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A REGIONAL ECONOMIC FORECASTING PROCEDURE APPLIED TO TEXAS

by James G. Hoehn

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Abstract

A method for building a time series regional forecasting model is proposed and implemented for the state of Texas. The forecasting ability of this method is subjected to a number of diagnostic tests and is found to be useful. The method places little reliance on economic theory, is available to any regional economist with knowledge of ordinary least squares regression analysis, and provides insights into the regional economic process. This paper complements 'Some Time Series Methods of Forecasting the Texas Economy," by Hoehn, Gruben, and Fomby, Working Paper No. 8402, Federal Reserve Bank of Dallas.

A Regional Economic Forecasting Procedure Applied to Texas

In recent years, there has been a rapid proliferation of regional models, fostered by the accumulation of regional economic data. Interest in these models derives from recognition of the disparate economic behavior of different regions, the desire of state and local governments to make better budget plans and design improved development policies, and the desire by business firms to improve marketing strategies. Unfortunately, the infant industry of regional modelbuilding has yet to prove very useful in understanding or forecasting regional economies. Regional modeling presents an intrinsically interesting field for the study of alternative statistical modeling methods, partly because of the linkages between the national and regional economies.

In practice, the usefulness of regional forecasts is likely to depend more on seasoned judgment than on access to formal forecasting procedures. However, formal models can aid and augment judgment, and in the process of building them, insights into the regional economic process are provided.

This paper proposes a method of building a regional forecasting model and applies the method to construct a model for the state of Texas. Although the model built here is subjected to a number of somewhat sophisticated statistical tests, the procedure for building it requires only ordinary least squares regressions familiar to all economists. The modelbuilding method consists of two stages: first, "Granger causality" tests are performed to find variables that provide significant leading information about the series to be forecast; second, these variables are used to build parsimonious forecasting equations. In the second stage, some significant leading variables are excluded to achieve parsimony. Parsimony is needed to deal with the problems of multicollinearity and the scarceness of degrees of freedom.

In earlier exploratory work by Hoehn, Gruben, and Fomby (1984a, 1984b), it was found that potentially useful leading relations (interactions) existed between seven Texas series and past values of (1) their own, (2) each other, and (3) certain national variables. A number of exploratory models designed to assess the potential value of those relations for forecasting were recognized to be too unparsimonious to provide efficient forecasts relative to univariate methods. Among these probing efforts were a closed-regional model that was essentially a seven-vector autoregression, a "trickle-down" model in which five national variables were "driving variables" for each Texas variable (regional interactions were excluded), and "Bayesian vector autoregressive" models, such as those advocated by Anderson (1979). The first two reflected little effort to deal with the problem of parsimony and, hence, did not represent actual forecasting procedures. The third has been advocated by Litterman and associates [for example, Litterman (1979, 1982); Doan, Litterman, and Sims (1983)] as, in effect, a better way to deal with the multicollinearity and degrees-of-freedom issues and, therefore, a superior alternative to the principle of parsimony.

The modelbuilding strategy pursued here employs only the significant leading relations in the data, and in a parsimonious way. For a sample of ten ex ante forecasts, the model built here provided consistent and sometimes significant improvements over the univariate methods. These results need to be interpreted with some caution, particularly in view of the smallness of the sample of forecasts. Nevertheless, the results are of interest because significant improvement over the univariate methods is not often achieved by existing multivariate models, including structural econometric models.[1] Because the modelbuilding strategy is reasonably straightforward and easy to implement, it may serve as a useful procedure in forecasting of other regional economies or in other applications.

This paper is intended to complement and extend Hoehn, Gruben, and Fomby (1984a). A number of results and concepts in that paper are used here.

Identification of a Parsimonious Multivariate Autoregressive Model

The seven Texas variables to be forecast are (1) the Texas Industrial Production Index (TIPI), (2) the Dallas-Fort Worth Consumer Price Index (CPIDFW), (3) employment according to the survey of business establishments (PAYROLL), (4) employment according to the household survey (TEMP), (5) the labor force (TLF), (6) personal income (TPY), and (7) retail sales (TRET).

These are the same as in Hoehn, Gruben, and Fomby (1984a), except that here personal income and retail sales have not been deflated. In Hoehn, Gruben, and Fomby (1984a), they were deflated by CPIDFW. The data series used began with 1969:IQ and ended in 1983:IIQ. The sample period for model construction ended in 1980:IVQ, preserving ten quarters for out-of-sample simulation.

The size of the samples--both the within-sample period of model construction and the out-of-sample period of forecast performance evaluation--were rather small and require some justification. The lengths of available data series vary, but all were available from 1969. Using the entire length of an available series where possible in an equation might have given the univariate equations an advantage over the multivariate equations if the structure was stable over time. This is an advantage of autoregressive integrated moving averages (ARIMAs) that forecasters would want to exploit. Truncating the series to begin in 1969 preserves, in a sense, a "level playing field" for comparing forecasting accuracy of the two kinds of models. A better justification for beginning with 1969 is the problem of structural change. Such change, due either to real changes in the regional economy or to changes in data collection and assimilation, make data in the distant past less relevant. Holt and Olson (1982) examined the improvement in forecasting accuracy from exponentially weighting data used to estimate a transfer function model for Texas personal income. This procedure involved weighting the observations k periods in the past by a factor of λ^k. For quarterly data, they found that a λ value of around 0.95, depending on the forecast horizon, produced the best forecasting model. After ten years, the weight would be about 0.13 (that is, 0.95^{40}) of that on the current observation. In addition, Holt and Olsen found that merely reducing the sample length from 18 to 13 years was sufficient to deliver most of the forecasting improvement relative to the model estimated over the full sample and without weighting. In the estimation of the present model, there are 12 years of data to estimate the initial model, and that period is effectively expanded up to 14 years in updating the estimates during the forecasting period. While the results of Holt and Olsen suggest that earlier data may be of slight value, data more recent than 1980 would still help. Other than using the later data in updating the coefficient estimates, we cannot extend the sample forward without reducing the period of forecast performance evaluation. The forecasting period might be too small for very powerful evaluation of forecasts, as later results will show. But lengthening the forecasting period would reduce the sample for model construction, which would render the primary objective of uncovering useful forecasting and structural relationships more difficult to achieve.

All Texas and national variables are transformed to natural logarithms and differenced once to achieve stationarity. Only in forecast performance evaluation are logarithmic levels employed. Performance of forecasting methods is evaluated by root means of squared errors (RMSEs), where the error is the forecast (logarithmic) level of the series minus the actual (logarithmic) level of the series. Although forecast horizons extend as far as ten quarters ahead, emphasis is placed on the accuracy of one-quarter-ahead to six-quarter-ahead forecasts. The model was used to generate a sample of ten one-quarter-ahead forecasts, nine two-quarter-ahead forecasts, and so on.

The form of the model is that of a multivariate autoregression (MAR):[2]

$$\begin{bmatrix} b_1(L) & b_2(L) \\ 0 & b_3(L) \end{bmatrix} \begin{bmatrix} \vec{y}_t \\ \vec{x}_t \end{bmatrix} = \begin{bmatrix} \vec{\mu}_1 \\ \vec{\mu}_2 \end{bmatrix} + \begin{bmatrix} \vec{e}_t \\ \vec{u}_t \end{bmatrix}$$

where $\vec{y}_t$ is the (7x1) vector of logarithmic first differences of Texas variables,

$\vec{x}_t$ is a (kxl) vector of logarithmic first differences of national variables,

$\vec{e}_t$ is a (7x1) vector of disturbances,

$\vec{u}_t$ is a (kxl) vector of disturbances,

$$b_1(L) = I - b_{11} L - b_{12} L^2 - \ldots,$$
$$b_2(L) = \quad - b_{21} L - b_{22} L^2 - \ldots,$$
$$b_3(L) = I - b_{31} L - b_{32} L^2 - \ldots,$$

where L is the lag operator ($L^k z_t = z_{t-k}$),

$$E[\vec{e}_t \vec{e}'_{t-k}] = \begin{cases} \Sigma_e & \text{if } k = 0 \\ 0 & \text{otherwise,} \end{cases}$$

$$E[\vec{u}_t \vec{u}'_{t-k}] = \begin{cases} \Sigma_u & \text{if } k = 0 \\ 0 & \text{otherwise,} \end{cases}$$

and
$$E[\vec{u}_t \vec{e}'_{t-k}] = \begin{cases} \Sigma_{eu} & \text{if } k = 0 \\ 0 & \text{otherwise.} \end{cases}$$

The model can also be represented as a set of equations, one for each of the seven y-variables plus one for each of the k x-variables. Such a representation will be useful below.

An important feature of the model is that the x-vector is exogenous with respect to the y-vector. While national variables may have interactions, and while they influence the regional variables, they are themselves assumed to be unaffected by the regional variables.

A significant limitation of the model is that the disturbances are assumed to be non-autocorrelated. This assumption can be made to be reasonably plausible through sufficiently large powers of L in the b_i coefficient matrices. A more flexible modelbuilding strategy would allow the disturbance vectors to be moving average processes, as in the multivariate ARIMA models. The added flexibility can reduce the number of parameters needed to adequately characterize the data, yet identification of multivariate ARIMAs is quite problematic. Also, the more restrictive MAR form imposed here will be more transparent to most regional economists. The ordinary least squares estimation technique used is also much more familiar.[3] Hence, the model-building procedure will be easy for others to imitate.

Model identification entails the choice of the variables to be included in $\vec{x}$ and the imposition of appropriate zero restrictions in the $b_{ij}(L)$ matrices of polynomials in the lag operator L. The latter essentially represents a choice of lag lengths. The method proposed here for identification proceeds in two stages.

First, "Granger causality" tests were performed to find significant leading relationships.[4] Formally, these causality tests were performed as follows: let y_{it} be the ith element of $\vec{y}_t$. For each $i = 1, 2, \ldots, 7$, run the following regressions and determine their sums of squared errors:

(a) $y_{it} = a_0 + a_1 y_{i,t-1} + a_2 y_{i,t-2} + e_{1it}$

(b) $y_{it} = b_{0j} + b_{1j} y_{i,t-1} + b_{2j} y_{i,t-2}$

$+ b_{3j} y_{j,t-1} + b_{4j} y_{j,t-1} + e_{2it}$

for all $j \neq i$.

(c) $y_{it} = c_0 = c_1 y_{i,t-1} + c_2 y_{i,t-2}$

$+ c_3 x_{1,t-1} + c_4 x_{1,t-2} + e_{3it}$

where $x_{1t} = \Delta \ln LEAD_t$ and LEAD= U.S. Index of Leading Indicators.

(d) $y_{it} = d_0 + d_{1k} y_{i,t-1} + d_{2k} y_{i,t-2}$

$+ d_{3k} x_{1,t-1} + d_{4k} x_{1,t-2}$

$+ d_{5k} x_{j,t-1} + d_{6k} x_{j,t-2} + e_{4it}$

for $1 \leq k \leq 14$.

Expression (a) represents a single regression, a second-order univariate autoregression. For example, for $i = 1$, the growth rate of TIPI is regressed on its first two own-lags. The results of regression (a) could be used to establish the potential value of past own-lags in forecasting, when compared with a random walk model. However, other well developed procedures for assessing the importance of autocorrelation, involving autocorrelation functions and the fitting and testing of ARIMA models, were given primary focus.

Expression (b) represents six different regressions. Pursuing the example, the growth rate of TIPI is regressed not only on its first two own-lags, but also on two lagged growth rates of CPIDFW; then TIPI's growth rate is regressed on two own-lags plus two lagged growth rates of PAYROLL; and so on. Results from (a) and (b) can be used to construct bivariate "causality" tests among the regional variables by using the F-statistic to test the null hypothesis that $b_{3j}=b_{4j}=0$. In three of the six such tests involving TIPI as the left-hand-side variable, the null hypothesis was rejected at the 0.05 level of significance. These three cases involved growth rates of TEMP, PAYROLL, and TLF as right-hand-side variables. In addition to the F-test or "causality test," the standard error of each of the regression equations in (b) was compared with that of equation (a). The reduction or increase in the standard error from inclusion of a variable, defined here as the "information gain," provides a quantitative assessment of the potential usefulness of the variable in forecasting. For example, the standard error of the equation for TIPI was lowered by about 10 percent by including TEMP as a right-hand-side variable, by about 7 percent by including PAYROLL, and by about 6 percent by including TLF.

Regression (c) employs two lagged growth rates of the U.S. index of leading indicators as right-hand-side variables, in addition to two own-lags. Together (c) and (a) can be used to construct tests of "causality" running from the leading indicator index to the regional variables. For example, the growth rate of TIPI was found to be significantly related to past growth rates in the leading index. In addition, it was found that inclusion of the leading index reduced the standard error by about 12 percent.

In (d), the regional variable, y_{it}, is regressed on two own-lags, two lagged growth rates of the leading index, and two lagged growth rates of one of thirteen other national variables. A causality test for each of these 13 other variables is performed using the results of (d) and (c), and the information gain (reduction in standard error) is assessed. In the example of TIPI, it was found that, once the leading index was included, none of the other 13 national variables provided significant information gain (the hypothesis that the d_{5j} and d_{6j} were zero could not be rejected).

The battery of causality tests just described was repeated for each of the regional variables and reported in Hoehn, Gruben, and Fomby (1984a). These results constitute the first stage of model identification and provide candidates for inclusion in the equations of the MAR.

In the second stage, a search was undertaken to determine the best specification of each equation. In each equation, two lagged growth rates of each of the candidate right-hand-side variables were tried all at once, then in more limited combinations. Two criteria were used to select the final specification: low standard error of the equation and parsimony. Judgment was necessary, since the specification that met one of the criteria did not always meet the other. Like most other identification methods for time series models, the model identification procedure is neither deterministic nor replicable. For example, the initial unparsimonious treatment of the TIPI equation included two lags each of TIPI itself, all three Texas labor series, and the U.S. leading index. That equation's standard error was found to be reduced by excluding the labor force and establishment-survey employment from the equation, and including only the first lag of the leading index and TIPI itself. Some other combinations were tried. The objective was to find an equation with only a few parameters and a relatively low standard error.

Specification of the Model

The specification finally chosen for the first equation in the parsimonious MAR is:

$$(1)\quad \Delta \ln TIPI_t = \underset{(.0040)}{.0031} + \underset{(.13)}{.25}\,\Delta \ln TIPI_{t-1} + \underset{(.27)}{.48}\,\Delta \ln TEMP_{t-1} + \underset{(.27)}{.49}\,\Delta \ln TEMP_{t-2} + \underset{(.08)}{.24}\,\Delta \ln LEAD_{t-1} + e_{1t}.$$

see = .01308 Q(18) = 11.9

$\bar{R}^2$ = .44 I = 24.7

Values in parentheses are standard errors of parameter estimates. The standard error of the equation (SEE) is 0.01308. This standard error can be compared with the standard deviation of $\Delta \ln TIPI$, the latter essentially representing the standard error of the random walk model. This comparison is formalized by the I-statistic:

$$I = \left[1 - \frac{\text{standard error of MAR equation}}{\text{standard deviation}}\right] \times 100$$

Because the standard error is 24.7 percent below the standard deviation of $\Delta lnTIPI$, we say that the information gain associated with the equation, I, is 24.7. The Q-statistic reported is the sample size times the sum of squared autocorrelations in the residuals, for the first 18 lags.

Prior to fitting equations for (nominal) personal income and retail sales, it was necessary to perform the sets of "causality tests," as these were performed in Hoehn, Gruben, and Fomby (1984a) only for their deflated counterparts. The results indicated that lagged growth rates in CPIDFW and TRET were promising candidates for inclusion in the equation for TPY, and that TEMP and TPY belonged in the equation for TRET. There was also evidence that the (national) finished goods producer price index was a significant aid to predicting TPY, but that price index was eventually excluded in the process of choosing a parsimonious model.

The other equations for Texas variables were derived in a similar manner. Only once was a right-hand-side variable excluded on a priori grounds. The U.S. Consumer Price Index and the GNP deflator were excluded from the equation for the Texas labor force, even though they significantly improved the fit (lowered the standard error) of the equation. Otherwise, all equations were derived from purely statistical criteria. It can be regarded as a favorable result that the equations arrived at, listed below, appear quite reasonable in view of available rough prior notions about the regional economy.

$$(2)\quad \Delta lnCPIDFW_t = \underset{(.0023)}{.0036} + \underset{(.18)}{.22}\,\Delta lnCPIDFW_{t-1} + \underset{(.15)}{.36}\,\Delta lnCPIDFW_{t-2} + \underset{(.13)}{.25}\,\Delta lnPPI_{t-1} + \underset{(.007)}{.015}\,\Delta lnRFF_{t-1} + e_{2t}$$

see = .007027 $\quad$ Q(18) = 12.5

$\bar{R}^2$ = .60 $\quad$ I = 35.7

(3) $$\Delta \ln PAYROLL_t = \underset{(.0013)}{.0025} + \underset{(.11)}{.63}\, \Delta \ln PAYROLL_{t-1} + \underset{(.08)}{.19}\, \Delta \ln TEMP_{t-1} + e_{3t}$$

see = .004174 $\qquad$ Q(18) = 7.9

$\bar{R}^2$ = .55 $\qquad$ I = 32.5

(4) $$\Delta \ln TEMP_t = \underset{(.0025)}{.0095} - \underset{(.17)}{.43}\, \Delta \ln TEMP_{t-1} - \underset{(.18)}{.42}\, \Delta \ln TEMP_{t-2}$$

$$+ \underset{(.24)}{.57}\, \Delta \ln PAYROLL_{t-1} + \underset{(.05)}{.08}\, \Delta \ln LEAD_{t-1} + e_{4t}$$

see = .007557 $\qquad$ Q(18) = 16.7

$\bar{R}^2$ = .14 $\qquad$ I = 5.8

(5) $$\Delta \ln TLF_t = \underset{(.0017)}{.0111} - \underset{(.15)}{.20}\, \Delta \ln TLF_{t-1} + e_{5t}$$

see = .006417 $\qquad$ Q(18) = 13.1

$\bar{R}^2$ = .02 $\qquad$ I = 0.4

(6) $$\Delta \ln TPY_t = \underset{(.0049)}{.0084} + \underset{(.13)}{.16}\, \Delta \ln TPY_{t-1} + \underset{(.08)}{.13}\, \Delta \ln COIN_{t-2} - \underset{(.25)}{.58}\, \Delta \ln CPIDFW_{t-1}$$

$$+ \underset{(.22)}{.73}\, \Delta \ln CPIDFW_{t-2} + \underset{(.08)}{.23}\, \Delta \ln TRET_{t-1} + \underset{(.18)}{.34}\, \Delta \ln PPI_{t-1} + e_{6t}$$

see = .009878 $\qquad$ Q(18) = 18.7

$\bar{R}^2$ = .36 $\qquad$ I = 18.4

(7) $$\Delta \ln TRET_t = \underset{(.0075)}{.0272} - \underset{(.13)}{.19}\, \Delta \ln TRET_{t-2} - \underset{(.14)}{.47}\, \Delta \ln TRET_{t-3}$$

$$+ \underset{(.30)}{.63}\, \Delta \ln TEMP_{t-1} + \underset{(.22)}{.57}\, \Delta \ln TPY_{t-1} + e_{7t}$$

see = .01616 $\qquad$ Q(18) = 14.7

$\bar{R}^2$ = .30 $\qquad$ I = 17.3

These equations include four national variables: the Index of Leading Economic Indicators (LEAD), the Index of Roughly Coincident Indicators (COIN), the Producers Price Index for All Finished Goods (PPI), and the federal funds rate (RFF). In order to construct forecasts for more than one quarter ahead, the model must be able to generate forecasts for those national variables. This is accomplished by appending to the MAR the following equations, which treat the national variables as block exogenous:

$$(8)\quad \Delta\ln LEAD_t = \underset{(.005)}{.023} + \underset{(.14)}{.80}\,\Delta\ln LEAD_{t-1} + \underset{(.14)}{.30}\,\Delta\ln LEAD_{t-2}$$

$$\qquad\qquad - \underset{(.22)}{1.13}\,\Delta\ln COIN_{t-1} - \underset{(.23)}{.83}\,\Delta\ln PPI_{t-1} + u_{1t}$$

see = .01681 $\qquad$ Q(18) = 4.5

$\bar{R}^2$ = .64

$$(9)\quad \Delta\ln COIN_t = \underset{(.0021)}{.0034} + \underset{(.08)}{.54}\,\Delta\ln LEAD_{t-1} + u_{2t}$$

see = .0416 $\qquad$ Q(18) = 22.6

$\bar{R}^2$ = .52

$$(10)\quad \Delta\ln PPI_t = \underset{(.0029)}{.0063} + \underset{(.15)}{.50}\,\Delta\ln PPI_{t-1} + \underset{(.15)}{.19}\,\Delta\ln PPI_{t-2} + u_{3t}$$

see = .009672 $\qquad$ Q(18) = 15.1

$\bar{R}^2$ = .38

$$(11)\quad \Delta\ln RFF_t = \underset{(.025)}{.017} + \underset{(.17)}{.38}\,\Delta\ln RFF_{t-1} - \underset{(.17)}{.37}\,\Delta\ln RFF_{t-2} + u_{4t}$$

see = .1695 $\qquad$ Q(18) = 12.0

$\bar{R}^2$ = .11

These four equations were built using criteria similar to that of the earlier seven. Candidates for right-hand-side variables were confined to lagged values of the four national variables themselves, and simple equations were chosen with low standard errors. Further improvements might be made by searching a larger set of national variables for promising right-hand-side variables for these equations.

The I-measures of information gain suggest substantial gains may be available from the use of the model relative to a naive model. Table 1 compares the model's standard errors with those of three alternatives:

(i) The random walk model

$$\Delta \ln y_t = \mu + e_t$$

(ii) The second order autoregression, or ARIMA(2,1,0)

$$\Delta \ln y_t = \mu + \phi_1 \Delta \ln y_{t-1} + \phi_2 \Delta \ln y_{t-2} + e_t$$

(iii) ARIMAs identified by the methods of Box and Jenkins, or ARIMA(p,1,q)

$$\Delta \ln y_{t-1} = \mu + \phi_1 \Delta \ln y_{t-1} + \dots + \phi_p \Delta \ln y_{t-p}$$

$$+ e_t - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}.$$

The identified and estimated Box-Jenkins ARIMAs (iii) are described in appendix A.

The I-measure reported for equations (1) through (7) above ,epresents the reduction from the first to the fourth column of table 1. The fourth column can be compared with the second and third columns to determine the degree of improvement relative to univariate equations. Such a comparison indicates quite substantial improvement in the equations for personal income, industrial

Table 1 Comparison of Standard Errors of Equations

Right-hand-side variables	(1) Random walk	(2) ARIMA(2,1,0)	(3) Box-Jenkins	(4) Model
TIPI	.01736	.01579	.01538	.01308
CPIDFW	.01093	.00768	.00769	.00703
PAYROLL	.00618	.00442	.00432	.00417
TEMP	.00802	.00825	.00802	.00756
TLF	.00644	.00641	.00644	.00642
TPY	.01211	.01200	.01176	.00988
TRET	.01953	.01919	.01809	.01616

production, and retail sales; significant but lesser improvement for consumer prices and household-survey employment; and no gain for the labor force. (The labor force is exogenous in the model's equation, a first-order univariate autoregression.)

It should be noted that the procedure for selecting the model ensured that it would have favorable comparisons against univariate equations in terms of standard errors. A more important issue is whether the multivariate model provides better out-of-sample forecasts. We should not expect a selected model's degree of superiority relative to ARIMAs to hold up out-of-sample. Nevertheless, unless a model provides better within-sample performance, it is unlikely to do as well as ARIMAs out of the sample.

Out-of-Sample Stability of the Model

The coefficients of the model were re-estimated each quarter during the post-sample forecasting period. As one might expect, the coefficients did, in some cases, change substantially as new data were incorporated in estimation. However, the equations did not display marked instability. Indeed, the range of variation in the coefficients over time seems rather modest in view of the severe economic conditions during the post-sample period. Table 2 displays the initial, lowest, highest, and final values of the coefficients for each equation. The model as finally estimated using data through 1983:II is presented in appendix B. Somewhat surprisingly, the measures of fit of the equations and the ratios (t-statistics) of estimated coefficients to their standard errors did not deteriorate over time. $\bar{R}^2$ (R^2 corrected for degrees of freedom) rose for five of the seven equations for Texas variables and fell for two. ($\bar{R}^2$ did fall for three of the four national variable

Table 2 Range of Coefficients as Estimation Period Extended

Left-hand-side variable	Right-hand-side variable	Initial	Low	High	Final
$TIPI_t$	$TIPI_{t-1}$	.25	.22	.35	.25
	$TEMP_{t-1}$	.48	.48	.75	.69
	$TEMP_{t-2}$	.49	.39	.49	.42
	$LEAD_{t-1}$	.24	.20	.26	.23
$CPIDFW_t$	$CPIDFW_{t-1}$	.22	.21	.25	.24
	$CPIDFW_{t-2}$	.36	.29	.36	.31
	PPI_{t-1}	.25	.23	.27	.23
	RFF_{t-1}	.02	.01	.02	.02
$PAYROLL_t$	$PAYROLL_{t-1}$	.63	.62	.74	.74
	$TEMP_{t-1}$	.19	.16	.20	.16
$TEMP_t$	$TEMP_{t-1}$	-.43	-.45	-.43	-.45
	$TEMP_{t-2}$	-.42	-.43	-.37	-.43
	$PAYROLL_{t-1}$	.57	.54	.65	.62
	$LEAD_{t-1}$	.08	.08	.09	.08
TLF_t	TLF_{t-1}	-.20	-.24	-.18	-.24
TPY_t	TPY_{t-1}	.16	.08	.17	.11
	$COIN_{t-2}$	.13	.11	.13	.13
	$CPIDFW_{t-1}$	-.58	-.58	-.47	-.56
	$CPIDFW_{t-2}$	.73	.65	.73	.71
	$TRET_{t-1}$	.23	.23	.31	.30
	PPI_{t-1}	.34	.31	.40	.40

Table 2 - Continued

Range of Coefficients as Estimation Period Extended

Left-hand-side variable	Right-hand-side variable	Initial	Low	High	Final
$TRET_t$	$TRET_{t-2}$	-.19	-.20	-.10	-.11
	$TRET_{t-3}$	-.47	-.48	-.43	-.44
	$TEMP_{t-1}$	.63	.60	.85	.85
	TPY_{t-1}	.57	.47	.67	.61
$LEAD_t$	$LEAD_{t-1}$	.80	.70	.80	.75
	$LEAD_{t-2}$	.30	.26	.32	.28
	$COIN_{t-1}$	-1.13	-.95	-1.13	-.96
	PPI_{t-1}	-.83	-.89	-.66	-.66
PPI_t	PPI_{t-1}	.50	.50	.54	.54
	PPI_{t-2}	.20	.18	.20	.18
RFF_t	RFF_{t-1}	.38	.25	.38	.28
	RFF_{t-2}	-.37	-.37	-.23	-.23
$COIN_t$	$LEAD_{t-1}$	.54	.52	.55	.54

equations.) The standard errors of four of the equations for Texas variables rose, and three fell. However, the standard errors generally decreased relative to the standard deviation of growth rates: the I-statistic rose in five of seven equations. There are no compelling reasons for altering the model from its original specification, although de novo analysis might lead to some improvement. The Box-Pierce statistics do not indicate any serious model inadequacy. (The equation for the U.S. coincident index, as finally estimated, does display marginally significant autocorrelation of errors, however.)

The relation between coefficient stability and stability of the model's forecasting properties is not very precise. Nevertheless, coefficient instability would be a negative indication for a model. The reasonable stability of the model reinforces the notion that the model is fairly robust and that the underlying structure of the regional economy did not change radically during the weakness of the early 1980s.

Out-of-Sample Performance of the Model

The RMSE serves as the absolute measure of forecast accuracy. It is strictly appropriate if the costs of forecast errors are quadratic in the errors. This is a reasonable assumption, is analytically most tractable, and directly relates to the least squares estimation procedure [Granger and Newbold (1977, p. 280)]. The performance of the model is evaluated by relative efficiency and conditional efficiency. Relative efficiency is defined here as the ability of the model to produce forecasts with lower RMSEs than univariate ARIMAs. Conditional efficiency, as defined by Granger and Newbold (1977, p. 283), is a somewhat stronger criterion. If a model produces forecasts with RMSEs that cannot be significantly reduced by combining its forecasts with univariate Box-Jenkins forecasts, then it is conditionally efficient with respect to the Box-Jenkins forecasts. In this section we examine relative efficiency; in the next section, conditional efficiency.

In examining relative efficiency, the two univariate benchmark models were again employed--ARIMAs identified by the methods of Box and Jenkins and arbitrarily specified ARIMA(2,1,0) equations. Each model was updated ten times. Just as for the MAR, initial estimation of ARIMAs used the sample from 1969:IQ to 1980:IVQ; the second estimation used the sample from 1969:IQ to 1981:IQ, and so forth, until a tenth estimation used the sample from 1969:IQ to 1983:IQ. After each estimation, forecasts were generated for the seven Texas variables for the quarter following the end of the estimation sample until 1983:IIQ. Hence, the first forecast provided one forecast for each horizon from one to ten quarters; the second produced one forecast for each horizon up to nine quarters, and so forth.

RMSEs for the 1981:IQ to 1983:IIQ out-of-sample forecast period are presented in table 3 for the MAR, in table 4 for the Box-Jenkins ARIMAs, and in table 5 for the arbitrarily specified ARIMA(2,1,0)s. Table 6 presents forecast accuracy rankings for the MAR, Box-Jenkins ARIMAs and an unweighted average of the two to be discussed in the next section. The model performed rather well when compared with the Box-Jenkins ARIMAs, outperforming them in 30 of the 42 possible comparisons, and in 20 of 21 one- to three-step-ahead forecast comparisons. The MAR also generally performed well relative to the arbitrarily specified ARIMA(2,1,0) equations. For the one-, two-, and

Table 3 Root Mean Square Errors for Parsimonious MAR

Step	TIPI	CPIDFW	PAYROLL	TEMP	TLF	TPY	TRET
1	.0211	.0067	.0073	.0061	.0064	.0120	.0244
2	.0421	.0118	.0147	.0086	.0066	.0200	.0455
3	.0614	.0194	.0264	.0120	.0036	.0328	.0697
4	.0877	.0282	.0408	.0162	.0051	.0498	.0899
5	.1116	.0412	.0558	.0211	.0080	.0684	.1090
6	.1297	.0554	.0643	.0228	.0079	.0926	.1284

Table 4 Root Mean Square Errors for Box-Jenkins ARIMAs

Step	TIPI	CPIDFW	PAYROLL	TEMP	TLF	TPY	TRET
1	.0240	.0078	.0072	.0068	.0067	.0143	.0292
2	.0446	.0156	.0150	.0101	.0071	.0311	.0516
3	.0626	.0250	.0267	.0129	.0040	.0547	.0713
4	.0842	.0357	.0411	.0169	.0048	.0724	.0863
5	.1075	.0501	.0567	.0202	.0079	.0795	.1025
6	.1260	.0679	.0658	.0220	.0084	.0856	.1252

Table 5 Root Mean Square Errors for ARIMA(2,1,0)s

Step	TIPI	CPIDFW	PAYROLL	TEMP	TLF	TPY	TRET
1	.0234	.0078	.0074	.0072	.0061	.0183	.0247
2	.0446	.0148	.0148	.0105	.0064	.0296	.0478
3	.0584	.0231	.0270	.0133	.0039	.0457	.0697
4	.0808	.0325	.0415	.0172	.0057	.0605	.0908
5	.1049	.0455	.0572	.0201	.0080	.0723	.1092
6	.1259	.0621	.0657	.0215	.0083	.0929	.1249

Table 6 Ranking of Forecast Accuracy[a]

Step	TIPI	CPIDFW	PAYROLL	TEMP	TLF	TPY	TRET
1	MCA	MCA	ACM	MCA	MCA	CMA	MCA
2	MCA	MCA	MCA	MCA	CMA	MCA	MCA
3	MCA	MCA	MCA	MCA	MCA	MCA	MCA
4	ACM	MCA	MCA	MCA	ACM	MCA	ACM
5	ACM	MCA	MCA	ACM	CAM	MCA	ACM
6	ACM	MCA	MCA	ACM	MCA	ACM	ACM

a. M = Model, A = Box-Jenkins ARIMA, C = Average

Sum of RMSEs for 7 Texas Variables

Step	Model	Box-Jenkins ARIMA	Average
1	.0840	.0960	.0847
2	.1493	.1751	.1600
3	.2253	.2572	.2391
4	.3177	.3414	.3272
5	.4151	.4244	.4181
6	.5011	.5009	.5001

three-quarter-ahead forecasts, the model very clearly outperformed Box-Jenkins ARIMAs. The RMSE for each of these three horizons and each of the seven Texas variables was lower for the MAR in every case, except for the one-quarter-ahead forecasts of PAYROLL where the difference was very slight. The four-, five-, and six-quarter-ahead forecasts presented a mixed picture. The model's sum of RMSEs across the seven variables was smaller for the four- and five-step-ahead forecasts, but very slightly higher for the six-step-ahead forecasts (for which we had only a sample of five for each variable). The model outperformed ARIMAs for four of the seven variables in the four-step-ahead forecasts, but for only three variables in the five- and six-step-ahead forecasts.

One might consider the size of the errors to be quite large in economic terms, especially at the longer forecast horizons. This may be a result of the unusual weakness of the regional economy during the period. With the exception of the labor force, most of the forecast errors were negative (actual values typically fell below predicted values), and the errors over longer forecast horizons tended to accumulate as the recession continued. This accumulation of negative error occurred for both the ARIMA equations and the model.

As one would expect, the RMSEs of one-period-ahead forecasts were generally larger than within-sample standard errors, both for the MAR and for the ARIMAs. In some cases, the difference was quite large. For example, the RMSE for TIPI, using the model, was 61 percent higher than the within-sample standard error, and for the ARIMA was 56 percent higher. This could result from the unusual turbulence of the regional economy in the simulation period, a changing economic structure, or model inadequacy.

Although one might have expected the ARIMAs to be more robust because of their relative parsimony, the MAR displayed no greater increase in RMSEs relative to standard errors. Indeed, while the ARIMA's RMSEs were above standard errors for all variables except TEMP, the MAR's RMSEs were lower than standard errors for both TEMP and CPIDFW, and stayed the same for TLF. The average increase in RMSE relative to standard errors across the seven Texas variables was 26 percent using the model and 28 percent using the ARIMAs.

In view of the smallness of the out-of-sample forecasting period, it is natural to ask how significant, in a statistical sense, the evidence is that the model can outperform ARIMAs. A test designed to detect "causality" as described in Ashley, Granger, and Schmalensee (1980) can be adapted for this purpose. Essentially, the test involves regressing d_t on s_t, where

$$d_t = e_t^a - e_t^m,$$

$$s_t = e_t^a + e_t^m,$$

and e_t^a and e_t^m are forecast errors for the ARIMA and model forecasts, respectively. The regression is of the form:

$$d_t = \alpha + \beta \, [s_t - \bar{s}] + u_t.$$

If the mean square error of the MAR is lower than that of the ARIMAs, either α or β or both must be nonzero. The null hypothesis, that the model does not provide better forecasts, is rejected if the F-statistic for and is sufficiently large, and if estimates of and have appropriate signs. One ambiguity of the test involves the signs of coefficients; it is in essence a four-tailed test. The true significance level of the F-statistic is something less than one-half that found in tables of the F-distribution, if estimated regression coefficients are of the correct signs. The correct sign for β is always positive. The correct sign for a is negative if the mean errors are negative, as they are for all variables and horizons, except for TLF, whose mean errors are positive for all horizons.

The F-statistics of the Ashley-Granger-Schmalensee tests are displayed in table 7. The F-statistics can be judged against critical values from distribution tables. For one-step-ahead forecasts, the relevant distribution has 2 numerator and 8 denominator degrees of freedom; for two-step-ahead, 2 numerator and 7 denominator degrees of freedom; etc. Halving the significance level from the F-distribution tables, and assuming correct signs of coefficients, an F-statistic in table 7 is significant at the 0.05 level (or lower) if above 3.11 for one-step-ahead forecasts, 3.26 for two steps ahead, 3.46 for three steps ahead, and 3.78 for four steps ahead.

The results suggest significant improvement in MAR forecasts of consumer prices and personal income beyond one quarter ahead, compared with ARIMA forecasts, and significant improvement also in one-quarter forecasts of household-survey employment. None of the other improvements is significant, using the test criterion. However, the test has low power due to the smallness of the sample.

The results for Texas personal income are considerably stronger than for an alternative forecasting equation studied by Ashley (1980 and 1983). He reports some evidence, that the growth rate in forecasts of personal income

Table 7 Statistics for Significance of Model-Forecasting Efficiency (Ashley-Granger-Schmalensee Test)

Forecast variable	Forecast horizon 1-Step	2-Step	3-Step	4-Step
TIPI	1.28[a]	.20[a]	.06	.83[c]
CPIDFW	1.26	3.76	3.34	3.43
PAYROLL	.12[c]	.35	1.31[b]	.81[b]
TEMP	5.57	1.40	.42[b]	.16
TLF	.94[a]	.32	2.18[a]	.91[b]
TPY	.29	3.64	3.27	4.57
TRET	1.31	3.03	.36[a]	1.14[c]

a. α was of wrong sign, but not significantly different from zero.
b. β was of wrong sign, but not significantly different from zero.
c. Both α and β were of wrong sign, but not significantly different from zero.

could be improved slightly relative to an ARIMA(4,1,0) by using a bivariate model with three own-lags and one current growth rate in national GNP. The improvement was slight, was measured over a single forecast of one to eight quarters, and depended on high-quality, judgmentally adjusted structural econometric forecasts of GNP. The bivariate equation produced forecasts inferior to the ARIMA(4,1,0) when GNP forecasts were generated using a strictly formal method (a first-order autoregression). The results for the MAR reported here are considerably stronger. The forecasts for the growth rate for Texas personal income were considerably better than those of ARIMAs, and significantly so. Furthermore, our model does not require as an input any judgmental forecasts of exogenous variables.

Combination Forecasts

Another approach to improving forecast accuracy is that of combining forecasts of different methods. Given the two methods we have constructed, it is easy to combine them by, for example, averaging them. RMSEs of the average forecasts are shown in table 8. The simple average was never less accurate than both the model and the ARIMA, for any horizon or variable. It always came in at least second among the three possible methods, and in five of forty-two cases, it came in first. Furthermore, the average forecast tended overall to be nearly as accurate as the model for one-period-ahead forecasts and those at the longer horizons as well. The sum of the seven variables' RMSEs for the combined forecast, as shown at the bottom of table 6, was actually lower than that of the model at the six-period-ahead horizon, and was always lower than that of ARIMAs.

Table 8 Root Mean Square Errors for Average Forecasts

Step	TIPI	CPIDFW	PAYROLL	TEMP	TLF	TPY	TRET
1	.0224	.0071	.0072	.0062	.0065	.0118	.0264
2	.0432	.0136	.0149	.0091	.0059	.0249	.0484
3	.0619	.0220	.0266	.0122	.0037	.0429	.0698
4	.0859	.0318	.0410	.0164	.0049	.0599	.0873
5	.1095	.0455	.0562	.0206	.0079	.0729	.1055
6	.1278	.0616	.0650	.0223	.0081	.0887	.1266

The simple average forecast need not be the best weighting scheme. It seems that, because the model forecast generally outperformed the average forecast, more weight should be given to the model than the ARIMA. But the weights do not have to be the same for all variables or forecast horizons. In an attempt to determine appropriate weights empirically, the RMSE-minimizing weights were calculated, subject to the constraint that they summed to one.[5] In table 9, these weights are presented for one- and four-quarter forecast horizons. The results of this exercise are not very encouraging. In only three cases out of fourteen are the weights within the interval from zero to unity. The sample is probably too small. Probably the best conclusion to be drawn from the study of combinations, simple and weighted, is that there is no strong evidence that model forecasts can be much improved by combining them with those of ARIMAs. Hence, we may provisionally regard the MAR as conditionally efficient with respect to the Box-Jenkins ARIMAs.

Conclusion

The results must be interpreted with caution, particularly in view of the smallness of the sample of forecast errors. However, the evidence presented suggests that the model can provide relatively efficient forecasts, in the sense that the magnitude of forecast errors tends to be less for the model than for univariate ARIMAs. The results are stronger than those in other studies of regional forecasting. Models offering systematic forecasting improvements over univariate ARIMAs are not common in practice. The relatively straightforward modelbuilding procedure applied here to the Texas economy could be employed to forecast other regional economies as well.

Table 9 Optimal Weights
(ARIMA/model)

Variable	One-quarter-ahead	Four-quarter-ahead
TIPI	-1.63/2.63	6.28/-5.28
CPIDFW	-.19/1.19	-1.89/2.89
PAYROLL	1.70/-.70	-3.04/4.04
TEMP	.06/.94	-.27/1.27
TLF	-1.10/2.10	1.91/-.91
TPY	.29/.71	-.79/1.79
TRET	-.78/1.78	1.65/-.65

Indeed, the methodology might be useful in any forecasting problem where there are numerous potential sources of information for forecasting, but including all of them is inappropriate due to issues of degrees of freedom and multicollinearity.

Multivariate ARIMA methods, such as those proposed by Tiao and Box (1981), are more flexible than the MAR method proposed here, and might provide further gains in forecasting accuracy. However, many practical forecasters will find the MAR much easier to implement. Other less time-consuming multivariate methods exist, such as the "vector autoregressions" of Anderson and of Kuprianov and Lupoletti (1984), which can be implemented with a single computer run and no diagnostic efforts.[6] However, there is no evidence that they can provide efficient regional forecasts relative to univariate methods. Neither is there any clear evidence that structural econometric models of regions can provide efficient forecasts in any systematic way.

A further advantage or byproduct of the method here proposed is that, in performing the two stages of MAR modelbuilding, insights into the regional economic process may be generated that are not generated by other methods. Of course, there will always be a place for a number of different methods. In the final analysis, many kinds of models can shed light on the forecasting problem and on economic relationships. An ideal forecast might take all into account in an optimally weighted combination.

The author has begun work at the Federal Reserve Bank of Cleveland on forecasting the Ohio economy, which is structurally very different from the Texas economy. Aside from fulfilling instrinsic interest in forecasting Ohio, the results of this study will be compared with those for Texas in the following respects:

(1) the persistence of autocorrelation in growth rates of regional series,

(2) the importance of linkages to the national economy in providing useful forecasting relationships, and

(3) the value of certain regional series, particularly the employment series, in forecasting other regional series.

Footnotes

1. See Granger and Newbold (1977, pp. 289-302) for an assessment of the comparative accuracy of time series versus econometric macro forecasts. See Nelson (1984) for a comparison of univariate ARIMAs and judgmentally adjusted econometric models in real-time macroeconomic forecasting.

2. The name and acronym for the model form are the traditional ones, and those preferred by Granger (1982). "It now seems obligatory to provide an acronym, or catchy abbreviation, whenever a new time series model, technique, or computer program is introduced. . . . As this proliferation continues it seems likely that soon, competing initials for the same model, or the same initials for different models, will arise. . . . It can be . . . argued that unnecessary proliferation of these abbreviations should not be encouraged . . ." (p. 103).

3. The ordinary least squares estimation technique ignored the correlation between errors in different equations. The "seemingly unrelated regression" estimation technique might have provided slightly better forecasting equations.

4. This use of the term causality is controversial. "It is doubtful that philosophers would completely accept this definition, and possibly cause is too strong a term, or one too emotionally laden, to be used. A better term

might be temporally related, but since cause is such a simple term we shall continue to use it." Granger and Newbold (1977, p. 225).

5. Nelson (1984) conducts similar analysis of optimal weights for ARIMA and judgmentally adjusted macroeconometric model forecasts. However, he does not enforce the requirement that the weights sum to unity. Granger and Ramanathan (1984) show that a linear combination forecast with weights not constrained to add to one and with a constant term can lead to improved forecast accuracy relative to a combination with the sum of weights constrained to one and without a constant, as in this paper. The method of Granger and Ramanathan requires estimation of three free parameters, compared with only one in the traditional method, employed in this paper. As the reader will note, the sample was evidently rather small even for the estimation of a single parameter. The author did try estimating three parameters, but the results were uninfomative.

6. Kuprianov and Lupoletti (1984) build a "vector autoregression" (not the "Bayesian" variety) for quarterly employment and deflated personal income for five states and the District of Columbia, with two exogenous national variables, and a lag length of six quarters. The method here differs in the method of choosing variables to be included and in the method of choosing the appropriate lag lengths. The longest lag in the MAR was three quarters, and that occurred in only one equation.

Appendix A: Box-Jenkins ARIMA Models

(1) $$(1-L)\ln TIPI_t = .01783 + (1+.63L)e_{1t}$$

see = .01538
I = 11.1
$\chi^2(18)$ = 19.4

(2) $$(1-.89L)(1-L)\ln CPIDW_t = .02051 + (1-.38L)e_{2t}$$

see = .00769
I = 29.7
$\chi^2(18)$ = 9.1

(3) $$(1-.73L)(1-L)\ln PAYROLL_t = .01145 + e_{3t}$$

see = .00432
I = 30.1
$\chi^2(18)$ = 9.1

(4) $$(1-L)\ln TEMP_t = .00884 + e_{4t}$$

see = .00802
I = 0
$\chi^2(18)$ = 18.4

(5) $$(1-L)\ln TLF_t = .00931 + e_{5t}$$

see = .00644
I = 0
$\chi^2(18)$ = 17.9

(6) $$(1-.31L)(1-L)\ln TPY_t = .0210 + e_{6t}$$

see = .01163
I = 4.0
$\chi^2(18)$ = 12.0

(7) $$(1-.10L+.12L^2+.36L^3)(1-L)\ln TRET_t = .0418 + e_{7t}$$

see = .01787
I = 8.5
$\chi^2(18)$ = 10.3

Appendix A: Continued

Autocorrelation functions

Lag	TPY	TRET
1	.30	.18
2	.13	-.14
3	.18	-.38
4	.01	.10
5	-.03	.22
6	.14	.27
7	.27	-.09
8	-.04	-.28
9	.14	.07
10	.11	.19

χ^2 Test for white noise

	TPY		TRET	
To lag	χ^2	Significance	χ^2	Significance
6	8.3	.21	17.2	.01
12	15.4	.22	30.9	.00
18	18.5	.42	44.9	.00
24	20.4	.67	58.7	.00

Note: Autocorrelation functions and χ^2 tests for nonautocorrelation for the other five Texas series are found in Hoehn, Gruben, and Fomby (1984a).

Appendix B: Final Estimate of Model

(1) $$\Delta \ln TIPI_t = \underset{(.0038)}{.00005} + \underset{(.12)}{.25}\,\Delta \ln TIPI_{t-1} + \underset{(.28)}{.69}\,\Delta \ln TEMP_{t-1}$$

$$+ \underset{(.12)}{.42}\,\Delta \ln TEMP_{t-2} + \underset{(.08)}{.23}\,\Delta \ln LEAD_{t-1} + e_{1t}$$

see = .01467 $\quad$ Q(21) = 8.2

$\bar{R}^2$ = .42 $\quad$ I = 23.1

(2) $$\Delta \ln CPIDFW_t = \underset{(.0020)}{.0040} + \underset{(.15)}{.24}\,\Delta \ln CPIDFW_{t-1} + \underset{(.13)}{.31}\,\Delta \ln CPIDFW_{t-2}$$

$$+ \underset{(.11)}{.23}\,\Delta \ln PPI_{t-1} + \underset{(.006)}{.018}\,\Delta \ln RFF_{t-1} + e_{2t}$$

see = .006910 $\quad$ Q(21) = 22.4

$\bar{R}^2$ = .61 $\quad$ I = 36.5

(3) $$\Delta \ln PAYROLL_t = \underset{(.0012)}{.0008} + \underset{(.10)}{.74}\,\Delta \ln PAYROLL_{t-1} + \underset{(.09)}{.16}\,\Delta \ln TEMP_{t-1} + e_{3t}$$

see = .004846 $\quad$ Q(21) = 4.8

$\bar{R}^2$ = .61 $\quad$ I = 36.7

(4) $$\Delta \ln TEMP_t = \underset{(.0019)}{.0095} - \underset{(.16)}{.45}\,\Delta \ln TEMP_{t-1} - \underset{(.16)}{.43}\,\Delta \ln TEMP_{t-2}$$

$$+ \underset{(.18)}{.62}\,\Delta \ln PAYROLL_{t-1} + \underset{(.039)}{.077}\,\Delta \ln LEAD_{t-1} + e_{4t}$$

see = .007212 $\quad$ Q(21) = 17.8

$\bar{R}^2$ = .17 $\quad$ I = 7.8

Appendix B: Continued

(5) $\Delta \ln TLF_t = \underset{(.0016)}{.0116} - \underset{(.14)}{.24}\, \Delta \ln TLF_{t-1} + e_{5t}$

see = .006389   Q(21) = 17.4

$\bar{R}^2$ = .04   I = 1.4

(6) $\Delta \ln TPY_t = \underset{(.0038)}{.0062} + \underset{(.12)}{.11}\, \Delta \ln TPY_{t-1} + \underset{(.07)}{.13}\, \Delta \ln COIN_{t-2}$

$- \underset{(.22)}{.56}\, \Delta \ln CPIDFW_{t-1} + \underset{(.20)}{.71}\, \Delta \ln CPIDFW_{t-2} + \underset{(.07)}{.30}\, \Delta \ln TRET_{t-1}$

$+ \underset{(.17)}{.40}\, \Delta \ln PPI_t + e_{6t}$

see = .01016   Q(21) = 15.3

$\bar{R}^2$ = .48   I = 26.5

(7) $\Delta \ln TRET_t = \underset{(.0064)}{.0182} - \underset{(.13)}{.11}\, \Delta \ln TRET_{t-2} - \underset{(.14)}{.44}\, \Delta \ln TRET_{t-3}$

$+ \underset{(.31)}{.85}\, \Delta \ln TEMP_{t-1} + \underset{(.21)}{.61}\, \Delta \ln TPY_{t-1} + e_{7t}$

see = .01773   Q(21) = 16.8

$\bar{R}^2$ = .26   I = 13.8

(8) $\Delta \ln LEAD_t = \underset{(.0051)}{.0162} + \underset{(.14)}{.75}\, \Delta \ln LEAD_{t-1} + \underset{(.14)}{.28}\, \Delta \ln LEAD_{t-2}$

$- \underset{(.21)}{.96}\, \Delta \ln COIN_{t-1} - \underset{(.23)}{.66}\, \Delta \ln PPI_{t-1} + u_{1t}$

see = .01833   Q(21) = 10.2

$\bar{R}^2$ = .56

Appendix B: Continued

(9) $$\Delta \ln COIN_t = \underset{(.0019)}{.0012} + \underset{(.07)}{.54}\,\Delta \ln LEAD_{t-1} + u_{2t}$$

see = .01425 Q(21) = 26.2

$\bar{R}^2$ = .51

(10) $$\Delta \ln PPI_t = \underset{(.0025)}{.0048} + \underset{(.14)}{.54}\,\Delta \ln PPI_{t-1} + \underset{(.14)}{.18}\,\Delta \ln PPI_{t-2} + u_{3t}$$

see = .009475 Q(21) = 20.0

$\bar{R}^2$ = .40

(11) $$\Delta \ln RFF_t = \underset{(.0226)}{.00087} + \underset{(.13)}{.28}\,\Delta \ln RFF_{t-1} - \underset{(.13)}{.23}\,\Delta \ln RFF_{t-2} + u_{4t}$$

see = .1672 Q(21) = 13.2

$\bar{R}^2$ = .07

References

Anderson, Paul A. 1979. "Help for the Regional Forecaster: Vector Autoregression," Federal Reserve Bank of Minneapolis Quarterly Review, vol. 3, no. 3 (Summer), pp. 2-7.

Ashley, Richard A. 1980. "Texas Forecasting Studies: Time Series Analysis," BP 80-3 Study for the Legislative Budget Board by the Bureau of Business Research, University of Texas at Austin (September 3).

______________. 1983. "On the Usefulness of Macroeconomic Forecasts As Inputs to Forecasting Models," Journal of Forecasting, vol. 2, no. 3 (July-September), pp. 211-23.

______________, C.W.J. Granger, and R. Schmalensee. 1980. "Advertising and Aggregate Consumption: An Analysis of Causality," Econometrica, vol. 48, no. 5, pp. 1149-67.

Box, George E.P., and Gwilym M. Jenkins. 1970. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.

Doan, Thomas A., Robert B. Litterman, and Christopher A. Sims. 1983. "Forecasting and Conditional Projection Using Realistic Prior Distributions," National Bureau of Economic Research Working Paper No. 1202.

Granger, C.W.J. 1982. "Acronyms in Time Series Analysis (ATSA)," Journal of Time Series Analysis, vol. 3, no. 2, pp. 103-07.

__________, and Paul Newbold. 1977. Forecasting Economic Time Series. New York: Academic Press.

__________, and R. Ramanathan. 1984. "Improved Methods of Combining Forecasts," Journal of Forecasting, vol. 3, no. 2 (April-June), pp. 197-204.

Hoehn, James G., and William C. Gruben, with Thomas B. Fomby. 1984a. "Some Time Series Methods of Forecasting the Texas Economy," Federal Reserve Bank of Dallas Working Paper No. 8402 (April).

__________. 1984b. "Time Series Forecasting Models of the Texas Economy: A Comparison," Economic Review, Federal Reserve Bank of Dallas (May), pp. 11-23.

Holt, Charles C., and Jerome A. Olsen. 1982. "Structural Change and Forecasting by Exponentially Weighted Regressions," Bureau of Business Research, University of Texas at Austin, BP 82-6 (July 16).

Kuprianov, Anatoli, and William Lupoletti. 1984. "The Economic Outlook for Fifth District States in 1984: Forecasts from Vector Autoregression Models," Economic Review, Federal Reserve Bank of Richmond vol. 70/1 (January/February), pp. 12-23.

Litterman, Robert B. 1979. "Techniques of Forecasting Using Vector Autoregressions," Federal Reserve Bank of Minneapolis Working Paper No. 115.

__________. 1982. "Specifying Vector Autoregressions for Macroeconomic Forecasting," Federal Reserve Bank of Minneapolis Working Paper No. 208 (July).

Nelson, Charles R. 1984. "A Benchmark for the Accuracy of Econometric Forecasts of GNP," Business Economics, vol. 19, no. 3 (April), pp. 52-58.

Tiao, G.C., and G.E.P. Box. 1981. "Modeling Multiple Time Series with Applications," Journal of American Statistical Association, vol. 76, no. 376 (December), pp. 802-16.