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Department of Agricultural Economics
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ABSTRACT

This paper examines the predictive performance of structural and vector autoregressive models for forecasting monthly cotton prices. Two distinct time periods were selected for testing: a period of major policy shock and a period of more normal market conditions. The study also investigates a composite approach, using vector autoregressions to determine the future values of exogenous variables of the structural model. Multi-dimensional testing procedures were adopted to evaluate the accuracy of forecasts. Simulation results demonstrate the superior performance of the structural model in handling major policy changes, while the time series approach shows greater accuracy in forecasting normal price movement. Although the composite approach failed to show improvement in forecasting accuracy, a joint specification of the structural model and the time series properties of exogenous variables may merit further investigations.

KEY WORDS

Composite approach, Cotton price forecast, Multi-dimensional evaluation, Structural model, Vector autoregression.

1. INTRODUCTION

Structural econometric models and vector autoregressions have been widely adopted by economists for forecasting, policy analysis, and behavioral hypothesis-testing research. Traditionally, these two approaches have been viewed as distinct and competitive. The structural model emphasizes the theoretical description of behavioral relations that impose identifying restrictions on model specification. The vector autoregressive model, on the other hand, focuses upon reduced form estimation with few parameter restrictions and does not attempt structural interpretation of data.

In the past, researchers who used these two approaches have generally maintained a self-contained attitude, claiming the superior predictive performance of their approach over the other. Despite this competitive state of affairs, some model-builders have begun to explore the complementary nature of these two approaches, especially in the investigation of combining vector autoregressive models with structural models to determine the future values of exogenous variables (Fair, 1986) or to adjust the constant terms of stochastic equations of macroeconomic models (Klein, 1984).

This study attempts to combine the structural and vector autoregressive approaches of econometric modeling work in agriculture, using the setting of the U.S. cotton subsector. The cotton market is particularly interesting because it has recently undergone a substantial policy change that may be difficult for any model to capture in exante forecasts. Because the 1985 Farm Bill provided marketing loans, U.S. cotton prices fell from $0.67 per pound to $0.27 per pound within a one-week period. The drop created a challenging period for testing a model's capability in forecasting. Under such circumstances, structural models equipped with relevant policy variables and adequate specifications may predict well, while time series models are not expected to perform so well.

The paper is presented in five sections. First we discuss the theoretical aspects of model performance analysis. We then relate these to the issues of combining structural and time series models. A comprehensive set of the multi-dimensional forecast evaluation criteria is proposed. In section III an overview of the structural econometric model of the U.S. cotton industry is presented. This is followed by a brief discussion of the time series method employed in this simulation study. The predictive testing results of the structural and vector autoregressive models, both singly and in combination, are presented in section IV. The final section of this paper contains a summary and some suggestions for further research.

2. EVALUATION AND INTEGRATION OF FORECASTING MODELS

In evaluating econometric model performance, there are four major areas of concern: (1) the stochastic disturbance terms associated with the model, (2) the parameters of the model, (3) the assumed input values of exogenous variables, and (4) the specification of the model. A structural econometric model in its forecasting form (pure and adjusted), can be written as (Chen, 1981):

$$\hat{Y}_t = g(0, \hat{x}_t; \hat{r}) \qquad (1), \text{ or}$$

$$\hat{Y}_t = g(0, \hat{x}_t; \tilde{r}) \qquad (1a).$$

In an actual forecasting exercise, the model is used to generate the predicted values of the endogenous variable $\hat{Y}_t$ based on estimated values of parameters $\hat{r}$, the expected values of the structural disturbances, $E(e_t)=0$, and the assumed input values of exogenous variables $\hat{x}_t$ over the prediction period. Largely due to data revisions and the availability of non-sample and non-model information, the econometric forecaster must adjust the constant terms of the model in the preparation of a forecast. Therefore, as shown by Equation (1a), a vector of the adjusted values of the parameters, $\tilde{r}$ instead of $\hat{r}$ is actually used in the model.

A Set of Evaluation Criteria

Model evaluation is a multiple dimension problem. We look at the model's forecast performance from several perspectives. A model's performance can be evaluated over the historical period of observations (within sample evaluation) for which the parameters ($\hat{r}$) of the model were estimated or over a different time period (outside sample evaluation). Parameter updating may or may not be allowed. The model's forecasts should take into account exogenous variable uncertainty and the fact that forecast error variances vary across time. If the actual values of the exogenous variables (x_t) are used, the evaluation is for an expost forecast, while an exante forecast uses the predicted values of exogenous variables $(\hat{x}_t)$. The model's forecast can be dynamic or static. The static forecast uses actual values of lagged endogenous variables (Y_{t-i}), while the dynamic forecast is based on the predicted values of lagged endogenous variables $(\hat{Y}_{t-i})$. In addition, a model can be evaluated on its own or as it contributes to forecasts from a combination with one or more additional models.

The design of the simulation experiments and the particular aspects of forecast evaluation that we considered in this paper are summarized in Table 1. To highlight these forecast evaluations, a total of 30 simulation experiments are listed in the table. Entries in Table 1 are of six general types. SIMi entries refer to forecasts from structural models for the time period of policy shocks due to the implementation of the marketing loan program in 1986. Here the index i runs from 1 to 7, as seven different aspects of forecast evaluation are considered. The VARi entries refer to forecasts from a vector autoregression. Finally, the SAVi entries refer to evaluations of the combined structural and autoregressive models. The same types of simulations were performed with another sample period of observations to represent an ordinary time period in 1984. Entries of TESi, VESi, and TAVi are 1984 simulation runs of the structural model, vector autoregression, and their combinations, respectively.

Table 1. SIMULATION EXPERIMENT DESIGN:
Multi-Dimensional Predictive Performance Evaluation

	Within sample	Outside Sample					
	No Parameter Updates	Parameter Updates			No Parameter Updates		
	Expost	Expost	Exante		Expost	Exante	
	Static (1 step)	Static (1 step)	Static (1 step)	Dynamic (5 steps)	Static (1 step)	Static (1 step)	Dynamic (5 steps)
1986 Policy Shock Period:							
Structure Model	SIM1	SIM2	SIM3	SIM4	SIM5	SIM6	SIM7
Vector Autoregression			VAR3	VAR4		VAR6	VAR7
STR/VAR Combined			SAV3	SAV4		SAV6	SAV7
1984 Ordinary Time Period:							
Structure Model	TES1	TES2	TES3	TES4	TES5	TES6	TES7
Vector Autoregression			VES3	VES4		VES6	VES7
STR/VAR Combined			TAV3	TAV4		TAV6	TAV7

A common approach in model evaluation is to track the model's performance within the sample period for which the parameters were estimated. In this context, historical curve-fitting has become a dominant factor in model research. To deviate from this approach, we extend our model evaluation to an outside sample, and allow parameter updates for both the static (1-step-ahead) and dynamic (5-steps-ahead) conditions. Successive re-estimation is assumed to improve parameter precision and model performance over its simulation path.

In a realistic forecasting environment, the input values of exogenous variables are also unknown. In this study, both the expost and exante forecasting performances are evaluated. Although a good deal of information is available to forecasters on the future values of the exogenous variables, a simple extrapolation of the exogenous variable is commonly used. For our simulation research, a naive no-change extrapolation was used to generate the exante values of exogenous variables under static and dynamic assumptions. In actual forecasting situations in which the future is truly unknown, a realistic model evaluation must be outside the sample, exante and dynamic--the 7th simulation entry presented in Table 1.

Integration of Structural and Time Series Models

Integration of alternative econometric models has been considered by several authors. Early work of Bates and Granger (1969) suggests integration of models through linear combinations of several forecasts. While this work continues to generate interest among researchers, the method described by Bates and Granger was not used in this paper. An alternative approach to integration is outlined in a paper by Ashley (1983). Here the author uses time series analysis to model the residuals from a structural econometric model. Forecasts of the relevant dependent variable are then generated as the sum of the forecast of the econometric model and the forecasts of the residuals. A variant of this procedure is suggested by Klein and Sojo (1986). They used time series analysis to extrapolate the high-frequency (monthly) data to improve the exante forecast of the related low frequency (quarterly) endogenous variables in the structural model. An adjustment is added to the right-hand side of each econometric equation so that the equation generates the same value for the left-hand side as that given by the time series model. This procedure is an alternative to the usual subjective adjustment factor, which is often used in real time econometric forecasting. We do not follow this approach in our paper either.

Here we use time series analysis to generate forecasts of the relevant exogenous variables in an econometric equation. These forecasts are generated in the usual way from the historical regularities in the data. Ashley (1983) considered the forecasting properties of such a procedure. His results suggest that improvement in forecasting accuracy is possible if the exogenous variables can be forecasted with sufficient precision.

Consider the structural equation given in equation (1), where y_t represents an endogenous variable of the forecasting model; g(.) represents a functional relationship that transforms the contents of the parenthesis into y_t; x_t represents a vector of observed exogenous variables; and r represents a matrix of unknown parameters, which are to be estimated with an appropriate GNLS (generalized nonlinear least squares) estimator.

In many cases the form of equation 1 is simplified to be linear. This permits a simple representation, as in equation (2):

$$Y_t = A_0 + A_1 X_t + e_t \qquad (2),$$

where X_t is again an exogenous variable, e_t a white noise residual, and A_0, A_1 appropriately estimated GLS parameters. A common procedure would be to substitute lagged X_t (X_{t-1}) into equation (2) to generate a structural forecast of Y_{t+k} at all future dates.

If, however, through time series techniques, one can identify the process that generates X_t as a $k^{\underline{th}}$-order AR, then an alternative to the above procedure would be to substitute the time series forecasts from this autoregression into equation (2). Suppose that AR is given as equation (3):

$$X_t = B_0 + B_1 X_{t-1} - \ldots + B_k X_{t-k} + v_t \qquad (3),$$

where X_t is the exogenous variable in equation (2) and v_t is a white noise innovation. Forecasts from equation (3) can be generated by application of the chain-rule of forecasting--where forecasts at horizons h > 1 are found by substituting earlier forecasts into equation (3) and treating them as if they were the actual values. Equation (4) is a representation of this rule for the h-step-ahead forecast:

$$\hat{X}(t+h) = \hat{B}_0 + \hat{B}_1\hat{X}(t+h-1) + \hat{B}_2\hat{X}(t+h-2) + \ldots\ldots$$
$$+ \hat{B}_h X(t) + \ldots\ldots + \hat{B}_k X(t+h-k) \qquad (4).$$

Here $\hat{B}_0$, $\hat{B}_1$, ..., $\hat{B}_k$ are appropriately estimated GLS parameters. Note here that $\hat{X}(t+h-k)$ represents the earlier k<u>th</u>-step-ahead forecast from the recursion. The entries in Table 1 labeled SAVi and TAVi represent forecasts from combinations of this type.

3. AN OVERVIEW OF THE STRUCTURAL MODEL

The structural model of the U.S. cotton industry presented in this paper is a 67-equation model with 15 behavioral equations and 52 identities. From the specification viewpoint, it is a fully integrated model linking the domestic market block with a Farm Program Simulator and the world market block. The Farm Program Simulator is by far the largest block in the model, with 58 variables describing policy instruments and parameters, and producers' operating returns and costs in detail.

Implicit Revenue Function and Farm Program Simulator

In modeling farm commodity sectors for policy analysis, numerous alternative specifications have been explored in the past. Previous model work has concentrated on either supply response studies that elaborate farm program analysis or the construction of complete sector models that include a few government policy variables. To provide comprehensive treatment of the impact of government policy actions, a theoretical specification of implicit revenue function is introduced (Chen, 1987).

Based upon microeconomic theory, econometric relations of firms take several different forms, e.g., the production function and efficiency conditions, production and factor demand functions, supply functions, and cost and revenue functions. Although they have equal standing in economic theory, the specifications are different in terms of parametric information and data requirements (Klein, 1982). This cotton model follows the cost and revenue function approach, for which the producer is assumed to maximize the expected net returns subject to the constraints imposed by government programs.

This specification takes into account the implicit nature of producers' revenue in terms of direct and indirect government program benefits. A simplified representation of the producers' net operating return (NOR), is expressed as the difference between total operating return (OR) and cost (OC). Based upon the implicit revenue function specification, the interactions of program instruments with cotton market variables are summarized in the following equation (Chen, 1987):

$$\begin{aligned} OR &= CR + NLR + DFG + LDFG + DVG + DAG \\ &= [b_0 * PF * SY * SA] + [(1-b_0) * PNL * SY * SA] \\ &\quad + [(PT - Max(PL, PF)] * SYG * [1 - (r_1*SARP + r_2*SPLD)] * SALO \\ &\quad + [(PL - PLR) * SYG * [1 - (r_1*SARP + r_2*SPLD)] * SALO \\ &\quad + [PDVG * SYG * (r_2 * SPLD * SALO)] + [0.75 * SYG * (0.33 * PT)] \end{aligned} \qquad (5).$$

Here, producers' operating return (OR) is the sum of cash receipts (CR), net loan receipts (NLR), deficiency payment (DFG), loan deficiency payment (LDFG), diversion payment (DVG), and disaster payment (DAG). This equation also contains the various program instruments: loan rate (PL), loan repayment rate (PLR), net loan rate (PNL), target price (PT), program payment yields (SYG), percent of ARP acreage reduction (SARP), percent of paid land diversion (SPLD), base acreage (SALO), and diversion payment rate (PDVG). Also included in the equation are the cotton market variables of price received by farmer (PF), yield per acre (SY), and planted acres (SA). There are two sets of behavior response parameters, b_i, and r_i, in equation (6). The former, b_i, describes the producers' decision in allocating cotton output to be sold on the spot market and in the determination of CCC loan entry or redemption. The latter, r_i, represents the producers' decision for participating in the acreage reduction program, either the mandatory acreage reduction program (ARP) or the voluntary paid land diversion (PLD).

In view of the complexity of the current farm program, a separate Farm Program Simulator has been developed. Development of the Farm Program Simulator helps provide the transmission mechanism in the model, tracing the effect of farm program changes on acreage response, market price determination, CCC loan activity, inventory stock adjustment, farm income, and government payment.

Structural Characteristics of the Model

The model contains two major blocks of equations: one for the domestic market and the other for the world market. The domestic market block contains monthly equations of domestic mill consumption, ginning, and export sales. Memphis prices, average price received by farmers, cash receipts, and other income components are also determined monthly. The annual crop production equations include planted acreage for four major crop regions of the Southeast, Southwest, Delta, West, and Texas. The yield per acre equation for the U.S. is endogenously determined. This allows crop production estimates for the U.S. as a whole, providing acreage detail on a regional basis. The acreage response equation reflects profit maximization behavior derived from the implicit revenue function. Producers' net operating return, diversion payment, and intercrop competition are the key exogenous variables. Soybeans were found to be a significant competing crop in the Southeast and Delta areas, as sorghum grain was in the Southwest and Texas.

In developing world market equations, the theoretical specification of trade flow and market share, particularly the two-stage decision process model, was adopted. The model contains annual equations for total world cotton import demand and U.S. export market share, and monthly equations for U.S. cotton exports. The key variables in export equations are U.S. cotton prices at the Memphis market and world market prices at Liverpool and the weighted average exchange rates of six major countries. Total mill consumption, harvest acreage, and production for the rest-of-world totals are also determined endogenously in the model. The basic identity for achieving the supply-utilization balance of this two-region model is also included.

Price Determination Equations for Policy Impact Simulation

Price and income equations are the heart of commodity sector models for forecasting and policy analysis. These equations are subject to critical evaluation through an ordinary time period of stable price movements and a period of substantial policy changes. In the 1985 and 1986 crop seasons, cotton market prices have been influenced significantly by the marketing loan program. This policy action was designed to boost U.S. exports, to reduce stock levels, and to ensure competitive U.S. prices on the international market. The effect of this action was a shift of the effective price floor from the domestic loan rate to adjusted world prices, the former being substantially higher. Developments of this type had never occurred in the historical period. One would suspect that the structural parameters of the model would be unstable. If so, the model would not be useful for forecasting the future path.

However, the theoretical structure of the price equation of the model for simulation experiments has properties suitable for forecasting these types of policy changes. The theory underlying this price equation can be sketched as follows. First, the behavioral equation for the U.S. monthly cotton price is estimated by a deviation term relating the Memphis price to the effective price floor. Second, through an identity relation, as shown in equation (5), we can change the effective price floor from the original specification of the effective domestic loan rate to adjusted world prices. This mechanism is particularly useful for evaluating the impacts of the marketing loan program. Third, these price equations are constructed to reflect the theoretical framework of stock-demand functions. Following the conditional expectation hypothesis, three expectation terms are also used in the model (equation 6). This specification has proven to be particularly valuable in tracking developments in the domestic and international markets and in reflecting the dynamic process of market equilibrium.

Identity for the Memphis Cotton Price (6)

$$COLPMME116 = COLPMDPLL + (COLPFLLD1 * COLPLE + COLPFLLD2 * COLAWP)$$

where COLPMME116 is the cotton market price, c/lb, Memphis slm 1 1/16 inch; COLPMDPLL is the deviation of Memphis price from the effective price floor; COLPLE is the effective loan rate, c/lb, using base loan rate adjusted by interest charge and storage costs through the crop season; COLAWP is the adjusted world price, c/lb, the Liverpool market price, the A index series, adjusted by transportation costs and quality differences between the U.S. and Liverpool markets. COLPFLLD1 and COLPFLLD2 are two dummy variables used to represent policy changes and implementation of the 1985 Farm Bill provision for marketing loans, August 1, 1986; COLPFLLD1 equals one prior to August 1986 and zero otherwise; COLPFLLD2 equals one after August 1986 and zero otherwise.

Behavioral Equation for Cotton Price Deviation from Effective Price Floor (7)

$$\begin{aligned} COLPMDPLL = & \underset{(2.28)}{-0.3899} * COLPMME116F \underset{(1.47)}{-0.2234} * COLHTDT \underset{(2.20)}{-0.0734} * COLHTDTX \\ & \underset{(3.57)}{-0.0009} * COLDA2 \underset{(4.22)}{-21.1698} * COLHTDTR + \underset{(12.23)}{17.0763} * USMXPRC + \underset{(4.12)}{73.7951} \end{aligned}$$

Sum Sq	2104.95	Std Err	4.5652	LHS Mean	9.9990
R Sq	0.8063	R Bar Sq	0.7947	F 6,101	70.051
D.W.(1)	0.9062	D.W.(12)	1.9932	t statistics in parentheses.	

where COLPMDPLL is the cotton price deviation from the effective price floor, c/lb, Memphis market; COLPMME116F is the seasonal adjustment factor of the Memphis cotton price estimated by the Census Bureau X11M method; COLHTDT is the U.S. monthly ending stock-to-demand ratio; COLHTDTX is the expected U.S. stock-to-demand ratio at the end of the current crop year; COLDA2 is the expected U.S. total supply for the second-crop-year-ahead, including expected ending carry-over stock and the new crop; COLHTDTR is the rest-of-world ending stock-to-demand ratio; and USMXPRC is the dummy variable for measuring the entry of P.R.C. into the U.S. export market in the early 1980's.

4. THE TIME SERIES MODEL

The method used to summarize the time series properties of the data is a Bayesian vector autoregression (see Litterman, 1986). This prior treats each variable as a random walk, with varying degrees of tightness to permit differential degrees of series interactions. We include in this general specification the seasonal dummy variables, for which we provide no prior. The essential feature of this model is that the researcher specifies the degree of interaction among the variables of a multiple time series. While the prior is centered on a random walk for each variable, by specifying differential levels of tightness on each variable in each VAR equation, the researcher can allow the data to have more or less influence on the resulting forecast. Several expositions on this model are in the literature (see especially Doan, Litterman and Sims, 1984). We need not give extensive discussion of it here.

Three types of information must be specified in the "Litterman prior." Overall tightness reflects the prior standard deviation on the coefficient on the first lag of the dependent variable. This was set at .25 to be consistent with our earlier study of empirical data (see Bessler and Kling, 1986). Doan and Litterman recommend setting overall tightness in the neighborhood of .1 or .2 (Doan and Litterman (1985, p. 11.9). The rate of decay on tightness of coefficients of lagged variables (beyond one period) was set at 1.0, see again Doan and Litterman (1985, p. 11.9). Finally, the interseries tightness parameters were set following some initial pretesting. Table 2 summarizes that information.

The FPE loss function criterion was examined over the period 1978 through 1983. The model was specified by the application of Hsiao's (1979) recursive procedure. This provided a guide to where to place strong or loose restrictions on the data. When the FPE model included a variable in a particular equation, that variable in that equation was assigned a prior tightness value of .8--indicating that the data had a considerable influence on the resulting forecast.

TABLE 2. Prior Tightness Levels on Coefficients in the Vector Autoregressive Model

	Equation				
lagged variables	World price	Expected supply	U.S. stocks	World stocks	Memphis price
---------					
World price	1.0	.1	.1	.8	.1
Expected supply	.8	1.0	.8	.8	.1
US stocks	.8	.1	1.0	.1	.1
World stocks	.1	.8	.1	1.0	.1
Memphis price	.1	.1	.1	.1	1.0

Priors were specified by pretesting the data with FPE criteria.

We deviated slightly from this procedure by assigning a prior tightness value of 1.0 to the lags of a particular variable (see diagonal elements of Table 2). When the FPE-specified model did not include a variable in a particular equation, that variable was given a prior tightness value of .1 in that particular equation, indicating that this variable had little influence on the resulting forecast of the particular equation.

Clearly our procedure is an *ad hoc* way of providing priors (indeed, some may not call the results "a prior" at all). However, the procedure does provide a quick method of reducing the variable interactions. The alternative procedure of searching for optimal tightness settings over earlier periods (see Doan, Litterman, and Sims, 1984) was viewed as too costly and not followed. A third procedure of actually eliciting priors of real world experts was considered but also viewed as too costly. The forecasts from this specification are discussed in the results section below.

5. THE EMPIRICAL SIMULATION RESULTS

Results from forecasting over the period August through December 1986 are given in tables 3 and 4. This period is significant because the government program for cotton changed in a manner that caused prices in August to differ substantially from those in previous periods. Forecasts from the structural model are labeled "Structure" in the table; those from the time series model are labeled "Vector Auto"; and those from the combined model are labeled "Combined". The forecasts are evaluated under seven dimensions of the forecasting problem--within sample with no parameter updating, and so forth. The VAR models and the Combined Structure/VAR forecasts are presented for just four model types: outside sample with parameter updating and static; outside sample

Table 3 PREDICTIVE PERFORMANCE: 1986 POLICY SHOCK PERIOD
Actual and Predicted Monthly Cotton Prices

	1986				
	Aug	Sep	Oct	Nov	Dec
Actual Price, Cotton Memphis 1-1/16 Cents/lb	26.60	33.58	41.93	44.09	51.09
Within Sample, No Parameter Update					
Expost, Static					
Structure (SIM1)	25.13	33.76	42.95	44.04	51.85
Outside Sample, Parameter Update					
Expost, Static					
Structure (SIM2)	25.27	33.74	42.97	44.18	51.99
Outside Sample, Parameter Update					
Exante, Static					
Combined (SAV3)	27.23	25.49	35.37	47.57	44.86
Structure (SIM3)	28.54	29.69	36.00	46.20	47.19
Vector Auto (VAR3)	64.16	20.67	35.03	44.33	46.09
Outside Sample, Parameter Update					
Exante, Dynamic					
Combined (SAV4)	24.09	25.68	25.97	26.39	26.29
Structure (SIM4)	24.60	42.88	43.45	44.78	44.93
Vector Auto (VAR4)	64.16	55.73	55.97	55.98	55.98
Outside Sample, Parameter Update					
Expost, Static					
Structure (SIM5)	25.14	33.82	43.02	44.09	51.91
Outside Sample, No Parameter Update					
Exante, Static					
Combined (SAV6)	27.23	25.61	34.78	46.29	44.62
Structure (SIM6)	28.54	29.90	36.17	46.25	47.23
Vector Auto (VAR6)	64.16	22.28	35.06	44.60	46.39
Outside Sample, No Parameter Update					
Exante, Dynamic					
Combined (SAV7)	24.09	23.63	22.04	21.99	21.82
Structure (SIM7)	25.41	43.09	43.62	44.81	44.97
Vector Auto (VAR7)	64.16	62.86	62.72	62.31	62.03

*Multi-dimensional evaluation procedures as shown in Table 1

Table 4 PREDICTIVE PERFORMANCE: 1984 ORDINARY TIME PERIOD
Actual and Predicted Monthly Cotton Prices

	1984				
	Aug	Sep	Oct	Nov	Dec
Actual Price, Cotton Memphis 1-1/16 Cents/lb	63.05	60.67	60.83	60.44	60.83
Within Sample, No Parameter Update Expost, Static					
Structure (TES1)	61.48	63.49	62.12	61.54	62.08
Outside Sample, Parameter Update Expost, Static					
Structure (TES2)	68.91	68.49	63.28	62.19	62.36
Outside Sample, Parameter Update Expost, Static					
Combined (TAV3)	76.56	71.59	65.13	67.84	62.25
Structure (TES3)	67.32	68.96	64.33	63.92	62.30
Vector Auto (VES3)	65.72	60.40	59.83	60.45	60.14
Outside Sample, Parameter Update Exante, Dynamic					
Combined (TAV4)	78.15	77.69	73.60	73.52	72.96
Structure (TES4)	68.91	68.96	64.81	65.00	65.25
Vector Auto (VES4)	65.72	65.15	65.17	65.20	65.20
Outside Sample, Parameter Update Expost, Static					
Structure (TES5)	68.52	70.68	69.24	68.68	69.14
Outside Sample, No Parameter Update Exante, Static					
Combined (TAV6)	76.08	72.03	68.98	70.87	66.52
Structure (TES6)	66.84	68.96	68.30	68.46	67.19
Vector Auto (VES6)	65.72	60.64	59.95	60.32	60.04
Outside Sample, No Parameter Update Exante, Dynamic					
Combined (TAV7)	75.54	75.84	73.92	74.09	73.72
Structure (TES7)	66.30	68.96	68.77	69.55	70.01
Vector Auto (VES7)	65.72	63.93	63.77	63.69	63.76

*Multi-dimensional evaluation procedures as shown in Table 1

with parameter updating and dynamic; outside sample with no parameter updating and static; and outside sample with no parameter updating and dynamic.

The structural model tracks the 1986 cotton prices very well. Under both static (one-step horizons) and dynamic (five-step-ahead horizons) simulations, the forecasts are quite close to the actual prices realized in the period. The VAR failed to forecast the drop in price in August. While the VAR adjusts quickly to the new level of prices in the static model (in September the VAR begins to forecast in the low twenty cents per pound range), it shows no evidence of adjusting in the dynamic forecasts.

The VAR did not capture the structural change information in the latter (dynamic) models and thus continued to forecast business as usual; the dynamic model is a five-step-ahead forecast while the static model is a one step ahead forecast. Parameter updating is not particularly helpful in improving the static model, but does show considerable improvement in the dynamic model.

From table 4 note that the structural model outperforms the VAR and the combined forecast in the RMSE sense at all horizons and over all model types. The MSE performance of the structural model (Table 4) is not improved by combining the VAR forecast with the structural model. In fact, under the static version of the forecast, the MSE (Table 4) of the VAR is actually higher under the parameter updating scenario. The MSE of the VAR falls by about 15% when parameter updating is allowed in the dynamic version of model evaluation.

Table 5 and 6 present the forecasts from the period August 1984 through December 1984. The same forecast (simulation) types are presented for this early period. Our reasons for considering this period is that it represents a more business-as-usual period (no structural change), even though we found it fell within a period when a government farm program of payment-in-kind (PIK) was in effect. At that time the farm commodity market was under substantial downward price pressures due to macroeconomic policy and worldwide surpluses of grains and oil crops. Table 5 presents the forecasts of all models over the 1984 period. Here the results are quite the opposite of those presented for the 1986 period. The MSE calculations for 1984 are shown in Table 6.

The VAR model outperforms both the structural model and the combined forecasts according to the MSE metrics in all versions of the forecast simulations. Parameter

Table 5 ROOT MEAN SQUARE ERRORS FOR COTTON PRICE FORECASTS
1986 Policy Shock Period

	Within sample	Outside Sample					
	No Parameter Updates	Parameter Updates			No Parameter Updates		
	Expost	Expost	Exante		Expost	Exante	
	Static (1 step)	Static (1 step)	Static (1 step)	Dynamic (5 steps)	Static (1 step)	Static (1 step)	Dynamic (5 steps)
Structure Model	0.88	--	3.84	5.12	--	3.74	5.15
Vector Autoregression	--	--	18.17	21.28	--	17.93	25.11
STR/VAR Combined	--	--	5.65	15.82	--	5.69	19.21

updating of the VAR does not seem to be helpful: in fact, it results in a higher MSE than both the static and dynamic specifications. The static model outperforms the dynamic model, as we would expect. The structural model performs better under the static version of the simulation experiment in the early time period (again, as we would expect). Parameter updating is quite helpful in both the static and dynamic specifications (it reduces MSE by about 31% in the former and about 28% in the latter). This is quite different than the result found in the VAR simulations (where parameter updating was apparently harmful).

Table 6 ROOT MEAN SQUARE ERRORS FOR COTTON PRICE FORECASTS
1984 Ordinary Time Period

	Within sample	Outside Sample					
	No Parameter Updates	Parameter Updates			No Parameter Updates		
	Expost	Expost	Exante		Expost	Exante	
	Static (1 step)	Static (1 step)	Static (1 step)	Dynamic (5 steps)	Static (1 step)	Static (1 step)	Dynamic (5 steps)
Structure Model	1.72	--	4.76	5.64	--	6.98	7.87
Vector Autoregression	--	--	1.32	4.19	--	1.31	3.02
STR/VAR Combined	--	--	8.68	14.14	--	10.06	13.49

The combined forecasts for the early period (1984) did not perform well. Here the combination performed better than both the VAR forecasts and the structural forecasts. This is apparently due to either misspecification of the time series process, which generated the VAR variables, or misspecification of the econometric model. Under the former hypothesis we probably would expect to see poor forecasts of the Memphis price from the VAR as well, but of course we do not observe this. Of course, the structural model was not constructed with the VAR forecasts. If the time series model and the structural model were constructed as one system, the combined model might have shown better results.

6. SUMMARY AND SUGGESTIONS FOR FUTURE RESEARCH

In the early works on composite forecasting some researchers argued that several alternative models can often be combined to yield mean squared errors that are lower than either of the individual forecasts (Bates and Granger, 1969, and many others). Rarely have the composites performed worse than all of the individual models. In fact, some researchers express disappointment when the composite does not show improvement over the best individual method. Here we have a situation where the integration of structural and time series models performs worse than the individual methods over one forecast evaluation period (1984), and shows no improvement as compared with the best method over another forecast evaluation period. Thus, we must label our attempt to improve forecasting accuracy by combining the two approaches as a failure. However, the results do suggest areas where we can look to improve future efforts.

The areas for future study seem to be the joint specification of the structural model and the time series properties of the exogenous variables. Here we treated the specification separately and merely fed the process that projected the exogenous variables into the structural specification. Perhaps a joint specification would improve the behavioral relationship and forecast performance. Errors in the process that generated several of the exogenous variables probably could be correlated with those from the structural equations (perhaps a seemingly unrelated regressions, SUR, estimation method should be explored).

Other areas for further research include more detailed analysis of the time series prior imposed on the data. Recall that we used a random walk prior with variable degrees of series interactions. Under further study, this may prove to be an unreasonable prior. We suggest a more formal data analysis (similar to that done in Doan, Litterman and Sims, 1984) be undertaken in future research with these data.

The 1984 experience of the structural model suggests that important consideration should be given to non-sample and non-model information such as the situation in the PIK period of 1984. It may be productive in the future to use the VAR forecasts as "objective" adjustments to the structural equation intercept. Here we used the VAR forecasts of exogenous variables as input to the structural equation. An alternative procedure would be to use the VAR forecasts to adjust the structural forecast. Following Klein (1986), we can adjust the structural forecast equation with the VAR forecast in normal time periods. This will be equivalent to adjusting the intercept on the structural equation in an objective and replicable fashion. Heretofore, the subjective adjustment procedure has been criticized as being not replicable.

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