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* James G. Hoehn, formerly an Economist at the Federal Reserve Bank of Dallas, is an Economist at the Federal Reserve Bank of Cleveland. William C. Gruben is Senior Economist at The Federal Reserve Bank of Dallas. Thomas B. Fomby is Professor of Economics at Southern Methodist University.

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Some Time Series Methods of Forecasting the Texas Economy

James G. Hoehn and William C. Gruben,
with Thomas B. Fomby

This paper describes, in some detail, the methodology employed in exploratory efforts toward building a quarterly forecasting model for the economy of the state of Texas.

The success of business and government decisions depends upon the accuracy of forecasts of the economic environment. For many decisionmakers, explicit regional economic forecasts have become essential. Furthermore, because the various regions of the United States respond somewhat differently to economic events, an efficient forecast must generally incorporate information about the region as well as about overall national trends. The value of regional economic analysis and forecasting lies in the recognition of regional disparities.

Regional economic analysis, both theoretical and empirical, is presently in its infancy, but appears to be in a period of rapid growth, aided by the accumulation of regional data and by an increasing emphasis on regional analysis within the Federal Reserve System. Two recent papers of particular interest concerning regional forecasting models are Anderson (1979) and Kuprianov and Lupoletti (1984). Although numerous structural models of regional economies exist, there is at present no clear evidence of which we are aware that they are useful for forecasting.

Many regional forecasts, like those for the nation as a whole, are based largely on informal, or "judgmental," methods. Here we explore formal forecasting methods which are intended to uncover the value of regional and national information available for both formal and judgmental forecasters of the Texas economy. The success of any forecaster may depend more on superior judgment than on access to formal methods. Nevertheless, formal methods can augment and rationalize judgments and can locate promising sources of information about future trends.

We explore observed relations between series that hold potential for aiding forecasting. In pursuing this approach, we examine relationships of each element in a set of Texas variables to their own past changes, to past changes in other variables in that set, and to past changes in U.S. variables. The movement in some variables may be accurately forecast by relying predominately on their own past movements. In other cases, variables may be more accurately forecast with models incorporating not only data on their own past movements, but also data on other events occurring in Texas or in the nation, or both. All types of model construction used are essentially cases of the general multivariate transfer function model. Univariate ARIMA (autoregressive-integrated-moving average) models were used to examine the simplest class of forecasting techniques: those that use only the information contained in a series' own past. A closed-regional model examined the effect of adding a second source of information: that of the history of the other Texas variables in the set. A "trickle-down" model measured the value of national data in forecasting each of the set of Texas variables. Finally, "Bayesian" VAR (vector autoregressive) models used both national and regional information in forecasting each of the set of Texas series. These models have engendered considerable interest, due to recent studies by Paul Anderson (1979) and Robert Litterman and associates.

The approaches to forecasting are examined for performance on quarterly data both within the 1969-80 sample and in an out-of-sample period from the first quarter of 1981 through the second quarter of 1983. The results are necessarily somewhat tentative, the more so because a significant portion of 1981-83 performance evaluation period was characterized by general economic weakness.1/ Generalizations are difficult because each of the seven Texas series has quite different properties. Nevertheless, our explorations suggest:

(1) "Naive" univariate time series methods frequently provide forecasts that compare favorably with more complex models. In fact, our experience suggests that the forecasting performance of ARIMA models is not easily exceeded, and rarely by a substantial margin.

(2) To a limited extent, past movements in some regional series, particularly the labor series, appear to foreshadow future movements in Texas Industrial Production and in Dallas-Fort Worth consumer prices. (It is not known, however, whether the movements in the regional labor series are merely proxying for persistent national fluctuations.)

(3) National data appear to provide information about the future course of some Texas series (particularly industrial production, consumer prices in the Dallas-Fort Worth area, and deflated retail sales). The implication is that regional forecasters generally should not ignore national information.

(4) The VAR approach has potential for efficiently incorporating information of all three types (own-lag, regional interaction, and trickle-down). This potential efficiency derives from the extremely

flexible scheme it provides for incorporating prior information. However, our experience suggests that the VAR approach is unlikely to provide better forecasts than univariate ARIMA models, without considerable effort and expense. A VAR model that borrowed priors from Anderson's (1979) seminal regional VAR model performed considerably worse than ARIMAs. A VAR model with priors that incorporated rough notions derived from the properties of other kinds of models provided substantially improved forecasting accuracy out of sample. Some reasonably straightforward ex post alterations in the priors, derived from a one-dimensional grid-search procedure, led to further improvements in forecast accuracy, nearly approaching that of the ARIMAs, generally speaking. Whether it or some other version of a VAR model will aid forecasters cannot yet be determined. About all that can be said with any degree of confidence is that, unless the priors are "fine-tuned" by a sophisticated analyst with a strong "feel" for the data, the resulting model should not be expected to provide very useful forecasts.

CONCEPT OF THE FORECASTING PROBLEM

Formally, the task is to design forecast methods for a set of seven variables which are measures of economic conditions in Texas. Our approach to forecasting is made possible by a new generation of highly efficient computers and by the accumulation of data on aggregate regional variables. In the most general and formal terms, a forecast function $f_j(.)$ for the j-period ahead (j-step) forecast of variable y is:

$$\hat{y}_{t+j} = f_j(S_t)$$

where $\hat{y}_{t+j}$ is the j-quarter ahead forecast and S_t is the set of relevant information available at the time the forecast is made. Essentially, f_j is the recipe or technology to be applied to the available information in constructing forecasts j quarters in advance.

We take as our objective to specify f_j and S such that $E(y_{t+j}-\hat{y}_{t+j})^2$ is minimized, for $0 < j \leq 4$. In particular, we seek forecast functions for the Texas Industrial Production Index (TIPI), the Dallas-Fort Worth Consumer Price Index (CPIDFW), employment according to the survey of business establishments (henceforth referred to as "payroll employment", or in statistical tables as PAYROLL), total nonagricultural civilian employment according to the survey of households (henceforth referred to as "household employment" or TEMP), the Texas labor force (TLF), deflated personal income (RTPY), and deflated retail sales (RTRET).

It is necessary in practice to restrict severely the forecasting function. If derived from economic theory, f_j would generally be a very complex nonlinear function involving all the elements of S_t. To facilitate analysis, however, we limit our search to relatively simple, and mostly linear functions. The selection of an appropriate information set typically involves a blend of both prior information and empirical evidence. Prior information, supplied by economic theory, suggests a set of variables that have potential for improving forecasts. Most data in the universe are irrelevant, such as the price of shoelaces in Johannesburg, which economic theory suggests is unimportant in explaining movements in the Texas economy. We have classified relevant variables into three categories: (1) observed past realizations of y, or "own lags," (2) observed past realizations of other regional variables, or "regional interaction variables," and (3) observed past realizations of national or "trickle-down" variables. Empirical evidence is used to simplify further the information set, by elimination of some of the variables suggested by theory.

The second aspect of making the forecast method operational requires the specification of the function f_j to be applied to the relevant information set. We largely confine attention to linear functions, estimated by ordinary least squares or Theil's mixed estimation. In addition, we estimate the equations only for one-step forecasts, and apply recursive methods to forecast more than one quarter ahead.2/

The success of a formal forecasting equation depends upon the intelligent blending of both prior and empirical information. The two major types of approaches are structural econometric models and time series techniques. Although structural econometric models are often employed for forecasting, they are designed primarily to explain the evolution of variables in terms of established economic theory. Given the past history of exogenous and endogenous variables, and forecasted paths for the exogenous variables and shocks, a structural model can generate forecasts for the endogenous variables. For example, arbitrary paths for exogenous variables capturing government policy can be entered into the model to predict the results of any policy. One can also use econometric models to predict the effect of a structural change; for example, an increased propensity to consume or an increase in the price of imported oil.

Structural models are only capable of generating forecasts conditional on forecasts of or assumptions regarding the exogenous variables. They do not themselves forecast the exogenous variables. Hence, a structural model converts the problem of forecasting endogenous variables to the problem of forecasting exogenous variables, but provides no solution to the latter. Structural models can provide forecasts only if some means of forecasting exogenous variables is appended to them. Typically, forecasted paths for exogenous paths are arrived at judgmentally. Furthermore, forecasters using structural models alter the forecasts by the use of "add factors." Add factors shift the estimated relationships in a way that reflects the forecaster's judgement about the inadequacy of his model's structure in fully exploiting the information at hand.

Time series models are designed strictly for forecasting. They supply formal, strictly non-judgmental and replicable forecasting procedures. In the simplest of these models, the univariate time series models, the future path of any variable is predicted strictly from its past movements. Multivariate methods predict the future of a variable from past movements in a number of variables. Given the present state of structural models, time series models, even the univariate variety, sometimes forecast as well or better than structural models. Time series models are generally easier to construct and can be built from data sets that would be inadequate for a complete specification of structural relationships. However, they cannot explain the behavior of the economy, and cannot be used to provide adequate predictions of the effects of arbitrary policy actions or structural change.3/ And, if a correctly specified structural model and optimal predictions of its exogenous variables are available, it will produce better forecasts than any time series model. Although they can be extremely useful for forecasting, time series models cannot provide adequate answers to most of the questions that concern economists and policymakers.

An essential difference between structural models and time series models lies in the simultaneity of the former and the recursivity of the latter. Only structural models can express the simultaneous relationships of established economic theory. However, simultaneity generally precludes structural "identification"--disentangling the underlying structural relationships with available data. The difficulty arises from the simultaneous action of several factors operating in the same direction at the same time. Economic realizations are the outcomes of an experiment that is poorly designed. Structural models are therefore estimated after numerous, generally incredible assumptions, or identifying restrictions, are imposed on their equations and random disturbances--restrictions which generally have a poor foundation in established economic theory.

The forecasting functions of structural models may exist, but are generally very difficult or impossible to derive. Forecasts are provided by a complicated process of model simulation. On the other hand, time series models are recursive, in that a variable's current value is explicitly related to past values of it and, possibly, other variables. Such a model is a ready-made forecasting procedure: it explicitly states a recipe for predicting future values of variables strictly as a function of past values of variables. The lack of simultaneity, which renders the model incapable of representing the theoretical economic structure, at the same time facilitates forecasting. More importantly, structural economic systems that cannot be identified--and our contention is that they quite frequently cannot--nevertheless generally give rise to economic behavior which can be usefully forecasted using time series methods.

A linear structural model gives rise to a unique multivariate time series model. But the reverse is not true. A time series model is consistent with an indefinitely large number of structural models. If the correct structural model is known, fully identified, and efficiently estimated from a large sample, it can generate superior forecasts. In practice, however, structural models fall well short of this ideal. Consequently, the relative forecasting efficiency of the two kinds of models depends on the relative limitations of each, and can ultimately be assessed only by examining forecast performance.

UNIVARIATE ARIMA MODELS

The univariate autoregressive-integrated-moving average (ARIMA) models treat each Texas variable in isolation in estimation and in forecasting. Such a model takes the form, denoted ARIMA(p,d,q), of:

$$(1-L)^d(1-\phi_1L-\ldots-\phi_pL^p)y_t = \mu + (1-\theta_1L-\ldots-\theta_qL^q)a_t$$

where L is the lag operator ($L^kx_t = x_{t-k}$), y_t is the natural logarithm of the series, and a_t is a normally distributed unobservable random variable with zero mean, finite and constant variance, and zero autocorrelation at all lags. There are p autoregressive terms (lagged y's) and q moving average terms (lagged a's). Typically, economic time series that exhibit growth must be transformed to natural logarithms and differenced once (d equal to one) in order to make the assumptions about the disturbance term plausible for any p and q.

ARIMA models can be identified using methods established by Box and Jenkins (1970). These methods first infer plausible candidates from sample autocorrelations, subject them to diagnostic tests, and repeat this process, if necessary, until an adequate model is found. Table 2 gives the first ten autocorrelations for the growth rates (first differences of natural logarithms) of seven Texas variables, for quarterly data from 1969 through 1980. Whether or not individual autocorrelations are significant at the .05 level (two-tailed test) can be determined in a simple way. If a series is serially uncorrelated, then sample autocorrelations will have a mean of zero and a standard deviation of approximately $n^{-.5}$ for large samples, where n denotes the sample size. Our sample is a small to moderate sized one, so we expect to identify only very simple models. (Simple models are also more likely to remain viable over time, facilitating simple updating of the equation in out-of-sample forecasting.) Given our sample size of 47 quarters, two standard deviations are approximately .29. Tests for serial independence involving sets of autocorrelations are based on the Box-Pierce (chi-square) statistic with Ljung correction factor, and are reported with significance levels at the bottom of Table 2 for lags from 1 to 6, 1 to 12, 1 to 18, and 1 to 24.

TABLE 1: SAMPLE MEANS AND STANDARD DEVIATIONS OF FIRST DIFFERENCES OF NATURAL LOGARITHMS

Variable	--1969 through 1980-- Mean	Standard Deviation	--1969 through 1983:2-- Mean	Standard Deviation
TIPI	.01716	.01736	.01483	.01908
CPIDFW	.01926	.01093	.01832	.01089
PAYROLL	.01107	.006180	.009701	.007660
TEMP	.008835	.008023	.008486	.007817
RTPY	.01090	.01362	.009950	.01344
RTRET	.01009	.02203	.008949	.02226
TLF	.009311	.006444	.009413	.006480

TABLE 2: SAMPLE AUTOCORRELATIONS OF FIRST DIFFERENCES OF NATURAL LOGARITHMS, 1969 to 1980

Lag	TIPI	CPIDFW	PAYROLL	TEMP	RTPY	RTRET	TLF
1	.46	.68	.72	-.10	.19	.18	-.20
2	.18	.62	.46	-.11	-.07	-.04	-.16
3	.08	.54	.27	.14	.13	-.19	.01
4	-.12	.38	.15	.04	-.16	.03	.17
5	.06	.26	.04	-.13	-.32	.05	-.02
6	-.02	.19	-.06	.08	.08	.07	-.02
7	-.16	.09	-.15	.17	.01	-.16	.20
8	-.23	-.07	-.24	-.32	-.24	-.34	-.19
9	-.33	-.04	-.23	.06	.01	.01	.02
10	-.20	-.10	-.23	.10	.15	.05	.19

Chi-Square Statistics for White Noise

To lag:

6	13.5	70.9	13.2	3.5	10.4	4.2	4.8
12	33.2	73.6	26.5	14.7	15.5	15.7	15.8
18	41.2	76.9	30.2	18.4	19.6	22.5	17.9
24	48.7	88.9	39.1	24.0	19.6	22.5	21.8

Marginal Significance Levels of Chi-Square Statistics

To lag:

6	.04	.00	.01	.74	.11	.66	.57
12	.00	.00	.00	.26	.22	.21	.20
18	.00	.00	.02	.43	.36	.21	.46
24	.00	.00	.01	.46	.45	.06	.59

Inspection of the last four columns indicates that household employment, the labor force, real personal income, and real retail sales can be regarded as random walks with drift, i.e., quarterly growth rates in these series are essentially uncorrelated. It is therefore unpromising to attempt to forecast these variables by means of trend projection. To exemplify this result in the simplest of terms, each quarter is a new draw from the same hat, and if any of these series advance sharply in one quarter, that information alone should not lead us to revise our forecast of the next quarter's growth rate. The Box-Jenkins forecast for these variables is always that they will increase at their average growth rate of the sample period, regardless of recent growth rates.

Growth rates of industrial production, consumer prices, and payroll employment, on the other hand, display considerable autocorrelation, implying that the past growth rates in these series can be used meaningfully to project future growth rates. Growth rates in industrial production are significantly autocorrelated at lag one, but generally are not significantly autocorrelated at longer lags, suggesting a single moving average parameter. The autocorrelations for payroll employment's growth rates are quite high at the first several lags, and decay in an approximately geometric pattern, suggesting a single autoregressive parameter. Finally, consumer price growth rates show significant autocorrelation for several lags, but they decay in a pattern that does not seem geometric. A mixed process with one autoregressive and one moving average parameter is suggested.

These suggested models are found adequate, in that the residuals are insignificantly different from white noise. Estimates are presented in Table 3. The standard errors of the estimated equations are substantially lower than the standard deviations of growth rates given in Table 1. The percentage reduction of a model's standard error relative to that of another we shall denote as the information gain:

$$I(B,A) = ((SEE(A) - SEE(B))/SEE(A)) \times 100,$$

where SEE(A) is the standard error of the equation for model A, and SEE(B) is the standard error of the equation for model B. The "gain" can be negative if the standard error of model B is larger than that of model A. Comparing our ARIMAs to a naive model of average growth (ARIMA(0,1,0)), we reduce the standard error 10.5 percent for the growth rate of industrial production, 28.9 percent for the consumer price inflation rate, and 29.4 percent for the growth rate of payroll employment. The gain for the other series is zero, since the "naive" model and the ARIMA model for each are indistinguishable. Hence, own-lags contribute substantial information for forecasting growth rates of consumer prices, payroll employment, and industrial production, and little for the other series.

As an alternative to Box-Jenkins, we have fitted arbitrarily specified ARIMA(2,1,0) models for each of the logged series--that is, growth rates are regressed against two lagged growth rates. Autoregressive

TABLE 3: UNIVARIATE ARIMA MODELS

(1) Texas Industrial Production

$(1-L)\ln TIPI_t = .01783 + (1+.63L)e_t$

SEE = .01538
I = 11.1

To Lag	Chi-Square	Significance
6	6.2	.19
12	15.1	.13
18	19.4	.25
24	24.3	.33

(2) Consumer Price Index, Dallas-Fort Worth

$(1-L)(1-.89L)\ln CPIDFW_t = .02051 + (1-.38L)e_t$

SEE = .007688
I = 29.7

To Lag	Chi-Square	Significance
6	1.7	.67
12	6.5	.69
18	9.1	.87
24	17.0	.71

(3) Payroll Employment

$(1-L)(1-.73L)\ln PAYROLL_t = .01145 + e_t$

SEE = .004318
I = 30.1

To Lag	Chi-Square	Significance
6	.8	.94
12	7.2	.70
18	9.1	.91
24	19.0	.65

All other series (TEMP, RTPY, RTRET, TLF) are modeled in natural logs as random walks with drift, e.g., $(1-L)\ln TEMP_t = .008835 + e_t$, etc.

models of low order may work about as well as models identified with Box-Jenkins methods. The results presented in Table 4 are consistent with that notion. The standard errors of the equations are slightly higher for the ARIMA(2,1,0) models than for the Box-Jenkins models for industrial production, payroll employment, household employment, and deflated personal income, but the reverse holds for consumer prices, deflated retail sales, and the labor force. (Later, we will find that the Box-Jenkins and ARIMA(2,1,0) models provided forecasts out of sample which had roughly comparable performance.)

THE CLOSED-REGIONAL MODEL

Potential improvements over univariate forecasting models can come from incorporating information from either other regional series or national series. In this section, we explore the value of the information in regional series.

We began our exploration by estimating regressions for growth rates of each of the seven Texas variables, using as explanatory variables either two lagged growth rates of the series itself, or those plus two lags of one of the other six Texas variables. This resulted in seven equations for each of seven dependent variables, or 49 in all. The percentage reduction in the standard error arising from the inclusion of another Texas variable provides a measure of the value of that other series in improving forecasts. The gain for each of the seven Texas series' growth rates from inclusion of other Texas series are given in Table 5.

For example, the ARIMA(2,1,0) benchmark equation for TIPI is:

$$\Delta \ln TIPI_t = \mu + \phi_1 \Delta \ln TIPI_{t-1} + \phi_2 \Delta \ln TIPI_{t-2} + a_t$$

From within-sample estimation of this model, we get the standard error, s_a, listed in Table 4 as .01579. The regressions that assess the reduction in the standard error from including one of the other six regional series simply add two lags of the relevant potential information variable. For example, we assess the gain from using the series PAYROLL by running the following regression:

$$\Delta \ln TIPI_t = \mu + \phi_1 \Delta \ln TIPI_{t-1} + \phi_2 \Delta \ln TIPI_{t-2} + \beta_1 \Delta \ln PAYROLL_{t-1} + \beta_2 \Delta \ln PAYROLL_{t-2} + e_t.$$

From this regression, we get s_e, and calculate the gain as:

$$\text{Gain} = ((s_a - s_e)/s_a) \times 100 = 6.7,$$

the value given in Table 5. This is interpreted as a 6.7 percent information gain. Negative values for the gain, frequent in Table 5, occur whenever inclusion of another variable increases the standard error, rather than decreasing it. It should be emphasized that the data in Table 5 does

Table 4: UNIVARIATE ARIMA(2,1,0) MODELS 1/

Variable(y)	SEE	$\bar{R}^2$	I(C,A) 2/
TIPI	.01579	.19	9.0
CPIDFW	.007681	.51	29.7
PAYROLL	.004426	.59	28.4
TEMP	.008252	-.03	-2.9
RTPY	.01364	.01	-0.1
RTRET	.02175	.02	1.3
TLF	.006407	.04	0.6

1/ $(1-L)(1-\phi_1 L-\phi_2 L^2) \ln y_t = a_t$

2/ $I(C,A) = \left[1- \frac{\text{standard error, ARIMA(2,1,0)}}{\text{standard deviation of } (1-L)\ln y}\right] \times 100$

TABLE 5: REGIONAL INFORMATION GAIN 1/

Dependent Variable	Independent Variable: TIPI	CPIDFW	PAYROLL	TEMP	RTPY	RTRET	TLF	Row Sum
TIPI		-1.6	6.7*	10.1*	3.7	4.7	5.9*	29.5
CPIDFW	-2.1		6.3*	8.3*	4.5	4.7	5.4*	27.1
PAYROLL	1.7	-.9		3.2	1.9	-1.1	.1	4.9
TEMP	2.4	-.0	5.0*		-1.8	-.4	-1.1	7.7
RTPY	-1.1	3.4	-2.3	.3		.5	1.1	1.9
RTRET	-2.2	7.3*	-1.4	-1.1	-2.0		-2.2	2.4
TLF	.3	3.6	-.8	-2.2	-1.8	.5		-0.4
Column Sums	-1.0	11.8	13.5	18.6	12.1	8.9	9.2	
Column Sums, Excluding Rows for CPIDFW and TLF:	0.8	8.2	8.0	12.5	9.4	3.7	3.8	

1/ Reduction in standard error relative to ARIMA(2,1,0). (Measures effect of including two logged growth rates of another regional series.)

* Significant at the .05 (2-tailed) level, using an F statistic with 2 numerator degrees of freedom and 40 denominator degrees of freedom.

not reflect regressions including all of the variables at once, but only shows the results of including lagged variation in one other Texas series in addition to own-lags.

These regression results suggest that regional interaction variables alone could significantly aid forecasts of industrial production and consumer prices, with information located in the three labor series. Household employment and deflated retail sales appear to gain some information from consumer prices. The Texas Industrial Production Index has little value in aiding forecasts of other variables, though forecasts of it benefit from looking at other regional series. The series that provide the most information about regional trends in general are the two employment series.

A closed-regional model, which will later be considered in out-of-sample forecasts, was constructed. In it, the growth rate of each Texas variable was related to two lagged growth rates of itself and all other Texas variables. (The closed regional model might be thought of as an unconstrained VAR in growth rates.) The closed regional model can be represented formally as:

$$\Delta \ln \vec{y}_t = \mu + \phi_1 \Delta \ln \vec{y}_{t-1} + \mu_2 \Delta \ln \vec{y}_{t-1} + \vec{e}_t^{\,R},$$

where $\vec{y}_t$ is the (7x1) vector of Texas variables, μ is a (7x1) vector of estimated constants, ϕ_1 and ϕ_2 are both (7x7) matrices of estimated coefficients, and $\vec{e}_t^{\,R}$ is a (7x1) vector of nonautocorrelated random disturbances. Each variable's equation has 15 parameters, leaving only 30 degrees of freedom.

Table 6 reports the gain of the closed regional model relative to the ARIMA(2,1,0) equations and F-statistics for the significance of "regional interaction" terms. The results tend to confirm the notion that regional interactions aid forecast of industrial production, but fail to confirm the large gain for consumer prices expected on the basis of the results in Table 5. Results are more promising for household and payroll employment, suggesting that interactions are more complex than the simple two-variable equations are capable of exploiting. The closed regional model provides a 12 1/2 percent reduction in the standard error of the consumer price growth rate, a 9 percent reduction for household employment, and a 7 percent reduction for industrial production, relative to the two-lag autoregression. The use of all Texas variables in the set of seven to predict each is not necessarily more efficient than using a subset, as some contrasts between Table 5 and Table 6 suggest. (Consider, for example, the success in predicting CPIDFW, as described in Table 5, compared to the results in Table 6.) Further analysis could probably uncover a more efficient closed-regional model with exclusion restrictions or Bayesian priors. For example, the industrial production and consumer price equations could exclude all but own-lags and the three labor series. Household and payroll employment could use each other, while the deflated personal income and retail sales equations could include the consumer price index. We have not pursued this approach in this initial exploration. A cleaned-up model would evoke skepticism because of the "data mining"

Table 6: CLOSED REGIONAL MODEL

Dependent Variable	SEE	$\bar{R}^2$	I(R,C) 1/	F(12,30) 2/
TIPI	.01466	.30	7.2	1.56
CPIDFW	.006723	.63	12.5	2.07
PAYROLL	.004397	.51	0.7	1.04
TEMP	.007492	.16	9.2	1.75
RTPY	.01378	-.01	-1.0	0.93
RTRET	.02293	-.09	-5.4	0.76
TLF	.006262	.08	2.3	1.16

1/ Information gain, relative to ARIMA(2,1,0) model.

2/ The .10 critical value is 1.77; the .05 critical value is 2.09.

entailed in its construction. As it stands, the closed-regional model appears very much "overparameterized."

THE TRICKLE-DOWN MODEL

Because economic conditions in Texas are affected by the same events as the nation as a whole, it is appropriate to search among national economic indicators for sources of information about future conditions in Texas. A search among 14 possible national information variables was made to find a subset which captures most of the information available, while retaining degrees of freedom. In this search, we have regressed growth rates of each of the seven district variables on (1) 2 own-lags, (2) 2 own-lags plus 2 lagged growth rates of the index of leading economic indicators, and (3) the variables mentioned in (2) plus 2 lagged growth rates of one of 13 other potential information variables. The design of our search reflects the prior notion that the leading index is the single most promising source of information. The results are summarized in Table 7. That table presents the information gain, first, from using the leading index, in addition to two own-lags, and second, from the _further_ addition of one of the other 13 candidate variables.

For example, we begin with the ARIMA(2,1,0) model, which is a regression on two own-lags. For TIPI, this equation is:

$$\Delta \ln TIPI_t = \mu + \phi_1 \Delta \ln TIPI_{t-1} + \phi_2 \Delta \ln TIPI_{t-2} + a_t,$$

with associated standard error, s_a. Then we include two lags of the leading index:

$$\Delta\ln TIPI_t = \mu + \phi_1\Delta\ln TIPI_{t-1} + \phi_2\Delta\ln TIPI_{t-2} + \beta_1\Delta\ln LEAD_{t-1} + \beta_2\Delta\ln LEAD_{t-2} + e_t$$

with associated standard error s_e. The gain for TIPI from LEAD is then s_a minus s_e, as a percentage of s_a. Table 7 gives this gain as 12.2. Now 13 more regressions were run that included--in addition to the two lags of LEAD and two own-lags--two lags of one of the other 13 national variables. Extending our example, we can add the coincident index to the TIPI equation:

$$\begin{aligned}\Delta\ln TIPI_t = \mu &+ \phi_1\Delta\ln TIPI_{t-1} + \phi_2\Delta\ln TIPI_{t-2} \\ &+ \beta_1\Delta\ln LEAD_{t-1} + \beta_2\Delta\ln LEAD_{t-2} \\ &+ \beta_3\Delta\ln COIN_{t-1} + \beta_4\Delta\ln COIN_{t-2} + u_t,\end{aligned}$$

with associated standard error s_u. The gain from COIN, given inclusion of LEAD, is then $((s_e - s_u)/s_e) \times 100$, given in Table 7 as -1.2, a negative "gain." In reading Table 7, it should be kept in mind that all regressions included the two lags of LEAD as well as two own-lags.

Given our special concern with forecasting aggregate real activity, we chose among the national variables those that held promise of forecasting industrial production, the two employment series, and the two deflated series. Search among possible national information variables led to selection of 5 key variables: (1) the composite index of leading indicators, (2) the index of approximately coincident indicators, (3) the index of industrial production, (4) total nonagricultural employment, and (5) Moody's all-industry average corporate bond yield. A "trickle-down" model was constructed which relates growth rates in each of the seven Texas variables to two own-lags and two lags of each of the 5 key national variables. Thus, while the closed regional model emphasized regional interactions and ignored national data, the trickle-down model emphasizes national data and ignores regional interactions. Table 8 shows the standard errors of the equations and information gain relative to the ARIMA(2,1,0) models. It achieved considerable within-sample success in predicting consumer prices, deflated retail sales, and industrial production, whose weakness during the forecasting period may have reflected largely national factors. The F-statistics for the significance of trickle-down variables (last column of Table 8) are highly significant for consumer prices and significant for deflated retail sales. The trickle-down model outperforms the closed regional model for four of the seven Texas variables within the sample. A comparison of the results in Tables 7 and 8 suggest that consumer prices, deflated retail sales, and deflated real income are more closely linked to national conditions than to regional conditions. On the other hand, the comparison suggests employment is more closely related to regional conditions.

TABLE 7: NATIONAL INFORMATION GAIN

INFORMATION VARIABLE	TIPI	CPIDFW	PAYROLL	TEMP	TLF	RTPY	RTRET
LEAD	12.2**	5.9*	2.0	4.0	-1.5	-1.0	1.5
COINC	-1.2	9.9*	1.9	-1.0	-0.2	7.9*	10.6**
IPI	-2.5	10.0*	3.5	0.6	4.5	12.2**	17.4**
LHR	2.0	1.7	-2.4	-2.0	-2.6	-0.3	0.6
NEMP	0.9	9.7*	-2.3	-1.0	-2.0	6.2*	6.8*
FYFF	-1.3	13.5*	-0.9	-2.5	-0.9	0.1	-0.0
FYAVG	-0.1	15.4*	-0.2	2.7	1.7	7.3*	7.0*
GMPY72	-0.6	2.6	-2.3	-2.3	-0.9	-2.2	-1.7
PUNEW	-1.1	10.6*	-2.1	2.9	9.2**	3.4	2.4
PWFSA	-0.4	14.0*	-1.8	-0.1	2.0	0.9	-1.1
PW561	0.4	0.4	-2.3	-1.6	-1.8	7.5*	0.9
PW53	-0.1	-0.5	-2.1	-2.1	-0.6	6.5*	1.0
DGD	-2.2	-2.3	-2.3	6.9*	8.5*	-2.3	-1.7
DGNP72	-1.3	0.5	-1.3	-0.0	0.7	-0.2	4.5

* Statistically significant at the .05 level.
** Statistically significant at the .01 level.

TABLE 7: Continued

INFORMATION VARIABLE	ROW SUM	ROW SUM, EXCL. CPIDFW AND TLF
LEAD	23.1	18.7
COIN	27.9	18.2
USIP	45.7	31.2
LHR	-3.0	-2.1
LHEMR	18.3	10.6
FYFF	8.0	-4.6
FYAVG	33.8	16.7
GMPY72	-7.4	-9.1
PUNEW	25.3	5.5
PWFSA	13.5	-2.5
PW561	3.5	4.9
PW53	2.1	3.2
DGD	4.6	-1.6
DGNP72	2.9	1.7

TABLE 8: INFORMATION GAIN FROM TRICKLE-DOWN EQUATIONS

DEPENDENT VARIABLE	SEE	$\bar{R}^2$	I(T,C) 1/	F(10,32) 2/
TIPI	.01441	.32	8.7	1.84
CPIDFW	.005844	.72	23.9	4.06
PAYROLL	.004430	.51	-0.1	0.99
TEMP	.007924	.06	4.0	1.36
RTPY	.01265	.15	7.3	1.69
RTRET	.01842	.30	15.3	2.85
TLF	.006441	.03	-0.5	0.96

1. Information gain, measured by percent reduction in standard error relative to ARIMA(2,1,0) model.

2. The .10 critical value is approximately 1.82; the .05 critical value is approximately 2.16; the .01 critical value is approximately 2.98.

OUT-OF-SAMPLE PERFORMANCE OF ARIMA, CLOSED-REGION, AND TRICKLE-DOWN MODELS

The usefulness of the closed-region and trickle-down models can be further assessed by constructing forecasts outside of the sample and comparing their accuracy relative to the univariate forecasting equations. The out-of-sample forecasting period began in the first quarter of 1981 and ended in the second quarter of 1983. Each model's parameters were reestimated each quarter to reflect new data, but the general form of the model was kept constant. (Kalman filters were used for reestimating all the models except the Box-Jenkins ARIMAs, which are generally nonlinear.) In particular, the Box-Jenkins ARIMAs were not reformulated, even though that might have improved their forecasting accuracy somewhat. This may tend to bias results somewhat against the Box-Jenkins models. In forecasting more than one quarter ahead with the trickle-down model, ARIMA(2,1,0) equations were employed to arrive at forecasts of the exogenous national variables, and those equations were also reestimated each quarter.

We obtained a sample of 10 one-period(step)-ahead forecasts, 9 two-period-ahead forecasts, and so on, to 5 six-period-ahead forecasts, for each of the seven variables, for each of the four models. The forecast error is the actual (log) of the variable minus the forecast of (the log of) the variable. We report three measures of forecast accuracy for one to six steps ahead, constructed from the series of forecast errors:

(1) mean error, or ME,

(2) mean absolute error, or MAE,

and (3) root mean squared error, or RMSE.

We assign the greatest weight to the root mean squared error in performance evaluation.

The univariate model RMSEs are an appropriate benchmark for evaluating multivariate alternatives. If more complex models cannot do better, then univariate forecasting models are probably the appropriate formal method to which judgment should be applied in producing regional forecasts. Table 9 presents the measures of accuracy for forecasts generated by the two alternative ARIMA models. The mean errors were negative for all variables except the labor force, as one would expect for a period in which economic growth was well below the average of the 1969-80 period. The RMSEs also generally exceeded the standard errors of the within-sample equations, often quite substantially. There was often little difference in forecast accuracy between the Box-Jenkins and ARIMA(2,1,0) alternatives. This again tends to confirm the notion that autoregressive models of low order may do as well, or nearly as well, out-of-sample as ARIMAs built using Box-Jenkins identification methods, at least for seasonally adjusted series. However, not too much should be made of this result, because some of the Box-Jenkins models would have been respecified during the out-of-sample period by a real-time forecaster.

The closed-region model has been placed at something of a competitive disadvantage relative to the alternatives, because it has included two lags of all seven regional series, whether they were statistically significant or not, and without the use of any prior information. In other words, it equations are "overparameterized."

Consequently, it is not surprising that this model achieves few successes relative to the univariate benchmarks or the trickle-down model, as seen by comparing figures in Tables 9 and 10. Nevertheless, the closed-regional model slightly outperformed univariate equations in forecasts of the Texas Industrial Production Index and in one- and two- quarter-ahead forecasts of consumer prices in the Dallas-Fort Worth area. These limited successes occurred partly because the model predicted slower growth than ARIMAs after the onset of recession, and hence had lower mean errors in these cases. However, the hopes for predicting the three labor series offered by this model's within-sample properties were not realized in out-of-sample forecasts.

The trickle-down model also suffers from overparameterization, though probably a little less than the closed-regional model. The trickle-down model had mixed success compared with the univariate equations for all Texas variables except the labor force, where it failed as one would expect. Overall, the trickle-down model forecasted better than the closed-regional model. This tends to confirm the suggestion made by within-sample analysis that regional forecasters can ill-afford to ignore national information. In view of the relative overparameterization of the closed-regional model, any contrast in performance should be interpreted cautiously. However, the contrast is consistent with the notion that regional forecasters may get more information from exploiting national data sets than from studying intraregional interactions. That conclusion might

TABLE 9: OUT-OF-SAMPLE FORECAST PERFORMANCE OF UNIVARIATE MODELS

		BOX-JENKINS			ARIMA(2,1,0)		
VARIABLE	STEP	ME	MAE	RMSE	ME	MAE	RMSE
TIPI	1	-.0097	.0199	.0240	-.0073	.0171	.0234
	2	-.0251	.0364	.0446	-.0194	.0340	.0446
	3	-.0518	.0523	.0626	-.0469	.0483	.0584
	4	-.0786	.0786	.0842	-.0760	.0760	.0808
	5	-.1001	.1001	.1075	-.0975	.0975	.1049
	6	-.1199	.1199	.1260	-.1197	.1197	.1259
CPIDFW	1	-.0043	.0061	.0078	-.0034	.0064	.0078
	2	-.0134	.0137	.0156	-.0117	.0127	.0148
	3	-.0238	.0238	.0250	-.0212	.0212	.0231
	4	-.0346	.0346	.0357	-.0307	.0307	.0325
	5	-.0487	.0487	.0501	-.0433	.0433	.0455
	6	-.0674	.0674	.0679	-.0611	.0611	.0621
PAYROLL	1	-.0033	.0055	.0072	-.0036	.0054	.0074
	2	-.0082	.0110	.0150	-.0087	.0106	.0148
	3	-.0186	.0205	.0267	-.0192	.0212	.0270
	4	-.0336	.0348	.0411	-.0337	.0352	.0415
	5	-.0487	.0489	.0567	-.0488	.0494	.0572
	6	-.0603	.0603	.0658	-.0600	.0600	.0657
TEMP	1	-.0020	.0061	.0068	-.0021	.0063	.0072
	2	-.0044	.0078	.0101	-.0047	.0079	.0105
	3	-.0084	.0099	.0129	-.0085	.0106	.0133
	4	-.0122	.0149	.0169	-.0119	.0153	.0172
	5	-.0159	.0187	.0202	-.0152	.0186	.0201
	6	-.0190	.0193	.0220	-.0183	.0192	.0215

TABLE 9: Continued

		BOX-JENKINS			ARIMA(2,1,0)		
VARIABLE	STEP	ME	MAE	RMSE	ME	MAE	RMSE
RTPY	1	-.0052	.0101	.0127	-.0049	.0108	.0140
	2	-.0091	.0141	.0164	-.0091	.0139	.0172
	3	-.0156	.0213	.0229	-.0159	.0221	.0238
	4	-.0233	.0255	.0296	-.0241	.0270	.0310
	5	-.0307	.0307	.0343	-.0307	.0307	.0345
	6	-.0372	.0372	.0414	-.0378	.0378	.0425
RTRET	1	-.0057	.0196	.0235	-.0061	.0197	.0233
	2	-.0159	.0302	.0379	-.0175	.0316	.0394
	3	-.0304	.0403	.0477	-.0333	.0431	.0509
	4	-.0493	.0493	.0581	-.0542	.0542	.0628
	5	-.0616	.0616	.0686	-.0681	.0681	.0749
	6	-.0743	.0743	.0790	-.0815	.0815	.0866
TLF	1	.0004	.0058	.0067	.0012	.0054	.0061
	2	.0017	.0062	.0071	.0023	.0051	.0064
	3	.0012	.0032	.0040	.0019	.0034	.0039
	4	.0016	.0040	.0048	.0027	.0045	.0057
	5	.0027	.0076	.0079	.0039	.0071	.0080
	6	.0033	.0066	.0084	.0044	.0064	.0083

TABLE 10: OUT-OF-SAMPLE FORECAST PERFORMANCE OF CLOSED-REGION AND "TRICKLE-DOWN" MODELS

VARIABLE	STEP	CLOSED-REGION			"TRICKLE-DOWN"		
		ME	MAE	RMSE	ME	MAE	RMSE
TIPI	1	-.0076	.0164	.0218	-.0049	.0204	.0239
	2	-.0161	.0365	.0439	-.0068	.0343	.0417
	3	-.0419	.0555	.0615	-.0323	.0427	.0509
	4	-.0761	.0761	.0827	-.0545	.0567	.0629
	5	-.0999	.0999	.1090	-.0708	.0708	.0805
	6	-.1229	.1229	.1309	-.0916	.0916	.1022
CPIDFW	1	-.0037	.0054	.0074	-.0017	.0046	.0052
	2	-.0104	.0112	.0146	-.0068	.0090	.0111
	3	-.0201	.0233	.0260	-.0170	.0170	.0181
	4	-.0376	.0376	.0416	-.0263	.0263	.0280
	5	-.0591	.0591	.0613	-.0391	.0391	.0421
	6	-.0815	.0815	.0831	-.0568	.0568	.0587
PAYROLL	1	-.0030	.0559	.0083	-.0044	.0061	.0081
	2	-.0070	.0114	.0152	-.0100	.0132	.0168
	3	-.0172	.0201	.0263	-.0197	.0239	.0280
	4	-.0323	.0348	.0406	-.0325	.0356	.0410
	5	-.0461	.0480	.0551	-.0451	.0454	.0539
	6	-.0567	.0567	.0631	-.0561	.0561	.0629
TEMP	1	-.0001	.0079	.0096	-.0018	.0079	.0096
	2	-.0004	.0091	.0104	-.0031	.0118	.0139
	3	-.0044	.0100	.0118	-.0046	.0113	.0131
	4	-.0104	.0138	.0159	-.0068	.0133	.0146
	5	-.0164	.0200	.0218	-.0085	.0129	.0144
	6	-.0201	.0220	.0241	-.0121	.0141	.0159

TABLE 10: Continued

VARIABLE	STEP	CLOSED-REGION ME	CLOSED-REGION MAE	CLOSED-REGION RMSE	"TRICKLE-DOWN" ME	"TRICKLE-DOWN" MAE	"TRICKLE-DOWN" RMSE
RTPY	1	-.0025	.0105	.0124	-.0064	.0155	.0185
	2	-.0041	.0154	.0181	-.0091	.0212	.0241
	3	-.0103	.0208	.0219	-.0099	.0214	.0240
	4	-.0165	.0245	.0296	-.0155	.0229	.0255
	5	-.0183	.0238	.0280	-.0210	.0210	.0262
	6	-.0194	.0242	.0295	-.0309	.0309	.0357
RTRET	1	-.0071	.0205	.0255	-.0109	.0213	.0270
	2	-.0178	.0354	.0449	-.0170	.0289	.0372
	3	-.0299	.0449	.0562	-.0239	.0370	.0418
	4	-.0415	.0477	.0596	-.0398	.0398	.0456
	5	-.0436	.0477	.0596	-.0500	.0508	.0617
	6	-.0433	.0433	.0516	-.0687	.0687	.0798
TLF	1	.0020	.0077	.0084	-.0001	.0055	.0071
	2	.0041	.0064	.0077	.0012	.0084	.0101
	3	.0030	.0046	.0060	.0026	.0058	.0074
	4	.0026	.0052	.0057	.0086	.0118	.0185
	5	.0014	.0065	.0082	.0069	.0089	.0102
	6	.0001	.0070	.0081	.0072	.0086	.0107

be reversed if a comparable search were made among potential regional information variables (for example, the rig count and housing starts) as was made among national variables.

COMBINATION FORECASTS

As one method of combining the three sources of information, combination forecasts can be constructed as simple averages of the Box-Jenkins, closed-regional and trickle-down models. The out-of-sample forecast performance of the average combination forecasts are presented in Table 11. The accuracy of simple unweighted average combinations is generally comparable with the ARIMA forecasts. The combination forecast tends to be more accurate than ARIMAs for 3- and 4-step-ahead forecasts, although it tends to be slightly less accurate for 1- and 2-step-ahead forecasts. This result obtains despite the relative lack of success of the closed-regional and trickle-down models. The unweighted combination forecast performs noticeably better than ARIMAs for industrial production and consumer prices, but worse for the labor force.

The weights attached to each of the three components in the combination forecast need not--and generally, should not--be equal. We have not conducted an adequate analysis of appropriate weights, but the widely varying degrees of success of the three alternative models in predicting the various Texas series suggest that there ought to be unequal weights and that the gains from appropriately chosen weights might be substantial.

TABLE 11: OUT-OF-SAMPLE PERFORMANCE OF COMBINATION FORECASTS

VARIABLE	STEP	ME	MAE	RMSE
TIPI	1	-.0074	.0177	.0221
	2	-.0160	.0320	.0406
	3	-.0420	.0470	.0561
	4	-.0697	.0697	.0757
	5	-.0903	.0903	.0986
	6	-.1115	.1115	.1193
CPIDFW	1	-.0032	.0044	.0057
	2	-.0102	.0102	.0120
	3	-.0203	.0203	.0211
	4	-.0328	.0328	.0342
	5	-.0489	.0489	.0506
	6	-.0685	.0685	.0692
PAYROLL	1	-.0037	.0058	.0077
	2	-.0084	.0111	.0154
	3	-.0185	.0213	.0267
	4	-.0328	.0346	.0407
	5	-.0466	.0474	.0549
	6	-.0577	.0577	.0635
TEMP	1	-.0013	.0067	.0076
	2	-.0026	.0073	.0100
	3	-.0058	.0090	.0113
	4	-.0098	.0138	.0150
	5	-.0136	.0172	.0186
	6	-.0171	.0185	.0204

TABLE 11: Continued

VARIABLE	STEP	ME	MAE	RMSE
RTPY	1	-.0047	.0109	.0138
	2	-.0074	.0161	.0183
	3	-.0119	.0210	.0219
	4	-.0184	.0233	.0269
	5	-.0233	.0243	.0279
	6	-.0292	.0292	.0344
RTRET	1	-.0079	.0198	.0247
	2	-.0169	.0303	.0392
	3	-.0281	.0396	.0471
	4	-.0435	.0435	.0525
	5	-.0517	.0517	.0599
	6	-.0621	.0621	.0675
TLF	1	.0008	.0055	.0065
	2	.0023	.0057	.0072
	3	.0023	.0038	.0044
	4	.0043	.0060	.0086
	5	.0036	.0073	.0083
	6	.0035	.0064	.0084

"BAYESIAN" VECTOR AUTOREGRESSIVE MODELS

Given the prior notion that information about the future course of each Texas series ought to be present in both national and other Texas series, one can, as an alternative to forming combination forecasts, estimate a model that uses both. The problem with such an approach is that, as the information set is expanded, forecast accuracy can become poor as the model becomes overparameterized and precious degrees of freedom are spent. For example, the sample we employ to build models is only 47 quarters in length (excluding one lost from differencing). If only two lags of variables are used, one can incorporate at most 22 information variables. Forecast accuracy of a model with even a dozen free parameters is unlikely to be very good, as exemplified by the limited success of the closed-region and trickle-down models.

The problem at hand is to incorporate information from many available regional and national series, where well developed theory is unavailable, and where any one information variable alone is unlikely, in view of the above results, to contribute substantially to forecasting performance. It is just such a problem for which a "Bayesian" VAR framework is most promising. Prior restrictions are incorporated into a vector autoregressive model, using the RATS computer program (Doan and Litterman, 1981). RATS greatly facilitates the flexible use of priors. Essentially, the prior distribution is centered around a random walk, with parameters allowed to deviate from that specification in a degree determined by the tightness of the priors. Estimation is made using Theil's mixed estimation. The choice of prior distributions substantially affects the forecasting performance of the estimated model, as will be seen in the present context. Although some recent papers by Litterman and associates (Litterman, 1979 and 1982b; Doan, Litterman, and Sims, 1983) give attention to the importance of intelligent priors in designing VAR models, the only way they suggest of determining appropriate priors is through a performance criterion, such as minimizing root mean squared forecasting error. We will suggest an auxiliary method of determining appropriate priors.

At present, we know of three papers that attempt to assess the usefulness of VAR models for regional forecasting, only one of which employs prior distributions. The first, by Paul Anderson (1979), imposes a set of priors without any apparent diagnostic efforts and in a rather simple fashion. He implies that an efficient regional VAR model can be built in two weeks work. If true, this would seem to have radical implications for economic forecasting, for it offers a rather "automatic" method that requires little feel for the data or theoretical knowledge. Indeed, Anderson's discussion seems to imply that forecasting can be efficiently performed by feeding a list of variables--possibly a long list--and a simple predetermined random walk prior distribution into the computer and reporting the output of the first run.

Anderson compares the forecasting performance of his regional model with that of some structural models of other regions and finds his VAR model produces better forecasts. But he does not compare VAR forecasts against univariate model forecasts. Such a comparison seems important in view of the frequent finding that simple univariate models often outperform large structural models (Granger and Newbold, 1977: 289-300).

Two other studies construct VAR models, but do not impose Bayesian priors. It should be emphasized that any unfavorable conclusions presented below regarding the "Bayesian" VAR approach does not apply to these studies. Kinal and Ratner (1983) compare forecasts of an unconstrained VAR model of the New York state economy with ARIMA and simple transfer function models. They find that "...VAR predictions are more accurate overall" (p.26). A closer examination of their study, however, suggests that some of the ARIMA and transfer function model forecasts are implausibly poor. Nevertheless, their VAR forecast statistics offer some performance benchmarks for regional forecasters.

Kuprianov and Lupoletti (1984) build VAR models for each of the six political divisions of the Federal Reserve's Fifth District. Their VAR model is also unconstrained, except that the equations for national variables exclude regional variables. The specification is a promisingly parsimonious one in terms of the number of variables; the model for each state includes state employment and deflated personal income plus three national variables. However, the lag length, six quarters, may be excessive for efficient forecasting. Nevertheless, their study provides some useful out-of-sample forecast performance statistics which should be of interest to regional forecasters. One interesting aspect of their results is the quite disparate properties of different states' economic behavior.

An open question is whether VAR models, with or without priors, can outperform ARIMAs for regional economic forecasting,4/ and, if so, whether use of a predetermined set of priors, such as Anderson's, are sufficient to achieve relatively good performance. We doubt that an unconstrained model with many parameters can provide efficient forecasts.

The first VAR model we present used priors patterned after our understanding of Anderson (1979, appendix). (The priors of this and two subsequent models are described in Appendix B to this paper.) In this and the two other VAR models we present, we centered the prior distribution around a random walk and included an unconstrained constant and linear time trend in each equation. Anderson's system of priors, when applied to the Texas data, provided a VAR model with very poor forecasting performance relative to univariate benchmarks, as shown in Table 12, under the columns labeled "VAR I". Indeed, VAR I may be regarded as the most unsuccessful model of all studied.5/

A second approach involved setting priors based on judgements derived from the analysis in previous sections of the paper. Each of the seven series was treated separately. The results of univariate, closed-regional and trickle-down models were used to get rough notions about the extent to which a given Texas variable reflected its own past, other Texas variables as a block, and national variables as a block. Essentially, then, the priors were set along three dimensions. Even this is a rather crude approach, but it does use the "feel" for the data derived in our earlier analysis. For example, the growth rate of the Dallas-Fort Worth Consumer Price Index displayed considerable autocorrelation, so the own-lag coefficients were given wide prior distributions. The closed-regional model was of some help within-sample, but performed poorly out of sample. Hence, priors were tightened on lags of other regional variables. The national variable coefficients were given more freedom in light of the good performance of the trickle-down model.

The performance of this model, labeled "VAR II" in Table 12, generally represents a substantial improvement, and forecast accuracy approaches, but still generally falls a bit short of, the univariate benchmarks.

An ex post analysis of the effect of alternative priors suggested that the priors of the VAR II model were generally too tight. This was discovered by allowing the overall tightness parameter in the RATS program to vary, and assessing the effect on RMSEs of resulting forecasts, as shown in Table 13. This tightness parameter, when raised twofold (looser prior distribution), provided what appeared to be the best overall forecasting performance. Minimum RMSEs for deflated personal income and the labor force were achieved with much tighter priors, so the standard deviations of the prior distributions in their equations were reduced in a simple ad hoc fashion. Finally, the priors for the national variable equations were adjusted in a similar fashion. The result of these admittedly crude readjustments is a model we provisionally propose as an appropriate alternative to ARIMA models for forecasting the future course of the Texas economy. The relative accuracy of the model is suggested by examining its performance statistics, in the columns of Table 12 labeled "VAR III", with those of the other two.

Other regional VAR model builders may find some value in our experience. The success of the VAR II model, which incorporates prior information derived from the earlier analysis, suggests that a regional economist with a strong feel for the data and its interrelationships can do considerably better if he uses this knowledge than if he resorts to a simple "brute force" method. A second method of potentially improving forecast accuracy is that of fine-tuning the priors on the basis of out-of-sample experience with the VAR. We have experimented with both of these ways of improving the VAR model and found that they brought gains in forecasting accuracy. Given time and resources, further improvements could be realized along these lines.

SUMMARY AND CONCLUSION

Although statistical analysis of the kind we employ necessarily must be interpreted with caution, some tentative conclusions appear warranted. During the period from 1981 through the first half of 1983, univariate models generally did as well as the multivariate models studied. The ARIMA(2,1,0) specifications generally did about as well as those identified by Box-Jenkins methods. Three of the Texas series studied display persistence in their growth rates, while four others do not. Despite some efforts, multivariate models of three types did not produce any systematic improvement in forecast accuracy. Nevertheless, our analysis has not been exhaustive. Gains might be made by adopting a better selection criterion for information variables to be included in multivariate models, further tinkering with priors, forming combination forecasts from a larger set of models, or building seasonal models for seasonally unadjusted data. Our initial exploration has limited these refinements in order to get a feel the data, render transparent the

TABLE 12: OUT-OF-SAMPLE FORECAST PERFORMANCE OF VECTOR AUTOREGRESSIVE MODELS

VARI-		VAR I			VAR II			VAR III		
ABLE	STEP	ME	MAE	RMSE	ME	MAE	RMSE	ME	MAE	RMSE
TIPI	1	-.0130	.0192	.0256	-.0111	.0175	.0229	-.0078	.0156	.0199
	2	-.0316	.0395	.0478	-.0255	.0341	.0414	-.0181	.0270	.0346
	3	-.0592	.0628	.0699	-.0492	.0581	.0620	-.0368	.0467	.0504
	4	-.0865	.0865	.0935	-.0740	.0747	.0831	-.0568	.0594	.0668
	5	-.1077	.1077	.1156	-.0933	.0933	.1054	.0686	.0686	.0854
	6	-.1302	.1302	.1364	-.1197	.1197	.1316	-.0872	.0872	.1061
CPIDFW	1	-.0094	.0094	.0112	-.0036	.0059	.0073	-.0030	.0056	.0067
	2	-.0238	.0238	.0248	-.0105	.0117	.0139	-.0087	.0107	.0126
	3	-.0405	.0405	.0411	-.0211	.0211	.0244	-.0181	.0182	.0223
	4	-.0594	.0594	.0601	-.0350	.0350	.0387	-.0315	.0315	.0357
	5	-.0825	.0825	.0830	-.0535	.0535	.0570	-.0490	.0490	.0535
	5	-.1088	.1088	.1093	-.0778	.0778	.0802	-.0727	.0727	.0753
PAYROLL	1	-.0068	.0087	.0110	-.0046	.0069	.0088	-.0040	.0063	.0081
	2	-.0150	.0182	.0224	-.0104	.0146	.0174	-.0094	.0131	.0156
	3	-.0262	.0299	.0361	-.0202	.0261	.0298	-.0189	.0238	.0271
	4	-.0376	.0399	.0485	-.0315	.0374	.0427	-.0306	.0350	.0400
	5	-.0477	.0491	.0578	-.0417	.0470	.0529	-.0408	.0448	.0506
	6	-.0576	.0576	.0642	-.0528	.0528	.0611	-.0517	.0517	.0593
TEMP	1	-.0037	.0065	.0078	-.0030	.0057	.0069	-.0028	.0055	.0067
	2	-.0076	.0097	.0120	-.0059	.0080	.0096	-.0050	.0073	.0090
	3	-.0127	.0132	.0163	-.0105	.0116	.0131	-.0087	.0105	.0115
	4	-.0173	.0186	.0211	-.0150	.0169	.0189	-.0124	.0145	.0169
	5	-.0217	.0226	.0251	-.0201	.0210	.0237	-.0156	.0172	.0200
	6	-.0259	.0259	.0281	-.0271	.0271	.0292	-.0201	.0201	.0230

TABLE 12: Continued

VARI-ABLE	STEP	VAR I ME	VAR I MAE	VAR I RMSE	VAR II ME	VAR II MAE	VAR II RMSE	VAR III ME	VAR III MAE	VAR III RMSE
RTPY	1	-.0068	.0109	.0139	-.0116	.0139	.0173	-.0100	.0140	.0168
	2	-.0121	.0156	.0187	-.0186	.0216	.0252	-.0161	.0214	.0249
	3	-.0194	.0237	.0262	-.0251	.0278	.0324	-.0218	.0278	.0320
	4	-.0273	.0278	.0331	-.0310	.0310	.0371	-.0262	.0288	.0357
	5	-.0341	.0341	.0376	-.0361	.0361	.0396	-.0291	.0298	.0354
	6	-.0401	.0401	.0440	-.0380	.0380	.0406	-.0278	.0278	.0330
RTRET	1	-.0061	.0195	.0231	-.0176	.0209	.0278	-.0138	.0196	.0267
	2	-.0161	.0305	.0384	-.0305	.0337	.0426	-.0263	.0335	.0429
	3	-.0305	.0399	.0480	-.0403	.0450	.0532	-.0350	.0444	.0533
	4	-.0492	.0492	.0574	-.0513	.0513	.0600	-.0429	.0483	.0568
	5	-.0596	.0596	.0658	-.0567	.0567	.0640	-.0431	.0471	.0549
	6	-.0699	.0699	.0742	-.0642	.0642	.0686	-.0424	.0424	.0485
TLF	1	-.0010	.0054	.0066	-.0014	.0046	.0059	.0006	.0045	.0054
	2	-.0011	.0064	.0068	-.0024	.0050	.0056	.0009	.0044	.0052
	3	-.0028	.0039	.0047	-.0048	.0051	.0056	-.0003	.0023	.0030
	4	-.0036	.0045	.0058	-.0060	.0069	.0074	-.0004	.0036	.0040
	5	-.0038	.0063	.0082	-.0075	.0079	.0094	-.0008	.0051	.0055
	6	-.0045	.0081	.0088	-.0105	.0105	.0122	-.0023	.0055	.0057

TABLE 13: EFFECT OF ALTERNATIVE VALUES OF THE OVERALL TIGHTNESS PARAMETER (γ) ON ROOT MEAN SQUARED ERRORS OF VAR II

VARIABLE	STEP	$\gamma = 0.6$	$\gamma = 1.0$	$\gamma = 1.4$	$\gamma = 2.0$
TIPI	1	.0244	.0229	.0219	.0208
	4	.0852	.0826	.0796	.0751
CPIDFW	1	.0080	.0073	.0070	.0067
	4	.0427	.0385	.0370	.0360
PAYROLL	1	.0096	.0088	.0084	.0081
	4	.0443	.0427	.0417	.0407
TEMP	1	.0068	.0068	.0068	.0067
	4	.0183	.0185	.0185	.0184
RTPY	1	.0197	.0172	.0167	.0166
	4	.0405	.0359	.0360	.0370
RTRET	1	.0318	.0279	.0270	.0267
	4	.0671	.0591	.0582	.0591
TLF	1	.0053	.0057	.0059	.0059
	4	.0052	.0070	.0078	.0084

relative advantages of various basic approaches in dealing with exploitable forecasting relationships, and avoid the perils, and skeptical regard, of results attributable most to "data mining."

Some light has been shed on intraregional interactions. They are apparently not easy to exploit for forecasting purposes. Among the seven series studied, the two employment series seem the most important for the regional forecaster to watch. However, a more meticulous and comprehensive effort might lead to greater forecasting gains from other regional series outside the set of seven studied. National-regional interactions are somewhat easier to exploit, and appear to provide help in forecasting Texas industrial production, consumer prices, and deflated retail sales.

Further research is needed. After more meticulous and parsimonious treatment of the closed-region and trickle-down models, their forecasts could be combined with univariate forecasts according to a carefully designed weighting scheme. The VAR model, with further adjustments to priors and better selection of variables to be included, might be considered an alternative means of combining the three sources of information. However, given our experience, it seems that the time and expense of creating an efficient VAR model will probably be greater than indicated in previous studies using the VAR method for regional forecasting. Furthermore, it is an open question whether the VAR method of combining information from the three kinds of sources will succeed relative to the strategy of building three models for each and forming weighted combination forecasts. The latter procedure may in practice facilitate better use of theory and "feel" for the relationships, since it builds several simpler and more transparent models. It might also yield additional insights into the economic process.

It appears unlikely that structural econometric models, given their current imperfect state, can forecast much better than our linear projections specifically aimed at accurate forecasting. We have provided some benchmarks for forecasters of all types. It remains to be seen whether proponents of multivariate methods, such as structural or VAR models, can yet provide evidence that their models produce better forecasts for the Texas economy or other regional economies than "naive" univariate methods.

FOOTNOTES

1. McNees and Ries (1983) provide useful evidence on the extent to which accuracy of national forecasts deteriorates during recessions.

2. As a result, there may not be a model that uniformly outperforms all alternatives for all steps ahead, and some ambiguities arise in forecast performance evaluation.

3. Unfortunately, a new strand in the literature seeks to use VAR models for these purposes. This would be less objectionable if the results were interpreted with greater caution and subjected to some kind of analysis of sensitivity to likely biases. Some cautionary evaluations of this approach are found in Porter and Offenbacher (1983) and McCallum (1982, 1983).

4. Doan, Litterman, and Sims (1983) provide some evidence that VARs with well chosen prior distributions can improve national economic forecasts relative to univariate autoregressions, even in a system of ten variables. However, this result is subject to several caveats. The improvement over univariate equations is slight, the univariate benchmarks are arbitrarily specified rather than identified by Box-Jenkins methods, and the prior distributions were selected ex post. Nevertheless, the result is interesting in that, apparently, no other forecasting method has yet been shown to deliver a systematic improvement over univariate methods in a national model of as many variables and over as long a period. We conjecture that other time series methods, employing the principle of parsimony, could do so. One handicap of parsimonious models in any "horserace" is that they should generally be respecified over time by real-time forecasters.

5. One modification to VAR I was tried that made it more like Anderson's model. Instead of our five "key" variables, the national variables were those Anderson used. Forecasts accuracy measured by RMSEs was virtually the same for all seven Texas series.

APPENDIX A: Glossary of Variables

Regional Variables

(1) TIPI--Texas Industrial Production Index
(2) CPIDFW--Consumer Price Index, Dallas-Fort Worth; quarterly averages from interpolation of available monthly figures; deflated using the X11 procedure
(3) PAYROLL--Texas payroll employment
(4) TEMP--Texas nonagricultural civilian employment, according to the BLS survey of households
(5) TLF--Texas nonagricultural civilian labor force
(6) RTPY--Texas Personal Income, seasonally adjusted using the X11 procedure; deflated by the CPIDFW
(7) RTRET--Texas Retail Sales, seasonally adjusted using the X11 procedure; deflated by the CPIDFW

National Variables

Five "Key" Variables

(1) LEAD--Index of 13 Leading Economic Indicators
(2) COINC--Index of 4 Approximately Coincident Economic Indicators
(3) IPI--Index of Industrial Production
(4) NEMP--Total nonagricultural civilian employment, 16 years and over
(5) FYAVG--Moody's all-industry average corporate bond yield

Other National Variables

(6) GNP72--Real Gross National Product, in 1972 dollars
(7) GMPY72--Real Personal Income, in 1972 dollars
(8) LHR--Total nonagricultural civilian labor force, 16 and over
(9) GD--Gross National Product Deflator
(10) PUNEW--Consumer Price Index for all urban consumers, new series
(11) PWFSA--Producer Price Index, All Finished Goods
(12) PW561--Producer Price Index, Crude petroleum, not seasonally adjusted
(13) PW53--Producer Price Index, Gas Fuels, not seasonally adjusted
(14) FYFF--federal funds rate

NOTE: All regional and national series were seasonally adjusted by the publishing agency, except where noted above. 3 regional series were adjusted by the authors using the Commerce Department's X11 computer procedure. The national series were taken from the CITIBASE data bank, and most of the national variable names are those of that data file.

Retail sales suffered from a discontinuity at the beginning of 1978 due to a change in survey methods, but that discontinuity does not appear to be of much consequence to the present study.

Seasonally adjusted data were used in this initial exploration in order to render more transparent the resulting models and their relative success in exploiting economic relationships as opposed to their ability to deal with seasonality. Time series that include (seasonal) moving average parameters are generally best when seasonal factors are not strictly deterministic.

APPENDIX B: PRIOR DISTRIBUTIONS OF THE THREE VAR MODELS

Following Doan and Litterman (1981, pp. 10-5 to 10-8), let

$$S(i,j,l) = \gamma f(i,j)\, g(l)\, s_j s_i^{-1}$$

be the standard deviation of the prior distribution of the parameter relating the l^{th} lag of variable j in the equation for variable i, where s_i is the standard error of a univariate autoregression for variable i. Then alternative VAR models are specified by the overall tightness parameter γ, the matrix of values for f(i,j), and the lag decay function g(l). The prior distribution was centered around a random walk.

VAR I

$\gamma = .1$

$g(l) = l^{-1}$ for $0 < j \leq 4$

0 otherwise

$f(i,j) =$ 1.0 for i=j

.1 for Texas variables in other Texas variable equations, for national variables in other national variable equations, and for national variables in Texas variable equations.

.01 for Texas variables in national variable equations.

APPENDIX B: Continued

VAR II

$\gamma = 1.0$

$g(l) = l^{-1}$ for $0 < l \leq 4$
0 otherwise

f(i,j) given by the following matrix:

REGRESSOR (j)	TIPI	CPIDFW	PAYROLL	TEMP	RTPY	RTRET	TLF	LEAD	COINC	IPI	NEMP	FYAVG
TIPI	.30	.03	.06	.08	.02	.02	.06	0	0	0	0	0
CPIDFW	.06	.40	.06	.08	.02	.02	.06	0	0	0	0	0
PAYROLL	.06	.03	.40	.08	.02	.02	.06	0	0	0	0	0
TEMP	.06	.03	.06	.20	.02	.02	.06	0	0	0	0	0
RTPY	.06	.03	.06	.08	.15	.02	.06	0	0	0	0	0
RTRET	.06	.03	.06	.08	.02	.15	.06	0	0	0	0	0
TLF	.06	.03	.06	.08	.02	.02	.20	0	0	0	0	0
LEAD	.06	.10	.06	.06	.03	.05	.03	.35	.08	.08	.08	.08
COINC	.06	.10	.06	.06	.03	.05	.03	.08	.35	.08	.08	.08
IPI	.06	.10	.06	.06	.03	.05	.03	.08	.08	.35	.08	.08
NEMP	.06	.10	.06	.06	.03	.05	.03	.08	.08	.08	.35	.08
FYAVG	.06	.10	.06	.06	.03	.05	.03	.08	.08	.08	.08	.35

APPENDIX B: Continued

VAR III

$\gamma = 2.0$

$g(l) = l^{-1}$ for $0 < l \leq 4$
0 otherwise

f(i,j) given by the following matrix:

REGRESSOR (j)	TIPI	CPIDFW	PAYROLL	TEMP	RTPY	RTRET	TLF	LEAD	COINC	IPI	NEMP	FYAVG
TIPI	.40	.03	.06	.08	.02	.03	.01	0	0	0	0	0
CPIDFW	.08	.40	.06	.08	.02	.03	.01	0	0	0	0	0
PAYROLL	.08	.03	.40	.08	.02	.03	.01	0	0	0	0	0
TEMP	.08	.03	.06	.15	.02	.03	.01	0	0	0	0	0
RTPY	.08	.03	.06	.08	.10	.03	.01	0	0	0	0	0
RTRET	.08	.03	.06	.08	.02	.15	.01	0	0	0	0	0
TLF	.08	.03	.06	.08	.02	.03	.05	0	0	0	0	0
LEAD	.08	.10	.06	.06	.02	.05	.005	.20	.08	.05	.08	.04
COINC	.08	.10	.06	.06	.02	.05	.005	.03	.30	.05	.08	.04
IPI	.08	.10	.06	.06	.02	.05	.005	.03	.08	.30	.08	.04
NEMP	.08	.10	.06	.06	.02	.05	.005	.03	.08	.05	.35	.04
FYAVG	.08	.10	.06	.06	.02	.05	.005	.03	.08	.05	.08	.20

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