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THE OHIO ECONOMY: USING TIME SERIES CHARACTERISTICS IN FORECASTING

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Abstract

Time series methods are used to determine what information Ohio and national statistics convey about the current and future state of the regional economy. Properties of a number of quarterly series measuring aggregate economic activity and prices in Ohio are described, including their growth rates and variability, cyclicity, correlation at a moment in time, tendency to foreshadow each other's movements, and tendency to be foreshadowed by national economic indicators. These properties are of interest both for forecasting, either formal or judgmental, and for understanding structural characteristics of the Ohio economy. They are extensively tabulated here.

In sddition, some methods of forecasting, which exploit these time series properties, are assessed in an out-of-sample forecast period. The treatment of these methods and means for comparing them is elementary and somewhat pedogogical for the benefit of readers with little prior knowledge of time series forecasting methods.

The method for building a time series model described in Hoehn (1984) and applied to Texas with considerable forecasting success is applied, with some modificat on, to the economy of Ohio. A simple trickle-down model, specified a priori, is also implemented. Forecasts combining these methods are assessed.

The forecasts of the multivariate models are frequently found to be better than those of univariate autoregressions. In some cases, they are significantly superior, according to an indirect statistical test adapted from Ashley, Granger, and Schmalensee (1980). The results show that information can be identified as to source and quantified using very simple regression methods.

THE OHIO ECONOMY: TIME SERIES CHARACTERISTICS

The regional economist depends to a large extent upon economic statistics in assessing the current state and likely future course of his region. Consequently, an understanding of the properties of the available series can enhance his understanding and forecasts of the region. One way of acquiring this feel is purely judgmental in nature: the analyst accumulates understanding by informal thought and observation, generally over a period of years. More formal approaches involve building models. Structural models impose detailed and somewhat incredible assumptions ("identifying restrictions") about economic relationships in an attempt to extract knowledge otherwise hidden in the data. The time series approach allows description of the data without the requirement of imposing extensive assumptions or prior knowledge. It lets the data set speak for itself.

The premise of this study is that the regional economist can better understand the Ohio economy by studying the properties of important Ohio time series. The results show that information is available from sources that can be identified and quantified through simple regression methods that are widely understood.

I. The Regional Forecasting Problem

Regional economic time series exhibit variation from secular, cyclical, and seasonal sources. Regional forecasters attempt to assess current activity and to predict the future course of the regional economy by exploiting the information contained in various time series. Usually, this process of extracting information is quite informal and judgmental. In other cases, the process involves the use of a formal statistical model of some kind. This study seeks to provide formal tools for the Ohio forecaster.

Figure 1 illustrates the single series that is perhaps of greatest interest to Ohio forecasters: payroll or establishment-survey employment (seasonally adjusted). Although it has exhibited an upward trend, its growth has not proceeded smoothly. The strong dependence of Ohio on national conditions is obvious from the National Bureau of Economic Research peaks and troughs, denoted by "P's" and "T's," respectively. If history tends to repeat itself, then the regional forecaster can benefit from knowing the trend rate of growth, any predictable cyclical behavior, and any clues available from national data, such as the leading indicator index. Also, relations between the regional series may potentially aid in forecasting. This paper will describe these characteristics and assess their value to regional forecasters.

1.1 Regional Forecasting Models

Regional forecasting models have attracted interest among government and business planners and have proliferated with the availability of regional data. Many of these models are of the so-called structural variety, which involve use of detailed assumptions supposedly drawn from economic theory. Their construction reflects a primary goal of estimating the behavorial relationships (structure) corresponding to the theory, although they are employed for forecasting as well. For some applications, involving analysis of the effects of structural change or of the response of the regional economy to particular policies or events, a structural model is necessary. Despite the recent proliferation of structural models, little clear evidence exists on their ability to forecast well.[1]

Time series models, the alternatives to structural models, are primarily designed for forecasting. Such models can be built even in contexts in which the theory or data set required to build a structural model is unavailable.

Figure 1


ESTABLISHMENT-SURVEY EMPLOYMENT
SEASONALLY ADJUSTED
4750
4500
4250
4000
3750
3500
3250
1965
1968
1971
1974
1977
1980
1983
P
T
P
T
P
T
P
T

Most regional forecasting problems occur in such a context.

The remainder of this paper is organized as follows. A general survey of some related work is presented and forecasting context and data series are described. Subsequent sections characterize the univariate properties, intraregional relationships, and national-regional or so-called trickle-down relationships. These characteristics are then used to suggest candidate variables for inclusion in a multivariate autoregressive model (MAR) of the Ohio economy, using a stepwise regression procedure to select among the candidates. An *a priori* trickle-down model is also implemented. The latter two models' forecasting ability is compared with that of univariate autoregressions in the 1979-83 out-of-sample period.

III. A Brief Survey of Previous Work

A number of time series approaches have been implemented to facilitate regional forecasting. The univariate model represents the simplest approach and uses only the past history of each regional variable to predict its future. These models are the most straightforward to implement, and their forecasts are often as good as--and sometimes better than--more complex models. The forecasting accuracy of univariate models serves as an appropriate benchmark for evaluating the relative efficiency of other methods. The Box-Jenkins (1970) approach for identifying and estimating autoregressive integrated moving average (ARIMA) models is perhaps the most flexible and also the most popular framework for univariate time series modeling.

Multivariate models use the history of other variables to describe the movement in the series to be forecast--that is, they exploit delayed interactions, or lead-lag relations, between series. The identification and estimation of the appropriate multivariate model is problematic and is currently subject to research along different paths. The essential dilemma of the regional multivariate model is that of using as much information as possible by including as many relevant series in the equations, yet minimizing the inaccuracy due to multicollinearity and scarcity of degrees of freedom. For example, the more variables that are included, the more sources of information that are incorporated in the resulting model's forecasts, thus tending to improve accuracy. Yet, at the same time, inclusion of more variables will increase the standard errors of the estimates of the model's parameters, especially if variables are highly correlated, thus tending to reduce the accuracy of forecasts. Furthermore, as the results to follow will illustrate, more complex models may become unstable and break down out of the sample used to specify and estimate them. Unfortunately, no general procedure for solving this dilemma is available. Several recent efforts directed toward regional forecasting are of interest.

Anderson (1979) first implemented the "Bayesian approach" of Litterman (1979) for a regional model of the Ninth Federal Reserve District. The dilemma referred to above is dealt with in a clever and promising way: many variables and lags are included, but the variance of parameter estimates is limited by the imposition of a random walk prior distribution. The primary disadvantage of the procedure is the bias that it introduces into estimates of parameters. The greatest practical difficulty of the approach is the choice of appropriate "tightness" restrictions on the prior.' Litterman terms the model a "vector autoregression" (VAR) because of its (a) multivariate nature and (b) the absence of moving average parameters (only autoregressive parameters are present).

More recently, Amirizadeh and Todd (1984) have constructed five "Bayesian VAR" models for each of five states of the Ninth Federal Reserve District. They built an elaborate structure of linkages with forecasts of the national economy. They have undertaken real-time forecasting, and plan to publish their forecasts quarterly.

Kuprianov and Luppoletti (1984) adopt a VAR approach, but without imposing priors, and implement models for the individual states of the Fifth Federal Reserve District. The specification they employ uses six quarterly past values of state employment and deflated personal income, plus three national variables to forecast each of the two state variables.

Hoehn, Gruben, and Fomby (1984a, 1984b) and Hoehn (1984) explore a number of alternative methods for regional forecasting by applying them to the state of Texas and comparing their performance in an (admittedly short, 10-quarter) out-of-sample forecast period. The Bayesian VAR generally did not perform well relative to univariate ARIMAs, unless the VAR's prior distribution was tinkered with extensively, in which case its forecasting accuracy in some cases approached, but generally still fell short of, the univariate models. Models with many variables and no priors, using alternatively (a) other regional variables only (a closed-region model) or (b) national variables only (a trickle-down model), also performed poorly. Using the latter two models with univariate ARIMA models to form an unweighted combination forecast provided accuracy sometimes competitive with the ARIMAs alone.

Hoehn (1984), based on this experience with alternative models, proposed a method for building a forecasting model and implements it for Texas. (A more formal variant of that identification procedure, using the stepwise regression procedure, is described more fully below, where its application to Ohio series is presented.) Essentially, "causality tests" are first used to select a small number of variables that are candidates for inclusion in the equations Then, combinations of variables and lag structures are used to find well-fitting and parsimonious equations. The resulting model for Texas provided out-of-sample forecasts consistently superior to those of univariate ARIMAs, as measured by the criterion of the root mean square error (RMSE). For some variables and forecast horizons, the difference in forecasting accuracy between the multivariate and univariate model forecasts was significant at the .05 level. The model, while built according to strictly statistical criteria, also appeared quite reasonable in light of intuitions about the regional economy.

IV. The Forecasting Problem and the Approach

The objective of the present study is the construction of linear forecasting equations that predict the growth rates of Ohio variables by their own lagged growth rates and by those of each other and national series. For example, let $y_t(k)$ be the forecast of the change in the logarithm of a regional variable Y, for period t+k, for $k \geq 0$, formed at time t, when all t realizations are observed. For example, the k=1 case involves forecasting period t growth. A linear forecasting equation takes the general form:

$$y_t(k) = a_k + \sum_{j=1}^{q} b_{jk} S_{jt}$$

where a_k and the b_{jk} are parameters and S_{jt} is the jth element of a vector of q information variables available at time t. That vector, or information set, treats each relevant lag as a distinct variable in the above equation. The forecasting equations will be used to forecast the level of y, with particular emphasis on the one-to-four quarter $(0 < k \leq 4)$ horizons. The regional variables, Y, of concern, are the following seasonally adjusted Ohio variables:

(1)	Payroll Employment, total	(PAY ROLL)
(2)	Payroll Employment, Manufacturing	(MFG)
(3)	Payroll Employment, Nonmanufacturing	(NONMFG)
(4)	Household-survey Employment	(EMPL)
(5)	Civilian Labor Force	(LF)
(6)	Personal Income	(INCOME)
(7)	Retail Sales	(RETAIL)
(8)	Housing Starts	(STARTS)
(9)	Workweek in Manufacturing	(HOURS)
(10)	Consumer Prices	(PRICES)

Some of these series were seasonally adjusted by the reporting agency; others were seasonally adjusted either by the data vendor or by the authors. Some data were transformed from monthly averages to quarterly averages. The Ohio consumer price series required an elaborate method of construction from the Cleveland and Cincinnati Consumer Price Indexes. A fuller description of data sources and adjustments is in Appendix A. The series themselves, after these adjustments, but before transformation to logarithmic growth rates, are listed in Appendix B. The data series each began by at least the first quarter of 1965 (in the format we adopt, that quarter is denoted 65QI). The working data set for initial analysis included the growth rates for 65QIV through 78QIV, or 53 data points. The period from 79QI to 83QIV (20 data points) was saved for out-of-sample analysis of models constructed during the initial analysis.

V. Information Gain: A Pedagogy of the I-Statistic

The location of information available about the future course of a given Ohio series (the identity of the S vector) will be assessed by a systematic battery of nested hypothesis tests. The tests involve successive generalizations of the prediction equation to incorporate additional variables. The value of information will be measured by the improvement in the fit of an equation as the potentially informative variable is added. The techniques and their underlying statistical basis are presented in this section.

A regressor (so-called "explanatory" variable) x is informative (or contains information) about a regressand (so called "dependent" variable) y to the extent that knowledge of x conditions knowledge of y. Formally, if $E[y-E(y|x)]^2 < E[y-E(y)]^2$ then x is informative with respect to y. An obviously useful quantitative measure of the information value is the reduction in the conditional variance relative to the unconditional variance. It is an exact measure if the loss attending an error, $y-E(y|x)$, is proportional to its square. When scaled, or divided, by the unconditional variance, this theoretical measure of information value is identical to the squared correlation coefficient, r^2, where the relation between y and x is linear. An alternative measure, $1-(1-r^2)^{1/2}$, expresses the reduction of the expectation of the square root of the error (standard deviation of the disturbance term in the linear regression equation) relative to the standard deviation of y. This measure is referred to as the <u>information gain</u> from the use of x to condition expectations of y and is denoted $I_{x,y}$. It can be estimated from the standard deviation of y, s_y, and the standard error of the regression of y on x, $s_{y|x}$:

$$I_{x,y} = \frac{s_y - s_{y|x}}{s_y}$$

Where realizations of the statistic I are reported in this paper, they reflect multiplication by 100, so that information gains are expressed as a percentage of the standard deviation.

A set of variables, $x_1, x_2, \ldots x_K$, may be assessed for collective information gain by calculating:

$$I_{(x1,\ldots,xk),y} = \frac{S_y - S_{y|(x1,\ldots,xk)}}{S_y} = 1 - (1-\bar{R}^2)^{1/2},$$

where $\bar{R}^2$ is the corrected coefficient of determination.

More generally, the information content of x above may be of interest in contexts in which another variable, say z, or variables are also potentially informative. This context introduces some ambiguity, in that whether z is included or not will affect the incremental reduction in standard error. Hence, the information gain of x with respect to y is dependent on which other variables are in the information set. Even more generally, the information gain of a set of variables can be measured by the incremental reduction their inclusion in a multivariate linear model brings to its standard error, subject to the inclusion of a specified (possibly null) set of other information variables.

Consider the forecasting problem posed by the present study, in which current and future values of y are to be conditioned on past realizations of information variables. The information gain from own-lags is first assessed by performing regression (1) of y on its first two own-lags, in order to obtain the reduction in standard error of the regression equation relative to the standard deviation.

$$(1) \quad y_t = a + \sum_{j=1}^{2} b_j y_{t-j} + e_t$$

Then the information gain from any specified candidate variable x can be assessed by performing the regression:

$$(2)\quad y_t = a_, + \sum_{j=1}^{2} b'_j y_{t-j} + \sum_{j=1}^{2} c_j x_{t-j} + u_t.$$

The Granger causality test (see Granger and Newbold, [1977], pp. 224-6) is equivalent to a test of whether or not x is informative with respect to y, given past y. It is based on the F-statistic, calculated from the sums of squared errors of regressions (1) and (2), denoted S^e and S^u, respectively:

$$F(q,n-k-1) = \frac{(S^e-S^u)/q}{S^u/(n-k-1)}$$

$$\text{or}\quad F(2,n-5) = \left(\frac{n-5}{2}\right)\left(\frac{S^e-S^u}{S^u}\right).$$

where q is the number of restrictions tested (e.g., $c_j=0$) and k is the number of regressors in the unrestricted model. The I-statistic is:

$$I = \frac{S(y_t|y_{t-1}, y_{t-2}) - S(y_t|y_{t-1}, y_{t-2}, x_{t-1}, x_{t-2})}{S(y_t|y_{t-1}, y_{t-2})}$$

$$= \frac{[S^e/(n-k-1+q)]^{1/2} - [S^u/(n-k-1)]^{1/2}}{[S^e/(n-k-1+q)]^{1/2}}$$

$$= 1 - \left(\frac{S^u}{S^e}\right)^{1/2}\left(\frac{n-k-1+q}{n-k-1}\right)^{1/2}$$

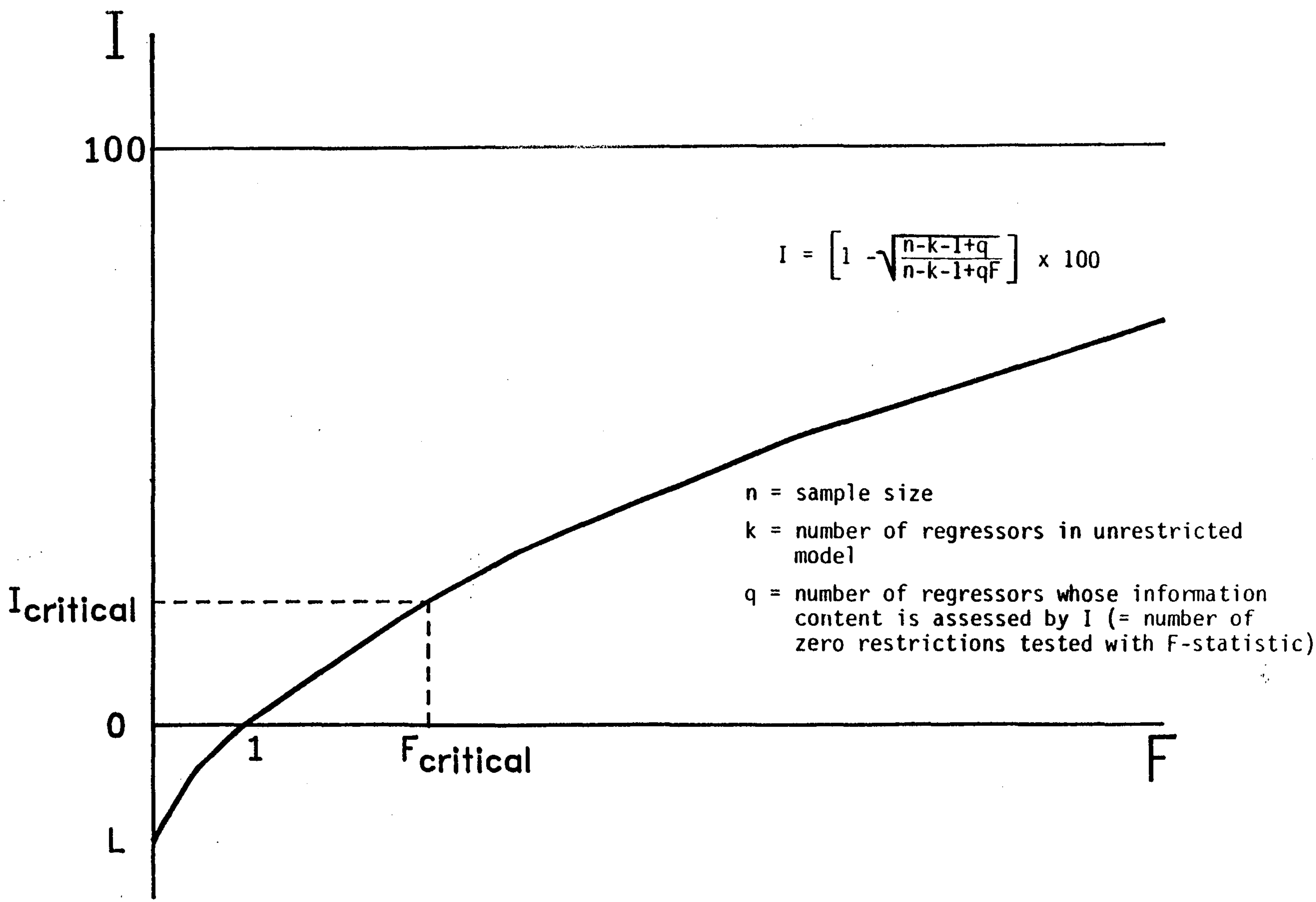
$$= 1 - \left(\frac{S^u}{S^e}\right)^{1/2}\left(\frac{n-3}{n-5}\right)^{1/2}$$

Notice that, aside from the adjustment factor $[(n-k-1+q)/(n-k-1)]^{1/2}$--which depends uniquely upon n, k, and q--equal sums of squared errors, which arise when the $c_i=0$, bring about a zero value for I. The adjustment factor effectively deflates measured improvement in fit for the expenditure of q additional degrees of freedom in the unrestricted regression (2). These expressions reveal the correspondence between F and I:

$$I = 1 - \left(\frac{n-k-1+q}{n-k-1+qF}\right)^{1/2}$$

$$= 1 - \left(\frac{n-3}{n-5+2F}\right)^{1/2}$$

Figure 2


I
100
$I_{critical}$
0
L
1
$F_{critical}$
F
$I = \left[1 - \sqrt{\frac{n-k-1+q}{n-k-1+qF}}\right] \times 100$
n = sample size
k = number of regressors in unrestricted model
q = number of regressors whose information content is assessed by I (= number of zero restrictions tested with F-statistic)

This relation is illustrated in Figure 2. The lower bound for I, which occurs if F=0, is denoted L:

$$L = I(F=0) = 1 - \left(\frac{n-k-1+q}{n-k-1}\right)^{1/2}$$

$$= 1 - \left(\frac{n-3}{n-5}\right)^{1/2}$$

L approaches zero as the sample size n increases. (It would be -73 percent for n=6!) L is the proportional reduction in a regression's sum of squared errors that is expected to occur from the inclusion of q noninformative regressors. It may also have some interpretation as a measure of the imprecision arising from finite degrees of freedom. Given a sample size of 53, as for the period up to 78QIV, L=-2.04 percent. For the sample through 83QIV, n=73 and L=-1.46 percent. L is, roughly, inversely proportionate to n; L is of order n^{-1}.

If F=1, the proportional reduction of sum of squared errors of L is achieved and I is zero. As F approaches infinity (as the linear relation becomes more precise), I approaches 100 percent. These two properties are desirable and illustrate the usefulness of I.

In the causality tests based on the extended sample period (n=73), the critical F-values are:

$$F_{.05}(2,68) = 3.13$$

and $F_{.01}(2,68) = 4.94$

which correspond to I-statistics of:

$$I_{.05}(2,68) = 1 - \left(\frac{70}{68+2(3.13)}\right)^{1/2} = 2.91 \text{ percent}$$

$$I_{.01}(2,68) = 1 - \left(\frac{70}{68+2(4.94)}\right)^{1/2} = 5.19 \text{ percent}$$

The most common criterion for inclusion of a variable in a model if the ad hoc rule that the t-statistic must exceed 2 in absolute value. This can be shown to be equivalent to the following inequality:

$$I > 1 - \sqrt{\frac{n-k}{n-k+3}}$$

VI. Univariate Properties

The mean and standard deviation of each series' growth rate provide measures of the average growth rate and its variability. Equivalently, they provide the parameter estimates for the simplest univariate model worthy of consideration, the random walk model. This model is of the form:

$$y_t = a_o + e_t$$

where a_o is the drift parameter and e_t is a random variable with zero autocorrelation at all lags (white noise) and a constant variance σ_e^2. The random walk model serves merely to re-establish the appropriate level of the forecast function after acquisition of a new quarterly data point. Future growth rates are revised only to the extent that the expected long-term average growth rate, a_o, is revised. In particular, cyclical behavior--persistence in high or low growth rates--is ruled out in the random walk model. The mean and standard deviation, taken as estimates of a_o and σ_e, respectively, are shown in table 1, in the first two columns, for the longer sample ending 83QIV, for the 10 Ohio series.

Cyclicity of growth in time series is the tendency of persistence in above- or below-average growth from one period to the next. This persistence can be described by the correlation between rates of change across different intervals. The series of such correlations at various intervals is called the autocorrelation function:

Table 1 Univariate Properties
Sample: 65QIV - 83QIV

Series	Mean	Standard Deviation	Autocorrelation at lag 1	2	3	4	Autoregression Equation: $y_t = a + b_1 y_{t-1} + b_1 y_{t-1} + b_2 y_{t-2} + e_t$ b_1	b_2	I'
PAYROLL	.0028	.0099	.57	.32	.22	.12	.58	.00	17.7**
MFG	-.0027	.0204	.45	.22	.07	-.07	.45	.03	10.1**
NONMFG	.0054	.0070	.42	.32	.38	.37	.35	.19	9.6**
EMPL	.0028	.0130	.08	-.08	.02	.06	.09	-.08	-0.8
LF	.0037	.0083	-.07	-.24	-.09	.19	-.09	-.27	2.4
INCOME	.0181	.0136	.40	.07	.06	-.05	.44	-	17.6**
RETAIL	.0164	.0258	-.26	.09	-.03	.06	-.24	.04	2.0
STARTS	-.0108	.1643	.06	.07	-.10	-.23	.05	.07	-1.0
HOURS	.0001	.0107	.11	-.07	.06	-.06	.11	-.09	-0.5
PRICES	.0169	.0098	.56	.46	.34	.31	.42	.24	19.1**

**Significant at the .01 level.

I = [(standard deviation - standard error of autoregression)/(standard deviation)] X 100.

$$r_j = n(n-j)^{-1} \frac{\sum_{t=j}^{n}(y_t - a_o)(y_{t-j} - a_o)}{\sum_{t=j}^{n}(y_t - a_o)^2}$$

Given the sample size n, no autocorrelations are significantly different from zero (at the .05 level, two-tailed) if they all fall between approximately $\pm 2n^{-1/2}$. With our samples of 73, the r_j must exceed 0.23 in absolute value to provide strong evidence of persistence from quarter to quarter. The autocorrelation function for lags one through four is presented in columns three through six of table 1.

The table reveals substantial positive persistence in growth rates for prices, payroll employment and its two components, and personal income. The presence of autocorrelation in both payroll sectors implies that cyclical variation in Ohio employment is attributable to both the manufacturing and nonmanufacturing sectors. The household survey based measure of employment, EMPL, exhibited no significant autocorrelation. (It is interesting to note that all of the foregoing results regarding autocorrelations of Ohio series are consistent with those for Texas in Hoehn, Gruben, and Fomby [1984]).

The significant autocorrelation in the five series mentioned above suggests a persistence in growth rates that can be exploited by the regional forecaster. An appropriate measure of the value of information contained in the history of the series can be found by first estimating a second-order autoregression (which we denote as AR2),

$$y_t = a + b_1 y_{t-1} + b_2 y_{t-1} + e_t,$$

using the ordinary least squares method, and then comparing the standard error of this equation, s_e, to the standard deviation of y, s_y. The comparison can be expressed in terms of the information gain, $[(s_y - s_e)/s_y] \times 100$.

Table 1, in the last three columns, reports the estimated regression coefficients and the autoregressive information measure for each regional time series. Results indicate that the one-quarter-ahead projection of the consumer price measure has a standard error about one-fifth less, when account is made of the last two quarterly growth rates. A gain of 18 percent is found for payroll employment, gains of about 10 percent are achieved for the two payroll categories and 8 percent for personal income. (These results only reflect the estimated information value of two lagged growth rates, whereas autocorrelation functions evaluate persistence at longer lags as well.)

VII. Intraregional Information

The value of regional series in foreshadowing each other can be measured in the following way. Regressions are performed to estimate the standard error of the equation specified by:

$$y_t = a_1 + b'_1\, y_{t-1} + b'_2\, y_{t-2} + c_1\, x_{k,t-1} + c_2\, x_{k,t-2} + u_t,$$

where y and x_k are two regional series. If the series x_k truly aids in forecasting y, then the standard error of this bivariate equation will be lower than for the autoregression (in which $c_1 = c_2 = 0$ is imposed). The joint significance test or F-test for the b, provides a "causality" test in the sense of Granger (Granger and Newbold, 1977, p. 225). Table 2, in the first 10 rows, reports results of these regressions. The reduction in the

Table 2 Information Gain[1]

Independent Variables	PAYROLL	MFG	NONMFG	EMPL	LF	INCOME	RETAIL	STARTS	HOURS	PRICES
	Dependent Variables									
Regional										
PAYROLL		2.29	4.51*	13.38**	7.49**	1.48	.49	3.10	1.95	-.98
MFG	-.42		4.90*	9.33**	3.92	3.02*	1.20	4.07*	3.84*	-1.45
NONMFG	-.53	2.65		9.35**	9.49**	1.33	-1.40	1.93	-.46	.20
EMPL	.48	-.84	3.40*		.01	4.26*	2.28	.30	6.25**	.87
LF	-1.25	-1.31	-1.03	1.87		-.73	-.43	-1.26	1.45	2.71
INCOME	-.16	.01	1.61	5.08*	3.12*		-.99	3.93*	3.09*	-1.20
RETAIL	-.55	-1.03	3.08*	-1.06	.60	-.52		-1.00	-1.07	-.64
STARTS	8.16**	10.34*	2.39	2.51	-1.29	9.45**	.55		11.36**	-1.22
HOURS	-.80	.51	2.81	.58	-1.43	-.72	-.38	.75		-1.31
PRICES	3.38*	2.25	3.65*	5.10*	-.44	.45	-1.21	.04	1.65	
National										
LEAD	19.25**	21.79**	6.49**	7.50**	.89	15.95**	1.80	5.25**	21.87**	-.16
COIN	14.51**	22.32**	6.70**	17.89**	2.89	15.42**	.13	2.70	12.02**	1.39
PRODUCT	8.02**	14.55**	3.39*	10.98**	.20	13.13**	-.57	3.56*	7.98**	-1.16
USPAYROLL	9.44**	10.62**	8.53**	15.39**	8.45**	9.45**	-.49	3.46*	5.10*	-.60
USMFG	6.61**	13.19**	6.65**	12.24**	4.19*	11.71**	.27	4.76*	7.81**	-1.36
USHOUSEHOLD	4.11*	7.91**	3.79*	11.73**	2.45	7.40**	-1.30	3.07*	1.45	.14
REALYP	4.53*	8.45**	3.26*	10.37*	2.60	2.61	-.85	-.02	6.03**	-.12
USLF	-1.22	-.88	-1.01	-.33	-1.01	-.93	2.16	-.25	.12	4.13*
CPI	6.93**	6.48**	4.83*	3.58*	-.86	2.18	-.22	5.30**	6.13**	2.60
PPI	2.32	2.17	1.28	4.20*	-.31	-.22	-.38	2.97*	2.80	1.76
DEFLATOR	5.20**	3.32*	5.62**	2.73	-.06	1.80	-.65	3.42*	2.99*	1.16

Table 2 continued, Information Gain[1]

Independent Variables	PAYROLL	MFG	NONMFG	EMPL	LF	INCOME	RETAIL	STARTS	HOURS	PRICES
USREALSALE	6.04**	7.96**	2.69	4.49*	.18	6.41**	.84	-.68	7.92**	-1.15
USSTARTS	3.43*	.69	4.64*	-.75	-.76	.73	.70	-.80	-.28	-1.16
REALGNP	4.78*	9.74**	3.27*	10.80**	.67	9.21**	.62	1.21	7.18**	-.83
GNP	-.76	.50	-.10	2.73	.28	1.65	-.35	5.78**	3.14*	-.75
USYP	4.31*	6.69**	-.67	.71*	-.04	3.11*	-.86	5.24**	7.39**	1.69
FUNDS	.98	1.42	-.94	.63	3.76*	-.92	.79	9.64**	2.85	.69
MOODY	7.67**	6.89**	4.11*	-.10	.25	4.13*	1.25	11.55**	10.72**	2.31

(Dependent Variables: PAYROLL through PRICES)

* Statistically significant at the .05 level; gain exceeds 2.91 critical value.

** Statistically significant at the .01 level; gain exceeds 5.19 critical value.

[1] For each combination of dependent and independent variables, the figures in the table show:

$$\left[I = \frac{(\text{standard error of the AR2 equation}) - (\text{standard error of the bivariate equation})}{\text{standard error of the AR(2) equation}} \times 100 \right]$$

standard error is expressed as a percent of the univariate autoregression equation's standard error.

Significant evidence, at the .05 level, is found for 25 different causalities, or leading relations, involving regional variables. Housing starts is the only series that provided significant leading information about the total payroll employment. Housing starts and personal income appear to be the two most useful regional series: they account for 5, 4, and 4 of the significant results, respectively. These series may. however, merely reflect the same underlying forces as are more clearly revealed in national indicators. Of the two components of payroll employment, the manufacturing sector measure contains leading information about the nonmanufacturing sector but not vice versa. Surprisingly, the manufacturing workweek, HOURS, tended to lag behind manufacturing employment. Hours had been included in this study in the expectation that they would provide leading information on employment. The consumer price and retail sales series were the only ones for which other regional variables provided no leading information.

VIII. National-Regional Information

The value of national series in foreshadowing regional series can be measured in a way analogous to the regional interactions of the previous section. Regressions are performed to estimate the standard error of the equation specified by the bivariate equation in section VII, where x_k is the quarterly logarithmic growth rate of one of the 18 national variables listed in the Appendix A glossary. Rows 11-28 of table 2 report the national variable information gains. Of 180 possible relations, 89 are significant at the .05 level. Most notable is the dependence of the employment series on national economic conditions. Of the two payroll sectors, the manufacturing sector is most dependent on the nation. This dependence conforms to available prior notions, which tends to confirm both the notions and the present methodology. Ohio payroll. employment tends to reflect, to a substantial degree, previous movements in the national leading and coincident indexes, the national payroll series, and several other indicators--even when lagged values (autoregressions) of the Ohio payroll series itself are taken into account. The manufacturing workweek and household-survey employment display a similar dependence on past national conditions that is similar to that of payroll employment. Movements in Ohio personal income and housing starts appear to reflect past national conditions more than their own past movements. Least dependent on past national conditions., surprisingly, are Ohio retail sales and consumer prices. (In the Texas study, retail sales and consumer prices were more strongly related to national indicators.) We cannot reject the notion that retail sales and consumer prices are exogenous with respect to the other series.

One of the most useful national indicators is the national payroll series, which is significantly causal with regard to all of the Ohio series except retail sales and prices. Others of particular value are the composite indices of leading and coincident series, industrial production, and manufacturing payrolls. The U.S. consumer price index and the long-run interest rate appeared to contain little leading information for the regional forecaster when we used data through 78QIV, but became more informative when the sample was extended. Generally, though, the price and interest rate series were relatively uninformative.

IX. A Trickle-Down Model

A simple trickle-down model was built that attempted to summarize the information from sources that actual regional forecasters are likely to be currently placing greatest emphasis on. In each equation for regional variables, right-hand-side variables included a constant, two own-lags, Ohio payroll employment, and one lag each of the national leading and coincident indexes. The two national series' equations include two own-lags and one lag of the other national series. The resulting model, which will be referred to as the trickle-down (TD) model, may be both too unparsimonious and not fully reflective of the information available from the causality tests. On the other hand, it embodies a rough prior notion about which series ought to be most valuable to the regional forecaster. Hence, it represents an interesting alternative and benchmark for a regional forecaster. It may be especially useful in combined forecasts, to be considered later.

The trickle-down model is presented in Table 3. As an illustration and an aid to interpreting that table, the equation for payroll employment is presented below. It should be noted that this equation is unique in one respect: because the lagged growth of payroll employment is the first own-lag of the equation, there is one less parameter than in the equations for the other nine regional equations.

$$\Delta \ln PAYROLL_t = \underset{(.0008)}{-.0004} - \underset{(.20)}{.06}\,\Delta \ln PAYROLL_{t-1} + \underset{(.12)}{.36}\,\Delta \ln PAYROLL_{t-2}$$

$$+ \underset{(.06)}{.18}\,\Delta \ln LEAD_{t-1} + \underset{(.13)}{.16}\,\Delta \ln COIN_{t-1} + e_t$$

$\bar{R}^2 = .56$
s.e.e. = .006524

Table 3 Trickle-Down Equations:

$$\Delta \ln y_t = a + b_1 \Delta \ln y_{t-1} + b_2 \Delta \ln y_{t-2} + c_1 \Delta \ln LEAD_{t-1} + c_2 \Delta \ln COIN_{t-1} + c_3 \Delta \ln PAYROLL_{t-1} + e_t$$

Using Data from 65QIV-83QIV

Dependent Variable	Parameter Estimates (and Standard Errors)						Goodness-of-Fit Measures		
y	a	b_1	b_2	c_1	c_2	c_3	$\bar{R}^2$	s.e.e.	I*
PAYROLL	.0004 (.0008)	-.06 (.20)	.36 (.12)	.18 (.06)	.16 (.13)	-- --	.56	.006524	19.5
MFG	-.0104 (.0028)	-.44 (.24)	.26 (.12)	.31 (.12)	.70 (.29)	.17 (.51)	.55	.01369	25.3
NONMFG	.0030 (.0012)	.02 (.19)	.20 (.12)	.07 (.05)	.03 (.12)	.20 (.25)	.31	-005882	7.5
EMPL	.0014 (.0014)	-.34 (.13)	-.31 (.12)	-.13 (.08)	.68 (.21)	-.13 (.34)	.29	.010960	16.1
LF	.0055 (.0011)	-.19 (.11)	-.38 (.11)	-.10 (.06)	.06 (.14)	.29 (.23)	.19	.007494	7.6
INCOME	.0148 (.0034)	-.08 (.18)	.07 (.11)	.18 (.08)	.39 (.20)	-.16 (.35)	.43	.01030	18.4
RETAIL	.0197 (.0043)	-.32 (.13)	.05 (.12)	.39 (.19)	-.62 (.49)	.90 (.76)	.06	.02498	1.2
STARTS	-.0120 (.0195)	-.18 (.13)	-.01 (.12)	4.16 (1.33)	-4.23 (2.93)	-.84 (4.47)	.16	.1510	9.0
HOURS	-.0022 (.0011)	-.35 (.13)	-.08 (.10)	.21 (.06)	.44 (.15)	-.78 (.24)	.44	.007976	25.5
PRICES	.0068 (.0023)	.42 (.11)	.19 (.12)	-.12 (.06)	.25 (.15)	-.35 (.24)	.35	.007898	0.7
LEAD	.0057 (.0024)	.84 (.12)	.22 (.13)	-- --	-.89 (.19)	-- --	.43	.01919	12.0
COIN	.0015 (.0016)	.02 (.16)	.22 (.12)	.51 (.09)	-- --	-- --	.54	.01276	15.7

* I is the percent reduction of the standard error of the trickle-down equation relative to the AR(2) regression equation..

X. The Stepwise Regression Model

Causality tests performed using the sample ending 78QIV (not reported) served as the point of departure for building a multivariate autoregression model for Ohio. The object was to find a well-fitting, yet reasonably parsimonious, equation for each of the regional series. In the equation for each series, every variable that was significant at the 0.10 level in the causality rests was a candidate for inclusion. The search for appropriate equations was made problematic by the large number of significant causal relations discovered.[3]

The mccel was constructed using a single-equation method; that is, each equation was chosen (identified) and estimated in isolation. More complex identification and estimation procedures might be slightly more efficient, though less transparent. A less formal and more judgmental, but similar methodology is described in Hoehn (1984). The present method employs a more "automatic" and formal procedure. The process of selecting the first equation of the models, for payroll employment, illustrates the present procedure, which is b. red on the stepwise regression technique. A subroutine from PEC (Program for Econometric Computation, Kim Pec, Yale University) was employed. This program proceeds by "forward stepping," or adding variables to the equation that obtained t-statistics of 1.96 or more in absolute value, and "backward stepping," or removing variables whose t-statistics fell below one in absolute value after other variables are included. The backward-stepping feature appears to reduce the importance of the order in which variables are included in the forward steps. (As a primitive check, the order of variables was exactly reversed for the PAYROLL equation, but the equation the stepwise procedure selected was unaffected by that reordering.) The stepwise procedure arrived at an equation for Ohio payroll employment that had (a forced constant plus) the second lag of Ohio housing starts, plus one lag of the national coincident index. This equation had a standard error of .006308. In a third step, the same stepwise routine was repeated except that two own-lags were forced (that is, included regardless of their significance). This resulted in inclusion of the first lag of the national leading index and payroll employment, the second lag of national real personal income, and two lags of national housing starts. This equation, with eight parameters in all, had a standard error of .005316. Finally, the significant lags of each of the causal variables was tried to see if its inclusion would substantially reduce the standard error. In only three cases did this occur: the first lag of Ohio housing starts reduced the standard error to .005194; the first lag of national real retail sales, to .005188; and the second lag of national payroll employment, to .005288. An ad hoc choice was made to tentatively include U.S. retail sales, but to exclude the other two. Last, some tinkering was done with the equation on an ad hoc basis. For the equation for payroll employment, elimination of the (insignificant) second own lag was tried, but that increased the standard error too much. The equation thus settled upon is that shown below.

$$\begin{aligned}
\Delta \ln PAYROLL_t = \; & -.0014 - .49\,\Delta \ln PAYROLL_{t-1} + .39\,\Delta \ln PAYROLL_{t-2} \\
& \quad (.0016) \;\; (.21) \qquad\qquad\qquad\qquad (.14) \\
& +.14\,\Delta \ln LEAD_{t-1} + 1.27\,\Delta \ln USPAYROLL_{t-1} \\
& \quad (.05) \qquad\qquad\quad (.35) \\
& -.35\,\Delta \ln REALYP_{t-2} + .0017\,\Delta \ln USSTARTS_{t-1} \\
& \quad (.14) \qquad\qquad\quad (.0006) \\
& +.0015\,\Delta \ln USSTARTS_{t-2} + .089\,\Delta \ln USREALSALE_{t-1} + e_{1t} \\
& \quad (.0006) \qquad\qquad\qquad (.049)
\end{aligned}$$

The stepwise model's other equations were determined in a similar manner based on the sample ending 78QIV. Their specifications are available from the authors upon request.

XI. Contemporaneous Correlations

The information gains described in the last three sections involve lead-lag relationships and ignore contemporaneous relationships. The latter cannot be used for forecasting the future. They are valuable, however, in estimating as-yet unreported realizations of variables conditional on reported figures for other variables. These conditional estimates are important to real-time forecasting and monitoring of the regional economy. For example, the analyst may desire to estimate personal income for a period for which employment data are available, but a direct measure of income is not. The contemporaneous correlations between growth rates of the 10 Ohio variables and the U.S. leading and coincident indices are shown in the upper half of table 4. The bottom half shows correlations between residuals of the autoregressions. These residuals are nearly uncorrelated with their own past values, so that their correlations with each other, unlike those of raw growth rates, are uncontaminated by autocorrelation that can lead to spuriously significant relationships. Sample correlations have an approximate variance of n^{-1}, so they are significant at the .05 level if they exceed approximately $2n^{-1/2} \simeq 0.23$.

Correlations among variables appear not to be due merely to autocorrelation. The national series, especially the coincident index, have substantial correlation with the employment and income series. The payroll employment hours, and income series generally display the highest correlations with other series. Payroll figures contain more information about current personal income than do household-survey figures. The low correlation between manufacturing and nonmanufacturing payrolls, despite their high correlation with the U.S. coincident index, suggests that shifts between them--intersectoral technology or preference shifts at the regional level--are important. (Lillian [1982], interprets national employment and unemployment fluctuations as arising from intersectoral shifts.)

Ohio consumer prices and the labor force show little dependence on the national business cycle or on other regional series. Housing starts and retail sales are weakly related to other series.

XII. Out-of-Sample Forecasting: Univariate Models

The ultimate proving-ground of any forecasting procedure is its performance outside of the sample over which it was identified and estimated. The partition of data available for the present study into a model-building period and an out-of-sample forecasting period was motivated by a desire to provide evidence of the efficiency of the forecasting model immediately. rather than after the passage of time to allow evidence to accumulate. The 10-quarter period of the Texas study appeared too short, because the systematic improvements of the MAR relative to the univariate benchmarks were generally not found to be statistically significant. A period of 20 quarters was therefore reserved for out-of-sample forecasting in the Ohio study. This period began in 79QI and ended in 83QIV. A longer reserved period would have had the cost of unreasonably reducing the amount of data that could be used to identify the appropriate forecasting model.

The k-step-ahead forecast error for a period t forecast is

$$e_{t,k} = y_t - y_{t-k}(k)$$

where y is the logarithm of the series (the level, not the growth rate) and $y_{t-k}(k)$ is the k-step-ahead forecast y_t formed at time t-k (conditioned on realizations dated t-k and earlier). The criterion employed for forecast performance evaluation is the root mean square error (RMSE);[4]

Table 4 Contemporaneous Correlations
65QIV-83QIV

Correlation Coefficients of Growth Rates

	PAYROLL	MFG	NONMFG	EMPL	LF	INCOME	RETAIL	STARTS	HOURS	PRICES	LEAD
MFG	.92										
NONMFG	.82	.54									
EMPL	.60	.61	.41								
LF	.19	.15	.18	.63							
INCOME	.87	.81	.69	.55	.21						
RETAIL	.28	.13	.41	.13	.08	.39					
STARTS	.00	-.08	.16	.02	-.06	.01	.14				
HOURS	.53	.56	.33	.44	.14	.69	.33	.25			
PRICES	-.23	-.23	-.20	-.17	-.09	-.10	.03	-.18	-.20		
LEAD	.35	.37	.22	.31	.01	.35	.27	.48	.64	-.28	
COIN	.87	.87	.61	.58	.16	.80	.26	.15	.67	-.29	.65

Correlation Coefficients of Residuals in Second Order Autoregressions
65QIV-83QIV

	PAYROLL	MFG	NONMFG	EMPL	LF	INCOME	RETAIL	STARTS	HOURS	PRICES	LEAD
MFG	.87										
NONMFG	.68	.29									
EMPL	.48	.53	.26								
LF	.05	.06	.05	.61							
INCOME	.84	.69	.63	.47	.16						
RETAIL	.33	.14	.49	.10	.04	.45					
STARTS	.15	.00	.27	-.01	-.07	.07	.14				
HOURS	.71	.67	.41	.40	.08	.77	.32	.21			
PRICES	.05	-.01	.07	.01	.00	.04	.07	-.13	-.10		
LEAO	.38	.32	.15	.24	.04	.23	.20	.38	.46	-.07	
COIN	.79	.75	.41	.39	.06	.65	.29	.22	.64	-.05	.67

$$RMSE(k) = \left[n^{-1} \sum_{t=1}^{n} e_{t,k}^{2} \right]^{1/2}$$

where n is the out-of-sample size and RMSE(k) denotes the root mean square error of the k-step-ahead forecasts.

The mean error

$$ME(k) = n^{-1} \sum_{t=1}^{n} e_{t,k},$$

provides insight into the extent to which the RMSE is due to bias in or to variance of the forecast relative to realized values.

In evaluating each forecasting method, the model was re-estimated each quarter to reflect a new quarter of data. The models were not re-identified each quarter, however, so that the procedure does not fully reflect the efficient use of new information that a real-time forecast would make. This consideration is only relevant for the stepwise model, because it was the only one not specified a priori.

An examination of the random walk model is particularly instructive because of its simplicity. Only one parameter, a_0 needs to be estimated to construct the random walk forecast. Since a_0 is merely the average growth rate, it can be calculated by dividing the difference between the log of the last value of the variable from the log of its initial value (at time period zero) by the length of the series, t:

$$a_{0,t} = t^{-1}(y_t - y_0)$$

where $a_{0,t}$ is the estimated value of a_0 conditioned on data available at time t, and y is the natural log of the variable. The forecast function, which associates a forecasted value of y with each k steps ahead, is

$$y_t(k) = y_t + k\, a_{0,t}$$

At t+k, the error $y_{t+k}-y_t(k)$ is calculated. The level of the forecast

Table 5 Out-of-Sample Information Gains: Reduction in 1-Period-Ahead RMSE
(figures in parentheses show gain due to reduction in ME)

	RMSE(ME) of Random Walk Model	AR2/RW	TD/AR2	SW/AR2	UC2/AR2
PAYROLL	.0121 (-.0077)	26.4 (36.4)	20.2*(-7.9)	14.6 (-3.4)	20.2*(-5.6)
MFG	.0252 (-.0104)	14.7 (22.2)	24.7*(1.4)	18.1*(-10.2)	22.8*(-4.2)
NONMFG	.0085 (-.0071)	28.2 (34.1)	0.0 (-13.1)	-9.8 (-14.8)	-1.6 (-14.8)
EMPL	.0161 (-.0063)	-1.9 (-1.2)	11.0 (9.8)	20.7*(21.3)	17.7*(15.9)
LF	.0102 (-.0041)	-3.9 (-7.8)	7.5*(17.0)	4.7*(31.1)	8.5*(24.5)
INCOME	.0155 (-.0063)	10.3 (11.6)	23.7*(0.0)	-4.3 (0.0)	11.5 (0.0)
RETAIL	.0212 (-.0064)	1.4 (-5.2)	11.0 (2.9)	5.7 (1.9)	12.0*(2.4)
STARTS	.2212 (-.0309)	-2.8 (2.5)	5.6 (-24.0)	17.6 (-11.1)	14.9 (-17.6)
HOURS	.0126 (.0003)	0.8 (0.0)	17.6 (-6.4)	5.6 (0.8)	14.4 (-2.4)
PRICES	.0143 (.0062)	7.7 (39.1)	0.0 (-0.8)	-3.8 (4.5)	-1.5 (1.5)
AVERAGE		8.1 (13.2)	12.1 (-2.1)	6.9 (2.0)	11.9 (-0.0)

Reduction in Four-Period-Ahead RMSE
(figures in parentheses show gain due to reduction in ME)

	RMSE(ME) of Random Walk Model	AR2/RW	TD/AR2	SW/AR2	UC2/AR2
PAYROLL	.0440 (-.0384)	12.7 (26.1)	6.8*(-5.7)	6.3*(16.7)	9.4 (5.5)
MFG	.0799 (-.0584)	1.1 (20.2)	14.8*(-3.3)	3.9 (6.3)	10.6 (1.5)
NONMFG	.0346 (-.0328)	15.6 (18.5)	-2.7 (-4.8)	-1.7 (4.5)	-0.3 (0.0)
EMPL	.0357 (-.0287)	-2.0 (-1.7)	4.9 (12.6)	6.0 (30.8)	7.7 (21.7)
LF	.0165 (-.0148)	-4.2 (-9.1)	21.5*(27.9)	34.9*(53.5)	30.8*(40.7)
INCOME	.0460 (-.0358)	2.4 (6.5)	5.1 (-1.8)	5.1 (5.6)	6.2 (2.0)
RETAIL	.0413 (-.0280)	-0.5 (-1.9)	1.9 (-1.9)	-1.2 (-13.7)	1.4 (-7.7)
STARTS	.5346 (-.1256)	-2.5 (3.6)	8.6 (-28.2)	25.2*(-7.6)	19.5 (-17.9)
HOURS	.0258 (-.0002)	1.2 (-0.4)	17.6 (-22.0)	7.8 (-3.5)	14.1 (-12.5)
PRICES	.0430 (.0265)	9.1 (49.5)	3.3 (2.3)	-5.9 (10.2)	-1.0 (6.4)
AVERAGE		3.3 (9.1)	8.2 (-2.5)	8.0 (10.3)	9.8 (4.0)

*Significant at the .05 level, according to a test adapted from Ashley, Granger, and Schmalensee (see text).

function is revised upward by that error. In addition, the growth rate, or slope of forecast function, is also revised at t+l by $(t+1)^{-1}$ times the error.

The ME and RMSE for the first 10 steps ahead for the random walk model were calculated and are reported in table 5 for steps 1 and 4. Three characteristics of the results are particularly worthy of note. First, the mean errors indicated that forecasts were typically for too-high growth, except for consumer prices (whose errors were on average positive) and the Ohio manufacturing workweek (whose forecasts were nearly unbiased). Second, the increase in RMSEs as the forecast horizon lengthens revealed that uncertainty about the series is unbounded as the horizon is extended for all series, except for the workweek. In other words, only the workweek appears to have a stationary trend. (In fact, it appears to be stationary in its <u>level</u>.) Consequently, none of the series, except hours, should be treated in any empirical analysis as having deterministic trends; their trends are stochastic. Third, the mean absolute error accounted for most of the magnitude of the RMSEs for all series, except the workweek, for forecasts of more than a quarter or two ahead. What this implies is that the main source of forecast errors was the overall weakness of the Ohio economy during most of the 79QI-83QIV period, rather than great variability in forecast accuracy from quarter to quarter.

The random walk model serves as the appropriate benchmark for the autoregressive model. The out-of-sample comparison can reveal whether the autoregression found in the within-sample period not only continued to occur in the out-of-sample period, but also was sufficiently stable in its character to be a dependable source of forecasting information. The out-of-sample performance of the second-order autoregressive equations generally compares favorably with the random walk model. The RMSE of the AR2 was lower than for the random walk for seven of the ten regional variables in one-step-ahead forecasts and for six of the 10 in four-step-ahead forecasts. These comparisons, and those between the AR2 and the other forecasting methods, are shown in table 5. In the cases for which the random walk model outperforms the AR2, the difference is modest. But some of the improvements of the forecasts of the autoregressive equations over those of the random walk are substantial. For example, the one-quarter-ahead forecasts of PAYROLL had an RMSE of .0089 in the AR2 model, 26 percent below the RMSE of .0121 for the RW model. The mean error was -.0033 in the AR2, compared with -.0077 in the RW model. The reduction in the RMSE in the AR2 model relative to the RW model can be attributed to reduction in the absolute value of the mean error; the latter reduction, .0044, represents 36 percent of the RMSE of the RW model. The figures in parentheses in table 5 indicate that the general improvement in forecast accuracy of the AR2 model relative to the RW model is due to reduction in the absolute value of the mean error. The autoregressive terms tended to presage or adapt to cyclical movements, which tended to exert a downward influence on the series in the 1979-83 period.

The improvement in forecasting performance of the AR2 relative to the RW model was greatest for payroll employment, its nonmanufacturing component, consumer prices, and personal income. The comparison was most unfavorable to the AR2 model for the labor force, household-survey employment, and housing starts. There was little difference in forecast accuracy for retail sales.

The out-of-sample results tend to confirm the presence of useful autoregression in PAYROLL, MFG, and PRICES. INCOME had borderline autoregressive properties within sample, but the out-of-sample results suggest moderately strong autoregression. NONMFG displayed no autoregression within sample, but substantial autoregression out of sample. Results for the 1979-83 period confirmed the lack of autoregression in EMPL, STARTS, HOURS, and RETAIL. LF was borderline within sample, but was ultimately seen to lack useful autoregression. All these conclusions are verified by the estimation, using the sample through 1983, of the AR2 equations and their associated I-statistics, shown in the bottom half of table 2.

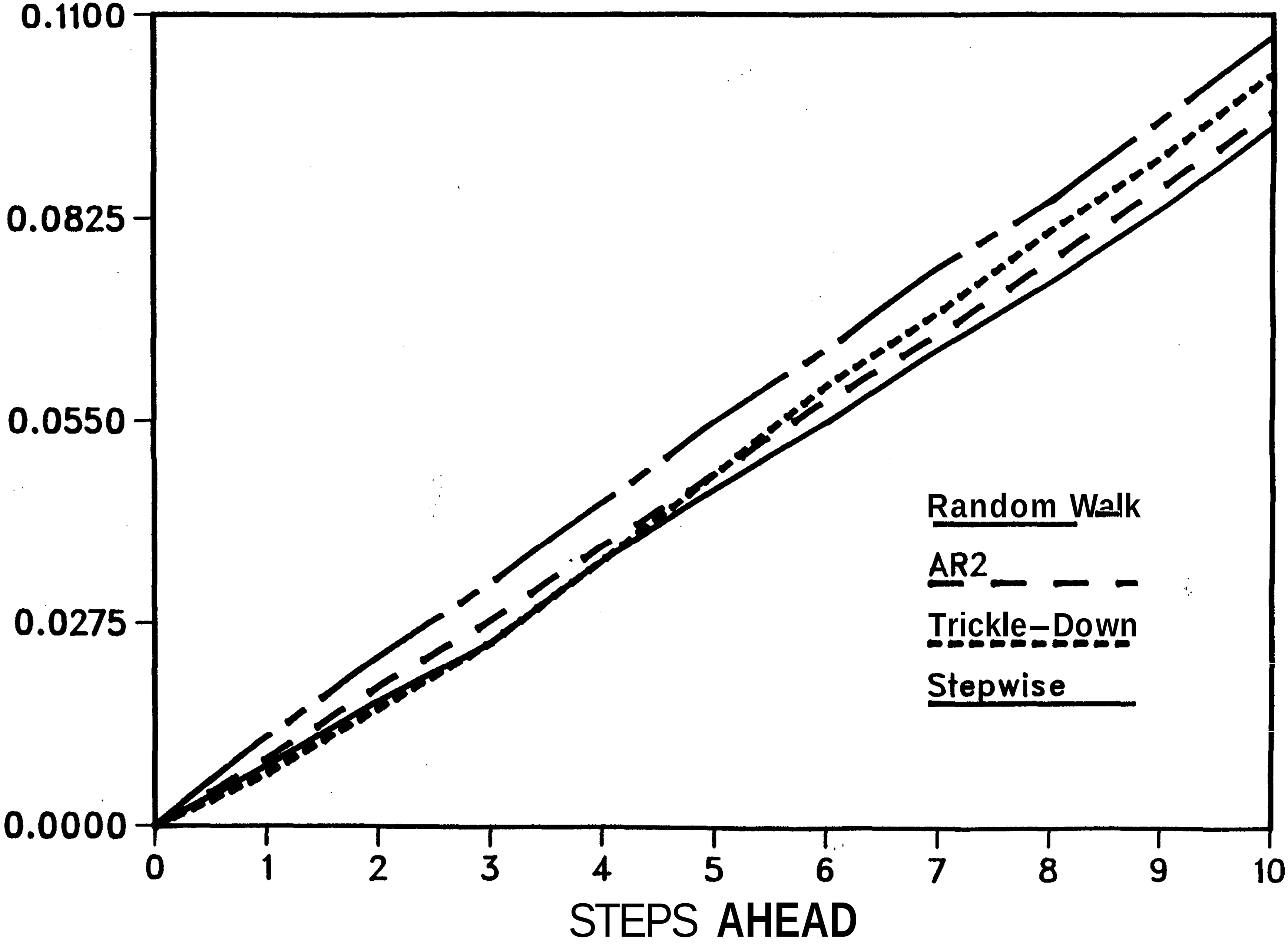
XIII. Out-of-Sample Forecasting: Multivariate Models

The univariate autoregression results serve as the appropriate benchmark for the multivariate models, which add terms to the autoregressive equations in an attempt to capture information from other national and regional data. The out-of-sample evidence generally suggests that such information can be extracted.

Table 5 displays the relative forecast performance of the trickle-down and stepwise models; their RMSEs are generally lower than those of the autoregressive model. Figure 3 depicts the performance of both the multivariate and univariate models, in their forecasts of payroll employment for forecast horizons of one to 10 quarters. The relative efficiency of multivariate as compared with the univariate autoregressions do not derive particularly from reduction in the magnitude of bias, but rather more to a closer "fine-tuning" of the forecast each quarter in light of national and regional data. The payroll variable had little importance in the trickle-down model. Hence, the trickle-down model's forecasting efficiency relative to the autoregressive model can be taken as an indication of the usefulness of the lagged trickle-down relationships. In other words, those relations are sufficiently strong and stable to be useful.

Figure 3.

ROOT MEANS OF SQUARE ERROR OF THE PAYROLL FORECASTS



The trickle-down model, as estimated with the 1965-78 sample, suggested strong information gain relative to the autoregressive model for PAYROLL, MFG, EMPL, INCOME, HOURS, and NONMFG. This strong gain carried over to comparisons of RMSEs in the 1979-83 period, for all these variables except NONMFG. Weaker gains in LF and STARTS found in 1965-78 were confirmed in the forecasting period. The absence of gain for PRICES was also confirmed. Finally, information gain for RETAIL was not found in either the 1965-78 or the 1965-83 sample, but arose in the forecast performance comparisons. Aside from the results for RETAIL, the short and long samples and the out-of-sample forecast simulation provide consistent results: information gains, I, and reductions in one-period-ahead RMSEs, were remarkably similar for each variable.

The statistical significance of the improvement in forecast accuracy of the TD model relative to the AR2 model can be measured by the method proposed in Hoehn (1984, pp. 27-8). The method involves an adaptation of a "causality" test suggested by Ashley, Granger, and Schmalensee (1980). At the .05 level, one-period-ahead forecast RMSEs are significantly lower for PAYROLL, MFG, LF, and INCOME. For four-period-ahead forecasts, the TD model is significantly better only for MFG and LF. In no case does the test find the TD forecasts significantly worse. The test has some problematic interpretations in some cases, and results do not often conform to intuitions, suggesting a limited usefulness of the test. These ambiguities arise from the need to make an essentially four-tailed test using a single F-statistic, usually used for one-tailed tests. As a result, the test is often of low power.

In forecasting with the stepwise model, the exogenous national variables used (14 different variables, not distinguishing different lags) were forecasted using second-order autoregressive equations. This may have handicapped the SW model somewhat in forecasts of more than one quarter ahead. Forecasts of two national variables, the leading index (LEAD) and the coincident index (COIN), were both 14 percent lower for one-steps-ahead, and 19 and 9 percent lower, respectively, for 4-periods-ahead, in the trickle-down model. Also a handicap is the maintenance of the specification of the equations throughout the period. Although the other models were not revised with regard to regressors either, their a priori specifications preclude the use of new data to revise the specifications. (Of course, the stepwise model's coefficient values were updated each quarter.)

The out-of-sample forecasting performance of the stepwise model relative to the autoregressive model confirmed a strong dependency of four regional variables to lagged national and regional information variables: EMPL, STARTS, PAYROLL, and MFG. Weaker confirmation was implied for LF, HOURS, and RETAIL. Finally, the information gain vanished for NONMFG, INCOME, and PRICES.

The stepwise model significantly outperformed the AR2 model at the .05 level, according to the test adapted from Ashley, Granger, and Schmalensee, in the following cases. For one-period-ahead forecasts, the improvement was significant for EMPL and LF; for four-period-ahead forecasts, the improvement was significant for PAYROLL, LF, and STARTS.

The properties of the errors in the TD and SW models were often somewhat different with regard to bias and variance around means. For example, consider the four-step-ahead forecasts of PAYROLL. The TD and SW models had similar RMSEs, of .0358 and .0360, respectively, representing improvements of 6.8 and 6.3 percent relative to the RMSE of .0384 in the AR2 model. Yet the source of error differed somewhat among the models, with mean errors of -.0291 in the TD model and -.0205 in the SW model. The SW model forecasts benefited from lower (absolute) bias, but suffered from a larger variation in accuracy from one quarter to the next. A forecast that combines the forecasts of the two models is particularly promising in such a case. Giving weight to the SW model might seem unpromising because of its higher RMSE. Yet giving the SW model weight in a combined forecast will definitely reduce the magnitude of bias. This benefit must be balanced against the cost, in terms of RMSE, that results from higher variance. But unless the errors of the two forecasting models are perfectly correlated, the variance of combined forecasts will be less than the sum of the variances of the components. As it turns out, the combined, unweighted forecast (UC2 for "unweighted combination of two" forecasts) has an RMSE of .0348, lower than the TD or SW models. The contrast with the AR2 model's performance is summarized in the last two columns of table 5, for one- and four-quarter forecasts. The UC2 forecasts do generally as well as the TD model, and better than the SW model for one-step-ahead forecasts. They generally do as well or better than the TD model for four-step-ahead forecasts, and better than the SW model at that forecast horizon for 8 of the 10 Ohio variables. According to the test adapted from Ashley, Granger, and Schmalensee, the improvement of the UC2 relative to the AR2 is significant at the .05 level for PAYROLL, MFG, LF, and RETAIL for forecasts one quarter ahead, but significant only for LF for the four-quarter forecasts. The improvements of the UC2 relative to the TD model do not appear substantial and are unlikely to be significant, according to casual inspection. Only small gains appear available from combining the models, as compared with giving the TD model all the weight. In the terminology of Granger and Newbold (1977, p. 283), the TD model is conditionally efficient with respect to the alternatives considered.

The importance of updating coefficients during the out-of-sample period was relatively easy to determine. Forecast performance for the TD model without updating was generally inferior to performance of the model with updating. Only for forecasts of HOURS, short-horizon forecasts for INCOME, and long-range forecasts of RETAIL were RMSEs lower without updating; in all other cases updating was helpful. Mean errors were always lower in absolute magnitude; updating had the effect of reducing projected growth during the weak conditions of the out-of-sample period. Generally, this reduction accounted for all of the improvement--indeed, the means of absolute error (MAEs) often reflected less improvement than MEs. For example, in one-period-ahead forecasts of PAYROLL, updating changed the ME from -.0051 to -.0040. But the MAE was only reduced from .0061 to .0056; the RMSE from .0078 to .0071. On average, updating reduced the RMSEs by 4.1 percent, 5.6 percent, and 4.4 percent, for one-quarter, four-quarter-, and 10-quarter-ahead forecasts, respectively, for the 10 regional variables.

In the stepwise model, updating brought similar but less consistent gains; the reduction in bias was less consistent, but generally smaller. PRICE forecasts were quite adversely affected. A more important, yet unanswered, question is what loss of forecasting accuracy resulted from not respecifying the stepwise model each quarter in light of new data. Some partial evidence on this question could be provided by respecifying the equations after the end of the out-of-sample period. For the PAYROLL equation, such respecification resulted only in the exclusion of the second lag on U.S. housing starts. This might be regarded as nearly the slightest possible change. However, we have not undertaken a systematic and fully satisfactory analysis of the benefits of period-by-period re-specification. Such benefits could conceivably alter comparisons between the TD and SW models. However, we do not place much emphasis on such a comparison; such a comparison is difficult to interpret in any case.

The use of the ordinary least squares estimation procedure can be to some degree inefficient in cases in which errors of equations estimated are correlated. Correlations in the errors of both multivariate models were frequently larger than $2n^{-1/2}$. Again, we have not undertaken a full and systematic study of this issue, but have examined its implications for the PAYROLL equation. In the TD model, PAYROLL, LEAD, and COIN form a system of three variables in the equations that determine forecasts of PAYROLL: the other regional variables' forecasts follow recursively. Applying generalized least squares (seemingly unrelated regression) to allow for a non-diagonal disturbance variance-covariance matrix offered a potential improvement, suggested by the high correlations between residuals of ordinary least squares equations for PAYROLL and COIN (0.69) and LEAD and COIN (0.61). When compared with the ordinary least squares estimates, the generalized least squares method reduced the magnitude of all the coefficients of the PAYROLL equation except the one on $COIN_{t-1}$. The effects of the equations for national variables were rather small. Forecasts of PAYROLL with the generalized least squares estimates of the TD model were somewhat worse than for the ordinary least squares version, where the comparison is of models whose coefficients were not re-estimated each quarter. The RMSEs of the generalized least squares version (of the ordinary least squares version) were .0085 (.0078), .0421(.0389), and .1103(.1083), for one, four, and 10 steps ahead, respectively. This comparison may have been affected by the special characteristics of the 1979-83 period, particularly since trickle-down effects of the national economic weakness were given less range by the generalized least squares coefficients' smaller values.[5]

IX. Conclusion

The location of information about each of 10 Ohio variables representing aggregate economic activity has been identified, measured, and subjected to confirming tests. Generally, the results verify two prior beliefs: (1) univariate forecasting models can be outperformed by simple multivariate models, although not consistently by a large margin, and (2) most (lagged) information other than from a variable's own past comes from national variables, and may be summarized reasonably well by the coincident and leading indices. Ohio housing starts, however, seems to contain independent leading information for other regional series such as employment.

Our study is also of interest as a practical application of statistical principles and forecasting methods in a context in which a number of sources of information are likely to be valuable. Conclusions in this regard may be quite sensitive to the particular data samples employed. The two models specified *a priori*, the univariate autoregressions and the trickle-down model, provided gains relative to their appropriate benchmark models that were, overall, approximately equal in the 1965-78 sample and the 1979-85 out-of-sample period. In the case of the trickle-down model, the relation between within-sample gain and out-of-sample gains in one period-ahead forecasts was remarkably close: the gain delivered out-of-sample approximated that of within the sample, on a variable-by-variable basis. The stepwise model, as might have been expected in light of the "overfitting" problem, could not deliver out-of-sample results to match those within the sample, nor was there much relation between them on a variable-by-variable basis. However, the stepwise model operated under several handicaps. Its specification was not revised, as would be done by a real-time forecaster using the stepwise procedure of model construction. Second, forecasts of more than one-step-ahead probably were handicapped by the use of univariate autoregressions to provide paths for the exogenous national variables.

The present study adds to the growing knowledge of how to deal practically with the tradeoff between the costs of ignoring information and the problems of "overfitting." Gains over univariate equations have been achieved in the present study of Ohio, as had been achieved for Texas (Hoehn, 1984). However, the particular methods employed are unlikely to be "optimal" in any sense." The restriction to linear and nonseasonal models (of seasonally adjusted data) and the equal weights in combined forecasting schemes are a source of inefficiency. Nevertheless, we contend that the understanding and forecasting of an economic system, whose true structure is unknown. can be enhanced by the simple and transparent time-series methods employed. Structural models in such a context might best be constructed after the stylized facts of the time series are uncovered.

Footnotes

1. Strictly speaking, a structural model cannot forecast in the same fashion as a time series model. The former is always "incomplete" in the sense that it forecasts the endogenous variables conditional on arbitrarily specified values of the exogenous variables, which the forecaster must provide. While this conditional nature of structural forecasting allows for interesting simulations of "what if" questions, it complicates forecast construction and performance evaluation in the more realistic case for which no future values of any variables are known when forecasts are made. This difference between structural and time series models makes this relative forecast performance difficult to assess. (See, for example, Granger and Newbold (1977, pp. 289-302).

2. These issues are more fully addressed in Hoehn, Gruben, and Fomby (1984a), pp. 34-49.

3. Ohio series displayed more frequently significant dependence on lagged national series than did Texas series, in conformance with prior beliefs. Also, this study of Ohio examined 19 national variables whereas only 14 were examined in the Texas study. In the latter, only 21 out of 92, or 24 percent, of the possible trickle-down causal relations were significant at the .05 level (see pp. 26-27, Hoehn, Gruben, and Fomby, 1984b). The proportion for this Ohio study was 47 percent. However, the comparison may be affected by the longer sample for Ohio.

4. The RMSE is an exact criterion for comparison of alternative forecast generating mechanisms if the loss function is proportional to the square of forecasting errors (see Granger and Newbold, 1977, pp. 279-280).

5. However, other studies have also suggested that the gains from accounting for contemporaneous correlations in errors in the estimation of linear forecasting models may be slight. Unpublished results by Hoehn for "VARs" of the Texas economy showed generally inferior forecasts for seven regional series, with updating.

6. Granger and Newbold (1977, pp. 268-9) offer some reasons why optimal forecasts are practically never available.

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Appendix A: Glossary of Variables

Regional variables*

Mnemonic	Description
EMPL	Total civilian employment (household survey), in thousands, Bureau of Labor Statistics (BLS). Seasonally adjusted by Chase Econometrics (Chase). Transformed from monthly values to quarterly averages by Hoehn and Balazsy (HB).
HOURS	Average weekly hours in manufacturing. BLS. Seasonally adjusted by Chase. Transformed from monthly to quarterly by HB.
INCOME	Personal income at annual rates, in billions of current dollars. Commerce Department. From Data Resources, Inc. (DRI).
LF	Labor force, in thousands. BLS. Seasonally adjusted by Chase. Transformed from monthly to quarterly by HB.
MFG	Employment in manufacturing, in thousands. BLS. Seasonally adjusted by Chase. Transformed from monthly to quarterly by HB.
PAYROLL	Total nonagricultural employment: total private and. government, in thousands. Seasonally adjusted by Chase. Transformed from monthly to quarterly by HB.
PRICES	Constructed average for consumer prices for Ohio. Constructed from bi-monthly series for Cleveland CPI and Cincinnati CPI, BLS. See special description of construction method, below.
RETAIL	Total retail sales, in millions of current dollars. Bureau of Census. Seasonally adjusted by Chase. Transformed from monthly to quarterly by HB.
STARTS	Total private housing starts, in thousands of units, at annual rates, Bureau of Census.

Special note of PRICES

The consumer price index for Ohio (PRICES) was constructed in the following manner. First, the seasonal adjustment factors for each month for the U.S. CPI was determined by dividing the U.S. CPI, not seasonally adjusted, by the U.S. CPI, seasonally adjusted. This factor was used to seasonally adjust values for the (bimonthly) Cleveland and Cincinnati CPIs. From these seasonally adjusted bimonthly figures, quarterly averages were constructed for each city. The average used the available months within each quarter (one or two) rather than interpolated values. Then the quarterly city values were averaged.

National Variables*

Mnemonic	Description
COIN	Coincidental Indicators Composite Index with Trend Adjustment.
CPI	Consumer Price Index (Revised) - All Items.
DEFLATOR	Gross National Product Implicit Price Deflator.
FUNDS	Effective Rate on Federal Funds.
GNP	Gross National Product
LEAD	Leading Indicators Composite Index with Trend Adjustment.
MOODY	Yield on Moody's Industrial Corporate Bonds.
PPI	Producer Price Index - Finished Goods.
PRODUCT	Total Industrial Production Index.
REALGNP	Gross National Product in 1972 Dollars.
REALYP	Personal Income in 1972 Dollars.
USHOUSEHOLD	Nonagricultural Employment (Household Survey). EHHEA
USLF	Civilian Labor Force.
USMFG	Manufacturing Employment.
USPAYROLL	Nonagricultural Establishments Employment.
USREALSALE	Total Retail Sales in 1972 Dollars.
USSTARTS	Total Private Housing Starts Including Farm.
USYP	Personal Income.

*The source of all the national variables is Data Resources Inc. All variables, except the two interest rates, are seasonally adjusted.

	PAYROLL	MFG	NONMFG	EMPL	LF	INCOME	RETAIL	STARTS	HOURS	PRICES
1965.1.	3305.71	1301.32	2004.39	3641.46	3837.55	23.474	1216.71	58.9557	42.3557	93.51
1965.2.	3343.82	1319.26	2024.56	3696.42	3891.75	23.927	1261.55	70.1119	42.3196	94.11
1965.3.	3380.57	1336.41	2044.16	3721.96	3903.80	24.321	1301.10	68.2178	41.9549	93.99
1965.4.	3428.11	1346.90	2081.21	3729.37	3891.34	25.174	1372.13	73.9105	42.3212	94.72
1966.1.	3472.64	1370.51	2102.13	3778.42	3937.43	25.824	1407.38	67.3413	42.5500	95.41
1966.2.	3517.54	1398.32	2119.22	3729.17	3994.60	26.467	1370.55	63.5059	42.5568	96.55
1966.3.	3561.05	1417.41	2143.64	3863.52	4013.75	27.070	1369.10	53.0827	42.2569	97.35
1966.4.	3598.94	1431.35	2167.59	3873.12	4027.71	27.506	1388.75	40.3014	42.1149	97.50
1967.1.	3608.87	1418.18	2190.69	3876.23	4046.38	27.465	1385.27	50.4926	41.4250	98.05
1967.2.	3587.07	1393.05	2194.02	3875.52	4062.54	27.271	1385.22	59.8254	41.2378	98.64
1967.3.	3619.58	1389.62	2229.96	3894.30	4056.72	27.996	1395.07	67.6509	41.5628	100.08
1967.4.	3665.63	1405.40	2260.23	3919.14	4085.66	28.710	1422.38	75.3344	41.5820	101.38
1968.1.	3706.51	1421.87	2284.64	3968.45	4129.55	29.590	1441.31	68.9895	41.7606	103.22
1968.2.	3742.16	1434.14	2308.02	4012.99	4161.76	30.458	1521.39	64.6745	41.6835	104.31
1968.3.	3760.95	1436.06	2324.89	4019.91	4179.79	31.013	1500.18	67.9404	41.6482	105.55
1968.4.	3794.36	1441.86	2352.50	4063.13	4226.35	31.675	1528.86	71.4335	42.0270	106.69
1969.1.	3844.74	1436.22	2408.52	4093.22	4240.71	32.638	1548.26	87.2617	41.9921	108.04
1969.2.	3874.63	1471.34	2403.29	4130.61	4274.70	33.289	1513.52	63.1127	41.9415	109.63
1969.3.	3903.19	1476.67	2426.52	4151.41	4307.77	34.053	1543.57	63.9546	41.8462	110.97
1969.4.	3926.45	1472.15	2454.30	4184.03	4359.41	34.553	1564.47	51.6944	41.6587	112.91
1970.1.	3928.41	1456.42	2471.99	4126.00	4302.00	34.682	1617.19	48.1332	40.9347	114.96
1970.2.	3889.50	1421.29	2468.21	4125.00	4362.00	34.717	1614.64	50.7259	40.4566	116.49
1970.3.	3891.90	1425.14	2466.76	4211.00	4440.00	35.241	1642.35	55.8340	40.7550	117.74
1970.4.	3815.21	1336.23	2479.98	4155.00	4440.00	34.931	1648.11	76.1825	40.1863	119.22
1971.1.	3840.38	1355.75	2484.63	4177.00	4396.00	35.549	1658.01	80.0137	40.5147	120.02
1971.2.	3852.15	1347.45	2504.70	4121.00	4381.00	36.441	1739.35	85.1369	41.0929	120.46
1971.3.	3837.74	1324.51	2513.23	4111.00	4418.00	36.536	1754.56	89.2520	40.5472	121.51
1971.4.	3825.65	1306.29	2519.36	4171.00	4472.00	37.269	1799.94	100.5150	40.6666	122.50
1972.1.	3870.24	1319.46	2550.78	4238.00	4517.00	38.084	1780.69	92.6401	41.1372	123.85
1972.2.	3918.74	1338.82	2579.92	4252.00	4515.00	39.065	1879.70	92.0566	41.4849	124.49
1972.3.	3957.72	1349.68	2608.04	4269.00	4502.00	39.868	1894.37	96.4343	41.6880	125.43
1972.4.	4001.86	1377.03	2624.93	4298.00	4527.00	41.163	1973.17	77.1623	41.9297	126.52
1973.1.	4068.51	1407.59	2660.92	4393.00	4590.00	42.699	2102.20	88.1004	42.5986	129.20
1973.2.	4098.89	1423.05	2675.84	4433.00	4640.00	43.390	2149.31	82.9020	42.3030	130.95
1973.3.	4122.22	1430.10	2692.12	4415.00	4620.00	44.492	2162.13	73.0888	42.2400	134.13
1973.4.	4158.30	1442.83	2715.47	4456.00	4646.00	45.537	2185.04	62.2327	42.1502	136.26
1974.1.	4165.51	1427.93	2737.38	4487.00	4664.00	46.028	2194.83	72.9120	41.4873	140.98
1974.2.	4175.80	1424.33	2751.47	4470.00	4685.00	46.823	2253.60	62.1917	41.0614	144.91
1974.3.	4186.49	1424.73	2761.76	4496.00	4719.00	48.062	2377.63	51.4689	41.2684	148.98
1974.4.	4149.63	1389.07	2759.56	4475.00	4749.00	48.661	2318.94	48.9805	40.9137	152.56
1975.1.	4043.34	1296.57	2746.77	4335.00	4739.00	47.849	2456.43	43.4947	39.8969	156.14
1975.2.	3997.81	1258.24	2739.97	4277.00	4733.00	47.832	2505.64	42.7666	39.8163	158.87
1975.3.	4000.76	1253.89	2746.87	4270.00	4731.00	49.005	2577.34	56.9474	40.4091	161.90
1975.4.	4022.77	1262.00	2760.77	4276.00	4671.00	50.621	2618.59	48.9888	40.8747	163.79
1976.1.	4077.36	1286.87	2790.49	4318.00	4715.00	52.592	2744.04	57.7334	41.4422	165.42
1976.2.	4098.51	1299.70	2798.81	4403.00	4766.00	53.796	2867.00	57.4002	41.1899	167.01
1976.3.	4092.98	1299.98	2793.00	4418.00	4755.00	54.548	2854.81	62.0505	41.5204	170.05
1976.4.	4108.55	1295.49	2813.06	4362.00	4744.00	55.999	2936.52	62.1752	41.3335	173.03
1977.1.	4137.41	1315.50	2821.91	4412.00	4770.00	57.065	2778.68	67.5369	41.2838	176.90
1977.2.	4217.90	1345.77	2872.13	4507.00	4813.00	59.675	2922.70	75.7961	42.2325	179.49
1977.3.	4271.66	1356.54	2915.12	4578.00	4862.00	61.915	2966.81	69.1987	42.1479	181.67
1977.4.	4285.79	1359.35	2930.44	4575.00	4870.00	63.258	3019.63	69.9616	42.2217	184.80
1978.1.	4296.75	1365.12	2931.63	4579.00	4840.00	63.666	3001.71	68.5598	41.5907	188.47
1978.2.	4390.34	1374.48	3015.86	4642.00	4916.00	66.534	3363.44	74.5421	42.1718	193.87
1978.3.	4425.59	1379.99	3045.60	4708.00	4974.00	68.382	3396.19	69.2710	42.3106	197.97
1978.4.	4462.30	1389.60	3072.70	4821.00	5090.00	70.643	3454.24	71.5874	42.3424	205.18
1979.1.	4490.39	1402.54	3087.85	4789.00	5079.00	72.739	3501.52	59.7860	42.2860	212.03
1979.2.	4494.36	1396.29	3098.07	4745.00	5030.00	73.303	3566.22	65.9268	41.0068	219.40
1979.3.	4483.15	1374.26	3108.39	4714.00	5032.00	74.505	3592.63	60.9738	41.3028	223.82
1979.4.	4470.13	1356.15	3113.95	4783.00	5082.00	75.343	3607.87	47.3228	41.2298	231.23
1980.1.	4459.75	1335.91	3123.94	4739.00	5053.00	76.040	3715.48	33.2533	40.8876	243.86
1980.2.	4366.33	1263.20	3103.13	4621.00	5072.00	75.814	3592.25	28.3647	40.1382	250.00
1980.3.	4303.95	1217.55	3086.40	4637.00	5123.00	75.847	3719.99	35.8695	40.2990	255.71
1980.4.	4344.10	1241.43	3102.67	4648.00	5100.00	78.694	3658.43	45.6467	41.1291	263.97
1981.1.	4347.02	1244.64	3102.38	4595.00	5066.00	79.571	3888.76	40.0926	41.0204	269.75
1981.2.	4333.38	1248.84	3084.54	4716.00	5145.00	80.780	3866.06	30.3190	41.1840	275.02
1981.3.	4325.13	1238.04	3087.09	4583.00	5078.00	82.357	3947.03	23.7796	41.0102	278.87
1981.4.	4265.21	1198.17	3067.04	4530.00	5100.00	81.903	3819.19	19.5838	40.3764	279.57
1982.1.	4200.14	1152.29	3047.85	4523.00	5103.00	81.060	3839.47	15.0037	39.8910	286.02
1982.2.	4151.45	1119.49	3031.96	4524.00	5149.00	81.970	3958.54	20.3666	40.2021	290.34
1982.3.	4108.10	1088.00	3020.10	4485.00	5128.00	82.302	3942.13	19.6019	40.3059	304.01
1982.4.	4039.88	1040.42	2999.45	4393.00	5105.00	82.003	4050.19	21.8211	40.0517	310.70
1983.1.	4043.80	1045.79	2998.01	4369.00	5056.00	82.365	4051.84	32.6917	40.6265	313.20
1983.2.	4060.61	1055.71	3004.90	4494.00	5175.00	84.790	4225.05	28.1086	41.1473	316.49
1983.3.	4092.98	1067.41	3025.57	4549.00	5122.00	88.229	4287.24	33.0860	41.5941	319.19
1983.4.	4137.10	1098.08	3039.02	4554.00	5107.00	90.958	4295.55	30.9514	42.2386	323.52