFORMATION ON THE USEFULNESS AND FLEXIBILITY OF BAYESIAN AND NONBAYESIAN VECTOR AUTOREGRESSIONS: FORECASTING MONTHLY U.S. CATTLE PRICES

Hector O. Zapata and Philip Garcia*

In general, the use of multiple time series models to represent economic behavior has not resulted in improved forecasting. Multivariate models permit an appealing high degree of interaction among variables but seem susceptible to overparameterization which often results in unacceptable predictions. Recently, Litterman (1979,1985), and Bessler and Kling (1986) have addressed this problem through the use of Bayesian procedures in a vector autoregressive (VAR) framework.[1] The approach uses information (priors) on the interrelationships among variables evaluated over a preforecast period to generate out-of-sample predictions. The information based on the data or the subjective knowledge of the researcher can lead to either symmetric or asymmetric priors. Once established, the priors are maintained throughout the out-of-sample forecast period. Results from their work suggest that this methodology can provide lower out-of-sample forecast errors.

The application of the above methodology has been constrained to stationary or stationarity induced series since the theory of VAR estimation is based on this condition. However, issues have been raised in the literature regarding the effect of differencing on the nature of multivariate interaction. Using Hsiao's (1979) Canadian money and income data, Lutkepohl (1982) has analyzed this problem concluding that "Differencing nonstationary univariate component series of a multiple time series to induce stationarity prior to building an AR model for the multivariate generation process is in general inadequate" (p. 238).

Here, we examine the accuracy of various multivariate (unrestricted VAR, and Bayesian VAR) as well as univariate time series models for forecasting monthly U.S. prices of slaughter steers ($/cwt), choice, 1100-1300 pounds, Omaha, (cattle prices hereafter) giving specific consideration to the stationary-nonstationary VAR problem and the implications for forecasting. Further, we modify Litterman's procedure by systematically updating the prior information imposed on the system throughout the out-of-sample forecast period. This flexible procedure permits the evaluation of the optimal weights in specifying the parameter distributions according to the most recent experience and the impact this has on forecasting performance. The performance of the models is assessed using the root mean square error (RMSE) for various forecast horizons. Sources of forecast errors are evaluated by the MSE decomposition and the quality of the forecast by the turning point criterion. The results provide added insights into the usefulness and flexibility of the Bayesian VAR methodology in forecasting agricultural prices.

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The remainder of the paper is organized as follows. First, a brief presentation on the use of VARs and Bayesian VARs (BVARs) in forecasting is provided. Subsequently, the specification of symmetric and asymmetric prior information follows. Next, an unrestricted VAR, BVARs, and an univariate ARIMA model are evaluated in terms of forecasting performance as applied to a cattle model for the U.S. cattle industry. Finally, main implications of the study are stated.

Vector Autoregressive Models (VAR)

Among the class of stationary vector stochastic processes, VAR models have been of considerable interest for economic forecasting. The estimable form of a k-dimensional VAR(p) process takes the form

(1) $Y(t) = D(t) + \Sigma_j A_j Y(t-j) + e(t)$

where $e(t)=(e_1,\ldots,e_k)'$ are vectors of k components and $A_1, \ldots, a_p$ are (kxk) matrices of the unknown parameters, j=1,2,...,p, and L is the lag operator such that $L^pY(t)=Y(t-p)$, and D(t) is the deterministic component. Several approaches have been proposed in the time series literature to specify the model in expression (1) [e.g., Akaike (1970), Granger and Newbold (1977), Wallis (1977), Chan and Wallis (1978), Cooper and Wood (1982), Tiao and Box (1981), and Lutkepohl (1985)]. The final prediction error (FPE) was used in this study to select the VAR structure because of the predictive nature of the criterion.[2].

The estimation of VARs is carried out by applying linear least squares (LS) separately to each equation. Since the i^{th} equation in expression (1) has the same design matrix as any other equation, use of LS results in efficient estimates. All estimation and forecasting is done on RATS.

Bayesian-VAR Analysis

Application of Bayesian methods to VARs was developed by Litterman (1979) with regard to forecasting macroeconomic data. Litterman's solution to the problem of filtering information useful for forecasting economic time series is based on the assertions that, first, there is a very low signal-to-noise ratio in aggregate economic data, i.e., univariate AR specifications capture only a small part of the total variation of the predictable movement of the variable in question, and second, that theory alone does not assure an economic structure will result in good forecasting performance, i.e., the researcher may be able to fit the structure adequately but without the same correspondence as to forecasting accuracy.

Litterman's basic idea[3] is to use symmetrical and/or asymmetrical prior information on all the specified variables in equation (1) to balance the tradeoff between oversimplification and overparameterization. Two forecasts samples are used in the evaluation: (1) a within sample period (preforecast period) which is used to determine optimal weights, and (2) an out-of-sample period over which forecasting accuracy is evaluated. The search process over parameters that fine-tune the prior is undertaken over the preforecast period, using out-of-sample forecast errors during this period as indicators of forecasting performance. The fine-tuned priors become the filters to extract as much information from the data as possible. The prior distribution Litterman proposed centers on a random walk process for each series in the VAR specification. Since the prior does not advocate any specific economic theory, it is viewed as "instrumental".

This methodology allows for specifying a non-informative (flat) prior around a deterministic (intercept) component, the value of which is determined entirely by the data. Litterman suggests an estimator which imposes the information that a random walk around an unknown deterministic component is a reasonable approximation for the behavior of an economic variable, so that the i^{th} equation in (1) is[4]

(2) $Y_i(t) = d_i(t) + Y_i(t-1) + e_i(t)$.

Specifying the lagged values of Y (Y_{t-1}) in a matrix X expression (1) can be rewritten as:

(3) $Y_i + XA_i + e$

where Y_i is (txl), X (txp), A_i (pxl), and e (txl). Expression (3) assumes a constant mean and variance and allows the covariance between observations to depend on the lag between them but not a particular time point. Writing the prior information in the form of stochastic linear restrictions as,

(4) $R_iA_i = r_i + v$

where R_i = diag $(0._h, \lambda/d^l{}_{ij})$ and R_i has dimension (pN+h)(pN+h), $0._h$ contains zeros corresponding to h deterministic components, $\lambda/s^l{}_{ij}$ are the elements corresponding to the l_{th} lag of variable j,

$$\lambda/s^l{}_{ij} = \begin{cases} \lambda/l^d & \text{if } i=j \\ \lambda w\hat{\sigma}_i/l^d\hat{\sigma}_j & \text{if } i\neq j \end{cases}$$

$$r_1 = [0_h, 1\ 0\ \ldots\ldots.\ 0]',$$
$$r_2 = [0_h, 0\ 1\ 0\ \ldots..\ 0]',$$
$$\vdots$$
$$r_n = [0_h, 0\ \ldots\ldots.\ 0\ 1]'.$$
$$v \sim N(0, \sigma^2 I)$$

$\hat{\sigma}_i, \hat{\sigma}_j$ are the standard deviations on innovations from univariate autoregressions for equations i&j, l=1,2,.........,P lags i=1,2,.........,K equations and j=1,2,.........,N variables.

More specifically, R_i is a diagonal matrix with zeroes corresponding to the deterministic components (h=1,2), and other elements, $\lambda/s^l{}_{ij}$, corresponding to l_{th} lag of variable j in equation i; $s^l{}_{ij}$ is the standard deviation of the prior distribution. r_i is a column vector of zeros and a 1 corresponding to the first lag of the dependent variable i.e., the mean of the A_i's is zero except for the first lag on the dependent variable in i^{th} equation which is one. The distribution term in (4) is normally distributed with mean zero and covariance matrix $\sigma^2 I$; the A_i's are jointly normally distributed and independent. A constant standard deviation on the first lag of the dependent variable in the i_{th} equation is specified through λ which decreases in a geometric or harmonic manner according to a parameter d at further lags of this variable. The tightness of λ's on other variables in the system is controlled by a parameter w. A flat prior is specified on the deterministic component.

Equations (3) and 4) can be written together as

$$(5) \qquad \begin{vmatrix} Y_i \\ \\ r_i \end{vmatrix} = \begin{vmatrix} X \\ \\ R_i \end{vmatrix} A_i + \begin{vmatrix} e \\ \\ v \end{vmatrix}$$

which is in the form of the Goldberger-Theil mixed estimator. Expression (5) is for the i^{th} equation. The estimate is given by

$$(6) \quad \hat{A}_{ip}(\hat{\sigma}_i) = (X'X + k_i R_i' R_i)^{-1}(X'Y_i + k_i R_i' r_i)$$

where $k_i = \hat{\sigma}^2{}_i / \lambda^2$.

Once the estimate in (6) is obtained, projections are generated using the estimated coefficients according to the "Chin Rule of Forecasting" [e.g., Wold (1962)]. Forecasts n-steps ahead are made based on information available up to and including observation t. The forecasting procedure used for VARs is also applicable to BVARs.[5] The quantitative evaluation is based on the root mean square error (RMSE) criterion[6] which is consistent with squared loss function; this function gives equal weights to over and under forecast, and appears frequently in applied work. The decision rule is based on the relative value of the RMSE; the model with minimum RMSE is selected as the best forecasting model, on the average.

The MSE can also be decomposed in three components which provided additional information as to the sources of forecast errors; the bias proportion, the regression proportion, and the disturbance proportion. The bias and the regression components (systematic errors) measure deviations from the optimal predictor, i.e., they are zero for the optimal predictor.[7] The disturbance component is a measure of deviations around the predicted line of a regression of actual on predicted values.

Granger and Newbold (1977, pp. 287-289) discuss some of the problems associated with using these measures, specially when there is a low correlation (r) between the forecast and actual series. For optimal forecasts, r should be very close to 1 so there use seems appropriate.

The qualitative measure is based on the turning point (TP) criterion [e.g., Naik and Leuthold (1986), and Kaylin and J. A. Brandt (1988)] which relies on a 4x4 contingency table to distinguish the peak TP from trough TP and upward no TP from downward no TP. Two ratios of interest in the qualitative evaluation are the accurate and worst forecast measures.

Application to the Cattle Model

The VAR model specification for cattle prices is based on the econometric model of Garcia, et al. (1988). The underlying principles used in constructing the VAR model rely on Zellner and Palm (1974) who showed that it is possible to derive multiple time series process from dynamic econometric specifications by imposing appropriate restrictions. Price of cattle (PC), average price of feeder steers (PFS), eight markets ($/cwt), and per capita income (PCI), $, comprise the trivariate VAR model (data sources provided in the references). The multivariate interaction between these series can be visualized as follows. Feeder steers is a main input in the production of cattle slaughter; thus, its price directly affects production decisions.[8] The relation of PFS and PC can be visualized as recursive through an underlying supply equation. Demand forces affecting PC are reflected through PCI which over the past decade has followed a steep upward trend.

Analysis of the autocorrelation functions for the raw data on PFS and PCI revealed a nonstationary behavior similar to that of the PC series; filtering through first differences, however, induced stationarity. As indicated previously, Lutkepohl (1982) has proposed that, in general, it is not adequate to difference the individual series in a multivariate framework. Since the interest here is to forecast monthly prices of cattle, both raw and first differenced data were used in the analysis with the intent of selecting the structure that generated the most accurate predictions.

Application of the PFE resulted on a VAR of order two [VAR2] model, for both raw and differenced data. RMSEs for one to six months ahead forecasts of the PC equation, 1984-1985 period, with monthly updatings for these models on raw data first differences are (2.47,2.27), (4.37,3.75), (5.84,4.71), (6.72,4.62), (7.44,4.51), and (8.01,4.68). At every forecast horizon the VAR2 model on first differences has smaller RMSEs; based on these relative values, one would normally eliminate the VAR2 on raw data and select the other model for forecasting comparisons; it is surprising, however, what the results show when the Bayesian methodology is applied to both models.

Implementation of symmetric priors (SP) was performed as follows: the period from January 1982 to December 1982 (preforcast period) was used to evaluate the out-of-sample forecasting ability of the VAR2 model and values of (d,w,λ) over the unit cube were searched at intervals of size 0.09 starting with 0.01. These intervals were selected as an initial step in the search process because it is impossible to know a priori the behavior of the contours of the log-determinant of the out-of-sample (twelve steps ahead) forecast error covariance (LNDFE). The three-dimensional symmetric search resulted in the minimum value for LNDFE at $(d=0.55,\ w=0.28,\ \lambda=0.10)$,[10] under a geometric lag decay specification applied to the raw data. The above symmetric VAR2 model (BVAR2GR) was used in generating out-of-sample forecasts (six steps ahead with monthly updatings) from January 1984 to December 1985[11] which are used in evaluating the various forecasting techniques.

It is impossible to determine a priori whether weighing the variables in a BVAR equally will result in better forecasting performance than specifying unequal weights. However, when it is reasonable to expect variables in a multivariate framework to interact on an asymmetric manner, controlling the degree of multivariate interaction may result in more accurate forecasts.

Since there is no certainty that a set of subjectively specified weights will result on more accurate forecasts, asymmetric behavior is evaluated as a combination of purely instrumental (data search) and subjective (expected economic relationships and correlation between variables in the VAR model) decisions. The application to the raw data was as follows: (a) steps a and b of the SP case and the optimal values (λ=0.10,d=0.55), the overall tightness and decay parameters respectively, were used; (b) asymmetric tightness parameters for w(i,j) were specified as follows. Firs, if i=j then w took a value of 1.0; second, for the PCI variable the asymmetric weights w(i,j) were searched over the interval 0.001 w(i,j) 1.0 for the other two variables in an equation. These intervals are selected to control the way variables interact in the VAR framework. For instance, it is reasonable to expect income to affect the level of cattle prices as income is an important determinant of consumer demand, but it is questionable to expect cattle prices to affect the level of income to the same degree; the effect of per capita income is tightened towards zero using Bessler and Kling's maximum tightness (0.001). Similarly, price of feeder steers affect price of cattle from the production side, and therefore, a high degree of interaction is expected between these two series (the two variables are highly correlated). Again, it does not seem reasonable to expect PFS to have much impact in terms of determining income levels.

The minimum RMSE was used as decision rule to select the optimal weights, the main reason for using the RMSE is that forecasts for PC (rather than all the variables in the system) are of interest. The results from this evaluation are presented in Table 1 and labeled ABVAR2GR. The PC and PFS equations carry half weight of their own effect when they appear on the other equation, PCI having almost no influence on these variables.[12] For the PCI equation, tight priors around PC an PFS result in better forecasting performance.

The Bayesian application to the first differenced data on the VAR2 model followed the same procedure applied to the raw data. The three dimensional symmetric search resulted in the minimum value for LNFE at (d=1.0,w=1.0,λ=0.10) under a geometric lag decay specification (BVAR2GD) which was used to generate out-of-sample forecasts (six steps ahead with monthly updatings) from January 1984 to December 1985. The asymmetric evaluation based on the minimum RMSE resulted on optimal weights as shown in Table 1 for the ABVAR2GD model.

The out-of-sample forecast evaluation for PC is provided in table 2 which contains RMSEs at forecast horizons of one through six month beginning with January 1984 to December 1985. The forecasting models of the previous sections are the unrestricted VARs of order two on raw and differenced data [VAR2R,VAR2D], the symmetric Bayesian VAR2s [BVAR2GR,BVAR2GD], and the asymmetric BVAR2s [ABVAR2G, ABVAR2GD]. As indicated previously, simple time series models are used as benchmark in the evaluation process.

The univariate time series model used to forecast monthly prices of cattle (PC) followed the traditional methodology of Box and Jenkins (1976); this model provides a basis to decide whether more complex processes such as vector autoregressions increase the amount of signal that can be extracted about prices of cattle. First differences of monthly PC, January 1975 to December 1983, were used to identify and estimate alternative structures because the autocorrelations of the raw data indicated nonstationary behavior (autocorelations of the raw data were close to one at initial lags and decayed very slowly as lag length increased). An ARIMA(2,1,2) was selected as the appropriate structure based on analysis of autocorrelations and partial autocorelations of the firs differences. The estimated equation is given by

$$(6)\quad \underset{(-14.88)}{(1 - 1.529B} + \underset{(8.23)}{0.846B^2)}\,(1 - B)Pc_t = \underset{(1.15)}{0.241} + (1 - \underset{(-8.20)}{1.276B} + \underset{(3.53)}{0.549B^2})z_t$$

$$Q = (4.74,\ 12.44,\ 17.61,\ 19.40)$$

where the values in parenthesis are t-ratios and Q represents the Q-statistic (Ljung and Box (1978)) at lags 1, 7, 13, and 19, respectively. One to six months ahead forecasts were generated from this equation for the 1984-1985 period with monthly updatings from January 1984 to DEcember 1985.

Generally, the results in Table 2 indicate that in terms of the RMSEs that the ARIMA(2,1,2) provides accurate forecasts for shorter forecast horizons, and in particular for the first, but that its accuracy decreases for longer horizons. For longer forecast horizons the VAR2 on firs differences (VAR2D) the Bayesian VAR2D and VAR2R models performed better, with the VAR2D and the asymmetric Bayesian model on raw data [ABVAR2GR] having the best performance. Notice that the unrestricted VAR2R performed the worst of all, but that its asymmetric (general) counterpart performed almost as good as the best model, i.e., the VAR2D.

This result is surprising because unrestricted VARs have traditionally performed worse than most available forecasting techniques. Intriguing, however, is the fact that application of Bayesian procedures to the raw (undifferenced) data tremendously improved forecasting performance when asymmetric behavior is allowed (the nonstationarity issue is evaluated closer to the implications section below). The VAR2D model reduces the RMSE (over the ARiMA model) by 6.97, 9.86, 11.80, 19.65, 27.65 and 31.78 percent for one to six months ahead, respectively.

The MSE decomposition reveals that the ARIMA(2,1,2) model becomes increasingly biased as the forecast horizon lengthened. For the VAR2D and the best Bayesian VAR model (ABVAR2GR), however, the bias component was close to zero for one to three months ahead forecasts. For longer forecast horizons the ABVAR2GR model had about 1/3 of the ARIMA(2,1,2) bias. This suggest that there is a significant bias reduction by allowing asymmetric behavior, particularly by tightening the distribution of the income coefficient.

The turning point evaluation (evaluation for one-month ahead shown in Table 4) generally indicated that the VAR2D and the ABVAR2GR models followed the actual movements more closely, with the latter being the best. For the one-month ahead forecasts, the ratio of accurate forecasts to the total was (0.58, 0.50, 0.63, 0.38, 0.63, 0.67, 0.63) for all models in Table 3, respectively; with all models not having worst forecasts for this step ahead. However, the accuracy of all models significantly deteriorated as the forecast horizon increased (the ratio of worst forecasts tot total for the six-month ahead forecasts was (0.11, 0.28, 0.28, 0.33, 0.17, 0.28, 0.06) for all models as in Table 3, respectively. Observe that imposing the random walk hypothesis through Bayesian procedures on unfiltered data tremendously improved the accuracy of the forecasts as measured by the TP for one to six months ahead.

Further Results and Implications

The application of VAR methodologies to both raw and differenced data merits additional consideration. Stationarity of a trivariate VAR2 model requires that the solution to the characteristic polynomial $|Il^2 - A_1 l - A_2| = 0$ must have characteristic values (CV) which are less than one in absolute value for all elements in A_1 and A_2, where A_1 and A_2 are 3x3 matrices of parameters associated with the first and second lag, respectively, of the VAR2 model. Table 4 provides a summary of the real and imaginary components of the CV for the characteristic polynomial associated with selected raw and differenced models. As expected, application of least squares to nonstationary data results in unstable parameter estimates since there are CV which are greater than one. Bayesian procedures in this application, however, almost eliminate the instability in parameter estimates (all CV are less than or equal to one). This is useful because from a practical perspective it eliminates the need for filtering (and therefore transformation of forecasts), it avoids possible distortion of multivariate interaction, and it may permit improved forecasting performance with parameters estimates that are fairly stable.

The previous results showed that asymmetric priors in a VAR context improved forecasting performance. Would new information which is incorporated to update asymmetric weights result in better forecasts? Three sample periods containing six observations each [(1984,1-1984,6),(1984,7-1984,12), and (1985,1-1985,6)] were used in a RMSE evaluation to analyze whether changes on the neighborhood of the weights for the ABVAR2GR model would affect forecasting performance. In general, the results indicate the following. First, loosening the effect of per capita income on the other equations, the PC equation in particular, worsens the RMSEs in relation to the base period (the base period refers to the results on table 1); and second, loosening the effect of PC and PFS on each other does not improve forecasting accuracy, in fact, RMSEs are not very sensitive to upward changes in asymmetric weights. This second result may be related to the high correlation between PC and PFS (0.93 for the 1975-1983 period). Generally, it can be concluded that updating asymmetric weights may not improve forecasting accuracy, and that considering the computational expense involved in analyzing the sensitivity of these weights, researchers should consider updating only when they have strong beliefs that economic patterns have appreciably changed (in the spirit of a true Bayesian framework).

For an individual decision maker whose profits are negatively related to forecast errors, these results imply that he can be better off by using forecasts from VAR and BVAR models rather than simpler ARIMA models. The VAR2 model on first differences resulted in best forecasting performance; however examination of Bayesian VARs with asymmetric priors also generate highly accurate forecasts. This approach has the advantage of maintaining multivariate interaction of the original data and avoids possible distortions caused by differencing of the data. Further, evaluating in terms of bias, the Bayesian asymmetric VAR results in forecasts with higher average precision at every forecast horizon.

Table 1. Optimal Weights for the Asymmetric Prior, Bayesian VAR of Order 2 (ABVAR2GR, ASBVAR2GD), First Estimation Period to 1982, Forecast Evaluation Over 1983, Raw and First Differenced Data.

Equation	ABVAR2GR*			ABVAR2GD*		
	Variables					
	PC	PFS	PCI	PC	PFS	PCI
PC	1.000	0.500	0.001	1.000	0.001	1.000
PFS	0.500	1.000	0.001	0.500	1.000	0.010
PCI	0.001	0.001	1.000	0.001	0.001	1.000

*The symmetric weights for ABVAR2GR and ABVAR2GD models are (d=0.55, w=0.28, λ=0.10) and (d=1.0, w=1.0, λ=0.10), respectively.

Table 2. Root Mean Squared Errors (RMSE) and MSE decomposition for One through Six Month Ahead Forecasts, Cattle Prices ($/cwt), 1975-1983. Initial Estimation Period, with Monthly Updatings to November 1985.

MODEL	Months Ahead RMSE / MSE Decomposition					
	1	2	3	4	5	6
ARIMA(2,1,2)	2.44[a]	4.16	5.34	5.75	6.22	6.86
	3.98	7.15	12.37	28.68	46.16	55.12
	5.90	14.02	19.06	11.48	4.07	2.26
	90.12	78.82	68.56	59.83	49.77	42.61
VAR2R	2.47	4.37	5.84	6.72	7.44	8.01
	10.77	18.95	26.57	41.77	53.99	60.81
	3.49	8.28	12.55	9.61	6.37	4.65
	85.74	72.78	60.87	48.62	39.63	34.54
VAR2D	2.27	3.75	4.71	4.62	4.50	4.68
	0.09	0.35	1.07	7.07	20.70	34.33
	9.00	17.40	23.07	16.78	7.34	1.89
	90.91	82.25	75.86	76.14	71.95	63.78
BVAR2GR	2.56	4.33	5.61	6.16	6.76	7.54
	3.42	7.15	12.88	28.19	45.38	55.90
	5.66	16.42	23.92	18.42	10.72	7.03
	90.92	76.43	63.20	53.39	43.90	37.07
BVAR2GD	2.41	4.38	5.86	6.11	6.17	6.38
	0.56	0.74	0.99	6.62	20.81	37.70
	17.53	31.88	42.41	41.38	30.93	19.64
	81.90	67.39	56.59	52.00	48.26	42.46
ABVAR2GR	2.46	3.95	4.83	4.88	4.95	5.22
	0.03	0.08	0.79	4.97	12.29	17.78
	2.54	10.14	16.39	12.69	7.91	6.15
	97.43	89.78	82.83	82.34	79.81	76.07
ABVAR2GD	2.40	4.30	5.68	5.84	5.78	5.89
	0.44	0.54	0.65	5.12	17.34	33.61
	18.67	32.69	41.95	40.87	30.84	18.55
	80.89	66.77	57.40	54.01	51.81	47.85

[a] In every column-block of four numbers, the first is the RMSE, and the other three correspond to the bias, regression and disturbance components, respectively.

Table 3. Turning Point Evaluation of the One-Month Ahead Forecasts from Selected Models for Cattle Prices.

TURNING POINT ELEMENT	MODEL ARIMA212	VAR2R	VAR2D	BVAR2GR	BVAR2GD	ABVAR2GR	ABVAR2GD
F11	1	0	0	0	0	3	0
F12	0	0	0	0	0	0	0
F13	3	4	4	4	4	1	4
F14	0	0	0	0	0	0	0
F21	0	0	0	0	0	0	0
F22	3	2	0	4	0	1	0
F23	0	0	0	0	0	0	0
F24	1	2	4	0	4	3	4
F31	0	0	0	0	0	0	0
F32	0	0	0	0	0	0	0
F33	5	5	5	5	5	5	5
F34	0	0	0	0	0	0	0
F41	0	0	0	0	0	0	0
F42	6	6	1	11	1	4	1
F43	0	0	0	0	0	0	0
F44	5	5	10	0	10	7	10
RAF	0.58	0.50	0.62	0.38	0.63	0.67	0.63
RWF	0.00	0.00	0.00	0.00	0.00	0.00	0.00

NOTE: RAF is a ratio of the accurate forecasts to the total and RWF is a ratio of the worst forecasts to he total.

Table 4. Characteristic Roots of the Characteristic Polynomial Associated with the nonBayesian and Bayesian VAR2 Models on Raw Data and the VAR2 Model on First Differences, Estimation Period 197-1983.

Root	VAR2R		ABVAR2HR		VAR2D	
	Real	Imaginary	Real	Imaginary	Real	Imaginary
1	1.97	0.00	1.00	0.00	0.39	0.18
2	1.04	0.41	0.94	0.13	0.39	-0.18
3	1.04	-0.41	0.94	-0.13	0.32	0.00
4	-0.07	0.11	0.10	0.00	-0.39	0.00
5	-0.07	-0.11	0.03	0.00	-0.13	0.13
6	0.11	0.00	0.02	0.00	-0.13	-0.13

FOOTNOTES

1. As Pagan (1987) notes, this approach is "Bayesian in spirit".

2. Lutkepohl (1985) compared various selection criteria for estimating the order of a VAR process in a simulation study, where performance of the various criteria under different sample sizes was evaluated. The results indicated that for the processes studied, Schwarz's BIC (SBIC) criterion chose the correct autoregressive order most often and resulted in smallest mean squared forecasting error. The SBIC tends to provide a parsimonious multivariate specification; in a practical sense, its effect on the accuracy of forecasts in a specific situation is uncertain.

3. Additional details are can be found in Bessler and Kling (1986).

4. Such specification admits nonstationary behavior, the limiting case being the one for which the data behaves as pure random walk.

5. Using the estimated values of A_k in expression (6) and using information available up to, and including, time t, the predicted values of Y(t+n) are given by the formula:

$$\hat{Y}(t+n) = D_i + \Sigma_{k1}\hat{A}_k\hat{Y}(t+n-k) + \Sigma_{k2}\hat{A}_kY(t+n-k)$$

where k1=1,....,n-1 and k2=n,....,K. Note that this procedure is recursive because a new value is obtained using previously generated forecasts.

6. This criterion is calculated by RMSE = $[N^{-1}(\hat{y}_f - y_f)^2]^{1/2}$.

7. The equations for these measures are: Bias Proportion = $(P_m - A_m)^2$/MSE, Regression Proportion = $(S_p - rS_a)^2$/MSE, and Disturbance Proportion = $(1 - r^2)S_a{}^2$/MSE, where P_m is the mean of the predicted values, A_m is the mean of the actual values, S_p is the standard error of the predicted values, S_a is the standard error of the actual values, and r is the correlation coefficient between actual and predicted values.

8. Corn is the main component of cattle feed in cattle feeding systems; furthermore, it is reasonable to expect the price of corn to appear in the VAR model. However, its multivariate interaction is not significant as indicated by correlation coefficients and a transfer function analysis. In the past few years, price of corn has been so low that it may not be an important decision variable.

9. Goodness-of-fit measures showed that the raw data VAR1 model was much more significant than the first differenced model. For instance, the VAR1 model on first differences had only one significant coefficient, the first lag on the PCI equation; additionally, the R-square for the PC equation on raw data was 0.96 in relation to 0.04 for the first differences over 1975-1983. RMSEs from this VAR1 model for one to six ahead forecasts of the PC equation, 1984-1985 period with

monthly updatings, were 2.78, 4.69, 6.14, 6.89, 7.67 and 8.67. These values are larger than those for the VAR2 models at every forecast horizon.

10. The symmetric prior case for the BVAR2GR model saw also examined under a Harmonic lag decay; this, however, did not improve forecasting performance
over the Geometric model. For both models the values for LNFE revealed a very flat structure; therefore, searching about the neighborhood of the optimal weights reported here was considered unnecessary.

11. This comprises all data available while the research was conducted.

12. This result is consistent with an analysis of the variance decomposition of forecast errors during 1983 for the three series (PC,PFS,PCI). The variance decomposition revealed that PC is exogeneous, particularly for shorter horizons, PFS becoming more influential as the forecast horizon increased. Throughout, PCI had effects of less than one percent.

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