

**Forecasting with Leading Indicators:
Lessons from the 1990 Recession in the United States**

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This paper examines the performance of economic forecasts during the 1990 recession in the United States and draws some lessons for forecasting from this experience. The paper has three specific objectives. The first is to examine short-term forecasts during this recession, focusing in particular on forecasts based on a time-series model using leading economic indicators. The 1990 recession provides an interesting case study for evaluating forecast performance under the unusual conditions of a broadly weak economy facing the prospect of oil supply disruptions and war in the Persian Gulf. A main conclusion from this investigation is that historical predictive relationships performed poorly during the onset and early months of the 1990 recession, resulting in large and persistent forecast errors. Given this finding, the second objective of the paper is to examine whether this instability of predictive relationships is limited to this one episode and to only a few variables. Our results suggest that, over past three decades in the U.S., predictive instability is the rule rather than the exception for certain classes of leading indicators, in particular financial market indicators. This leads to the third objective, which is to explore the performance of leading-indicator based forecasting systems which explicitly allow for time variation in the forecasting relationships.

Most economic forecasters had substantial difficulty predicting the sharp drops in economic activity in the fall of 1990, even well after the official peak of July 1990. Forecasts compiled by the Blue Chip survey of economic forecasters are summarized in Table 1.¹ In May 1990, the mean forecast of real GNP growth over 1990-1991 among the Blue Chip survey participants stood at 2.3%. Although oil prices jumped and the stock market crashed when Iraq invaded Kuwait in early August 1990, in the September 1990 survey the Blue Chip mean forecast for 1990-1991 had only declined to 1.2%, and only one-fifth of the forecasters predicted zero or negative GNP growth. When the forecasters were asked when the next recession would begin, only 10% in the May survey correctly predicted that it would begin in 1990. By September

1991, still only 50% forecasted that a recession would begin in 1990. The conventional view, however, is that the recession forecasts in the September survey were based not on formal models but rather on the forecasters' intuition.

To understand the sources of these poor forecasts it is useful to examine individual models or forecasting systems in detail. This results of such an analysis are reported here for the monthly leading indicator forecasting model developed in Stock and Watson (1989). This model uses seven leading indicators to forecast short-term growth of the U.S. economy, where short-term growth is measured by an index of four coincident indicators. Since its estimation in early 1989, this model has been used to produce three indexes on a monthly basis: an experimental coincident index (XCI), an experimental leading index (XLI), and an experimental recession index (XRI). The XCI is a monthly estimate of the current state of the economy, a composite index constructed from the four coincident economic indicators. The XLI is a forecast, based on current and past values of the leading and coincident indicators, of the growth of the XLI over the next six months. The XRI is an estimate of the probability that the economy will be in a recession in six months, and so ranges between zero and one. This model is summarized in Section 1.

The performance of this model over the 1990 recession is analyzed in Section 2. The forecasts produced by the system through the early summer of 1990 were quite accurate; for example, in June 1990 the XLI model forecasted a .4% (annual rate) decline in the experimental coincident index from June through September, when in fact the decline was only slightly greater, .8%. However, the XLI failed to forecast the sharp declines of October and November 1990. A key source of the forecast error was the use of financial variables during a recession that was associated with a neutral-to-expansionary monetary policy. These financial variables – a measure of the slope the U.S. Treasury bond yield curve and, to a lesser extent, a risk premium on short-term private debt relative to matched-maturity U.S. Treasury bonds – gave optimistic signals throughout this episode, even in the late fall of 1990 when the perception of

the business community and the general public was that a recession had already begun, and that a continued decline was inevitable.

These findings raise two questions. First, were these changing predictive relationships isolated to these financial spreads or were they generic to other series, both during this episode and during earlier periods? Second, what are the implications of these changing relationships for model-based forecasting with leading indicators?

These questions are addressed in the next two sections. Section 3 reports results from a preliminary investigation of the possibility that the instability of empirical reduced-form predictive relationships is widespread. The preliminary findings suggest that there is substantial evidence of instability in predictive relations, particularly involving quantities of money and credit. Section 4 presents forecasting results for a model in which the predictive relations are allowed to evolve over time, adapting to persistent forecast errors. The specific model used is a tightly parameterized time-varying parameter model specified with the set of leading indicators used to construct the XLI. Section 5 concludes.

I. The Model and Variable Selection

This section provides an overview of the experimental leading indicator forecasting system developed as part of the National Bureau of Economic Research's project on leading and coincident economic indicators. The purpose of the research project, of which this forecasting system is a part, is to take advantage of recent advances in computational capacity and the theory of time series analysis to reexamine the construction of economic forecasts using leading economic indicators.

This project has three components. The first is the XCI, which provides a monthly measure of the state of real economic activity in the economy. One motivation for constructing such an

index is that the standard broad measure of economic activity, real GDP, is collected quarterly; the available monthly series, such as industrial production and real personal income, are related to GDP but each series has substantial measurement error and a narrower or different scope than GDP.

The second component is the XLI, which is used to forecast short-term growth, specifically growth in the experimental coincident index over the next six months.

The third component is the XRI, an estimate of whether the economy will be in a recession six months hence. The prediction of business cycle turning points has been one of the core problems of business cycle analysis, and this line of research has been pursued by a number of authors (see for example Kling [1987], Hymans [1973], Neftci [1982], Wecker [1979], and Zellner, Hong, and Gulati [1987]). Rather than trying to forecast turning points directly, however, the approach underlying the XRI is to forecast a 0/1 variable that indicates whether the economy will be in a recession in a given month. Recessions and expansions are then defined as particular patterns of economic activity, so that whether or not the economy will be in a recession in, say, six months is equivalent to whether or not the path of overall economic activity six months hence falls in a recessionary or expansionary pattern. With quantitative definitions for these two patterns, the probability that the economy is in a recession during a future month can then be computed by the stochastic simulation of a model that forecasts future economic activity.

The coincident index and forecasts of growth rates

We now turn to a brief description of the model used to compute the XCI and the XLI; discussions of computational details can be found in Stock and Watson (1989, 1991).

Throughout, x_t refers to a vector of monthly coincident indicators – in our empirical implementation, industrial production, employee-hours in nonagricultural establishments, real personal income less transfers, and real manufacturing and trade sales, all specified in

logarithms, so that Δx_t is the monthly decimal growth rate of the four variables. Also y_t refers to a vector of monthly leading indicators, such as the number of building permits issued, where the variables in y_t have been transformed so that they are stationary, in the sense of not exhibiting stochastic or deterministic time trends. The XCI is a weighted average of current and lagged values of the four coincident variables in x_t designed to measure the common movements in these series over the business cycle. The XLI is a forecast of the growth of the XCI over the next six months at an annual rate, constructed using current and lagged values of x_t and y_t .

Both of these indexes are computed in the framework of a dynamic single index model of the form proposed by Sargent and Sims (1977) and used, for example, by Geweke (1977) and Singleton (1980); this is an extension to time series of the more familiar factor model often applied to cross-sectional data. The central notion of the dynamic single index model is that the comovements of the coincident variables at all leads and lags can be thought of as arising from a single common source c_t , a scalar unobserved time series that can be thought of as the overall state of the economy. The idiosyncratic component of the growth of each of the coincident variables (the part not arising from leads and lags of c_t) is assumed to be stationary and uncorrelated with the idiosyncratic components of the other variables, but otherwise can have a rich serial correlation structure.

The coincident part of the model is specified as,

$$(1) \quad \Delta x_t = \beta + \gamma(L)\Delta c_t + u_t$$

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

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

where (ϵ_t, η_t) are serially uncorrelated with a diagonal covariance matrix, where $D(L) = \text{diag}[d_{ii}(L)]$, and where L is the lag operator. To fix the timing c_t , one of the elements of $\gamma(L)$, say $\gamma_i(L)$, is set equal to γ_{i0} (in the empirical model, $\gamma_i(L) = \gamma_{i0}$ for three of the four coincident variables used).

Leading indicators are added to the model to help predict future values of c_t by replacing (3) with the vector autoregressive system,

$$(4) \quad \Delta c_t = \mu_c + \lambda_{cc}(L)\Delta c_{t-1} + \lambda_{cy}(L)y_{t-1} + \nu_{ct}$$

$$(5) \quad y_t = \mu_y + \lambda_{yc}(L)\Delta c_{t-1} + \lambda_{yy}(L)y_{t-1} + \nu_{yt}$$

where $\nu_t = (\nu'_{ct} \ \nu'_{yt})'$ is serially uncorrelated with mean zero and is independent of ϵ_t .

The XCI is the minimum mean square error (MMSE) linear estimate of the unobserved component c_t , using data on x_t through time t ; this is denoted $c_{t|t}$. The XLI is the MMSE estimate of the six-month growth in the coincident index at an annual rate, $200(c_{t+6} - c_t)$ (recall that x_t is specified in first differences of logarithms, that is, monthly decimal growth rates) using data on $(x_t, y_t, x_{t-1}, y_{t-1}, \dots)$; this corresponds to $200(c_{t+6|t} - c_{t|t})$. These MMSE estimates are obtained using the Kalman filter.

Two refinements of this model are needed for it to be used to generate real-time forecasts. First, many of the time series are subject to several revisions, and these revisions can be large. To obtain MMSE estimates and forecasts of (c_t, c_{t+1}, \dots) based on these preliminary data, the revisions process needs to be taken into account. The system which is used to generate real-time forecasts therefore contains additional equations which model the measurement error in the preliminary data. Second, some series, such as manufacturing and trade sales, are available with a one-month lag; these missing data make the mechanical application of the XCI/XLI model impossible. However, the Kalman filter setup is well-suited to handling these

missing observations, and the appropriate modifications are made in the version of the model used for real-time forecasting. The details of how these two data irregularities are handled are given in Stock and Watson (1992).

The coincident and leading series used in the model were selected using a modified stepwise regression procedure described in Stock and Watson (1989). The series are listed in Table 2.

Empirically, the XCI can be thought of as a monthly proxy for real GNP or real GDP. The correlation between the six-month growth of the XCI and real GNP is large, approximately .88. Although the mean growth of the XCI and real GNP are approximately equal over this period, XCI growth is more volatile and the regression coefficient of GNP growth onto XCI growth is .58. This implies that XCI growth of zero corresponds approximately to GNP growth of 1.3%.

Recession forecasts

A key aspect of this project is forecasting recessions, which is done using the XRI. This in turn requires a mathematical definition of recessions and expansions. Burns and Mitchell (1946, p. 3) provide a somewhat vague but nonetheless useful description of a recession as a substantial prolonged decline in economic activity that occurs broadly across various sectors of the economy. More recent working definitions used by business cycle analysts refine these ideas and emphasize three qualitative features which characterize a recession: the episode should be sufficiently long ("duration"), it should involve a substantial decline in economic activity ("depth"), and it should encompass most or all of the sectors of the economy rather than simply reflecting an isolated decline in a single sector or region ("diffusion").

The generally accepted business cycle chronology is maintained by the NBER's Business Cycle Dating Committee. In practice, each individual on the committee must trade off these various parts of the definition to decide whether a particular episode warrants classification as a recession. The committee eschews numerical rules, which would limit its flexibility in deeming a particular episode a recession.

The quantitative definition of a recession adopted here attempts to capture, in a simple way, the institutional process in which recessions are categorized. We define a recession in terms of the growth of the unobserved state of the economy, Δc_t ; this embodies the requirement that the recession be economy-wide, not specific to only one or two individual series. The problem of classifying a sequence $\{\Delta c_t\}$ as a recession or an expansion is treated as a problem in pattern recognition: if the sequence falls in a recessionary pattern then it is classified as a recession, if it falls in an expansionary pattern it is an expansion. The recessionary and expansionary patterns that are possible in a sequence $(\Delta c_{t-k+1}, \dots, \Delta c_t)$ of length k constitute subsets of \mathbb{R}^k ; whether such a sequence is an expansion or a recession depends on which subset the sequence falls in.

After some experimentation, we have adopted two elementary recessionary patterns. In the first, D_1 , Δc_t falls below a threshold $b_{r,t}$ for 6 consecutive months; in the second, D_2 , Δc_t falls below $b_{r,t}$ for 7 of 9 consecutive months, including the first and last month. Two elementary expansionary patterns are defined analogously, with growth being above rather than below a threshold $b_{e,t}$. These thresholds $(b_{r,t}, b_{e,t})$ are treated as random with a normal distribution, an attempt to capture the fact that our model omits some variables which might be examined by the NBER Business Cycle Dating Committee. Details about the computation of the recession probabilities are given in Stock and Watson (1992).

The published XRI is the estimate that the economy will be in a recession six months hence. The model is, however, capable of producing forecasts of being in a recession at any arbitrary date in the future or, for that matter, in the past. Thus $P_{t+k|t}$ denotes the probability of being in a recession in month $t+k$ given data through month t , so that in this notation the XRI is $P_{t+6|t}$.

Comparisons with the U.S. Department of Commerce's indexes

It is useful to contrast these three indexes with the indexes of coincident and leading indicators presently produced by the U.S. Department of Commerce (DOC). The DOC's

indexes evolved from a tradition of business cycle analysis dating from the pioneering work by Mitchell and Burns (1938), in which they originally proposed the use of a system of leading indicators to predict swings in the business cycle.

There are four main differences between the DOC coincident index and the XCI. First, the series in the XCI are the same four series as are used to construct the official DOC coincident index, with the exception that the DOC uses employment in nonagricultural establishments while the XCI uses employee-hours in nonagricultural establishments. Second, the XCI uses both current and lagged values of the coincident indicators but the DOC index uses only current values; this use of lagged values is a consequence of the MMSE filtering used to construct the XCI. (As a practical matter, most of the weight falls on contemporaneous values of the coincident indicators.) Third, one of the coincident series, real manufacturing and trade sales, is available only with a lag of an additional month; the missing data component of the XCI model, described above, adjusts for this to construct MMSE estimates using only the data on the three available series. Fourth, the methods used to construct the mean growth rates in the two indexes differ. The DOC coincident index normalizes the mean growth rate to be that of GDP, thereby permitting the weight on the cyclical component of the series to differ from that on the trend component. In practice, the weight on the cyclical component is 1.83 times the weight on the trend component for the DOC coincident index. A consequence of this is that, in periods of low growth, each of the component series might be showing positive but below-average growth, but the DOC coincident index would be showing negative growth. The XCI employs the same weights on the cyclical and trend components and thus avoids this problem. This point is particularly important for the dating of cyclical peaks and troughs when growth around the turning points is slow but positive. This difference between the XCI and the DOC index is discussed in detail in Green and Beckman (1992).

The XLI is conceptually quite different than the DOC leading index. The DOC leading index is the cumulation of a weighted average of the growth or changes in several component

indicators and is not evaluated in terms of explicit forecasting horizons. Rather, its component series are chosen so that historically the DOC leading index exhibits turning points approximately six months before cyclical peaks and troughs. In this sense, the DOC index plays two roles: to forecast growth in the overall economy, and to provide early signals of turning points. The XLI and the XRI separate these two functions: the XLI is specifically developed as a forecast of the growth in the XCI over the next six months, while the XRI is an estimate of whether the economy will be in a recession six months hence. By being more precise about what is being forecast and the time horizon of that forecast, the XLI and the XRI have the potential to be more directly useful and interpretable, and in any event it is easier to evaluate their performance.

2. Lessons from the 1990 Recession

Forecast performance

The probability model described in the previous section was developed and estimated using data through September 1988. Since May 1989, the XCI, XRI and XLI have been publicly released on a monthly basis, with release dates approximately coinciding with the release by the U.S. DOC of their composite indexes of leading, lagging and coincident indicators. Thus, the performance of the XLI and XRI since October 1988 provides a true out-of-sample test of the model.

Historical values of the XLI, XRI, and XCI are plotted in figures 1-3, respectively. The vertical lines denote NBER-dated cyclical turning points. At the time that this paper was written, the trough of the recession which began in 1990 has not yet been determined by the NBER Business Cycle Dating Committee. Based on currently available data, the XCI achieved its lowest value since the cyclical peak of July 1990 in March 1991. However, growth since March 1991 has been slow, well below average.

In theory, the recession probabilities plotted in figure 3 should be high six months prior to a recession. A striking feature of this plot is the good performance of these recession probabilities up to the July 1990 peak and their poor performance just before and during the 1990 recession.

The historical performance of the XLI model, based on data through July 1992, is examined in more detail in figure 4. Figure 4a plots the predicted and actual values of 3-month ahead growth in the XCI at annual rates, while figure 4b plots the predicted and actual 6-month growth (the predicted value being the XLI). This plot suggests it is useful to examine the performance of the model over three episodes: from October 1988 through May 1990; during the summer and early fall of 1990; and from January 1991 to the present. The performance within sample and during these first two out-of-sample episodes is summarized in Table 3 in terms of the RMSE and mean absolute errors (MAE) of the forecasts.

The performance during the first episode is quite good. During the fall of 1988 and the winter of 1989, interest rates rose substantially, by many reports in conjunction with an attempt by the Federal Reserve Board to control inflation; for example, the six-month Treasury bill rate rose from 7.5% in October 1988 to 8.85% in March 1989. With the easing of interest rates in the spring of 1989, the financial market indicators in the XLI became more optimistic: by July, the commercial paper - Treasury bill spread had fallen to 58 basis points, just above its postwar average and well below its March peak of 113 basis points. With this decline in interest rates and spreads, the XLI forecasted increased growth: based on unrevised data (i.e., as the XLI was originally computed), the XLI for March was -1.1%, while by July the XLI had risen to 0.7%. The behavior of the XLI forecasts was broadly consistent with the overall outlook at the time as reported in the economic and financial press, which was one of general concern over economic conditions in the early spring being replaced by cautious optimism in the late spring and early summer.² As can be seen from Figure 4, over this episode the XLI model provided very good forecasts of overall activity, not only at the six-month horizon for which it

had been optimized, but also at the three-month horizon. During this episode, the XRI indicated an increased probability of a recession: the XRI peaked at 32% in March 1989 and then quickly declined.

The second episode runs from June through November of 1990. The three month-ahead forecast based on data through June 1990, for June through September, was -8% (annual rates); actual growth in the XCI over this period was -4%. However, the slowdown – correctly predicted over the next three months – was predicted to be short, to be followed by positive but slow growth. As a consequence, the recession probability – computed for each future month using data through June 1990 – remained low, only 5% for each month from August 1990 through February 1991. This forecast of moderate growth in the fall of 1991 was, as it turned out, dramatically wrong: the XLI computed in August was 3.6%, while the actual growth of the XCI over this period was -7.3%, a forecast error of 10.9% (over 6% in GNP units at an annual rate). It should be emphasized, however, that shorter-run forecasts indicated an increased probability of a recession, although not until October or November 1990. For example, $P_{t|t}$, computed using data through October, was 28%; computed using data through November, it was 80%. Even so, the probability of a recession declined sharply with the horizon; in November, the three-month ahead recession probability was only 23%.

The third episode starts in January 1991. While the XLI forecast errors during this period have been larger than they were during the first episode and the within-sample period, they are much smaller than they were during the summer and fall of 1990. Importantly, with the exception of a brief period in early 1991, the XLI model has produced growth forecasts which are consistently overly optimistic, predicting above-average growth.

Although there are only two observations on the quarterly XCI and real GNP during the second episode, the relationship between these two series appears to have been stable during this period. Thus the poor performance of the XLI is not attributable to a breakdown of the link between the XCI and GNP, but rather the reflects a breakdown in the forecasting relationships between the leading and coincident variables.

An analysis of the sources of the forecast error was carried out in Stock and Watson (1992). After examining a variety of sources, the main conclusion of that investigation was that certain historical relationships which were incorporated into the XLI model failed to be sustained during the 1990 episode, most importantly the relationship between the financial variables in the model and the coincident measures of economic activity.

Behavior of financial spreads during the 1990 recession.

The four financial variables included in the XLI are a weighted average of nominal exchange rates, the yield on ten-year U.S. Treasury bond, the difference between the yields on ten-year and one-year U.S. Treasury bonds (the "yield curve spread"), and the difference between the yields on 6-month commercial paper and 6-month U.S. Treasury bills (the paper-bill spread). Historically, these two spreads have proven reliable predictors of future economic activity, and it is telling to examine their performance during the 1990 recession.

The yield curve spread has a long history as a predictor of economic activity, with a remarkably stable empirical relationship to aggregate output. Values of this yield spread over 1959 - 1992 are plotted in figure 5a. Historically, an inverted yield curve has signaled lower output growth over the next six months, as is revealed by comparing figure 5a and 5c (figure 5c presents the six-month actual growth of the XCI, that is, $c_{t+6}|_{t+6} - c_{t|t}$). Explanations of this relationship in terms of economic theory typically rely on the expectations theory of the term structure of interest rates. A leading explanation is that, if monetary policy is temporarily contractionary, then current short rates will exceed expected future short rates (either because of high current real rates or low expected future inflation), and this tight monetary policy will result in lower output growth. This view suggests that the slope of the yield curve is can be used as a measure of monetary policy. (Estrella and Hardouvelis (1989) provide a detailed discussion of the theory and evidence on the yield curve as a leading indicator.)

The behavior of the yield curve in the 1990 recession and since differs strikingly from its earlier patterns. It is useful to contrast the behavior of the financial variables around the

cyclical peak of July 1990 to their behavior just before the cyclical peaks in November 1973, January 1980, and July 1981. At each of these three earlier peaks, the yield curve was strongly inverted: the spread between ten- and one-year Treasury bond yields was respectively -.61, -1.59, and -1.39 in the month before each of these cyclical peaks, while its June 1990 value was +.38. Rather than being inverted prior to the recession, the yield curve was positively sloped and that slope was increasing. The yield curve has remained strongly positive, and as of this writing the value of the 10-year/1-year spread stands at its highest since World War II. Yet real economic growth (figure 5c) was very slow during 1991.

The second spread, the paper-bill spread, is plotted in figure 5b. This series also exhibits clear increases before the previous recessions. A natural interpretation of this relationship is that the spread measures the riskiness of private relative to public debt at the same (short) maturity, and therefore provides a measure of the private default premium. In worsening economic conditions, economic theory suggests that this premium will increase, which provides one explanation for the evident predictive power. (Detailed discussion of this and other theories of this predictive relationship, and an empirical evaluation of these theories, can be found in Friedman and Kuttner (1992) and Bernanke (1992).)

During the 1990 episode this predictive relationship, like that of the yield curve spread, also broke down. While the paper-bill spread widened in 1989, by the summer of 1990 it was at or below its postwar average value. Although it increased slightly in the late fall of 1990, this increase was brief and it has since been at very low levels which are historically associated with periods of robust economic growth.

One must be cautious about drawing general conclusions from this rather short episode. These findings do, however, raise the question of whether this forecasting instability was unique to this episode or whether it is instead symptomatic of widespread instability of reduced-form empirical relations.

3. Evidence of Instability in Reduced-form Forecasting Relations

for other leading indicators, 1960:1 - 1989:9.

This section investigates evidence of instability between a number of different leading indicators and monthly aggregate output, as measured by industrial production (IP), over 1960:1 - 1989:9. By using a different measure of output than the XCI and a sample period which excludes the three episodes studied in the previous section, this investigation has the potential to yield evidence that highlights different types and sources of instability than those already identified.

The tool used for this investigation is Nyblom's (1989) tests for parameter instability. Nyblom (1989) derived this test as the LM test in the Gaussian linear model of the null hypothesis that the coefficients in a linear time series regression are constant, against the alternative that they are a vector martingale relative to the information set generated by past observations. Two leading special cases of the alternative hypothesis are (a) that the parameters evolve according to a random walk (this is the model typically assumed in time-varying parameter regressions as discussed in the next section), and (b) that the parameters are constant except for a one-time break which occurs at an unknown time. Nyblom's (1989) test has power against both alternatives.

The test results are summarized in Table 4. Two types of instability are examined: instability in univariate autoregressions of the leading indicators (tests "(a)"), and instability in projections of growth of IP onto lagged IP growth and lagged leading indicator growth (tests "(b)" and "(c)"). The dating conventions used for the tests reflect the actual availability of data under the current reporting scheme by the U.S. Department of Commerce. In particular, the data on interest rates are shifted forward one month; because of lags in the test specifications (b) and (c), this corresponds to using interest rates to predict current values of IP. Because IP

is not reported until the middle of the month following the reporting period while interest rate data are available without a lag, in practice interest rates could be, indeed are, used to "forecast" IP for the current month.

The results indicate statistically significant parameter instability in many of the forecasting relations based on these leading indicators. The paper-bill spread exhibits an historically unstable relation to IP growth. The evidence of instability in the yield curve spread is weaker and depends on the number of lags included. There is little evidence of instability in the other two interest rate indicators examined, a long-term public-private spread and the federal funds rate.

In contrast, the monetary and credit quantity variables examined demonstrate considerable instability, both in their "marginal" (univariate autoregressions, column (a)) and "conditional" (as predictors of economic activity, columns (b) and (c)) forms. The possible exception is the lack of rejection of stability for the predictive equation based on real M2 growth; however, other evidence (e.g. Friedman and Kuttner (1989)) suggests that this relationship also is quite unstable.

Of the other leading indicators examined, there is evidence of instability for part time work due to slack work and, to a less extent, housing building permits. However there is no evidence of instability in the relationships involving exchange rates, average weekly hours of production workers, capacity utilization in manufacturing, the index of help-wanted advertising, and vendor performance. These disparate series do not constitute a comprehensive analysis of groups of leading indicators other than financial market indicators. However, these initial results suggest that predictive instability might be widespread among certain classes of indicators but not others. Of course, there are sound economic reasons to think that the class identified here, financial variables, might exhibit such instabilities because of the evolving structure of financial markets, changes in the operating procedures and objectives of U.S. monetary policy, and the increasing linkages of the U.S. financial markets to the world economy over this period.

4. Forecasting With Leading Indicators and Time-Varying Parameters

This section provides some preliminary results on forecasting with time-varying parameter (TVP) models specified with leading indicators. The key idea of this approach is that, by modeling the parameters as time-varying, persistent large forecast errors are recognized by the forecasting system and are used to reweight the variables for subsequent prediction. Vector autoregressive (VAR) systems with time-varying parameters have been explored by Doan, Litterman and Sims (1984) and Sims (1982), but with a limited set of series (see Sims (1992) for recent advances in real-time forecasting in VAR's using time-varying parameters). The approach here is to specify a tightly parameterized model of the time variation and to include a somewhat richer set of predictive variables than has been considered in these earlier empirical exercises, namely the leading indicators in the XLI model.

These experiments use the specification,

$$(6) \quad \Delta c_{t|t} = \mu_{c,t} + \lambda_{cc}(L)\Delta c_{t-1|t-1} + \sum_{i=1}^n \lambda_{cy,t}^i(L)y_{it-1} + \nu_{ct}$$

where $c_{t|t}$ is the XCI, y_{it} is the i -th of n leading indicators, and the time varying lag polynomials $\lambda_{cy,t}^i(L)$ and $\mu_{c,t}$ are parameterized as:

$$(7) \quad \lambda_{cy,t}^i(L) = \beta_{i,t} \gamma_{cy}^i(L)$$

$$(8) \quad \theta_t = \theta_{t-1} + e_t$$

where $\theta_t = (\mu_{c,t}, \beta_{1,t}, \dots, \beta_{n,t})'$ and e_t is a $(n+1) \times 1$ i.i.d. error with mean zero and covariance matrix $\sigma_e^2 I_{n+1}$, where I_{n+1} is the $(n+1) \times (n+1)$ identity matrix. This is a restrictive

parameterization of the time variation: only the total weight, not the lag structure, for each indicator is permitted to vary, and only one additional parameter, σ_e^2 , is added to the model. In addition, for this investigation we set the lag length of $\lambda_{cy}^i(L)$ to 6, $i=1, \dots, n$.

Equations (6) - (8) can be used without modification to construct one-month ahead forecasts. For longer forecasting horizons, forecasts of future values of y_{it} , $i = 1, \dots, n$ are needed. Here, these are computed by closing the system (6) - (8) with n additional equations which constitute a conventional first-order vector autoregression with the additional variables Δc_{t-1} included. Multiperiod forecasts are computed by iterating this system. Note in particular that the time varying parameters enter the system only in the first equation, that is, the equation predicting future values of c_t , a strong restriction.

The model (6) - (8) was estimated using monthly data on the XCI and the seven leading indicators in the XLI model over 1959:1 to 1988:9. Empirical results for three specifications are summarized in Table 5. In the first model (columns 2 and 3), $\sigma_e=0$, so (6) is simply estimated by OLS. The next two models allow for increasing parameter variation, respectively setting $\sigma_e=.01$ and $.02$, respectively. (To focus attention on out-of-sample contribution of the adaptive features of this model, the same lag polynomials $\gamma_{cy}^i(L)$ are used in each of the specifications; that is, each model uses $\gamma_{cy}^i(L)$ estimated by OLS, normalized so that $\beta_{i,t}=1$ when $\sigma_e=0$.)

Comparing the in-sample results (the first row of each panel), the OLS results produce the best fit; when σ_e is estimated (constraining $\gamma_{cy}^i(L)$ to be the OLS estimates), the maximum is close to zero ($\hat{\sigma}_e=.001$). Arguably, this reflects the fact that the included indicators were chosen in part because of their apparently stable relation to c_t through 1988:9.

The out-of-sample results are more useful in assessing the alternative models. During the first out-of-sample period, the first TVP model performs almost as well as the fixed-parameter model, with a forecast MAE at the six-month horizon of 1.21, only slightly above the 1.15 MAE for the fixed-parameter model. The second TVP model, with greater parameter variability, has worse performance during this period; however, the MAE of 1.84 still compares

favorably to all the MAE's during the in-sample period, even the MAE of 2.32 for the XLI reported in the first row of table 2.

The most striking result in table 5 is the extent to which the two adaptive models recognize the persistent forecast errors during the early months of the 1990 recession and, in response, alter their forecast functions. For example, at the six-month horizon, the MAE of the most adaptive model is 3.98, only slightly worse than its in-sample value and dramatically less than the fixed-parameter model. The TVP model with the intermediate degree of flexibility evidently adapts its forecasts less and has a MAE of 5.89, less than the fixed-parameter model but still large by historical standards. These results suggest that models which adapt in response to large forecast errors might usefully be used to forecast in periods of instability.

5. Summary and Conclusions

This analysis suggests three conclusions. First, the U.S. recession that began in 1990 posed a difficult challenge for many forecasting methods, ranging from the Blue Chip forecasts, which are largely based on a combination of judgment and large empirical Keynesian models, to the leading indicator approach described in sections 2 and 3. One focus of this paper has been the change in the predictive links between financial market indicators -- the paper-bill spread and especially the slope of the U.S. Treasury yield curve -- and economic activity (although as documented in Stock and Watson (1992) this breakdown of bivariate leading indicator - output relations extended beyond financial variables to almost all leading indicators during this period). This breakdown suggest a different source of shocks or perhaps even a different mechanism at work during the 1990 recession compared with the previous five U.S. recessions. In particular, the yield curve, if taken as an indicator of the policies of the Federal Reserve Bank, reflects a monetary policy that was perhaps neutral at the start of the recession and through the

subsequent two years grew increasingly expansionary, in contrast to the relatively tight monetary policies in place during the previous five recessions. In this sense, one of the puzzles is why U.S. monetary policy has been and remains so ineffective in stimulating growth in this recession, relative to earlier recessions.

Second, the examination of a somewhat longer list of indicators suggests that this predictive instability, while particularly pronounced during the 1990 episode, has been an ongoing feature of reduced-form time series relationships during the postwar period. Of the series examined, this is most pronounced for measures of the quantity of money and credit. The forecasting instability of the XLI model during the summer and fall of 1990 was in this sense a reflection of broader problems of forecasting economic activity using financial variables.

Finally, the initial investigation into forecasts based on leading indicators which employ tightly-parameterized models of time-varying weights suggests that techniques for handling this instability in theory might prove useful in practice. One need only observe the current political uncertainties about a European monetary union and the associated stresses on the European Exchange Rate Mechanism to realize that forecasters must plan on change rather than stability in institutional structure. This in turn suggests that historical empirical relationships among some time series variables, particularly financial variables, might continue to be of limited forecasting value. It also suggests continued research into forecasting techniques which adapt to evolving economic relations.

Footnotes

1. The Blue Chip survey is a private survey of approximately fifty professional economic forecasters, including large forecasting firms, individual forecasters in the private sector, and academic forecasters. Survey participants provide forecasts on the main macroeconomic aggregates (inflation, GDP growth, etc.).

2. For example, commenting on the May 31 release of the Department of Commerce's Leading Index in the New York Times on June 1 (p. C1), Michael P. Niemira of the Mitsubishi Bank stated that "the message is more strength still in the pipeline." The article later states, "Weakness in various measures of output and sales have signaled that economic growth is slowing and raised some concerns about a possible recession. The slowdown has also, however, raised hopes that the Federal Reserve might ease the tight grip it has kept on monetary policy for more than a year." In the Wall Street Journal that day (p. A2), Gary Ciminero of Fleet/Norstar Financial Group, was quoted as saying, "I think it (the DOC Leading Index) means that if we do encounter a more significant slowdown in the economy, its not going to occur in the next few months. I think we'll encounter a recession at the start of next year."

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Table 1

Macroeconomic Forecasts as reported by the Blue Chip Indicators

A. Forecasts of two-year Growth in Real GNP

Survey Date	Forecast period: 1989-1990			Forecast period: 1990-1991		
	Low 10	Avg	High 10	Low 10	Avg	High 10
May 10, 1990	1.5	2.0	2.4	1.6	2.3	3.0
Aug 10, 1990	0.8	1.3	1.8	0.7	1.7	2.5
Sep 10, 1990	0.8	1.1	1.4	0.0	1.2	2.4

B. Forecasts of the year in which the next recession will begin

Survey date	- - - Predicted first year of the next recession - - -					
	1989	1990	1991	1992	1993	1994
Feb 10, 1990	6%	23%	19%	23%	29% ^a	-
May 10, 1990	2	10	19	29	29	10 ^a
Sep 10, 1990	-	50	8	10	28	4 ^a

Notes:

Panel A. The entries under "Avg" are the average forecasts over the indicated 2-year period, averaged over the approximately 50 forecasts collected in the survey. The forecast date refers to the publication of the newsletter. "Low 10" and "High 10" are summary statistics reported by Blue Chip Indicators, respectively the average forecast of the lowest 10 and highest 10 of the forecasts reported in the survey. Source: Blue Chip Economic Indicators.

Panel B. This panel shows the distribution of answers to the question: "When will the next recession begin?" The forecast date refers to the date of publication of the newsletter. Source: Blue Chip Economic Indicators.

^aIncludes those who predicted the next recession would begin in the indicated year or later.

Table 2

Coincident and Leading Indicators in the XLI model

Transformation	Series and description
<i>A. Coincident Indicators</i>	
growth rates	Industrial production, total
growth rates	Personal Income, total less transfer payments, 1982\$
growth rates	Mfg and trade sales, total, 1982\$
growth rates	employee-hours in nonagricultural establishments
<i>B. Leading Indicators in the XLI</i>	
levels	Housing authorizations -- new private housing
growth rates	Manufacturers' unfilled orders: durable goods industries, 1982\$, smoothed
growth rates	Trade-weighted nominal exchange rate between the U.S. and the U.K., West Germany, France, Italy, and Japan, smoothed.
growth rates	Part-time work in nonagricultural industries because of slack work (U.S. Department of Labor, The Employment Situation, Household Survey), smoothed
differences	Yield on constant-maturity portfolio of 10-yr U.S. Treasury bonds, smoothed
levels	Spread between interest rate on 6-mo. corporate paper and the interest rate on 6 mo. U.S. treasury bills (Federal Reserve Board)
levels	Spread between the yield on constant-maturity portfolio of 10-yr U.S. T-bonds and the yield on 1-year U.S. T-bonds. (Federal Reserve Board)

Notes: The series described as "smoothed" were passed through the filter $(1+2L+2L^2+L^3)$. All variables except exchange rates and interest rates are seasonally adjusted.

Table 3

Forecasting Performance of the XLI: Summary Statistics

Sample Period	RMSE	MAE
62:1 - 88:9	2.89	2.32
80:1 - 88:9	3.50	2.94
80:1 - 90:8	3.54	2.83
88:10 - 90:8	3.72	2.32
88:10 - 90:4	1.45	1.20
90:5 - 90:12	8.21	7.47
91:1 - 92:1	4.22	3.63

Notes: The root mean square error (RMSE) and mean absolute error are computed for the difference between the XLI and the 6-month growth in the XCI. The dates in the first column correspond to the date that the forecast was made, so 92:1 corresponds to the last observation for which there currently is data on the actual growth of the XCI.

Table 4

Tests for Parameter Stability: Selected Leading Indicators, 1960:1-1988:9

Tests for parameter stability:

(a) $AR(k) y_t = \mu + \sum_{j=1}^k \beta_{1,j} y_{t-j}$, test stability of $\mu, \beta_1(L)$ (b) $\Delta \ln(IP_t) = \mu + \sum_{j=1}^k \beta_{1,j} y_{t-j} + \sum_{j=1}^k \beta_{2,j} \Delta \ln(IP_{t-j})$, test $\mu, \beta_1(L), \beta_2(L)$ (c) Same regression as (b), test stability of $\mu, \beta_1(L)$ only

Series	k = 4			k = 6		
	(a)	(b)	(c)	(a)	(b)	(c)
<i>A. Financial leading indicators in the XLI</i>						
fygt10fs	0.495	2.040	0.964	0.504	2.301	1.057
cp6_gm6f	0.377	2.547**	1.613**	0.655	3.187**	2.063**
gl0_glf	0.584	2.099	1.131	0.860	3.049*	1.864*
<i>B. Alternative interest rate measures</i>						
fyfff	1.070	2.186*	1.012	1.169	2.639	1.193
baa_gl0f	0.609	1.714	0.779	1.267	2.489	1.354
<i>C. Monetary and credit quantity variables</i>						
fmld82	2.103***	2.407**	1.446*	2.719***	3.539**	2.476***
fm2d82	2.065***	1.864	0.766	2.532***	2.809	1.615
fmbase	2.365***	2.912***	2.099***	2.047**	3.272**	2.233**
cci30m	0.660	1.761	0.856	0.833	2.856	1.699*
fcbcucy	1.156	2.484**	1.601**	1.367	2.936*	1.769*
<i>D. Other leading indicators</i>						
hsbp	1.185	2.214*	1.344*	1.477	2.448	1.441
mdu82s	1.130	1.925	1.254	1.195	2.384	1.570
exnwt2fs	0.627	1.776	0.829	0.661	2.257	1.038
lhnaps	1.882***	2.425**	1.452*	1.829*	3.464**	2.467***
lphrm	0.546	1.657	0.763	0.695	2.455	1.475
ipxmca	1.175	1.502	0.705	1.519	1.690	0.796
lhel	1.078	1.360	0.441	1.615	1.900	1.112
ivpac	0.774	1.645	0.955	1.307	2.082	1.302

Notes to Table 4:

Nyblom's (1989) tests for parameter stability were computed as described in the text. The "(a)" tests examine parameter stability in an autoregression; the "(b)" and "(c)" tests examine stability in the regression of the growth of industrial production on its lags and lags of the candidate leading indicator. The degrees of freedom for the six columns are, respectively, 5, 9, 5, 7, 13, 7. Critical values were obtained from Nyblom (1989), Table 2 as extended by Hansen (1990), Table 1.

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Series Definitions

FYGT10FS (AC)	FYGT10 is the INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA). FYGT10FS is the first difference, smoothed, led by one month.
CP6_GM6F (AC)	FYCP - FYGM6, led by one month, where FYCP is the INTEREST RATE: COMMERCIAL PAPER, 6-MONTH (% PER ANNUM,NSA) and FYGM6 is the INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)
G10_G1F (AC)	FYGT10 - FYGT1, led by one month, where: FYGT10 is the INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA), and FYGT1 is the INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
FYFFF**	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA), led by one month.
BAA_G10F (AC)	FYBAAC - FYGT10, led by one month, where: FYBAAC is the BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM) and FYGT10 is the INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
FM1D82*	MONEY STOCK: M-1 IN 1982\$(BIL\$,SA)(BCD 105)
FM2D82*	MONEY STOCK: M-2 IN 1982\$(BIL\$,SA)(BCD 106)
FMBASE*	MONETARY BASE, ADJ FOR RESERVE REQ CHGS(FRB OF ST.LOUIS)(BIL\$,SA)
CCI30M*	CONSUMER INSTAL.LOANS: DELINQUENCY RATE,30 DAYS & OVER, (% ,SA)
FCBCUCY (AC)	CHANGE IN BUS AND CONSUMER CREDIT OUTSTAND. (PERCENT, SAAR) (FCBCUC) minus the annual percentage growth in total nominal personal income (GMPY)
HSBP	HOUSING AUTHORIZED: INDEX OF NEW PRIV HOUSING UNITS (1967=100;SA)
MDU82S (AC)	MFG UNFILLED ORDERS: DURABLE GOODS INDUSTRIES, TOTAL (MIL\$,SA) (MDU), deflated by the PRODUCER PRICE INDEX: DURABLE MFG. GOODS (NSA) (PWDMD): log first difference, smoothed. PWDMD was seasonally adjusted prior to deflating by removing average monthly growth rates.
EXNWT2FS (AC)	EXNWT2 is the nominal weighted exchange rate between U.S. and: France, Italy, Japan, U.K., and West Germany, constructed using shares of total real imports as weights. EXNWT2FS is the log first difference, smoothed, led by one month.
LHNAPSS (AC)	LHNAPS is PERSONS AT WORK: PART TIME ECON REAS-SLACK WK, NONAG IND(THOUS,SA). LHNAPSS is the log first difference, smoothed.
LPHRM	AVG. WEEKLY HRS. OF PRODUCTION WKRS.: MANUFACTURING (SA)
IPXMCA**	CAPACITY UTIL RATE: MANUFACTURING,TOTAL(% OF CAPACITY,SA)(FRB)
LHEL*	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)
IVPAC	VENDOR PERFORMANCE: % OF CO'S REPORTING SLOWER DELIVERIES(% ,NSA)

Notes: All data were obtained from Citibase with the exception of those constructed by the authors, denoted by (AC).

* log first differences of the variable were used

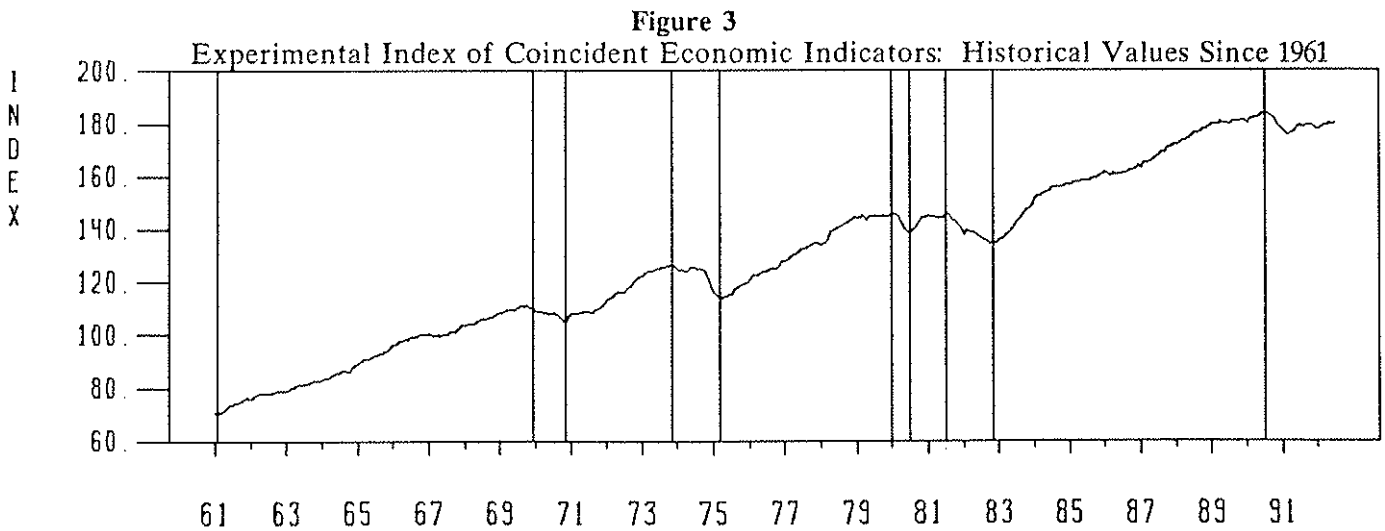
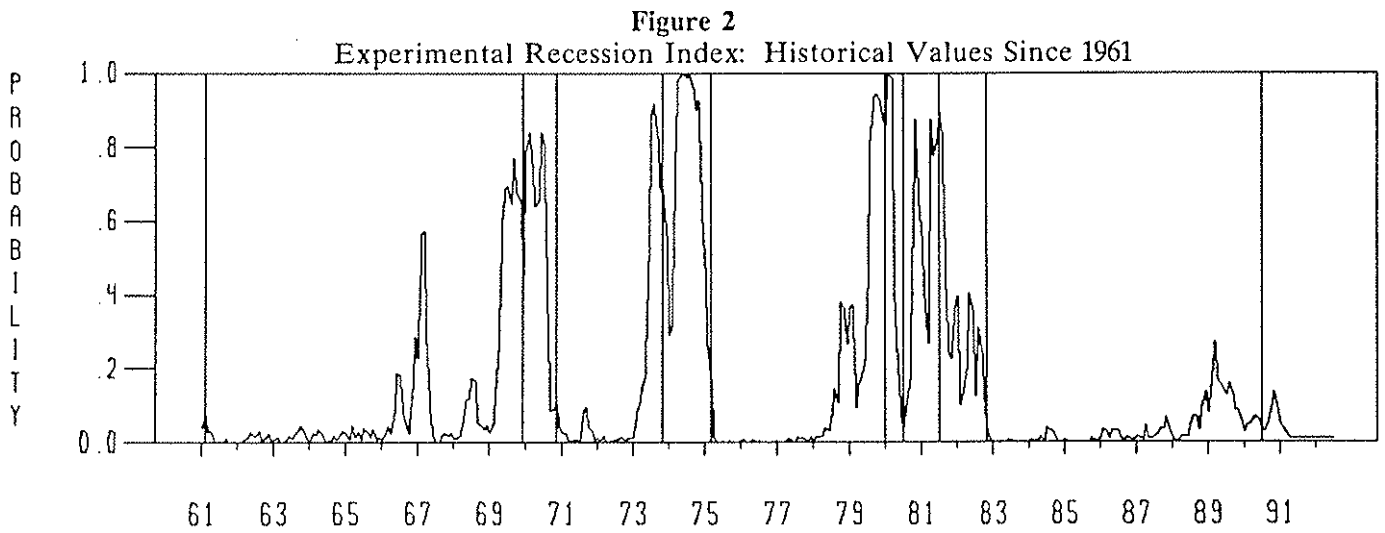
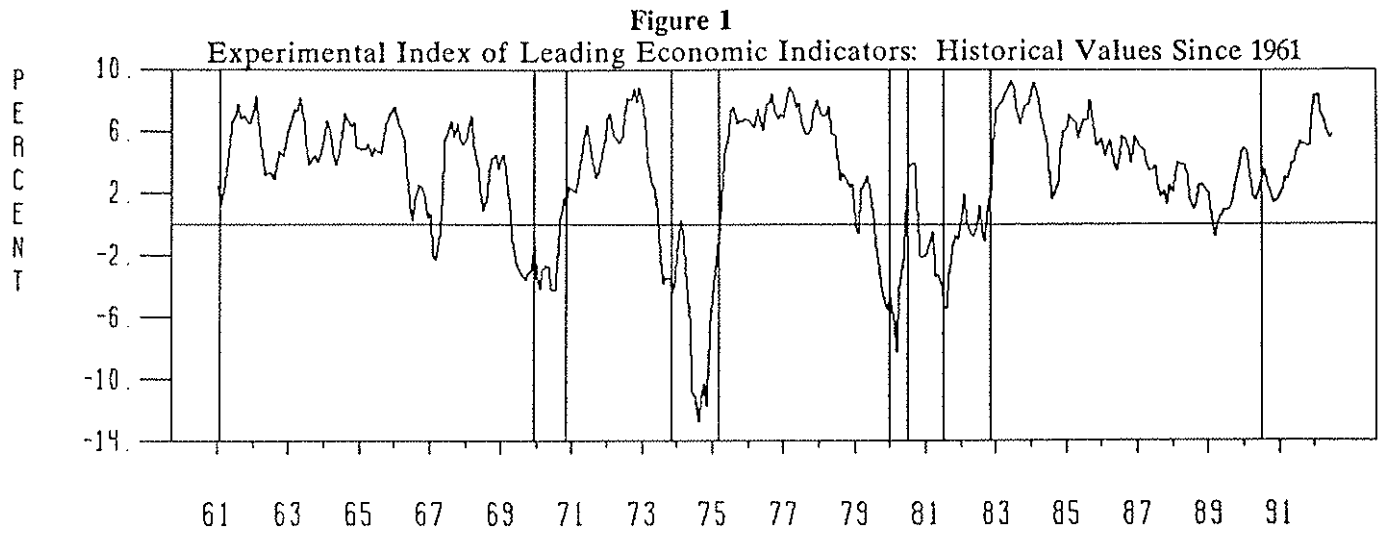
** first differences of the variable were used.

Table 5

Restricted Multivariate Model with Time-Varying Parameters:
Preliminary Results

Forecast Period	(1) $\sigma_e=0$ (OLS)		(2) $\sigma_e=.01$		(3) $\sigma_e=.02$	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
<i>A. 1 Month Ahead Forecasts</i>						
62:01-88:09	5.35	4.14	5.56	4.34	6.10	4.79
88:10-90:04	5.24	4.28	5.26	4.37	5.56	4.55
90:05-91:04	6.23	5.19	4.95	4.17	3.73	3.17
<i>B. 3 Month Ahead Forecasts</i>						
62:01-88:09	3.72	3.01	4.18	3.30	5.12	4.04
88:10-90:04	2.24	1.81	2.35	1.83	3.04	2.47
90:05-91:02	6.92	6.06	5.12	4.37	3.29	2.51
<i>C. 6 Month Ahead Forecasts</i>						
62:01-88:09	3.06	2.42	3.49	2.72	4.32	3.40
88:10-90:04	1.45	1.15	1.47	1.21	2.10	1.84
90:05-90:11	7.78	7.48	6.20	5.89	4.45	3.98

Notes: RMSE denotes the root mean square forecast error and MAE denotes the mean absolute forecast error. The $\sigma_e=0$ model simplifies to a restricted least squares regression, in which there is no time variation; positive values of σ_e introduce time variation and forecasts are computed using the Kalman filter as described for example in Engle and Watson (1987) and Harvey (1989). The model is given in (6) - (8) in the text. The first column presents the period over which the RMSE and MAE were computed. Estimation was over 62:01-88:09, so the RMSE and MAE for this period is in-sample. The remaining two subsamples provide out-of-sample evidence on the performance of the TVP model.



NOTE: The vertical lines denote NBER-dated cyclical peaks and troughs.

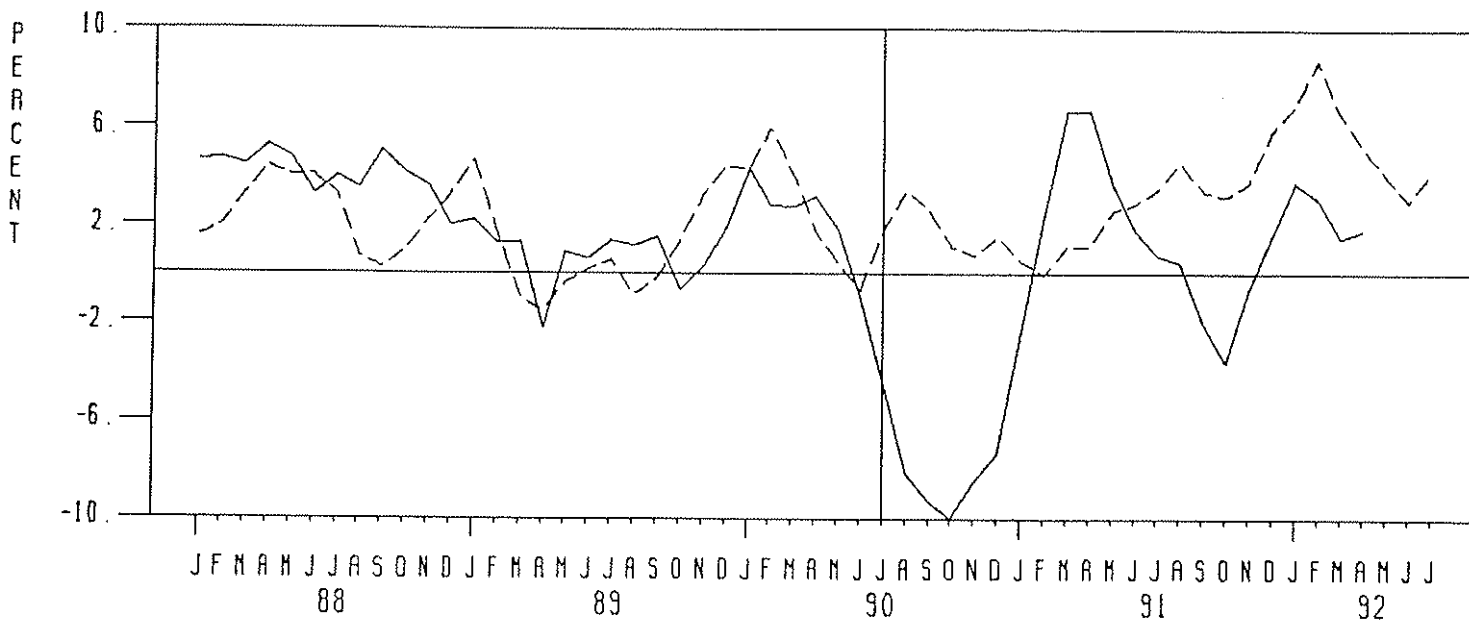


Figure 4a. Historical performance of the XLI model, 3-month growth (annual rate)

Key: solid line - actual growth of the XCI over the next 3 months
dashed line - 3-month growth forecast

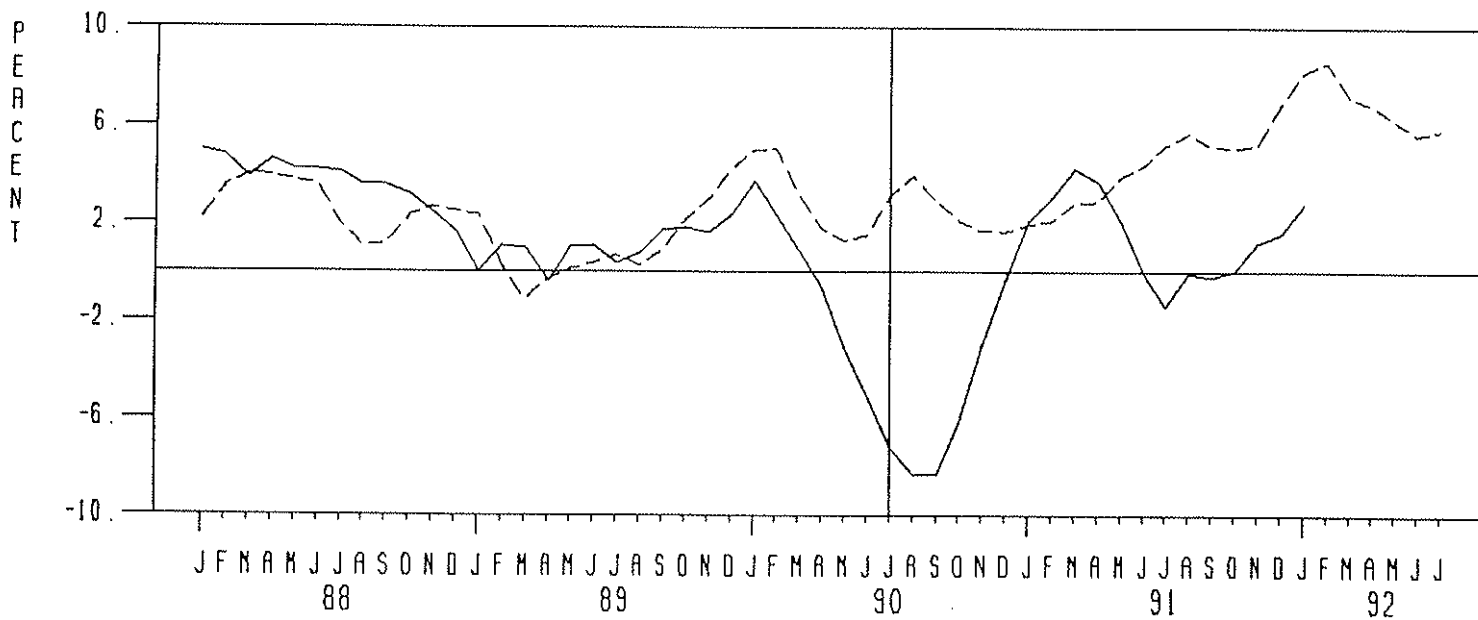


Figure 4b. Historical performance of the XLI model, 6-month growth (annual rate)

Key: solid line - actual growth of the XCI over the next 6 months
dashed line - 6-month growth forecast

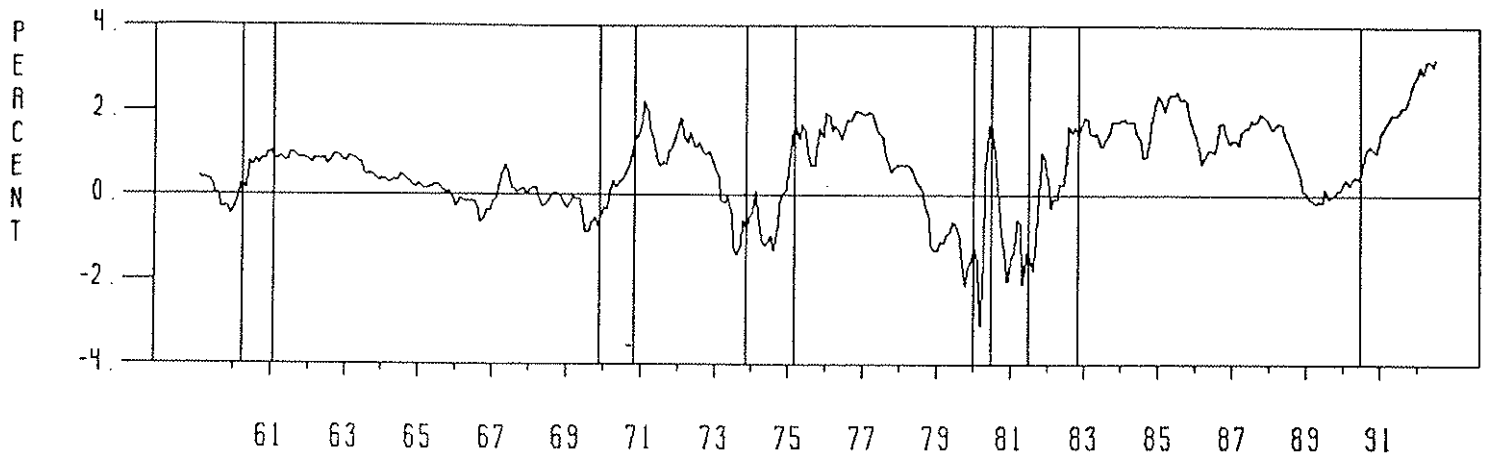
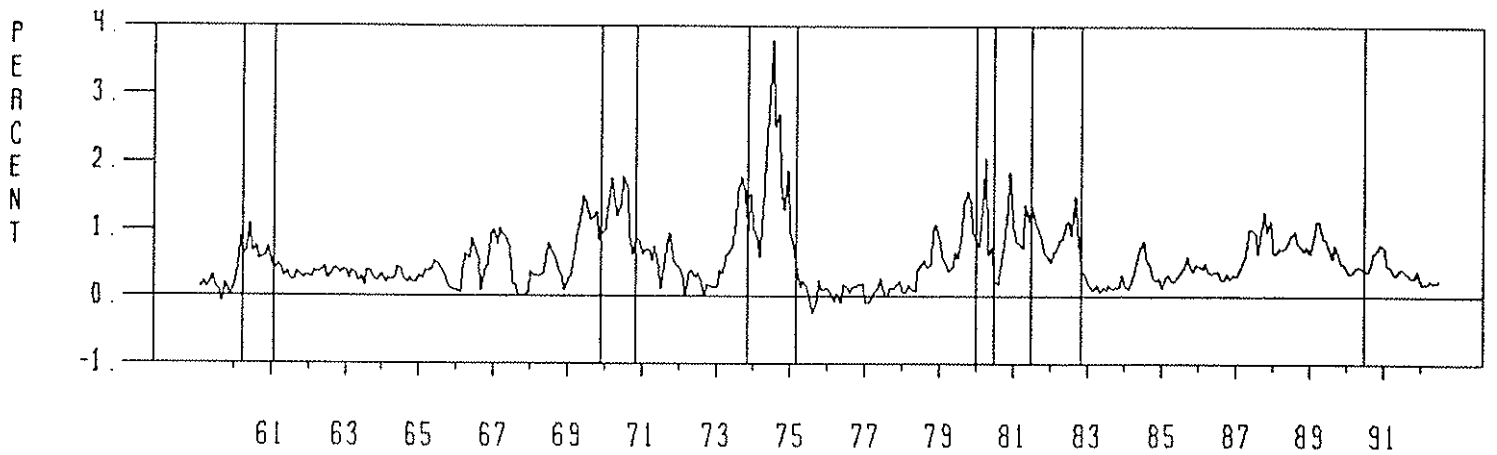
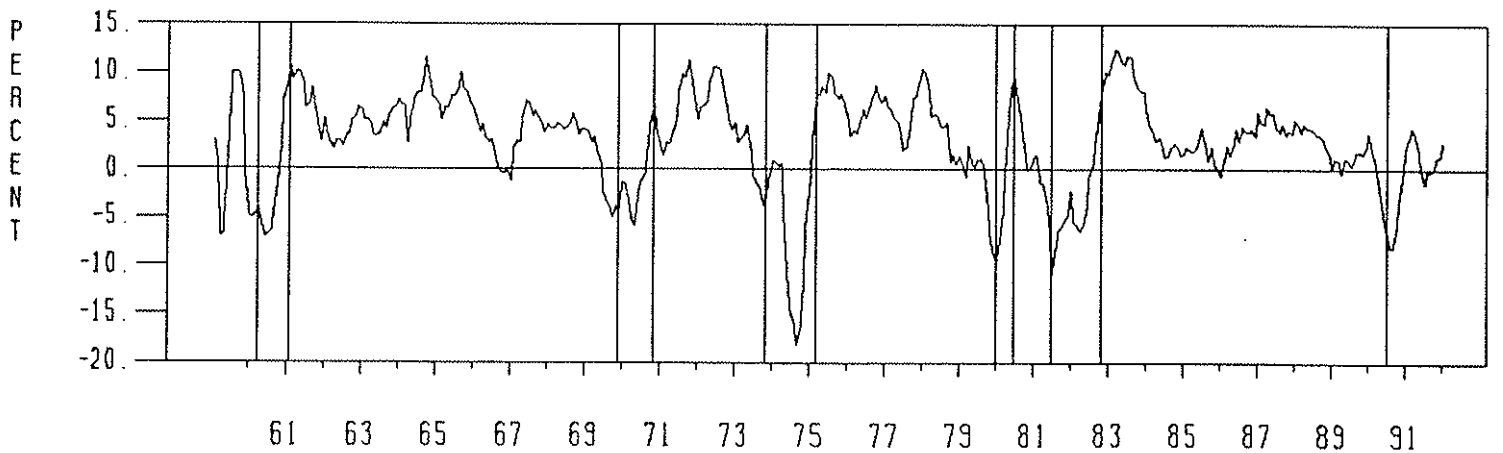


Figure 5
 A. Spread between yields on 10-year and 1-year U.S. Treasury bonds



B. Spread between 6-month commercial paper rate and yield on 6-month U.S. Treasury bills



C. Actual growth of the XCI over the next six months

