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New Indexes of Coincident and Leading Economic Indicators

1. *Introduction*

During six weeks in late 1937, Wesley Mitchell, Arthur Burns, and their colleagues at the National Bureau of Economic Research developed a list of leading, coincident, and lagging indicators of economic activity in the United States as part of the NBER research program on business cycles. Since their development, these indicators, in particular the leading and coincident indexes constructed from these indicators, have played an important role in summarizing and forecasting the state of macroeconomic activity.

This paper reports the results of a project to revise the indexes of leading and coincident economic indicators using the tools of modern time series econometrics. This project addresses three central questions. The first is conceptual: is it possible to develop a formal probability model that gives rise to the indexes of leading and coincident variables? Such a model would provide a concrete mathematical framework within which alternative variables and indexes could be evaluated. Second, given this conceptual framework, what are the best variables to use as components of the leading index? Third, given these variables, what is the best way to combine them to produce useful and reliable indexes?

The results of this project are three experimental monthly indexes: an index of coincident economic indicators (CEI), an index of leading economic indicators (LEI), and a Recession Index. The experimental CEI closely tracks the coincident index currently produced by the Department of Commerce (DOC), although the methodology used to produce the two series differs substantially. The growth of the experimental CEI is also highly correlated with the growth of real GNP at business cycle frequencies. The proposed LEI is a forecast of the growth of the proposed CEI over the next six months constructed using a set of leading variables or indicators. The Recession Index, a new series, is the probability that the economy will be in a recession six months hence, given data available through the month of its construction.

This article is organized as follows. Section 2 contains a discussion of the indexes and a framework for their interpretation. Section 3 presents the experimental indexes, discusses their construction, and examines their within-sample performance. In Section 4, the indexes are considered from the perspective of macroeconomic theory, focusing in particular on several salient series that are not included in the proposed leading index. Section 5 concludes.

2. *Making Sense of the Coincident and Leading Indexes*

2.1 THE COINCIDENT INDEX

The coincident and leading economic indexes have been widely followed in business and government for decades, yet have received surprisingly little attention from academic economists.[1] We suggest that one important reason for this neglect is that it is unclear what the existing CEI and LEI measure. That is, with what are the coincident indicators coincident? What do the leading indicators lead? Burns and Mitchell's (1938, 1946) answer was that the coincident indicators are coincident with the "reference cycle," that is, with the broad-based swings in economic activity known as the business cycle. This definition has intuitive appeal but, as Burns and Mitchell (1946, p. 76) recognized, lacks precise mathematical content. It is therefore unclear what conclusions one should draw from swings in the index.

To clarify the issues concerning the reference cycle, it is useful to consider how one might construct a monthly coincident index were real GNP data available accurately on a monthly basis. Would it be appropriate simply to let swings in GNP *define* the reference cycle? The "business

1. Exceptions include Auerbach (1982), Diebold and Rudebusch (1987), Hymans (1973), Kling (1987), Koch and Raasche (1988), the papers in Moore (1983), Neftci (1982), Stekler and Schepsman (1973), Vaccara and Zarnowitz (1978), Wecker (1979), Zarnowitz and Moore (1982), and Zellner, Hong, and Gulati (1987). One of Koopmans' (1947) criticisms of Burns and Mitchell (1946) is their lack of a formal statistical framework in which to interpret their results.

cycle" commonly refers to co-movements in different forms of economic activity, not just fluctuations in GNP; see Lucas (1977) for a discussion of this point. This suggests taking as primitive Burns and Mitchell's (1946, p. 3) definition that a business cycle "consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals. . . ." If so, it would be incorrect to define a recession solely in terms of monthly GNP. For example, suppose that a drought dramatically reduces agricultural output but that output in other sectors remains stable, so that aggregate unemployment remains steady. This scenario does not fit Burns and Mitchell's definition of a recession even if the decline in GNP is sustained. Rather, the reference cycle reflects co-movements in a broad range of macroeconomic aggregates such as output, employment, and sales.

The model adopted in this research formalizes the idea that the reference cycle is best measured by looking at co-movements across several aggregate time series. The experimental CEI is an estimate of the value of a single unobserved variable, "the state of the economy," denoted by C_t. This unobserved variable is defined by assuming that the co-movements of observed coincident time series at all leads and lags arise solely from movements in C_t. Of course, any particular coincident series, such as industrial production, might move in ways that are not associated with this unobserved variable. Thus each roughly coincident series is thought of as having a component attributable to the single unobserved variable, plus a unique (or "idiosyncratic") component. Each idiosyncratic component is assumed to be uncorrelated with the other idiosyncratic components and with the unobserved common "state of the economy" at all leads and lags.

Technically, this amounts to specifying an "unobserved single index" or "dynamic factor" model for the coincident variables of the type considered by, for example, Geweke (1977), Sargent and Sims (1977), and Engle and Watson (1981). The major features of the model and estimation procedure are summarized here, and the details are given in Stock and Watson (1988a). Let X_t denote an $n \times 1$ vector of the logarithms of macroeconomic variables that are hypothesized to move contemporaneously with overall economic conditions. In the single-index model, X_t consists of two stochastic components: the common unobserved scalar variable, or "index," C_t, and an n-dimensional component, u_t, that represents idiosyncratic movements in the series and measurement error. Both the unobserved index and the idiosyncratic component are modeled as having linear stochastic structures. Looking ahead to the empirical results, the coincident variables used in the analysis appear to be integrated but not cointegrated, so that model is specified in terms of ΔX_t and ΔC_t.[2] This suggests the formulation:

$$\Delta X_t = \beta + \gamma(L)\Delta C_t + u_t \quad (1)$$

$$D(L)u_t = \epsilon_t \quad (2)$$

$$\phi(L)\Delta C_t = \delta + \eta_t, \quad (3)$$

where L denotes the lag operator, and $\phi(L)$, $\gamma(L)$ and $D(L)$ are respectively scalar, vector, and matrix lag polynomials.

The main identifying assumption expresses the core notion of the dynamic factor model that the co-movements of the multiple time series arise from the single source ΔC_t. This is made precise by assuming that $(u_{1t}, \ldots, u_{nt}, \Delta C_t)$ are mutually uncorrelated at all leads and lags, which is achieved by making $D(L)$ diagonal and the $n + 1$ disturbances $(\epsilon_{1t}, \ldots, \epsilon_{nt}, \eta_t)$ mutually and serially uncorrelated. In addition, ΔC_t is assumed to enter at least one of the variables in (1) only contemporaneously. The system is estimated by maximum likelihood using the Kalman filter. The proposed CEI is computed as the minimum mean square error linear estimate of this single common factor, $C_{t|t}$, produced by applying the Kalman filter to the estimated system. Thus $C_{t|t}$ is a linear combination of current and past logarithms of the coincident variables.

It is tempting to interpret the single index specification as implying that there is a single causal source of common variation (or shock) among the real variables X_t (theoretical models can be developed in which this is the case; see Altug (1984) or Sargent and Sims (1977) for discussions). But one ought not read too much into the factor formulation. With three serially uncorrelated variables (the time series analog of a factor model of cross-sectional variables), the model lacks empirical content: Its parameters are exactly identified, so the various shocks that comprise the errors can always be recast in a single index form, and the factor merely summarizes the covariance among the three series. When there are more than three observable series or when the variables are serially correlated, the dynamic factor model is overidentified. Imposing $\gamma(L) = \gamma_0$ (as is done below for all but one of the coincident variables) further restricts the impulse

2. As an empirical matter, many macroeconomic time series are well characterized as containing stochastic trends; see, for example, Nelson and Plosser (1982). Were these stochastic trends to enter only through C_t, then X_t would contain a single common stochastic trend. Thus X_t would be cointegrated of order $n-1$ as defined by Engle and Granger (1987). For the coincident series considered here, however, this appears not to be the case: the hypothesis that the coincident series individually contain a stochastic trend cannot be rejected, but neither can the hypothesis that there is no cointegration among these variables.

response from η_t to ΔX_t to be proportional across the observable series. One interpretation of these restrictions is that there are multiple sources of economic fluctuations, but that they have proportional dynamic effects on the real variables. That is, the combination of shocks that induce business cycles might vary from one cycle to the next, but to a statistically good approximation, the relative movements of the components of ΔX_t in response to these shocks is the same.[3]

2.2 THE LEADING INDEX

Given this definition of the CEI, the next question is how to construct a leading index. The proposed LEI is the estimate of the growth of this unobserved factor over the next six months, computed using a set of leading variables; in the notation of (1)–(3), this is $C_{t+6|t}-C_{t|t}$. This represents a conceptual break with the existing DOC leading index. The objective of the historical NBER approach was to produce a series in *levels*, with turning points that preceded the reference cycle by several months. Thus the original NBER and the current DOC leading indexes can be thought of as forecasts of the level of the CEI several months hence. To the extent that one is interested in the relative growth rather than the absolute level of economic activity, however, it is more useful to forecast the growth of C_t. Forecasts of growth and future levels are, of course, closely linked: because the LEI is $C_{t+6|t}-C_{t|t}$, and the CEI is $C_{t|t}$, the sum of the CI and the LEI is $C_{t+6|t}$, which is a forecast of the (log) level of the CEI six months hence.

The LEI is constructed by modeling the leading variables (Y_t) and the unobserved state of the economy (C_t) as a vector autoregressive system with two modifications. First, the formulation recognizes C_t is unobserved. Second, the number of parameters to be estimated has been reduced by eliminating higher lags of the variables in all equations of the system except the equation for the coincident variable. The specific model estimated is the reduced form simultaneous equation system,

$$\Delta C_t = \mu_c + \lambda_{CC}(L)\Delta C_{t-1} + \lambda_{CY}(L)Y_{t-1} + \nu_{Ct} \quad (4)$$

$$Y_t = \mu_Y + \lambda_{YC}(L)\Delta C_{t-1} + \lambda_{YY}(L)Y_{t-1} + \nu_{Yt}, \quad (5)$$

where (ν_{Ct}, ν_{Yt}) are serially uncorrelated error terms. The orders of the lag polynomials $\lambda_{CC}(L)$, $\lambda_{CY}(L)$, $\lambda_{YC}(L)$, and λ_{YY}(L) were determined empirically using statistical criteria; the details are discussed in the next section. The leading variables Y_t were transformed as necessary to appear stationary.

3. More than one factor is typically used to fit models containing both real and nominal variables. For example, Singleton (1980) finds that two factors are necessary in a system containing yields on three-month, six-month, one-year, and five-year government securities, the unemployment rate, and manufacturers' shipments.

The parameters of the coincident and leading models are estimated in two steps. In the first step, the parameters of the coincident model (1)–(3) are estimated by maximum likelihood, where the Kalman filter is used to evaluate the likelihood function. In the second step, the leading model is estimated conditional on the estimated parameters of the coincident model. Technically, (1), (2), (4), and (5) are combined to form a state space model, with ΔC_t and its lags being unobserved elements of the state vector. The parameters of (4) and (5) are then estimated by maximum likelihood (using the EM algorithm), conditional on the estimates of the parameters of (1) and (2). A desirable consequence of this two-step procedure is that the coincident index ($C_{t|t}$), constructed as a weighted average of ΔX_t using (1)–(3), is consistent with the implicit definition of C_t in the full model (1), (2), (4), and (5). The main benefit of this approach is that it prevents potential misspecification in (4) and (5) from inducing inconsistency in the parameters of (1) and (2). The cost of this benefit is potential inefficiency: if the full system is correctly specified, the two-step procedure will produce consistent but inefficient estimators relative to the M.L.E. for the complete system (1), (2), (4), and (5). Thus the simplest way to think of the leading model is as a projection of $\Delta C_{t|t}$ onto leading variables in vector autoregressive (VAR) framework, except that the lack of observability of $\Delta C_{t|t}$ is handled explicitly. Finally, the LEI is computed as $C_{t+6|t} - C_{t|t}$ from the estimated model (1), (2), (4), and (5). Movements in the LEI arising from X_t are negligibly small and will be ignored to simplify the discussion below.

2.3 PREDICTIONS OF RECESSIONS AND EXPANSIONS

A traditional role of the LEI has been to signal future recessions and recoveries; indeed, it was to provide such signals that Mitchell and Burns (1938) developed their original list of indicators.[4] The value of identifying and forecasting cyclical turning points has been a matter of controversy among academic economists. One interpretation of this controversy is that the concepts of expansion and recession are incorrectly perceived to embody a view of the dynamic evolution of the economy that is at odds with the probabilistic foundations of formal macroeconomic models.

In forecasting turning points, recessions and expansions are treated as conceptually distinct objects, perhaps associated with fundamentally different behavior of the economy. In contrast, the structure of standard macroeconomic models does not change from an expansion to a contraction: in terms of the underlying theory of behavior, a month that falls in a

4. Moore (1979) recounts how the list was developed at the request of Treasury Secretary Morgenthau and evaluates the out-of-sample performance of the original series.

recession does not differ fundamentally from a month that falls in an expansion. To simplify the argument only slightly, traditional business cycle analysis is associated with treating recessions and expansions as periods of distinctly different economic behavior, defined by intrinsic shifts (essential nonlinearities) in the macroeconomic process by which the data are generated. The alternative view is that expansions and recessions have no intrinsic content, in the sense that they are not associated with fundamental shifts in the behavior of the economy, but rather are the results of a stable structure adapting to random shocks. According to this latter view, recessions and expansions are extrinsic patterns, not intrinsic macroeconomic shifts.[5]

The model described in the previous subsection is consistent with the "extrinsic" view: recessions and expansions are generated by certain configurations of random shocks to a linear time series model. Yet this does not invalidate the concept or the importance of forecasting business cycles. Recessions are important political, social, and economic events. Periods of prolonged, widespread expansion provide opportunities to workers and bounty to consumers; the most severe periods of contraction threaten governments and even forms of government. Thus the question becomes: is it possible to forecast those politically and socially important events that will come to be termed expansions and contractions? Can these patterns be recognized in advance?

The Recession Index is an estimate of the probability that the economy will be in a recession six months hence. This probability is computed using the same time series model used to calculate the proposed LEI, and is based on a definition (in terms of the sample path of ΔC_t) of what constitutes a recession and an expansion. Unfortunately, it is difficult to quantify precisely those patterns that will be recognized as expansions or contractions. Burns and Mitchell (1946, p. 3) considered the minimum period for a full business (reference) cycle to be one year; in practice, the shortest expansions and contractions they identified were six months. The Recession Index is computed by approximating a recessionary (expansionary) period in terms of negative (positive) growth of the CEI that lasts at least six months.[6]

5. Slutzky (1937) and Adelman and Adelman (1959) can be interpreted as arguing for the "extrinsic" view; Neftci (1982) and Hamilton (1987) develop techniques consistent with the "intrinsic" view. This debate is related to the distinction between exogenous shocks and endogenous instability being the source of aggregate fluctuations. The extrinsic/intrinsic terminology focuses on the identification and interpretation of recessions and expansions.

6. More precisely, a recession and an expansion are determined by partitioning future ΔC_t into three regions, or patterns. We define a month to be in a recessionary pattern if that month is either in a sequence of six consecutive declines of C_t below some boundary b_{rt}, or

3. *The Revised Indexes*

The proposed CEI is plotted in Figure 1, the proposed LEI is plotted in Figure 2, and the proposed Recession Index is plotted in Figure 3. The vertical lines in these and subsequent figures represent the official *ex post* NBER-dated cyclical turning points.

3.1 THE INDEX OF COINCIDENT ECONOMIC INDICATORS

Data and Empirical Results. The variables entering the proposed CEI and LEI, as well as the variables entering the current DOC coincident and leading indexes, are listed in Table 1. The proposed CEI is based on four series: industrial production, real personal income less transfer payments, real manufacturing and trade sales, and employee-hours in nonagricultural establishments. These are the series currently used by the DOC to construct its coincident index, except that the total number of employees (rather than employee-hours) is used in the Commerce series.[7] The data were obtained from the January 31, 1989 release of CITIBASE. Empirical results are computed using data starting in 1959:1.

The empirical results for the single-index model, specified with employment rather than employee-hours, are discussed in detail in Stock and Watson (1988b); the results for the model estimated with employee-hours are summarized here. Preliminary data analysis suggested modeling the logarithms of these four series as being individually integrated but not cointegrated. Dickey-Fuller (1979) tests were unable to reject the null hypothesis that each of the series are individually integrated. The Stock-Watson (1988a) q_f^{τ} test of the null hypothesis that the four series are not cointegrated against the alternative that there is at least one cointegrating vector (computed using four lags of the series and a linear time trend) yielded a statistic of -25.25, with a p-value of 60%. Similar evi-

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is in a sequence of nine declines below the boundary with no more than one increase during the middle seven months. Thus a recessionary pattern is the union of 15 sets contained in $\mathfrak{R}^{17}$. An expansionary pattern is defined analogously, with "increases" replacing "declines" and b_{et} replacing b_{rt}. This does not exhaust all possible patterns, and the remaining patterns are said to be indeterminate. Reasonable people might disagree on these boundaries: these regions might constitute fuzzy sets. This "fuzziness" is quantified by making b_{rt} and b_{et} normally distributed random variables. After ruling out the possibility that a given month falls in neither region, the NBER Recession Index is computed as the probability (given currently available data) that, six months hence, the time path of C_t will fall in a recession region. This entails integrating a 17-dimensional normal density conditional on (b_{rt}, b_{et}), which in turn have independent normal distributions.

7. We follow Moore's (1988) recommendation and use employee-hours rather than the number of employees in constructing the CEI. Because of overtime and part-time work, employee-hours measures more directly fluctuations in labor input than does the number of employees.

dence of non-cointegration was obtained from pairwise residual-based tests for cointegration as proposed by Engle and Granger (1987). The subsequent analysis therefore uses first differences of the logarithms of these series (ΔX_t).

Geweke (1977) and Sargent and Sims (1977) point out that the single index model (1)–(3) imposes testable restrictions on the spectral density matrix of the vector time series. Because ΔC_t and u_t are by assumption uncorrelated at all leads and lags, (1) implies that $S_{\Delta X}(\omega) = \gamma(e^{-i\omega})S_{\Delta C}(\omega)\gamma(e^{i\omega})' + S_u(\omega)$, where $S_{\Delta X}(\omega)$ denotes the spectral density matrix of ΔX_t at frequency ω, etc. Because $S_{\Delta C}(\omega)$ is a scalar and $S_u(\omega)$ is diagonal, this provides testable restrictions on $S_{\Delta X}(\omega)$. Performing this test for the coincident indicator model over six equally-spaced bands constructed using ΔX_t (the unconstrained estimate of the spectrum is the averaged matrix periodogram) provides little evidence against the restrictions imposed by the dynamic single-index structure: the χ^2_{30} test statistic is 19.8, having a p-value of 92%.

Figure 1 THE PROPOSED INDEX OF COINCIDENT ECONOMIC INDICATORS

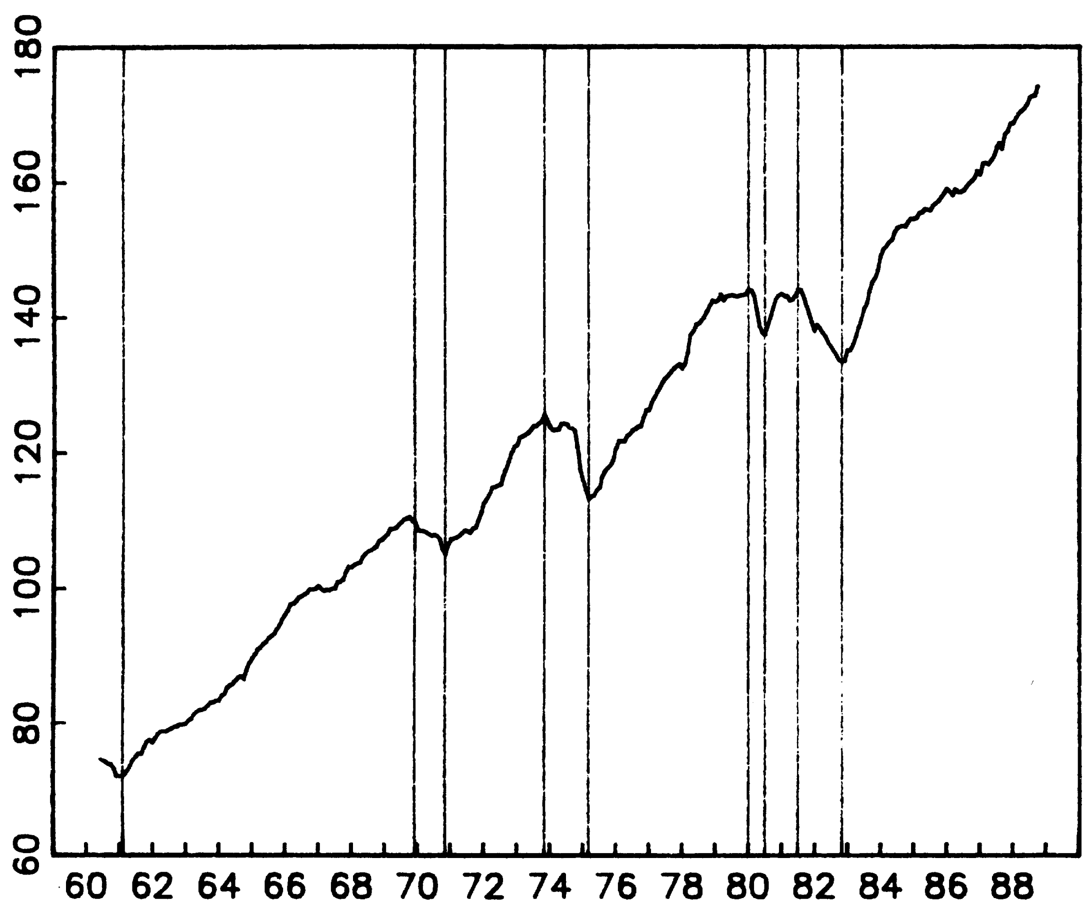
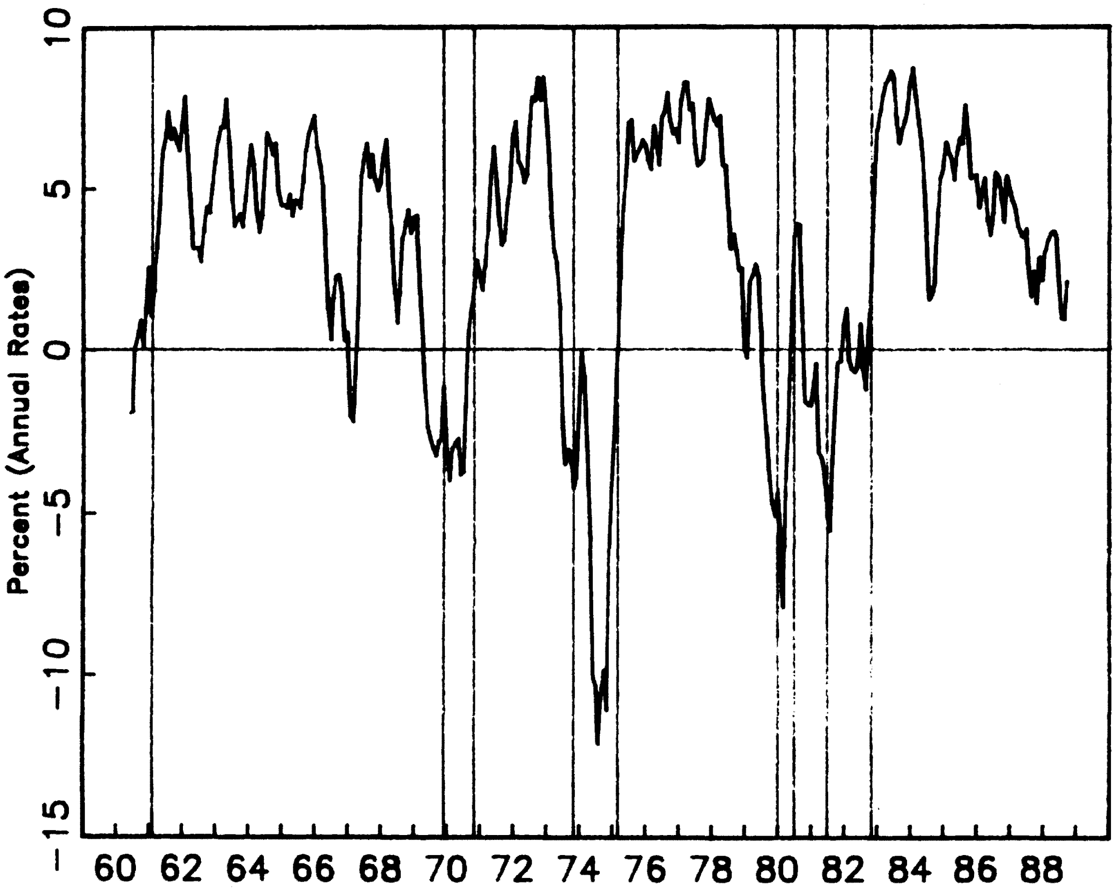


Figure 2 THE PROPOSED INDEX OF LEADING ECONOMIC INDICATORS

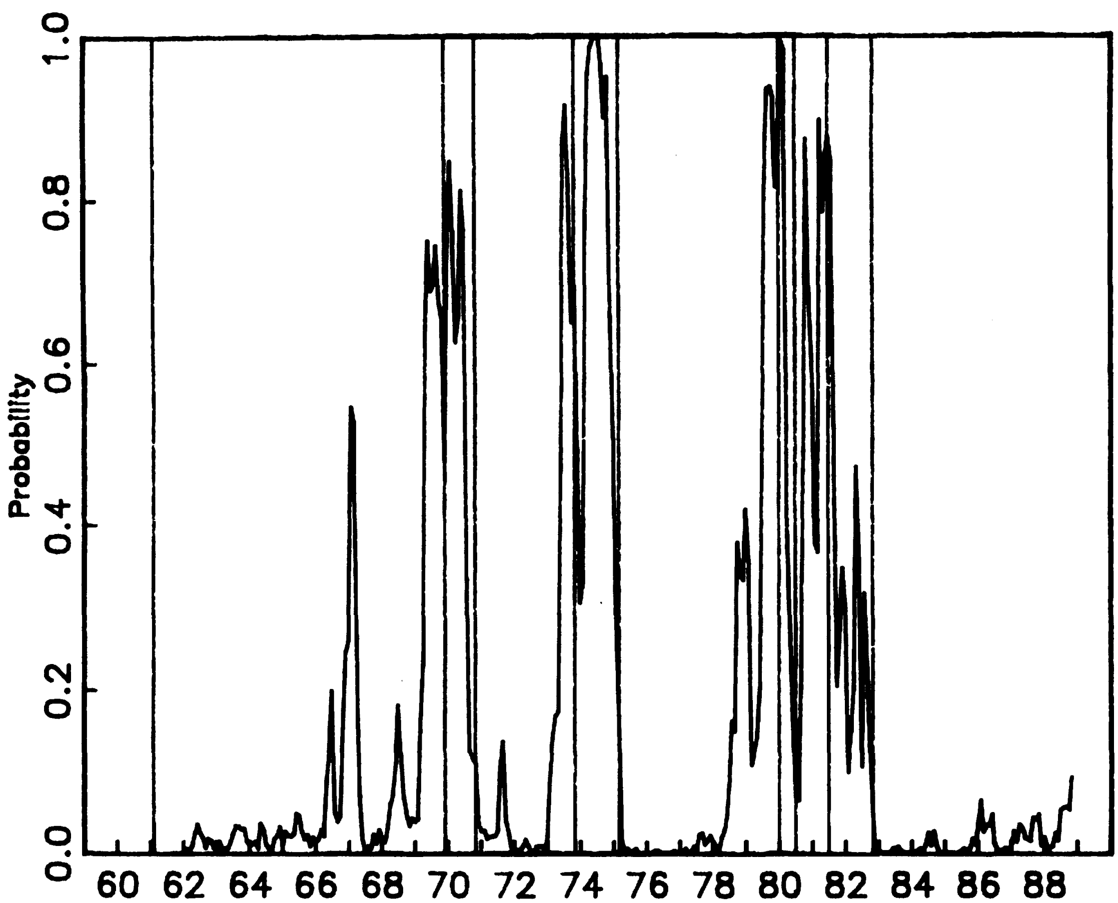


The maximum likelihood estimates of the parameters of the single index model (1)–(3) are presented in Table 2. A specification in which the factor enters each of the four equations only contemporaneously (i.e., $\gamma(L) = \gamma_0$) was found to be inconsistent with the data.[8] This is not the case, however, when lags of ΔC_t are permitted to enter the employee-hours equation: as indicated in panel B of Table 2, various diagnostic statistics provide no statistical evidence of (linear) misspecification of this model. Thus employment is better modeled as a slightly lagging rather than an exactly coincident variable.

As a further check on the fit of the model, several highly parameterized versions were estimated; the results for one specification are summarized in Table 2(D). The additional parameters are not statistically significant at the 5% level, and the $C_{t|t}$ series created using these specifications are essentially indistinguishable from the CEI reported above.

8. With $\gamma(L) = \gamma_0$, the one-step ahead forecast errors for employee-hours were correlated with past observations on ΔX_t.

Figure 3 THE PROPOSED RECESSION INDEX



The proposed CEI, the DOC coincident index, and real GNP growth. The proposed CEI is graphed in Figure 1. The figure portrays $C_{t|t}$ computed using the empirical model in Table 2, then exponentiated and scaled to equal 100 in July 1967. Visual inspection indicates that the cyclical peaks and troughs of the CEI coincide with the official NBER-dated turning points, with the exception of 1969, when the peak in the proposed series occurs two months prior to the official NBER turning point.

The proposed CEI is quantitatively similar to the existing DOC coincident index; both are graphed in Figure 4(a). The main differences are the slightly greater trend growth and cyclical volatility of the DOC series. The correlation between the growth rates of the proposed and DOC series is .95, and the average coherence for periods exceeding eight months is .97.[9]

9. This high coherence at low frequencies suggests that the population joint spectral density matrix of the proposed CEI and the DOC index might be singular at frequency zero, i.e., the two series might be cointegrated; but the series are constructed using different implicit weights on ΔX_t, and there is no statistical evidence against non-cointegration.

The growth in the experimental CEI closely tracks the growth in GNP. Figure 4(b) presents the six-month growth of the CEI ($C_{t+6|t+6} - C_{t|t}$) and the growth of real GNP over the subsequent two quarters, at annual rates. (The plotted GNP growth rate for January is the growth in GNP for the second and third quarters, relative to the first quarter; this same rate is plotted for February and March.) The six-month growth in the CEI exhibits greater cyclical swings, particularly in 1974, but the two series are

Table 1 VARIABLES CURRENTLY COMPRISING THE NBER AND DOC CEI AND LEI

A. Current NBER Base Variable List

Mnemonic	*Transformation*	*Description*
Coincident Variables		
IP	growth rates	Industrial production, total (BCD 47; in DOC CEI)
GMYXP8	growth rates	Personal Income, total less transfer payments, 1982$ (BCD 51; in DOC CEI)
MT82	growth rates	Mfg and trade sales, total, 1982$ (BCD 57; in DOC CEI)
LPMHU	growth rates	Employee-hours in non-agricultural establishments
Leading Variables		
HSBP	levels	New private housing authorized, index (Building Permits)
MDU82S	growth rates	Manufacturers' unfilled orders: durable goods industries, 1982$, smoothed
EXNWT2S	growth rates	Trade-weighted nominal exchange rate between the U.S. and the U.K., West Germany, France, Italy, and Japan, smoothed.
LHNAPSS	growth rates	Part-time work in non-agricultural industries because of slack work (U.S. Department of Labor, The Employment Situation, Household Survey), smoothed
FYGT10S	differences	Yield on constant-maturity portfolio of 10-yr U.S. Treasury bonds, smoothed
CP6 _ GM6	levels	Spread between interest rate on 6-mo. corporate paper and the interest rate on 6 mo. U.S. Treasury bills (Federal Reserve Board)
G10 _ G1	levels	Spread between the yield on constant-maturity portfolio of 10-yr U.S. T-bonds and the yield on 1-yr U.S. T-bonds. (Federal Reserve Board)

highly correlated (r = .86) and have a coherence in excess of .9 for periods over two years.

3.2. THE INDEX OF LEADING ECONOMIC INDICATORS

Variable Selection and Model Specification. The experimental LEI is a forecast of the six-month growth (on an annual percentage basis) of the CEI. In a break with tradition, the proposed LEI uses the most recently available data, rather than using only data for the month for which the coincident series are available. For example, the LEI released at the end of October is constructed using unfilled orders data for September, but interest rate and exchange rate data for October. This results in a more timely measure of future economic activity.

The development of the empirical LEI model required making three important sets of judgments: the choice of variables to include in the leading index, whether to transform or smooth some variables, and the number of lags of these variables to use in the ΔC_t equation.

Table 1 VARIABLES CURRENTLY COMPRISING THE NBER AND DOC CEI AND LEI (CONTINUED)

B. DOC Variable List (December 1988)
CEI
Industrial Production (BCD 47)
Personal income less transfer payments, 1982$s (BCD 51)
Index of Manufacturing and trade sales in 1982 dollars (BCD 57)
Employees on nonagricultural payrolls (BCD 41)
LEI
Average weekly hours of production or non-supervisory workers, mfg (BCD 1)
Avg weekly initial claims for State unempl. insurance (BCD 3)
Mrf's new orders, 1982$s, consumer goods and mat'ls industries (BCD 8)
S&P 500 (BCD 19)
Contracts and orders for plant and eqpt, 1982$s (BCD 20)
New private housing authorized index (Building Permits) (BCD 29)
Vendor Performance, percent of companies receiving slower deliveries (BCD 32)
Change in sensitive mat'ls prices, smoothed (BCD 99)
Money supply M2, 1982$s (BCD 106)
Change in business and consumer credit outstanding (BCD 111)
Change in mfging and trade inventories on hand and on order, 1982$s (BCD 36)

Note: The DOC leading index was revised beginning with the January 1989 data. The final two series in the index (BCD 111 and BCD 36) were dropped from the composite index, and two series were added: the change in manufacturers' unfilled orders in 1982 dollars, durable goods industries, smoothed; and an index of consumer expectations. No revisions were made to the DOC coincident index.

TABLE 2 MAXIMUM LIKELIHOOD ESTIMATES OF THE FACTOR MODEL (1)-(3) USING THE COINCIDENT INDICATORS

A. Measurement Equations:

$$\Delta IP_t = \underset{(.044)}{.708}\ \Delta C_t + u_t^{ip}$$

$$\Delta GMYXP8_t = \underset{(.045)}{.500}\ \Delta C_t + u_t^{gmyxp8}$$

$$\Delta MT82_t = \underset{(.033)}{.452}\ \Delta C_t + u_t^{mt82}$$

$$\Delta LPMHU_t = \underset{(.058)}{.527}\ \Delta C_t - \underset{(.078)}{.031}\ \Delta C_{t-1} - \underset{(.080)}{.142}\Delta C_{t-2} + \underset{(.054)}{.235}\Delta C_{t-3} + u_t^{lpmhu}$$

B. Transition Equations:

$$\Delta C_t = \underset{(.076)}{.616}\ \Delta C_{t-1} - \underset{(.074)}{.037}\ \Delta C_{t-2} + \nu_t;\ \sigma_\nu = 1.0 \text{ (Normalized)}$$

$$u_t^{ip} = \underset{(.103)}{-.079}\ u_{t-2}^{ip} + \epsilon_t^{IP};\ \sigma_{\epsilon_{ip}} = \underset{(.041)}{.470}$$

$$u_t^{gmyxp8} = \underset{(.042)}{-.068}\ u_{t-1}^{gmyxp8} + \underset{(.048)}{.143}\ u_{t-2}^{gmyxp8} + \epsilon_t^{gmyxp8} \sigma_{\epsilon_{gmyxp8}} = \underset{(.027)}{.776}$$

$$u_t^{mt82} = \underset{(.053)}{-.436}\ u_{t-1}^{mt82} - \underset{(.057)}{.246}\ u_{t-2}^{mt82} + \epsilon_t^{mt82};\ \sigma_{\epsilon_{mt82}} = \underset{(.033)}{.744}$$

$$u_t^{lpmhu} = \underset{(.050)}{-.487}\ u_{t-1}^{lpmhu} - \underset{(.064)}{.128}\ u_{t-2}^{lpmhu} + \epsilon_t^{lpmhu};\sigma_{\epsilon_{lpmhu}} = \underset{(.027)}{.662}$$

C. Marginal Significance Levels of Diagnostic Tests for Single-Index Model

	p-values of whether the dep. variable is predictable by lags of:							
Dep. Vble.	e_{IP}	e_{GMYXP8}	e_{MT82}	e_{LPMHU}	*IP*	*GMYXP8*	*MT82*	*LPMHU*
e_{IP}	*0.905*	*0.804*	*0.296*	*0.910*	*0.892*	*0.796*	*0.383*	*0.962*
e_{GMYXP8}	*0.860*	*0.994*	*0.927*	*0.137*	*0.671*	*0.893*	*0.820*	*0.060*
e_{MT82}	*0.256*	*0.852*	*0.800*	*0.590*	*0.392*	*0.969*	*0.798*	*0.820*
e_{LPMHU}	*0.875*	*0.825*	*0.137*	*0.716*	*0.774*	*0.625*	*0.162*	*0.592*

D. Comparison with a highly parameterized single index model (Model A)

Orders of lag polynomials: $\Delta(L)$, 5; $\gamma_{LPMHU}(L)$, 6; $\phi(L)$, 8

Likelihood ratio statistic (χ^2_{21}): 27.57, p-value = .153

$\mathrm{Corr}(\Delta C_{t|t}^{base}, \Delta C_{t|t}^{model\ A}) = .995.$

Notes: Panel A and B: The parameters were estimated using data from 1959:1–1987:12. Logarithms of variables were used, each series was standardized to growth rates with mean zero and unit variance prior to estimation. The sample means and standard deviations of the growth rates of the original series are: ΔIP: 0.0031, 0.0100; $\Delta GMYXP8$: 0.0027, 0.0047; $\Delta MT82$: 0.0028, 0.0110; $\Delta LPMHU$: 0.0017, 0.0049. *Panel C:* The entries are p-values from the regression of e_y against a constant and six lags of the indicated regressor; the p-values correspond to the usual F-test of the hypothesis that the coefficients on these six lags are zero (with only the usual corrections for degrees of freedom). The series e_y denotes the one-step ahead forecast errors from the single-index model, and growth rates of the original data are used.

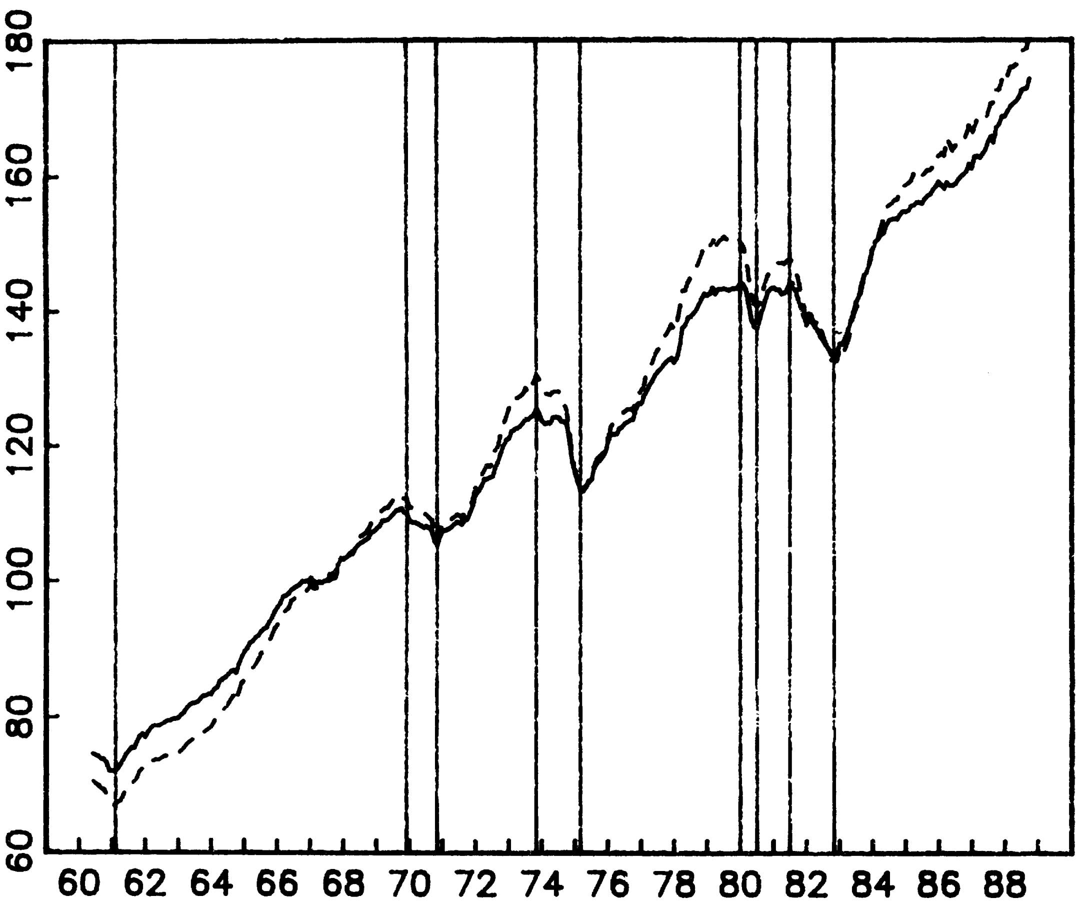
The leading variables were chosen from an initial list of approximately 280 series (Mitchell and Burns (1938) started with 487 series). This list included series from ten groups: measures of output and capacity utilization; consumption and sales; inventories and orders; money and credit quantity variables; interest rates and asset prices; exchange rates and foreign trade; employment, earnings, and measures of the labor force; wages and prices; measures of government fiscal activity; and other variables, primarily prominent leading indicators from the *Business Conditions Digest*. An important consideration in developing this list was to include series that have expectational components, that would (under some economic theory) respond rapidly to some shocks to the economy, or that would reflect policy actions. These variables were then screened by examining their bivariate relation to the growth of the DOC coincident index using the coherence and phase lead between each series and the growth of the DOC series, the ability of each series to Granger-cause the DOC series, and the marginal predictive content of each series for the growth of the DOC coincident index beyond that of the current DOC leading index. Several series that performed poorly according to these criteria were nevertheless retained because economic theory suggested that they should have some predictive content, or because they are currently included in the DOC leading index. This procedure resulted in a reduced list of approximately 55 time series. Of these 55 series, many measured closely related concepts.

A critical question is how to construct the LEI from this base list of 55 variables. The approach used here is similar to the traditional NBER approach in the sense that it results in a relatively short list of series, of which the LEI is a weighted average; a key methodological difference between the two approaches is our emphasis on multivariate rather than bivariate predictive content. Selecting the few "best" variables from this list is a daunting task: in theory over 200 million seven-variable indexes could be formed from these 55 series. We simplified this problem by adopting a modified stepwise regression procedure for constructing an LEI based on a relatively few series.[10]

Because the signal extraction error in the proposed CEI from the one-

10. Another strategy rejected at an early stage of this project would be to construct a broad-based index that included many or all of these 55 series. Strong restrictions on how these series entered would need to be imposed. Because the formulation and implementation of these restrictions would require considerable research judgment, one would need to be particularly cautious about out-of-sample performance. In addition, this approach would be less informative about which variables have important predictive content and would result in an index which is more difficult to interpret. Still, this would constitute an interesting and complementary research project.

Figure 4 A. THE PROPOSED INDEX OF COINCIDENT INDICATORS (SOLID LINE) AND THE CURRENT DOC INDEX OF COINCIDENT ECONOMIC INDICATORS (DASHED LINE)



factor model is relatively small, an LEI produced using the unobserved-components VAR can be approximated by regressing the six-month growth in the CEI ($C_{t+6|t+6} - C_{t|t}$) on current and past values of the candidate leading variables. This observation was used to construct several leading indexes. Starting with a base set of series, indexes were constructed by including twelve lags of each of the candidate trial variables in the six-step ahead regression; these were ranked according to a criterion that involved the full-sample R^2 and the R^2 based on the full-sample performance of the index when the model was estimated through 1979:9. The series with the greatest value of the criterion function was added to the index, and the procedure was repeated until the desired number of variables was added. The series proposed in Table 1 were obtained by considering those series that most often were found in the final index, starting from different sets of base variables. In addition, judgment was used in excluding some variables that were clearly fitting specific historical episodes in a way that had no plausible economic interpretation (a sign of overfitting).

Because the growth rates of some of the series contain considerable high frequency noise, some of the series were smoothed. Although this smoothing could in principle be done implicitly by estimating a larger number of regression coefficients, using smoothed series admits the possibility of reducing the number of estimated regression coefficients. The smoothing filter was chosen to be $s(L) = 1+2L+2L^2+L^3$, the filter used by the DOC (until the 1989 revision) to smooth several of their noisy series. This filter has desirable properties from the perspective of producing six-month ahead forecasts using first differences of leading variables. The product filter $(1-L)s(L)$ is a band-pass filter with gain concentrated at periods of four months to one year, zero gain at zero frequency and very low gain for periods less than two months. At a period of six months, the phase lag of this filter is 2.5 months.

The number of lags of each series in the ΔC_t equation of the LEI model (i.e., the order of $\lambda_{CY}(L)$ in (4)) was chosen using the Akaike information criterion (AIC) in a regression of $\Delta C_{t|t}$ on four lags of $\Delta C_{t|t}$ and the selected leading variables. The search was restricted to models with 1, 3, 6, or 9 lags of the variables for computational reasons.[11] Various tests for autoregressive order resulted in setting the orders of $\lambda_{CC}(L)$, $\gamma_{YC}(L)$, and $\gamma_{YY}(L)$ at 4, 1, and 1 respectively. The AIC calculations resulted in a model with six lags of housing starts and the private-public spread and with three lags of each of the other variables. The within-sample R^2 between the resultant LEI and the actual six-month growth of the proposed CEI is .634.

Overfitting the data (and the consequent poor out-of-sample performance) is a risk in any empirical exercise, and the danger is particularly clear here. The first potential source of overfitting—the selection of a final list of leading variables from a much longer list of series—is present both in our procedure and in the traditional NBER/DOC procedure for variable selection (see Zarnowitz and Boschan 1975a,b and Moore 1988). The DOC periodically sponsors a revision of the composite indexes; one interpretation of the need for these revisions is that the underlying relations (and important predictive variables) have changed in the economy, but another is that these revisions are important to correct for previous overfitting.[12] The methodology outlined above introduces a second possible source of overfitting, the estimation of regression coefficients.

11. This entailed examining 4^7 specifications. The AIC is known to overestimate the autoregression order if the order is finite (e.g., Geweke and Meese 1981). As a check, lags were chosen according to the Schwartz information criterion (BIC) and the Hannan-Quinn information criterion. These yielded similar choices of lag lengths, and in particular yielded similar estimated LEIs.

12. Recent revisions occurred in 1975 and 1983. A new set of revisions took effect with the January 1989 data. See Hertzberg and Beckman (1989).

It appears difficult to ascertain the asymptotic properties of this model selection procedure, but these properties can be investigated numerically. Two small Monte Carlo experiments were performed to shed light on the potential overfitting. The first simulated indexes that would be produced if *no* series had any true predictive content for the CEI. Fifty smoothed pseudo-random monthly time series of the form $x_{it} = s(L)\epsilon_{it}$, ϵ_{it} i.i.d. $N(0,1)$ were generated for $i = 1, \ldots, 50$, $t = 1959{:}1, \ldots, 1987{:}12$. The variable and model selection procedure described above was then applied to these time series, and the resultant seven-variable index was calculated. This experiment was repeated twice, and resulted in indexes with R^2's of .228 and .271. The R^2 for a model with no leading variables is .163 over this period (this is non-zero because lagged growth of $C_{t|t}$ predicts its future growth); thus the increment to the R^2 in these Monte Carlo experiments was respectively .065 and .108.

The second Monte Carlo experiment examined a situation where most of the variables have some predictive content, but the chosen series might not be those with the greatest true predictive ability. The estimated seven-variable leading model (4) and (5) was used to generate seven Gaussian pseudo-random leading variables over 1959:1–1987:12, plus a pseudo-random coincident index. For each of the seven pseudo-random leading variables, four more pseudo-random series were constructed by adding various degrees of measurement error to series.[13] Fifteen additional smoothed spurious series like those used in the first experiment were also generated, for a total of fifty pseudo-random potential leading series. The variable and model selection procedure was then used to produce a seven-variable index. The population R^2 for the model generating the data was .65. The average Monte Carlo R^2 of the chosen models across ten replications was .75, and these (suboptimal) models had an average population R^2 of .62. Thus imperfect knowledge of the correct model reduced the R^2 by .03 (.65−.62). Also, on average the sample R^2's were inflated by .13 (.75−.62) above their population counterparts.

These two experiments provide rough measures of the magnitude of the overfitting bias: in the first, approximately .08, in the second, .13.[14]

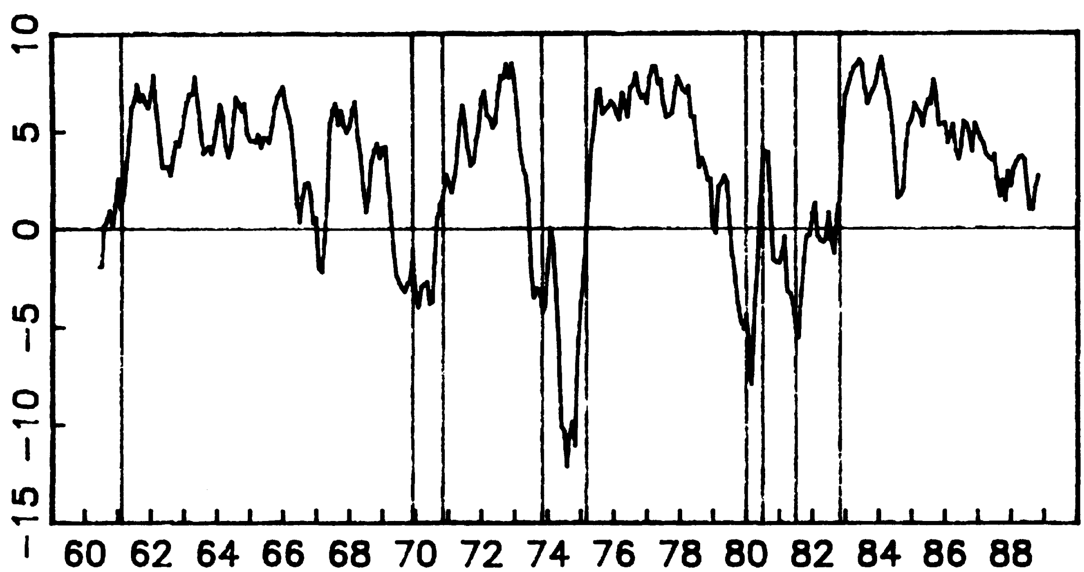
13. For each of the base pseudo-random leading series X_{it}, $i = 1, \ldots, 7$, the four additional pseudo-random series were constructed by setting $X_{ijt} = \Gamma_j(L)X_{it}+u_{ijt}$, where u_{ijt} are i.i.d. $N(0,\tau_j^2)$ random variables, $\Gamma_j(L) = 1, 1, L$, and L^2, and $\tau_j = 1, 5, 1$, and 1 for $j = 1, 2, 3$, and 4, respectively.

14. One reason to suspect that these experiments overstate the bias is that they do not incorporate any researcher judgment, although the construction of the proposed LEI did. In addition, the first experiment fails to recognize that the 55 actual series have many closely related variables (e.g., industrial production of consumer durables and industrial production in manufacturing); thus in actuality the variation across the series is not as great as in the first experiment.

The experimental LEI and its Historical Components. Historical values of the proposed LEI are plotted in Figure 2. A negative value of the index indicates a forecast of negative growth in overall economic conditions over the next six months. This index is negative prior to each of the four recessions since 1960. It is also negative during 1967, a year in which a recession did not occur.

The historical contributions of each of the seven leading variables to the index are plotted in Figure 5. These historical contributions are calculated by setting all series but the series in question to zero, then comput-

Figure 5 HISTORICAL DECOMPOSITION OF THE PROPOSED LEI (A) Total



(B) COMPONENT DUE TO HSBP

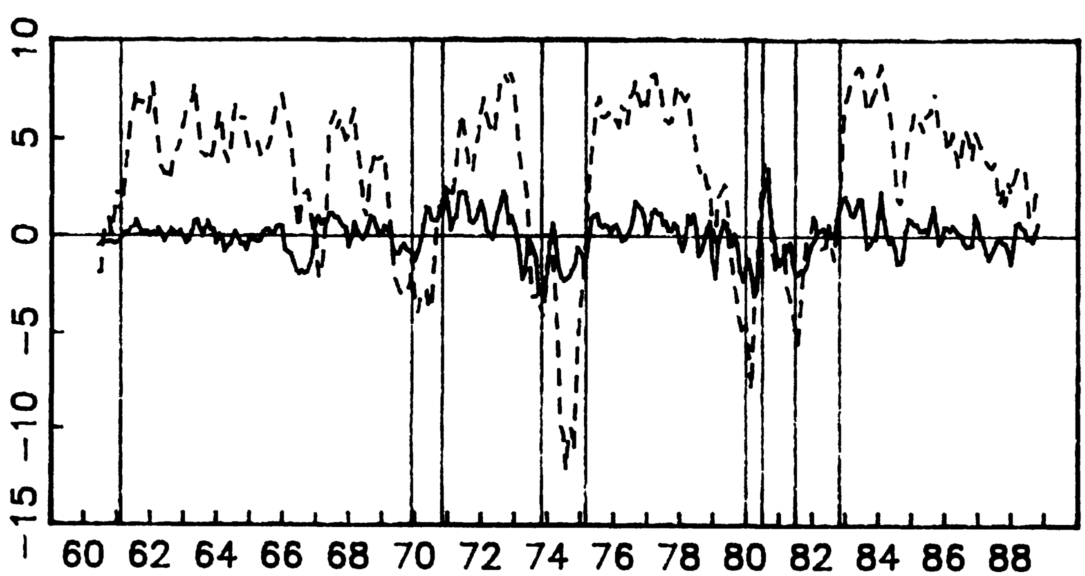
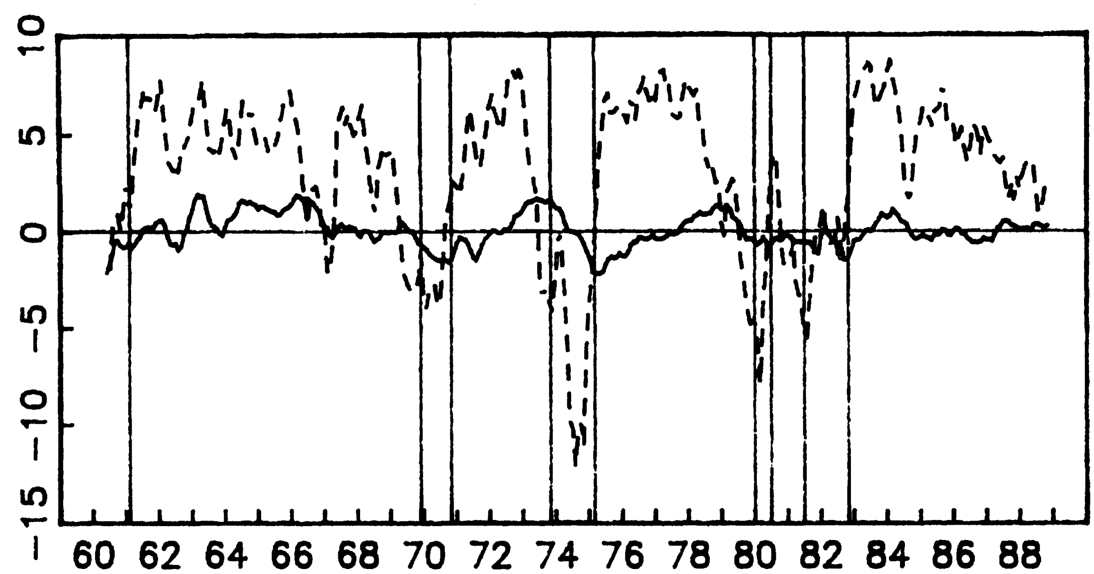
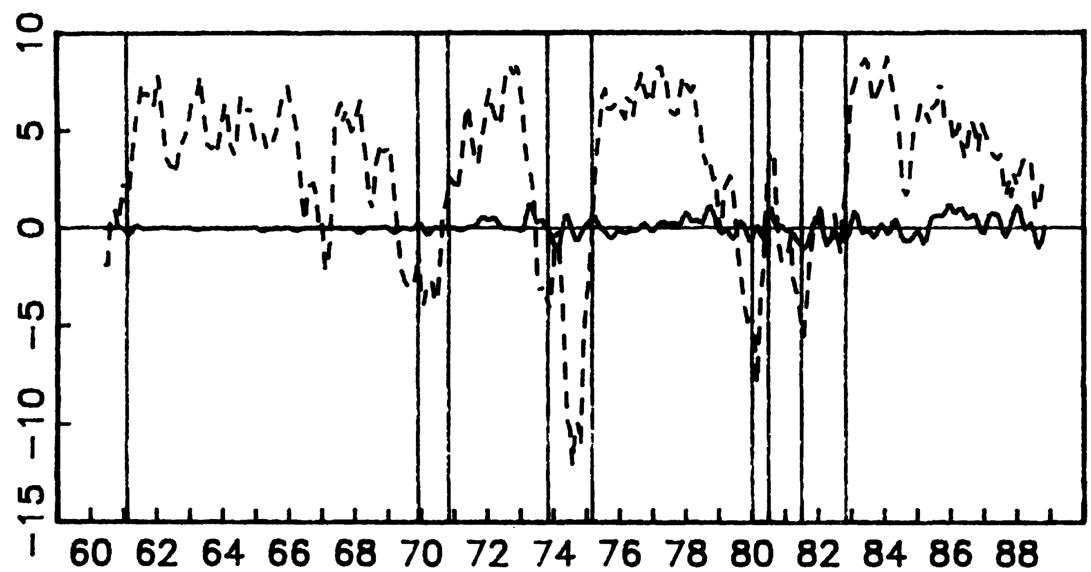


Figure 5 (CONTINUED) (C) COMPONENT DUE TO MDU82S



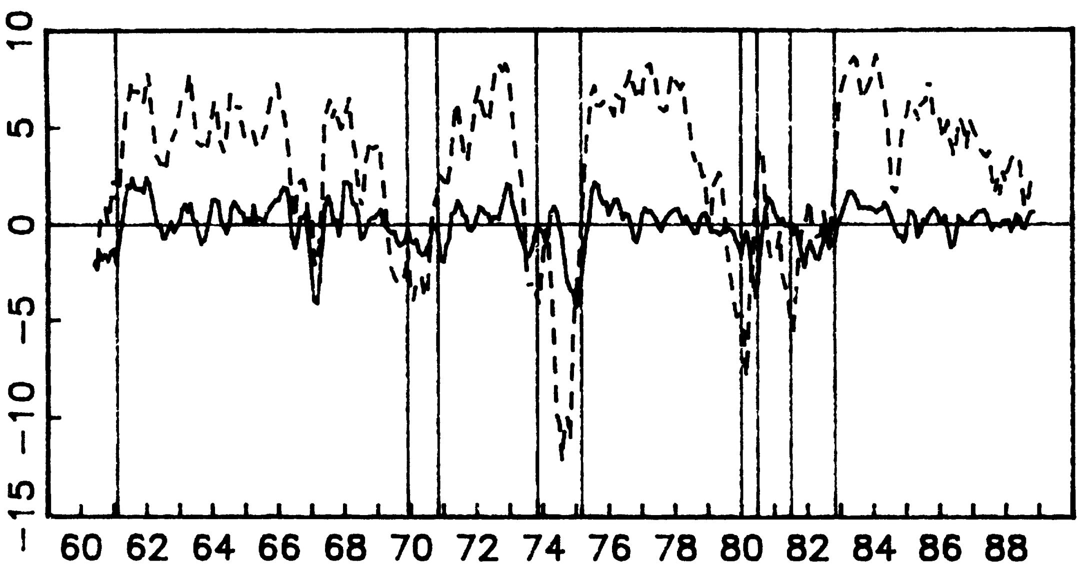
(D) COMPONENT DUE TO EXNWT2S



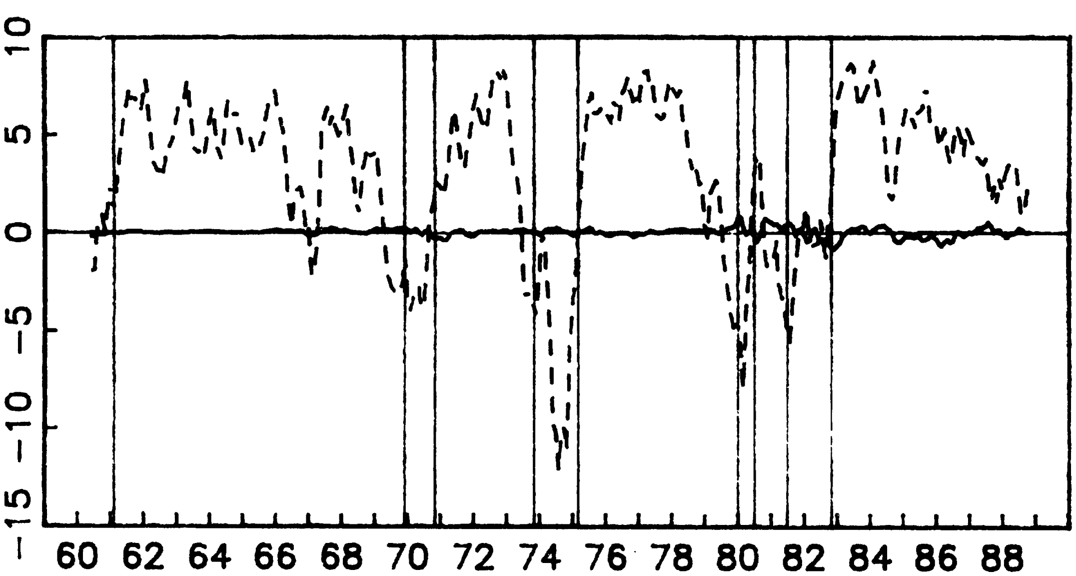
ing the LEI. Because the LEI is linear in Y_t, the sum of these historical decompositions, plus the mean six-month growth in the CEI (at annual rates), equals the LEI (graphed again in Figure 5(a) for convenience).[15]

15. Readers familiar with vector autoregressions (VARs) should not confuse the historical decompositions in Figure 5 with those found in the VAR literature for "orthogonalized" systems. The latter are based on an arbitrary transformation of the original linear model (chosen so that the shocks to each decomposition are mutually uncorrelated), whereas no such transformation is made in producing Figure 5.

Figure 5 (CONTINUED) (E) COMPONENT DUE TO LHNAPSS



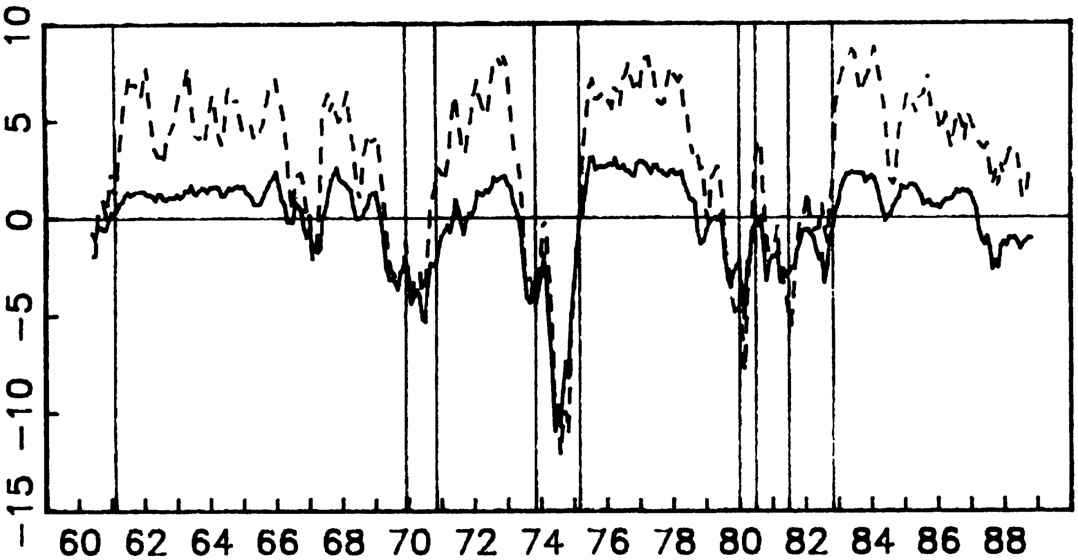
(F) COMPONENT DUE TO FYGT10



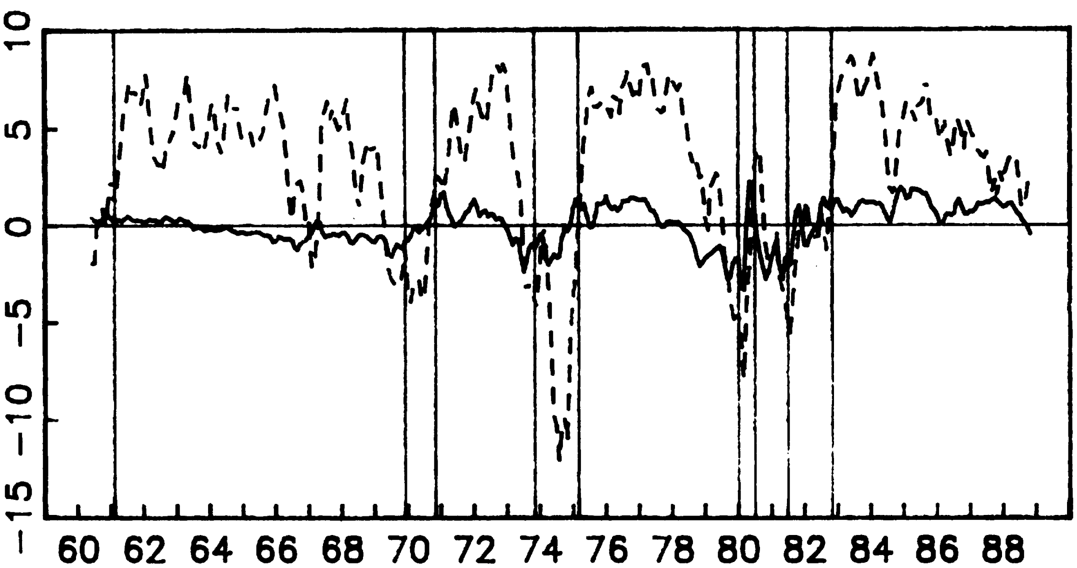
The implicit weights on the variables used to construct the LEI (the implied "distributed lag" coefficients) are plotted in Figure 6; the units are standard deviations of the leading variables.

Each of the series makes a contribution to the total. The largest historical contributions are from the spread between commercial paper and Treasury bills, from the spread between the yields to maturity on 10-year and 1-year Treasury Bonds, from housing starts, from manufacturer's unfilled orders in durable goods industries, and from the growth of part-

Figure 5 (G) COMPONENT DUE TO CP6 _ GM6 (CONTINUED)



(H) COMPONENT DUE TO G10 _ G1



time work due to "slack work." The implied distributed lag coefficients indicate that a rise in housing starts, a low private-public spread, a high long-term/short-term public spread (an upward-sloping yield curve), an increase in durables manufacturers' unfilled orders, and a decline in involuntary part-time work all are indications of strong overall growth over the next six months. To a lesser extent, a depreciation of the dollar and an increase in the long-term Treasury bond yield signify strong future economic activity.

Figure 6 IMPLICIT DISTRIBUTED LAG COEFFICIENTS ON LEADING VARIABLES

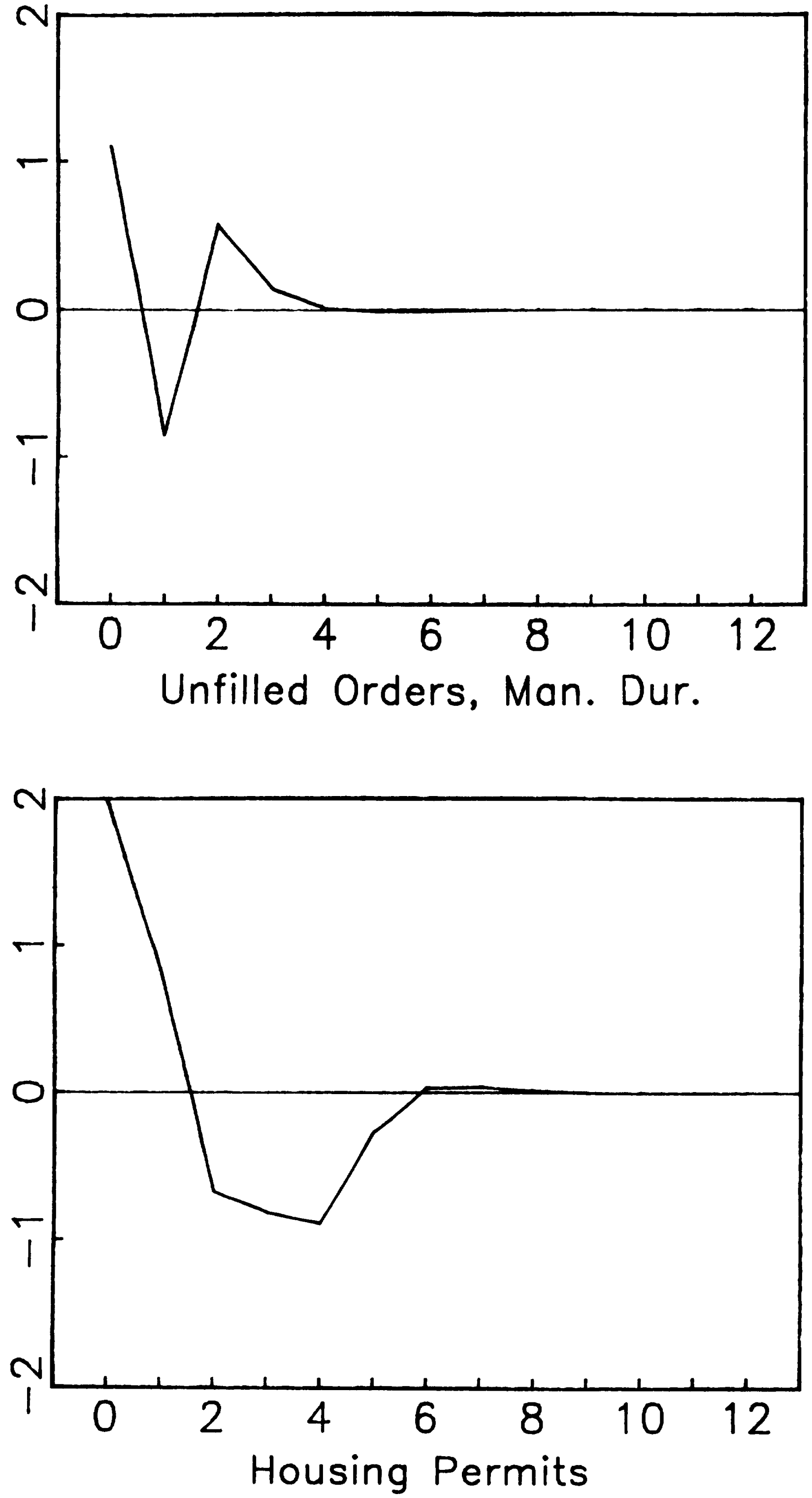


Figure 6 (CONTINUED)

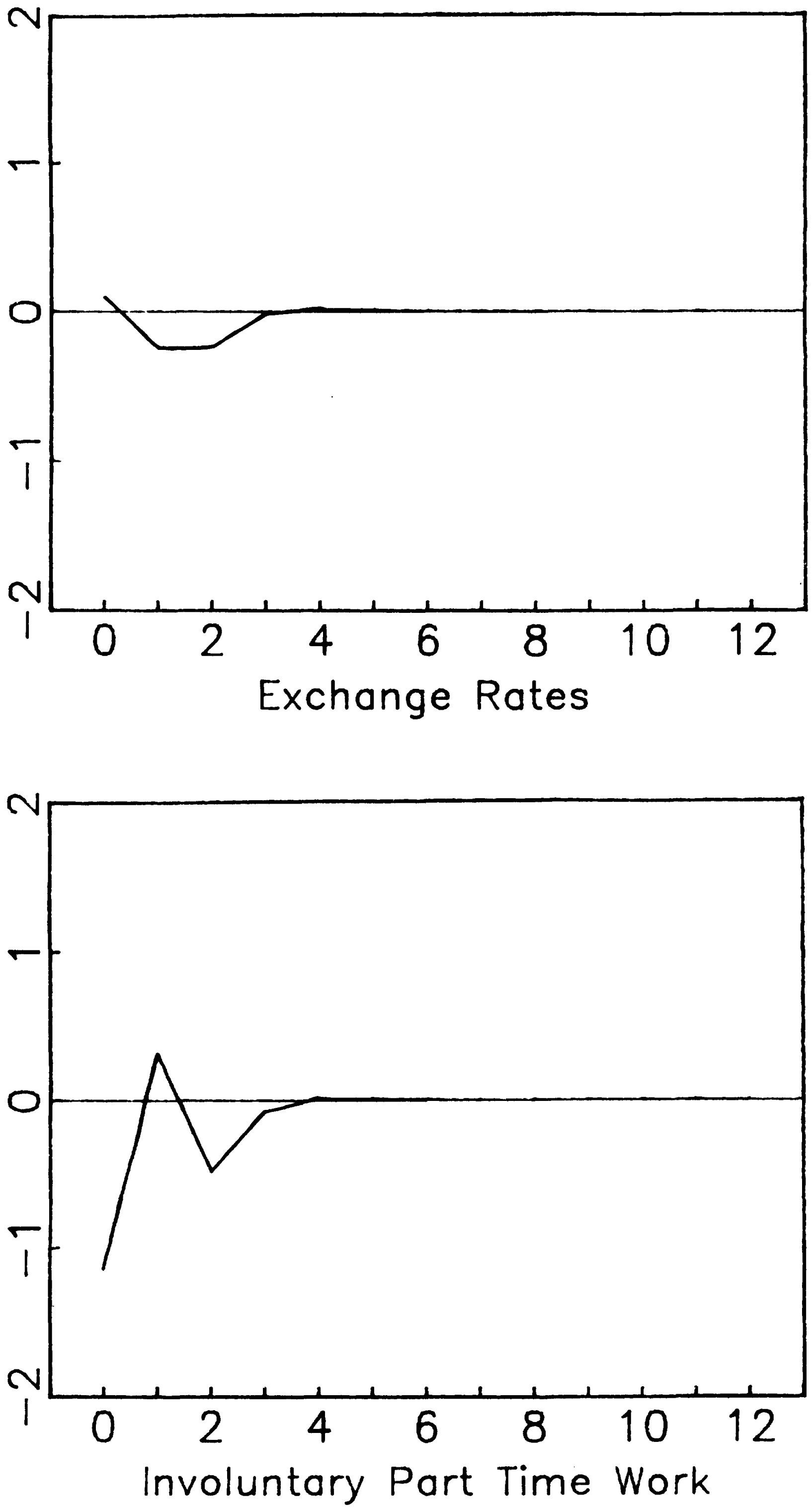


Figure 6 (CONTINUED)

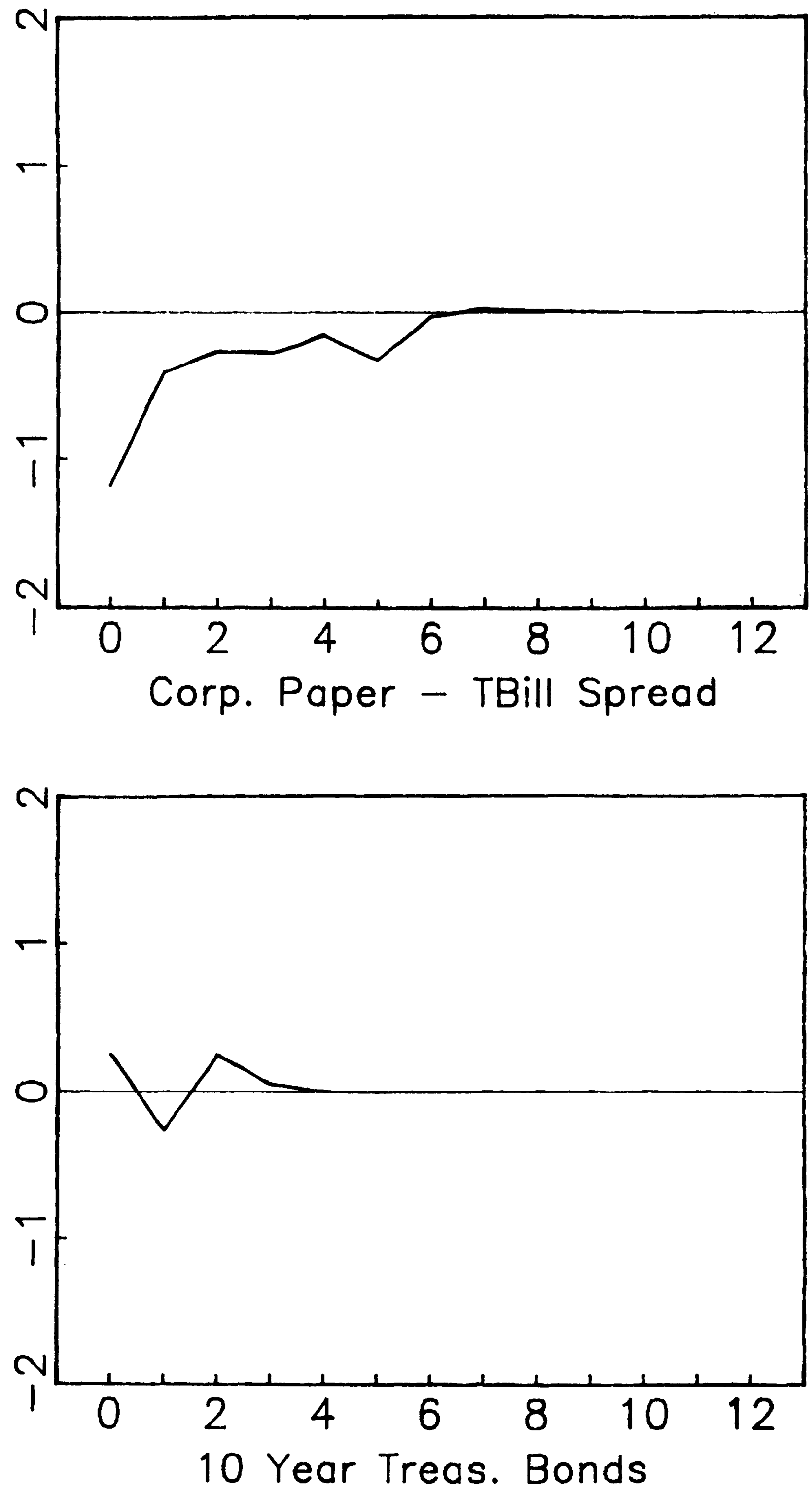
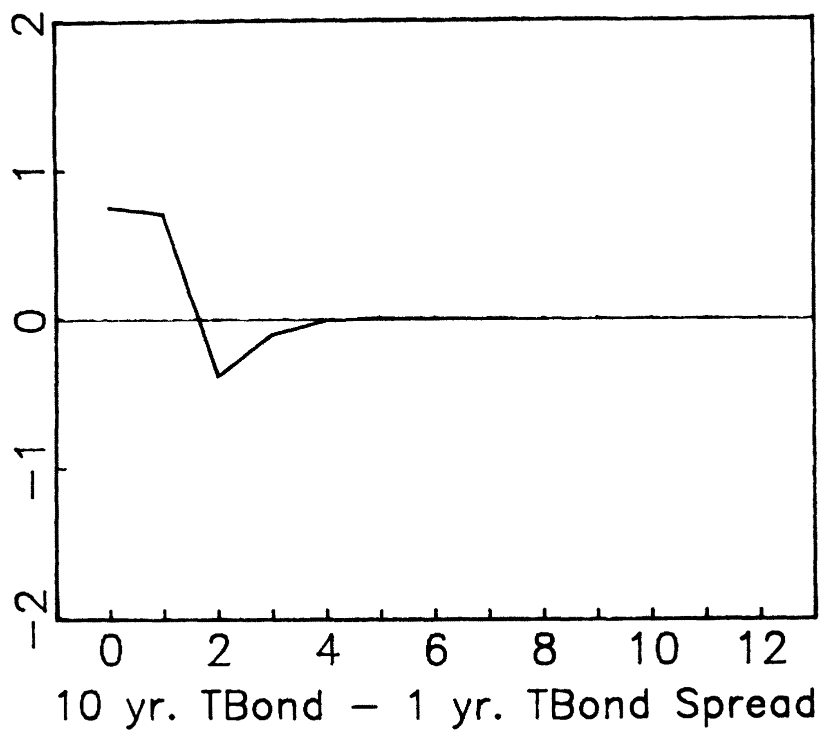


Figure 6 (CONTINUED)



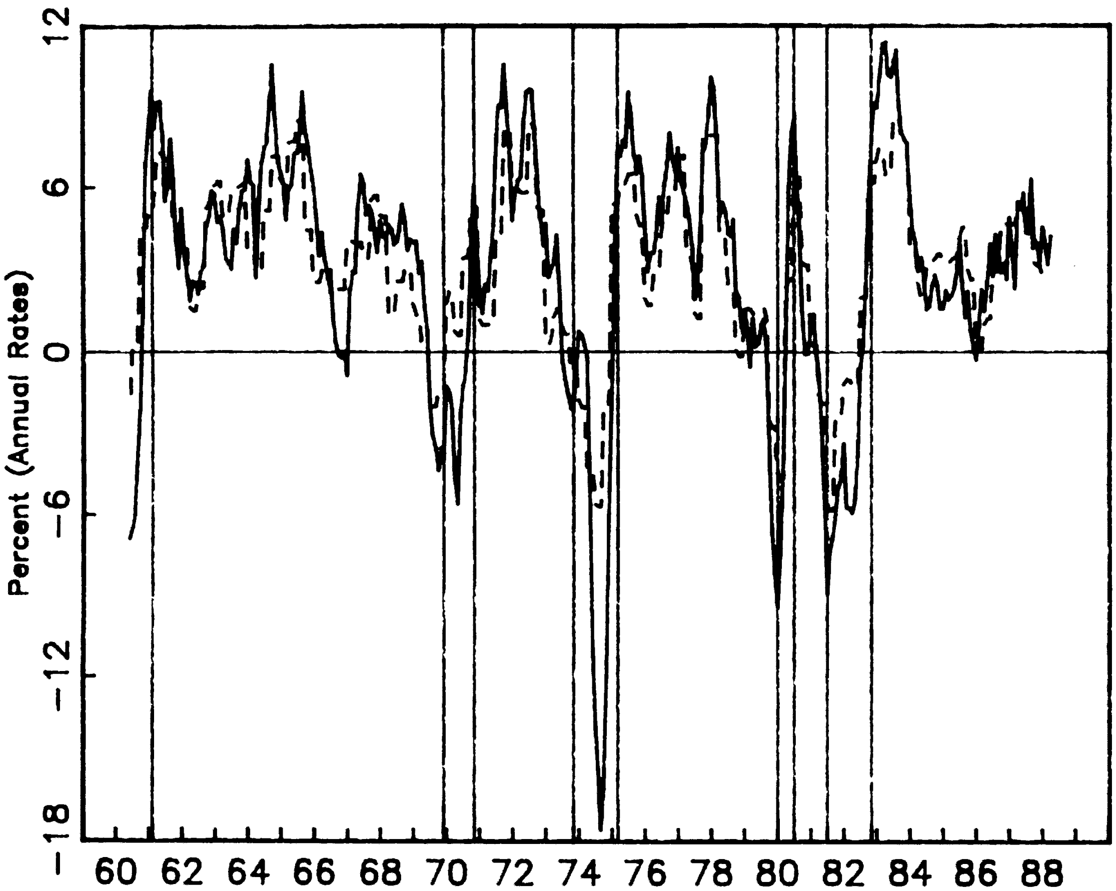
3.3. THE RECESSION INDEX

Historical values of the experimental Recession Index are plotted in Figure 3. The Recession Index is constructed using the four coincident variables and seven leading variables. Because this is the probability of a recession six months hence, the index ranges between zero and one. Ideally, these recession probabilities would lead the actual NBER-dated recessions by six months.[16]

An important check of the definition of recessions and expansions is the ex post ability of the model to confirm the NBER cyclical dates. Using all the historical data, there is close agreement between the actual NBER-dated recessions and the ex post assessments of whether there was a recession. Figure 7(a) presents the retrospective assessment of whether the economy was in a recession, with the probability calculated using the same definition as in the Recession Index. The greatest point of disagreement is the dating of the 1970 recession: the NBER chronology

16. These probabilities are evaluated by numerical integration over the recession and expansion regions described in footnote 6. The means (μ_e and μ_r) and variances ($\sigma_e = \sigma_r = \sigma$) of the random boundaries (b_{et}, b_{rt}) were chosen to minimize the sum of squared errors between the six-step ahead recession probability and the 0/1 recession-expansion variable six months hence. This criterion was computed over a grid of parameter values, and the resulting estimates are $\mu_e = .25$, $\mu_r = -1.50$, and $\sigma = 0.8$. It turns out that this objective function (and the recession probabilities) are somewhat insensitive to (μ_e, μ_r, σ).

Figure 6 B. SIX-MONTH GROWTH IN THE PROPOSED INDEX OF COINCIDENT ECONOMIC INDICATORS (SOLID LINE) AND TWO-QUARTER GROWTH IN REAL GNP (DASHED LINE) (CONTINUED)



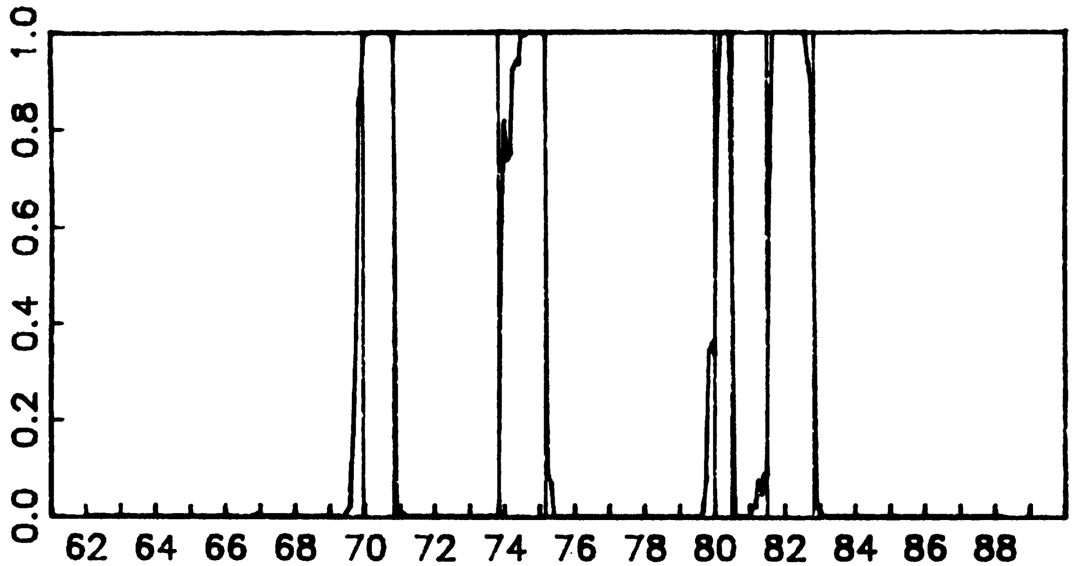
places the peak at December 1969, while this procedure places the peak at October 1969.

Also presented in Figure 7 are the contemporaneous assessments of whether the economy is in a recession (Figure 7(b)), the three-month ahead recession forecast (Figure 7(c)), and the six-month ahead recession probability (Figure 7(d); this is the proposed Recession Index).

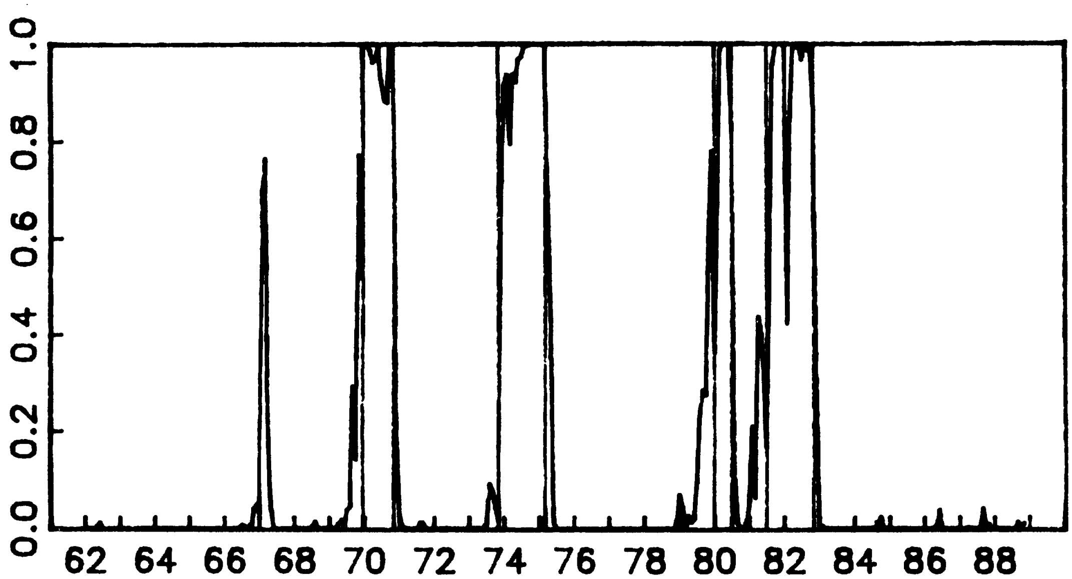
3.4. WITHIN-SAMPLE PERFORMANCE OF THE PROPOSED LEI AND RECESSION INDEX

The current DOC leading index has been the subject of considerable ongoing refinement, so one would expect it to be a good predictor of future economic activity. We therefore compare the within-sample performance of the proposed LEI and Recession Index to two sets of measures based on the DOC leading index. The first examines the ability of the DOC leading index to forecast the near-term growth in the CEI; the second examines the use of the DOC leading index to forecast future recessions.

Figure 7 RECESSION PROBABILITIES: (A) EX POST



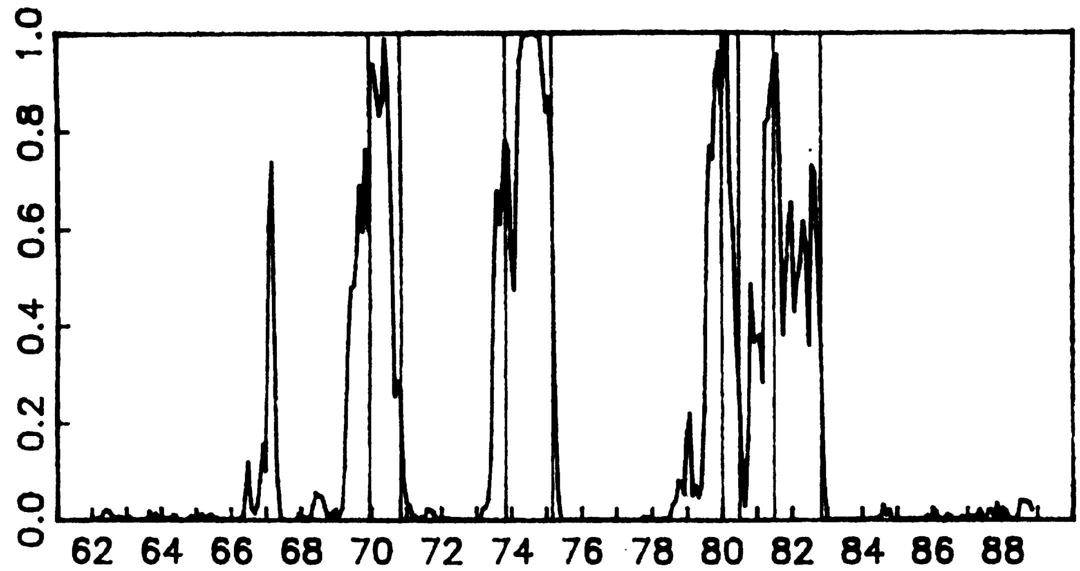
(B) CONTEMPORANEOUS



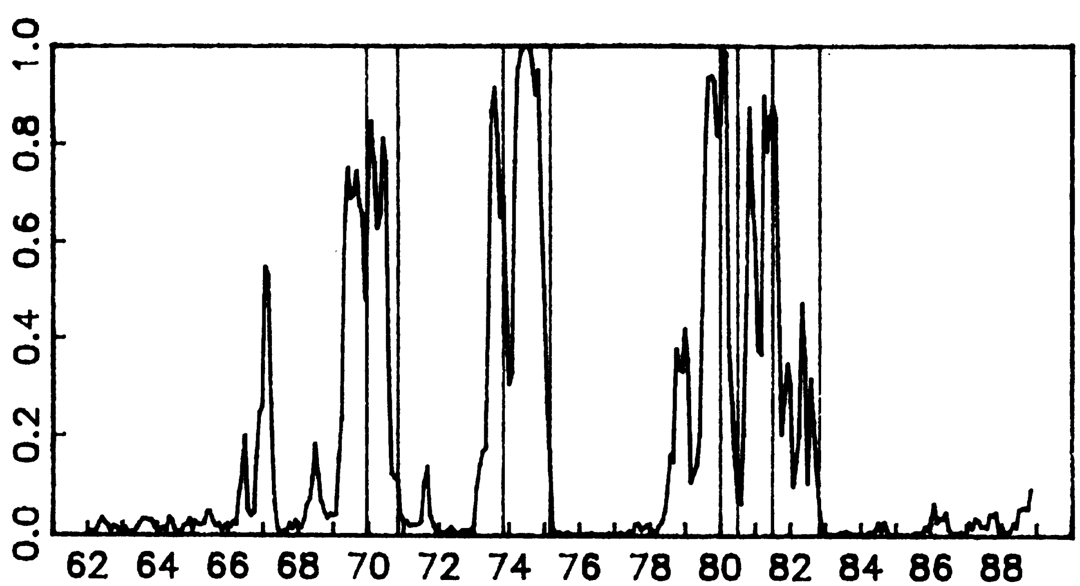
Forecasts of Growth. The within-sample fit of the proposed LEI is generally good. The within-sample R^2 between the LEI and the true six-month growth of the CEI ($C_{t+6|t+6}-C_{t|t}$) is .634 over 1961:1–1988:4. The LEI and the actual six-month growth of the CEI are plotted in Figure 8(a). The most noteworthy within-sample errors occurred in the middle of the 1982 recession: the LEI was predicting approximately zero growth, while the actual growth turned out to be sharply negative.

Because the six-month growth of the CEI is highly correlated with the two-quarter growth of GNP, one way to measure performance is to com-

Figure 7 (CONTINUED) (C) 3-MONTH AHEAD



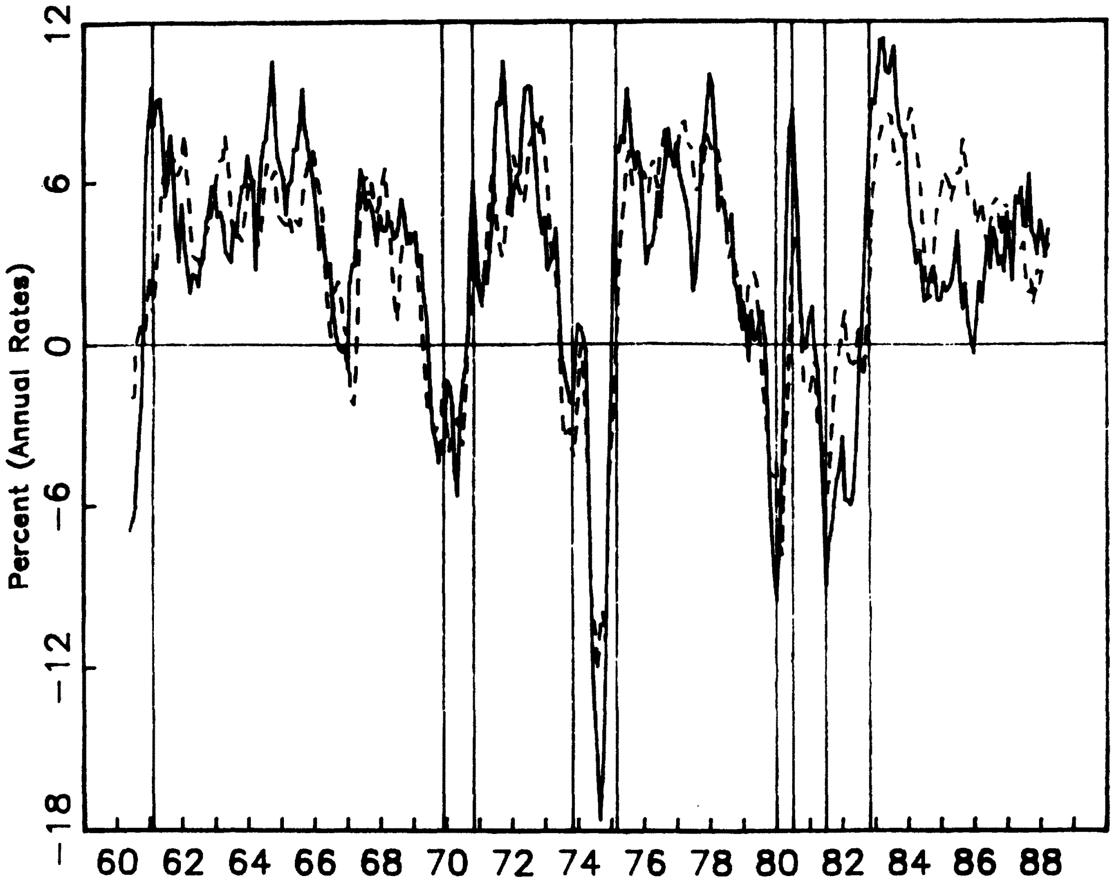
(D) 6-MONTH AHEAD



pare the growth forecast of the LEI with historical forecasts of GNP growth. Figure 8(b) presents the two-quarter growth in real GNP (con structed as in Figure 4(b)) and the ASA/NBER median forecast of real GNP growth over the subsequent two quarters.[17] Although the ASA/NBER median forecast anticipated the 1979–80 recession and contemporaneously recognized the 1980 recovery, it failed to forecast the severity of the 1974–75 recession and entirely missed the 1982 recession.

17. Prior to 1986, the ASA/NBER survey reports the median forecasts of the GNP price deflator and of nominal GNP, but not of real GNP. For this period the real GNP forecast was constructed as the ratio of these two median forecasts.

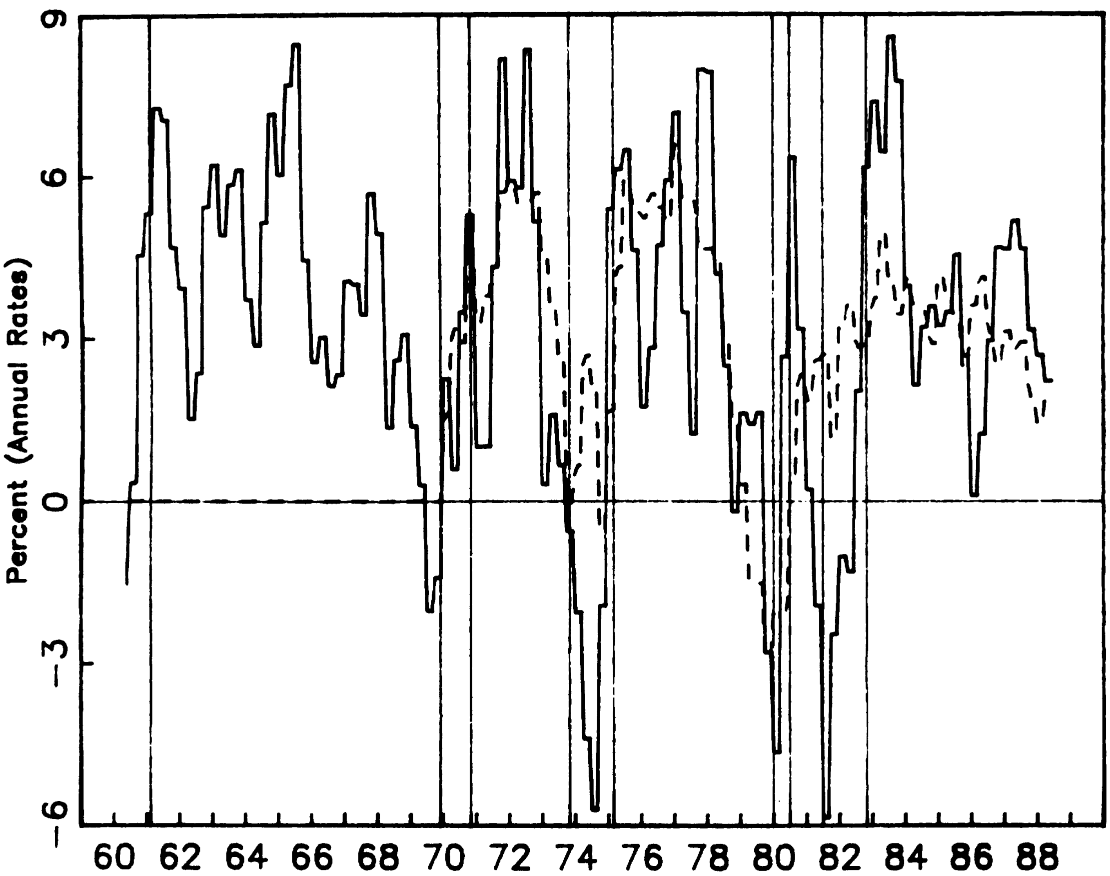
Figure 8 SIX-MONTH GROWTH IN THE CEI (SOLID) AND THE LEI (DASHED)



A natural question is whether the proposed LEI represents an improvement over the existing DOC leading index, and whether the DOC series is itself an accurate estimate of economic growth. One difficulty with evaluating the DOC series is that it is presented as a series in levels, with its primary mission to signal turning points in overall economic activity. It is, however, possible to use the DOC series as a forecast of overall growth in the DOC coincident index. Specifically, if the DOC leading index is a forecast of the DOC coincident index k months hence, then the percent difference between the DOC leading and coincident indexes is a forecast of the growth in the DOC coincident index over the next k months. Let L_t^{DOC} denote this percent difference. With $k = 6$, the R^2 between L_t^{DOC} and the six-month growth in the experimental CEI is .410 from 1960:2–1988:4; the maximal R^2 (as a function of k) is .416, which occurs at $k = 7$.[18]

18. The R^2s between L_t^{DOC} and $(C_{t+k|t+k} - C_{t|t})$ for $k = 3, 4, \ldots, 12$ are respectively, .364, .387, .399, .410, .416, .416, .413, .404, .393, and .382. The same results obtain to within ±.02 using the DOC coincident index rather than the experimental CEI. Note that historical values of the DOC leading index were revised in 1983. This suggests that the

Figure 8 B. TWO-QUARTER GROWTH IN REAL GNP (SOLID) AND ITS ASA/ MEDIAN FORECAST (CONTINUED)



The six-month growth of the proposed CEI is plotted with L_t^{DOC} in Figure 8(c) at annual rates. Although the two series are highly correlated, L_t^{DOC} exhibits somewhat greater fluctuations. In addition, the forecast implicit in L_t^{DOC} has been substantially stronger than the growth in the coincident index (or real GNP) since 1983, a point raised in popular discussions of the existing leading index.[19]

Forecasts of Recessions and Expansions. The DOC produces no series directly comparable to the proposed NBER Recession Index. To provide a basis for comparison, we examine two different recession forecasts based on the DOC leading index: a "three consecutive decline" rule-of-thumb and a limited dependent variable model with the DOC indexes as the predictive variables.

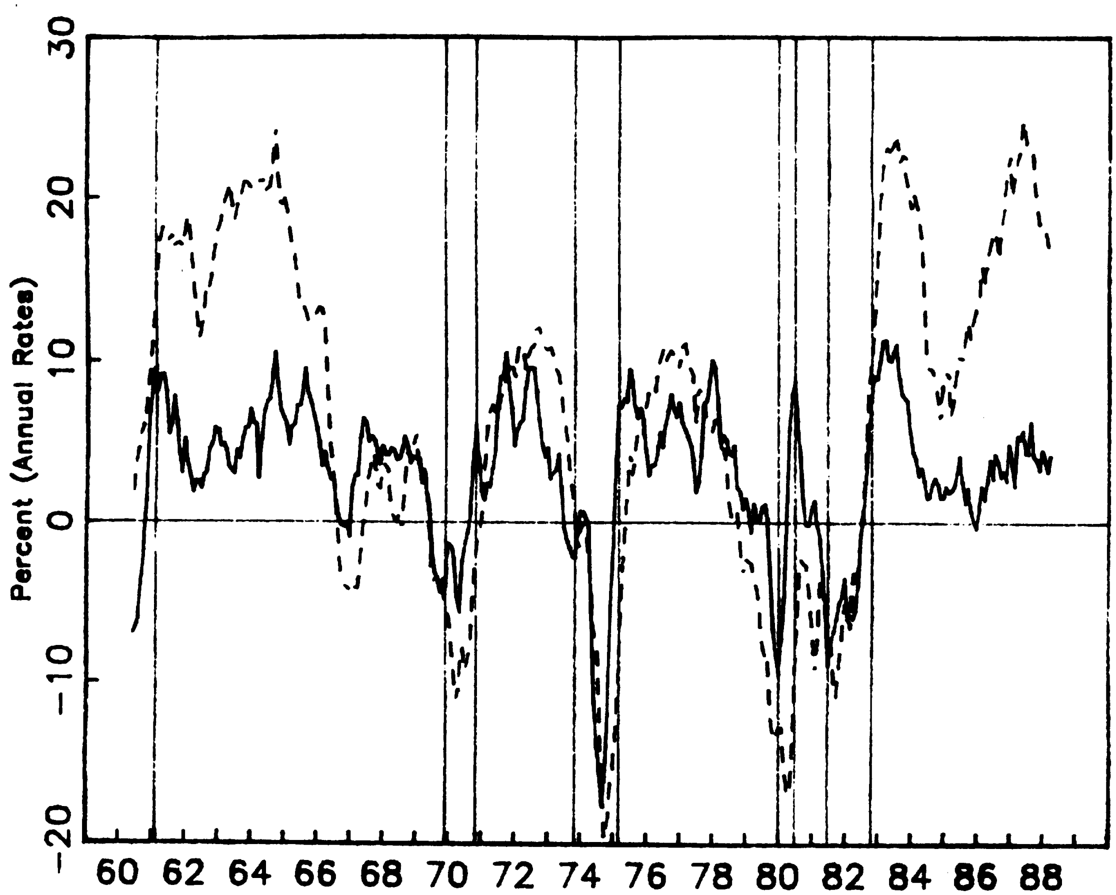
results prior to 1983 should be viewed as within-sample fits, and those after 1983 as out-of-sample forecasting experiments.

19. For example, Hunt (1988) points out that much of the strength in the DOC leading index during the mid-1980s was driven by the strong growth in stock prices.

Popular discussions of the DOC leading index use a three consecutive decline rule-of-thumb as a measure of whether the index is signalling a recession. This rule-of-thumb issues a recession signal (expansion signal) if, during an expansion (recession), the DOC leading index declines (rises) for three consecutive months. Applied systematically to the historical data, this rule-of-thumb results in a series of zeros and ones, where a zero indicates a recession signal and a one indicates an expansion signal.

One way to evaluate the performance of this recession signal is to compute the R^2 of the regression of the 0/1 variable that indicates whether the economy is actually in a recession k months hence against the series of 0's and 1's based on the DOC leading index. At a lead of k = 0 months, this R^2 is .289; at a lead of 3 months, it is .116; at 6 months, .028. The greatest of these R^2's is at a lag of 1 month, which is a "forecast" of whether the economy was in a recession in the month prior to the

Figure 8 C. SIX-MONTH GROWTH IN THE PROPOSED CEI (SOLID) AND THE SCALED PERCENT DIFFERENCE BETWEEN THE DOC LEADING AND COINCIDENT INDEXES (DASHED) (CONTINUED)



most recent month for which there are data. In contrast, the R^2 for the series in Figure 7(b)–7(d) are respectively .88 at 0 months lead, .64 at a lead of 3 months, and (for the proposed Recession Index) .50 at a lead of 6 months.

Although this rule-of-thumb is commonly used to forecast recessions, it is probably not the most efficient use of the information contained in the DOC index. As an additional comparison, logit models were estimated with the true 0/1 recession indicator six months hence as the dependent variable and with, alternately, lags of L_t^{DOC} and of the growth of the DOC leading index as predictive variables. The greatest of the resulting R^2's was .292, which obtained in a logit model with eight lags of L_t^{DOC} as the predictive variables.

In summary, these historical comparisons suggest that the proposed LEI and Recession Index are potentially substantial improvements over the existing indexes, both in performance and in ease of interpretation. Whether this potential is realized will, of course, depend on the future behavior of the indexes.

4. *Interpretation and Discussion*

The construction of the experimental LEI systematically focused on finding a set of macroeconomic variables that jointly have the ability to forecast future economic activity in a reduced-form model. This section examines the resulting index and its components from the perspective of macroeconomic theory.

4.1. DISCUSSION OF VARIABLES INCLUDED IN THE LEI

Long-term/short term treasury bond yield spread. One of the novel features of the experimental LEI is its use of interest rate spreads as macroeconomic predictors. It is generally recognized that a declining yield curve signals a future slowdown in economic activity. The 10-year/1-year Treasury bond spread became negative in 1959, 1966, 1973, 1978, and 1981; with the exception of 1966, each of these inversions in the yield curve preceded an NBER-dated cyclical peak by approximately one year. Similarly, five of the seven cessations of the inversion over this period preceded a cyclical trough by approximately six months to one year. Recent work in financial econometrics has produced the intriguing related result that measures of the slope of the yield curve are useful predictors of a variety of financial variables. For example, Campbell (1987) and Fama and French (1989) document that measures of the slope of the term structure at short horizons have predictive content for excess returns on a variety of assets.[20]

These observations are consistent with a macroeconomic theory in which real rates are temporarily high, perhaps because of tight monetary policy, which in turn results in a postponement of investment and a decline in future activity. Additionally, if market participants expect future growth to be low and believe a Phillips relation to hold, then inflation would be expected to drop and the yield curve would tend to invert. Thus this predictive content is consistent with a theory in which monetary policy works through interest rates and in which inflation and output growth are positively related. It seems to be more difficult to reconcile this finding with a simple real business cycle model in which the marginal product of capital equals the interest rate and in which persistent productivity shocks drive the business cycle: in this case, a positive productivity shock would result in a high marginal product of capital that is expected to decline over time as investment (and output) increases.

Private-public interest rate spread. Although the average spread from 1959 to 1988 is only 60 basis points, during and preceding the 1970 and 1980 recessions it exceeded 150 basis points, and during 1975 it rose to over 350 basis points. The predictive power of similar spreads has been documented by Bernanke (1983), who showed that the Baa-Treasury bond spread forecasted industrial production in the interwar period, and by Friedman and Kuttner (1989), who (independently) concluded that the corporate paper-Treasury bill spread has strong predictive power for industrial production over the period considered here. Like the slope of the yield curve, the private-public spread has recently been recognized as a predictor of various asset returns. Keim and Stambaugh (1986) find that monthly risk premiums on a variety of bonds can be explained with some success by the spread between the yield on long-term low-grade corporate paper and short-term Treasury bills (note however that the maturities in this spread are not matched).

One interpretation of these results is that the private-public spread measures the default risk on private debt. If private lenders can accurately assess increased default risks for individual firms or industries, these changes will, after aggregation, be reflected as increases in the spread. Thus the spread could serve as a useful aggregator of informa-

20. In related research, Knez, Litterman, and Scheinkman (1989) identify three common systematic risk factors underlying a variety of money market returns. They associate these factors with shifts in the yield curve, tilts in the yield curve, and changes in the public-private spread. Thus the three factors correspond closely to the three interest rate measures in the proposed LEI.

tion about the prospects of private firms, known best by those buying and selling the debt of those firms. An alternative interpretation would emphasize the allocative role of interest rates: an increase in the spread, all else equal, might induce some firms to postpone investment, resulting in a decline in aggregate demand.

Change in the 10-year Treasury bond yield. Previous research on the predictive content of various financial and monetary variables has emphasized the importance of interest rates or their changes (e.g., Sims 1980), so it is not surprising that changes in the long-term public bond rate have some forecasting content. Interestingly, including a measure of ex ante real rates (with various measures of expected inflation) does not improve the performance of the LEI. In fact, simulated out-of-sample experiments indicate that including a real rate would have dramatically worsened substantially the performance during the 1980s because of the historically high real rates since 1982.

Trade-weighted nominal exchange rate. A depreciation of the dollar relative to the currencies of its major trading partners makes a small positive contribution to the LEI. The sign and the magnitude are consistent with the depreciation being associated with a modest subsequent increase in net demand for domestically produced goods relative to foreign goods.

Part-time work in nonagricultural industries (slack work). An increase in slack work results in a substantial drop in the LEI, holding the components constant. This measure is closely related to indicators in the current DOC index (new claims for unemployment insurance and the average weekly hours of production workers in manufacturing); the procedure described in the previous section indicates that part-time work has preferable statistical properties compared with these other indicators. One interpretation of the predictive value of this series is that the initial response of some firms to productivity and demand shocks is not just to adjust inventories, but to vary labor input. In addition, this is measured better by part-time employment than by layoffs or by average hours.

Housing authorizations. This series, currently in the DOC leading index, could play several roles. Private housing is the most durable of consumer goods. Thus movements in housing authorizations could be a proxy for broader changes in demand for consumer durables, perhaps in response to movements in interest rates or to fluctuations in (the present value of) aggregate income. In addition, changes in housing authorizations could signal more widespread changes in future activity in the construction sector which, to the extent that there is a multiplier mechanism, might spill over into other sectors of the economy.

Manufacturers' unfilled orders (durable goods industries). The DOC has (independently) decided to include manufacturer's unfilled orders in durable goods industries in the revised DOC leading index starting in January 1989. Unfilled orders are much like negative inventories, and can be used (like inventories) to minimize production costs over time. Thus unfilled orders can be expected to increase in response to unexpected increases in demand or to temporary increases in production costs. The time series properties of unfilled orders will depend on the extent of production smoothing, production times, the relative mix of demand and supply shocks, and the lead-lag relation between new orders for durables and aggregate activity.

B. DISCUSSION OF SELECTED VARIABLES EXCLUDED FROM THE LEADING INDEX

The proposed LEI excludes some variables that appear in the current DOC index or which economic theory suggests could have important predictive power. Summary statistics for the effect of including several such series in the LEI are presented in Table 3. The first column presents the p-value for the F-test of the restriction that the coefficients on lags of the candidate additional leading variable are zero in a regression of the one-month growth of the CEI on the variables in the LEI and on six lags of the candidate variable. The second column contains the same statistic, except that 12 lags of the candidate variable are included in the regression. The third column contains the within-sample R^2 between the six-month growth of the CEI and the LEI, constructed using the base variables and lags described in Section 3 and 12 lags of the candidate variable. The fourth column contains the out-of-sample root mean square error from October 1979 to April 1988 based on an LEI model estimated through September 1979.[21]

Stock Prices. The present value theory of stock prices implies that movements in the stock market reflect changing expectations of future earn-

21. As a simplification, columns 3 and 4 of Table 3 are based on LEI models that were estimated using a conventional multivariate regression specified with $C_{t|t}$, y_t and the candidate leading variable. That is, C_t was not treated as unobserved as in the estimation of the LEI in Section 3, but rather was replaced by $C_{t|t}$. Now specified in terms of observables, the system was esimated by OLS equation by equation. The numerical error that arises from this simplification is slight because of the small signal extraction in $C_{t|t}$.

Table 3 EFFECT OF INCLUDING ADDITIONAL VARIABLES IN THE LEI: SUMMARY STATISTICS

Candidate Variable	—p-value— 6 lags	12 lags	R^2, 60:2 –88:4	RMSE, 79:10 –88:4
Base Model	—	—	.631	3.64
Base Model plus additional variables:				
Stock Prices				
S&P 500, growth rate	.130	.080	.658	3.57
Money and Credit				
M1 (82$s), growth rate	.662	.854	.635	4.46
M2 (82$s), growth rate	.315	.626	.642	3.64
M2 (82$s), linearly detrended growth rate	.322	.628	.641	3.73
Monetary Base (nominal), growth rate	.981	.353	.631	3.93
Change in bus. and cons. credit as % pers. inc.	.624	.720	.636	3.79
Consumer inst. loans, delinquency rate, >30 days	.260	.556	.635	3.73
Employment				
Avg weekly hours of manufacturing workers	.849	.972	.637	3.85
New claims for unempl. insurance, growth rates	.573	.603	.642	3.68
No. persons unemployed less than 5 weeks	.007	.003	.630	3.62
Sales and Consumption				
IP—consumer durables	.300	.507	.638	4.25
Pers cons expenditures, durable goods (82$s)	.721	.472	.643	3.66
Retail sales (1982$'s, smoothed)	.681	.660	.643	3.63
Retail sales, new cars (smoothed, seas. adj.)	.776	.268	.665	3.43
Inventories				
Mfg & trade inventories, total (82$s)	.497	.265	.640	3.58
Mfg & trade invt's: matl's & supplies (82$s)	.969	.990	.637	3.82
Mfg. & trade invt's: work in progress (82$s)	.258	.017	.634	3.70
Mfg & trade invt's: finished goods (82$'s)	.901	.874	.637	3.75
Additional Leading Indicators				
Contracts & orders for Plant & Eqpt (82$s)	.865	.769	.634	3.70
Mfg new orders, cons. goods & matl's (82$s)	.530	.515	.627	4.12
Construction contracts, comm & indust bldgs	.960	.906	.633	3.88

Notes: The first two columns present the p-value for the conventional F-test (without any additional degrees-of-freedom adjustment) of the hypothesis that the coefficients on the candidate leading variable are zero in a regression of $\Delta C_{t|t}$ on the base set of leading variables (with the same number of lags as are used to construct the NBER LEI), estimated by OLS, using 6 and 12 lags respectively of the candidate variable. The third column presents the within-sample R^2 when the LEI model is estimated using the full sample and 12 lags of the candidate variable. The final column contains the out-of-column RMSE between the LEI and $C_{t+6|t+6} - C_{t|t}$, in which the LEI model (augmented by 12 lags of the candidate variable) is estimated over 60:2–79:9.

ings of publicly traded corporations. Additional theoretical links from the stock market to future economic activity come through the role of stock prices as a determinant of the cost of capital (q-theory) and through wealth effects on consumption. Stock prices therefore ought to be an indicator of future growth, and indeed were identified as leading indicators by Mitchell and Burns (1938). Fama (1981) and Fisher and Merton (1984) document the substantial predictive value of stock prices for output. As they do for GNP at longer horizons, stock prices have strong predictive content for the growth in the CEI; the R^2 of a regression of $C_{t+6|t+6} - C_{t|t}$ on 12 lags of the growth in the Standard and Poor's 500 is .318, and the hypothesis that the growth of the S&P 500 does not Granger-cause $\Delta C_{t|t}$ can be rejected at the .5% significance level.

A result from this research is that the *marginal* predictive content of stock prices for the six-month growth in the CEI is modest. As reported in Table 3, the hypothesis that stock prices have no marginal (linear) predictive content for $\Delta C_{t|t}$ cannot be rejected at the 5% level.[22] Although the R^2 for the six-step ahead forecast increases somewhat when S&P 500 growth is included, this specification increases the number of estimated parameters in the $\Delta C_{t|t}$ equation from 28 to 40. Although there is some evidence that the stock market improves forecasting performance, this improvement is slight. These findings are consistent with a view that, from the perspective of forecasting, the expectational aspect of the stock market dominates its allocative role, and that these expectations can be captured by examining other variables.

Money and Credit. The marginal predictive content of money for output is one of the most studied relations in empirical macroeconomics; see Christiano and Ljungqvist (1988) and Stock and Watson (1989) for recent results and reviews of the literature. A primary focus of this literature has been whether the predictive content of money growth in a bivariate system is eliminated by including an interest rate. The proposed LEI provides an opportunity to examine the marginal predictive content of money in a system with measures of real activity and, notably, with a richer set of interest rates.

The predictive content of real $M2$ growth in a bivariate system with $\Delta C_{t|t}$ is substantial: Granger non-causality can be rejected at the 0.5% level, and the R^2 of the regression of $C_{t+6|t+6} - C_{t|t}$ onto 12 lags of real $M2$ is .435. As the results in Table 3 indicate, however, on the margin real $M1$, real $M2$, and the monetary base add nothing to the forecasting ability of

22. The large number of variables involved in the search suggests skepticism about the use of the usual asymptotic distributions for these test statistics. An informal way to correct for this is to use a more conservative critical value than usual, say 1%.

the LEI. The simulated out-of-sample performance of the index including $M1$ deteriorates substantially, indicating parameter instability. These results hold using either the growth rate of $M2$ or, as suggested by Stock and Watson (1989), the detrended growth rate.

These findings are consistent with several hypotheses. Friedman (1988) argues that even if money had predictive content during earlier periods, its reduced-form relation to output has changed (or vanished) as a result of financial deregulation. This is consistent with the observation that the economy has performed well in the last two years despite the absolute decline of real $M2$ between October 1986 and October 1988. Alternatively, the inclusion of interest rate spreads (in particular the yield curve) might be a more sensitive measure to monetary intervention than is the interest rate alone, the variable typically examined by other authors.

Measures of the quantity of credit have also received some attention as possible predictive variables. The change in business and consumer credit appears in the current DOC leading index; scaled to be a percent of personal income rather than in nominal dollars, this change has no statistically significant predictive content.

Employment. The DOC leading index contains two employment series not in the proposed LEI: average weekly hours of manufacturing workers and new claims for unemployment insurance. Neither make an important marginal contribution to the proposed LEI.[23] While the number of individuals unemployed less than five weeks is a statistically significant predictor of $\Delta C_{t|t}$ at the 5% level, the six-month ahead forecast is not improved by including it in the index.

Sales and Consumption. The Permanent Income Hypothesis and the Life Cycle Hypothesis imply that, like stock prices, changes in consumption reflect changes in expectations of future income. The Keynesian aggregate model suggests that changes in consumption can produce changes in income and employment. In real business cycle models, changes in consumption—even if predictable—reflect optimal responses to changes in productivity or other real disturbances and thus portend future movements in output. The standard versions of these theories refer to service flows from consumption goods, not to consumption expenditures. Theories that explicitly incorporate durability

23. New claims for unemployment insurance have the drawback of being sensitive to changes in unemployment insurance regulations and in patterns of application for unemployment insurance among those eligible.

suggest that expenditures on durables might be particularly sensitive to shocks perceived by consumers.

The predictive content of various measures of consumption is, however, slight. Of the four measures listed in Table 3, only real retail sales and auto sales reject Granger non-causality at the 5% level in a bivariate system with $\Delta C_{t|t}$. When the experimental LEI is augmented by the various measures of consumption, they have no statistically significant marginal predictive content. One interpretation of these results is that housing starts are a measure of demand for consumer durables, so that including housing starts (and interest rates) in the LEI reduces the predictive value of other measures of consumption.

Inventories. Theoretical models of inventory behavior variously suggest that inventories will be sensitive to changes in current demand, to innovations in current demand, to expected changes in future demand, or to (changes in, innovations in, expectations of) costs of production. In addition, theory suggests that inventories at various stages of production will respond differently to different types of shocks. A series on smoothed changes in manufacturing and trade inventories appeared in the current DOC leading index (it was dropped in the 1989 revision), and inventories exhibit a strong coherence with the $\Delta C_{t|t}$ at low frequencies. The marginal predictive content of inventories for output is, however, slight. Although the growth in real intermediate inventories makes a statistically significant contribution to forecasting $\Delta C_{t|t}$ when 12 lags are included (based on the conventional 5% level), the improvement in the six-month ahead R^2 is minimal.[24]

Investment variables in the DOC leading index. The Keynesian multiplier-accelerator model gives an important role to investment as a determinant of output. Real business cycle models hold that expectations of future demand and changes in productivity are important determinants of investment. Both theories suggest that measures of investment could help to predict future economic performance. The current DOC leading index includes two variables that measure investment but which have insignificant marginal predictive value when incorporated in the experimental LEI. Neither contracts and orders for plant and equipment nor

24. Reagan and Sheehan (1985) use VARs to examine inventories, orders, and production. They conclude that inventories (particularly work-in-progress) have important predictive content for production at the 1–3 year horizon and attribute less of a role to unfilled orders, particularly for non-durables. Their findings depend on the innovation triangularizations for their VARs, and they do not consider interest rates. Still, their results stand in contrast to the limited additional predictive content of inventories found here.

manufacturers' new orders make a discernible marginal contribution. Moreover, these series effectively receive zero weight when entered into the index.

5. Conclusions

A strength of the traditional system of leading and coincident indicators is its examination of many series without imposing too much prior information, and its subsequent identification of those series that appear to have the greatest predictive content for aggregate economic activity. The research reported here has adopted this approach and has attempted to improve upon it by recasting it in a form in which modern statistical theory can be applied. In particular, the emphasis has been on multivariate rather than bivariate predictive content.

This exercise in modern business cycle analysis has focused on forecasting with reduced-form models. We think, however, that the results provide three sets of observations for macroeconomic theory. First, the single-index model imposes restrictions on the joint time series properties of the major coincident series that are not rejected by the data. In principle aggregate shocks could enter these series separately, with different dynamic effects; in practice they appear not to. This does not imply that there is a single source of aggregate fluctuations, but rather that the multiple sources of fluctuations have proportional dynamic effects on these aggregate variables.

The second set of observations concern the variables that are included in the index. In particular, this systematic empirical investigation has identified two potent new variables not in the current DOC list of leading indicators: the spread between interest rates on private and public debt instruments of matched maturities and a measure of the slope of the public debt yield curve.

The third set of observations concerns those variables that are excluded from the LEI. Although arguments can be made in favor of some additional series, in general monthly measures of money and credit, employment, consumption, inventories, investment, and the stock market have little marginal predictive content for the coincident index. This is of additional interest in light of the emphasis placed on these series by modern macroeconomic theory.

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Comment

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Textbook classical statistical theory assumes that we begin an inference with a model known exactly except for the values of a few parameters, about which nothing is known. Most classical time series statistical theory is convenient only in "large samples." However, when we set out to forecast macroeconomic time series we find instead that economic theory gives us at best imprecise knowledge of the appropriate model. There are many time series available with plausible connections to the ones we would like to forecast, and the result is so many unknown parameters in any honest model that there are not enough data to determine parameter values well. Samples are not "large," in other words, relative to the level of our ignorance. And it seems apparent that on top of all these difficulties, the stochastic structure of the economy changes over time, not just (or even mainly) because of changes in economic policy, but because of shifts in population, technology, tastes, and resource availability.

In practice, those who forecast regularly understand that textbook