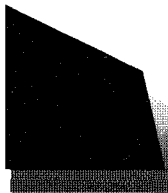


## Using econometric models to predict recessions

Mark W. Watson



On April 25, 1991, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) determined that the U.S. economy had reached a business cycle peak in July 1990 and had fallen into a recession. Could this recession have been predicted by econometric models? In this article I discuss how econometric models can be used to forecast recessions and provide a partial answer to this question by documenting the forecasting performance of one model, the NBER's Experimental Recession Index.

Econometric models describe statistical relationships between economic variables. By extrapolating these relationships into the future, econometric models can be used for prediction. Carefully constructed econometric forecasts can predict recurring patterns in the economy, but even the best econometric model can not anticipate unique events that have not left a statistical footprint in past data.

Recognizing these strengths and weaknesses, most economists base their forecasts on a combination of econometric analysis and judgment (or economic instinct). The relative weight given to judgment and econometric analysis depends on how unique the forecasting period is expected to be. For example, econometric models can be expected to work well for predicting the response of the economy to monetary expansions and contractions, since the statistical record contains many similar episodes. On the other hand, econometric models probably will perform poorly for predicting

growth in economic activity in Eastern Europe over the next five years, since the statistical record contains few transformations of command to market economies.

Since the focus of this article is on how, and how well, econometric models forecast recessions, I begin by defining a recession. A statistical model requires a precise definition, and, as we will see, different definitions lead to different econometric approaches. After I describe these econometric methods, I evaluate the recent forecasting performance of one econometric method: the NBER's Experimental Recession Index, which I developed jointly with James Stock of Harvard University. It turns out that this index did not perform well over the current recession. Unraveling the reasons for its poor performance says much about the causes of the current recession.

### What is a recession?

Contrary to popular wisdom, the official (NBER) definition of a recession is *not* "two or more quarters of consecutive decline in real GNP." The official definition is far less precise. Indeed, it is so imprecise that it is worth providing in detail. Burns and Mitchell (1946) give the official definition of a recession as one

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phase of a business cycle. A business cycle is defined as follows:

“Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitude approximating their own.”

Using this definition, the NBER Business Cycle Dating Committee somehow determined that the U.S. economy reached a cyclical peak in July 1990. Actually, this is not as difficult as it appears. As lawmakers have claimed about obscenity, recessions may be difficult to define, but you know one when you see it.

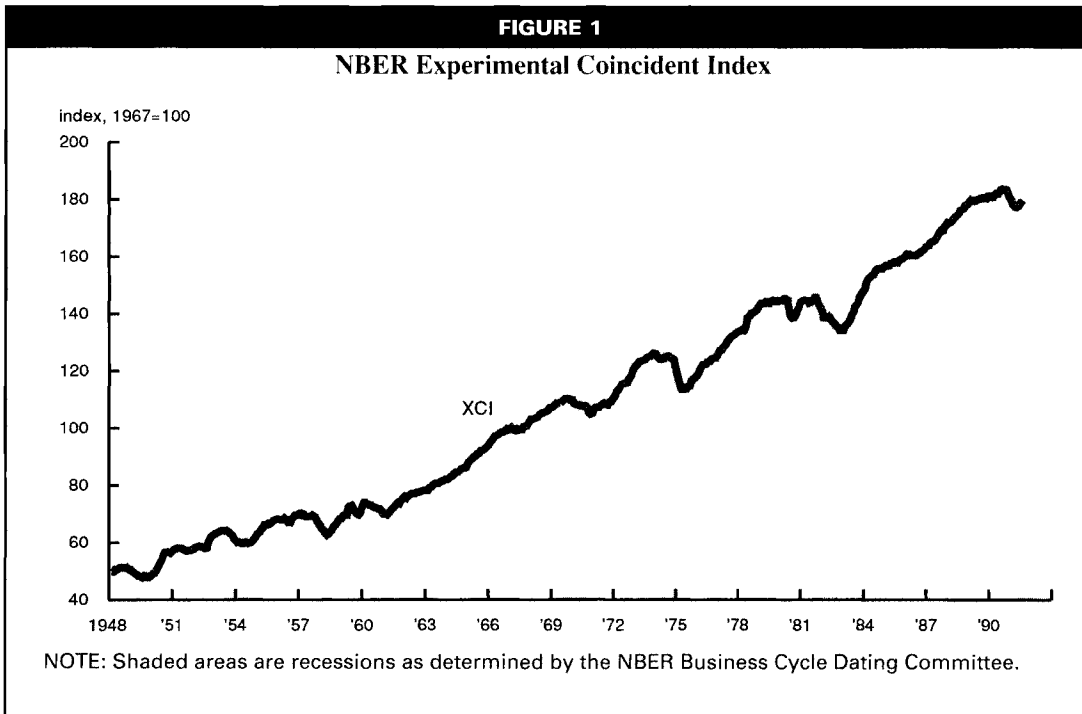
Figure 1 presents an index of aggregate activity constructed using four monthly coincident indicators; the index of industrial production, total nonagricultural employment, manufacturing and trade sales, and real personal income. The precise details underlying the

construction of the index are given in the Appendix. The shaded areas in the graph are the postwar recessions, as determined by the NBER. As is evident from the graph, recessions are periods of sustained and significant declines in the index.

It is interesting to compare the NBER official peak and trough dates to those that would be determined using the rule of two consecutive quarters of declining GNP. I do this in Table 1. The two sets of dates are more different than one might imagine. Recessions are often interrupted temporarily by one quarter of positive GNP growth; this causes the GNP rule to miss the peak or trough. This occurred during the recessions of 1949, 1973-1975, and 1981-1982. Moreover, two of the postwar recessions determined by the NBER—1960-61 and 1980—did not coincide with two quarterly declines in GNP. The NBER approach to dating recessions yields more reasonable results than the GNP method because it relies on a large number of monthly indicators rather than a single quarterly indicator.

#### The NBER's experimental indicators

There are two distinct econometric methods used for predicting recessions. The first is based on traditional macroeconomic models like the Wharton, DRI, or Michigan models.



**TABLE 1**

**NBER business cycle reference dates  
and periods of GNP decline**

Peak	Trough	GNP decline periods
11/48	10/49	49:I—49:II
7/53	5/54	53:II—54:II
8/57	4/58	57:IV—58:I
4/60	2/61	None
12/69	11/70	69:IV—70:II
11/73	3/75	74:III—75:I
1/80	7/80	None
7/81	11/82	81:IV—82:I
7/90		90:IV—91:I

NOTE: The GNP decline periods indicate periods during which GNP was declining for two or more consecutive quarters.

The second is based on economic indicators like those originally developed by Burns and Mitchell at the NBER in the 1930s, the Commerce Department's Composite Index of Leading Indicators, or the NBER experimental indicators that Stock and I developed. Traditional macroeconomic models were not developed to predict recessions, but they were developed to predict variables like real GNP. These models can be used to construct approximate recession predictions by using their forecasts to calculate the likelihood of two consecutive declines in real GNP. In contrast, the indicators

approach, as implemented in my work with Stock, predicts recessions using the official NBER definition. The remainder of this article will focus on this approach. Readers interested in a discussion of traditional econometric models or a more technical description of the indicators approach should read the discussion in the Box.

At the request of the Secretary of the Treasury in 1937, a research team at the NBER led by Burns and Mitchell identified a set of leading, coincident, and lagging indicators of economic activity for the U.S. economy. These indicators were chosen to tell policymakers where the economy was going, where it was, and where it had been. In the early 1960s, the NBER ceded re-

sponsibility for the system of economic indicators to the Commerce Department. Since then, the Department of Commerce has maintained the indicators, periodically updating the set of variables to reflect changes in the economy and data availability. The Department of Commerce publishes the indicators monthly, and the composite index of leading indicators is regularly reported in the financial and popular press.

In 1987, James Stock and I started an NBER sponsored project to rethink the system of economic indicators.<sup>1</sup> We developed three

## Econometric methods for predicting recessions

### Predicting recessions using traditional macroeconomic models

Traditional macroeconomic models describe the relationship between a set of "endogenous" variables, say  $Y_t$ , "exogenous" variables,  $X_t$ , and errors,  $\epsilon_t$ . The endogenous variables are the variables that the model is attempting to explain; in a typical model they include real GNP, investment, the rate of inflation, interest rates, and other variables. The exogenous variables are variables that the model takes as given and are important for explaining changes in the endogenous variables; in a typical model they include government purchases, tax rates, and the monetary base. The error terms capture changes in the endogenous variables not explained by the exogenous variables. They are modeled as random.

Symbolically, the model is represented as

$$(1) \quad Y_t = G(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}, X_t) + \epsilon_t,$$

which shows the relationship between the endogenous variables and their past values, the exogenous variables, and the errors. Forecasts of the endogenous variables  $j$  periods into the future constructed using information through time  $t$  are denoted as  $E_t Y_{t+j}$ , that is, the conditional expectation of  $Y_{t+j}$  given information available at time  $t$ . This forecast is the best guess of the endogenous variables at time  $t+j$  given information available to the forecaster at time  $t$ . (The forecast is best in the sense that it minimizes the average squared forecast error.)

The forecast,  $E_t Y_{t+j}$ , is just one summary of the information at time  $t$  relevant for predicting the

future. In principle, the macroeconomic model can be used to deduce the entire probability distribution of the future data conditional on information available at date  $t$ , that is,  $F_t(Y_{t+1}, Y_{t+2}, \dots, Y_{t+k})$ . The point forecasts are the mean of this distribution, but one could also calculate, for example, the conditional variance of  $Y_{t+j}$  or the 95 percent conditional confidence interval for  $Y_{t+j}$ . Indeed, given  $F_t(Y_{t+1}, Y_{t+2}, \dots, Y_{t+k})$ , one could calculate the probability of any event characterized by future values of  $Y_t$ . In particular, if a future recession is defined in terms of future  $Y_t$ s, then the probability of a future recession, conditional on information at date  $t$ , can be deduced. Fair (1991) uses this observation, together with stochastic simulation techniques, to calculate recession forecasts from his model. This procedure is simple, yet quite general.

### Using stochastic simulation to predict recessions in Fair's model

Fair's model contains 30 stochastic equations and 98 identities for a total of 128 endogenous variables; it also includes 82 exogenous variables. Given initial conditions,  $(Y_t, Y_{t-1}, \dots, Y_{t-p+1})$ , future exogenous variables,  $(X_{t+1}, X_{t+2}, \dots, X_{t+k})$ , and future disturbances,  $(\varepsilon_{t+1}, \varepsilon_{t+2}, \dots, \varepsilon_{t+j})$ , the model can be dynamically solved forward to yield  $Y_{t+j}$ . Taking the model as given, the only uncertainty about the future involves the values of the exogenous variables and the disturbances. Fair assumes that the  $\varepsilon_t$ s are independent and identically normally distributed and that exogenous variables follow simple autoregressive models with normally distributed shocks. This makes it easy to simulate future values of the errors and the exogenous variables by drawing from a random number generator. These simulated  $X$ s and  $\varepsilon$ s are used to solve the model to yield  $Y_{t+1}, Y_{t+2}, \dots, Y_{t+k}$ . This procedure is repeated many times and a histogram of the realizations  $(Y_{t+1}, Y_{t+2}, \dots, Y_{t+k})$  is an estimate of the conditional probability distribution  $F_t(Y_{t+1}, Y_{t+2}, \dots, Y_{t+k})$ .

Fair uses this stochastic simulation method to predict recessions by defining a recession using the "two consecutive declines in real GNP" definition. That is, the economy is in a recession at time  $t+j$ , if time  $t+j$  is in a sequence of two or more consecutive declines in real GNP. Since real GNP is an endogenous variable in Fair's model, this probability can be calculated from  $F_t(Y_{t+1}, Y_{t+2}, \dots, Y_{t+k})$ , the distribution of future values of the endogenous variables given information through time  $t$ . Using the simulated data, the probability of a recession at time  $t+j$  is approximated by the fraction of the simulations that were characterized by a recession at time  $t+j$ .

For example, to calculate the probability that the economy will be in recession in the first quarter

of 1992 using data through the first quarter of 1991, Fair proceeds as follows. First, he generates values for the exogenous variables and disturbances in his model for 1990:2 through 1991:2. These values are chosen from a random number generator that mimics the variability in the future values of these variables. Next, using these values, he solves for the endogenous variables over 1991:2-1992:2. This process is repeated many times, and the values of the endogenous variables are recorded after each simulation. The probability of a recession is calculated as the fraction of the simulations in which the real GNP growth in the first quarter of 1991 was in a sequence of two consecutive declines; that is, the fraction of simulations in which real GNP declined in 1990:4 and 1991:1 or in 1991:1 and 1991:2.

The method can be generalized in many ways. First, the definition of the recession event can be changed; the important thing is that it must be a function of the future values of  $Y_t$ . Second, in most circumstances the parameters of the econometric model are not known and are estimated from past data. This introduces additional uncertainty into the forecasts, since the forecasts depend on the model's parameters. This uncertainty can be incorporated by drawing new model parameters from the appropriate distribution for each simulation. As should also be clear, there is no need to assume that the errors of the model are normally distributed, nor that the exogenous variables follow simple autoregressive processes. All that is required is that the realizations of the errors and the exogenous variables can be simulated. More detailed discussion can be found in Fair (1991).

### The indicators approach to predicting recessions

Stock and I developed an alternative approach to predicting recessions. Our approach uses the NBER's definition of a recession rather than the declining GNP definition and is in the tradition of the system of economic indicators developed by Burns and Mitchell rather than large scale macroeconomic models. A description of our approach follows.

Recessions are discrete events: we are either in a recession or we are not. Discrete events can be quantified using 0-1 "indicator" variables. Let  $R_t$  denote a 0-1 indicator of a recession, so that  $R_t = 1$  if there is a recession at date  $t$  and  $R_t = 0$  otherwise. Let  $z_t$  denote a set of economic indicators that are useful for predicting future economic activity. Then the probability forecast of a recession at date  $t+j$ , given information at date  $t$ , can be written as

$$(2) \quad P(R_{t+j} = 1 | z_t, z_{t-1}, \dots) \equiv P_{t+j|t}.$$

$P_{t+j}$  is the probability that the economy will be in a recession at date  $t+j$ , computed using information through time  $t$ . The statistical question is what is the best way to parameterize this conditional probability, that is, what equation should be used to convert the information in the indicators into a recession probability.

In research utilizing cross section data, this is a well studied problem. Applied researchers often estimate “probit” or “logit” models relating an indicator variable, such as “union membership” or “completed college,” to a set of explanatory variables.<sup>1</sup> While the prediction problem considered here is conceptually similar, it differs in two important ways. First, the data are temporally dependent, which suggests that some degree of temporal smoothness should be incorporated in the functional form. Second, since lagged values of the indicators may be useful predictors, the number of explanatory variables is potentially very large.

The parameterization that Stock and I use borrows an important simplification from models designed to explain cross sectional data. Using the notation above, and abstracting from lags, the cross section model would parameterize the probability in Equation (2) as  $P_{t+j} = f(z_j\beta)$ , where  $f(\cdot)$  is a function that converts the “index”  $z_j\beta$  into a probability, that is, a number between 0 and 1. The single index,  $z_j\beta$ , summarizes all the relevant information in the explanatory variables. Figure 1 suggests that the XCI might be a useful dynamic index, in the sense that it adequately summarizes the relevant information in the explanatory variables for predicting recessions. The problem is to convert this index into a recession forecast.

To see how this is accomplished, it is useful to proceed in three steps. In the first step, a probability model relating the XCI to observable variables is developed. This serves to define the XCI. Next, a forecasting model for future values of the XCI is developed. Finally, a model relating recessions to the XCI is specified.

As mentioned above, the XCI is an index of four monthly indicators of aggregate activity: the index of industrial production; aggregate employment; personal income; and trade sales. Precise definitions are given in Table 2. The XCI is an index of the common movement in these series. It is calculated from a dynamic factor analysis model using statistical methods originally developed for signal extraction. Thus, the XCI represents the common “business cycle signal” contained in the four coincident indicators. The precise mathemat-

ical formulation of the XCI model is given in the Appendix, where the common business cycle signal is denoted by  $c_t$ . The XCI, plotted in Figure 1, is nothing more than an optimal estimate of  $c_t$ , constructed from current and lagged values of the coincident indicators. Thus, the first problem—relating the XCI to observed variables—is solved.

To solve the next problem—forecasting future values of the XCI—leading indicators are added to the model. Prediction is carried out using a vector autoregressive model or VAR, a common model for multivariate time series; the details are shown in the Appendix. The XLI is the “best guess” of growth in XCI over the next six months. Using the notation introduced above, the XLI is  $E_t(c_{t+6} - c_t)$ .

Recall that, using a standard macroeconomic model, we could go beyond “best guess” forecasts and obtain the entire probability distribution of future values of the endogenous variables. The same is true here: the model can be used to deduce the entire distribution of past, current and future values of  $c_t$  conditional on the observed indicators. For the purposes of predicting recessions this is important because the probability distribution of future  $c_t$ s summarizes all of the information in the model about future recessions.

Our formulation allows us to break up the construction of  $P_{t+j}$  into two pieces. First, we construct the probability distribution of the  $c_t$ s given the observed leading and coincident indicators, as described above. Next we relate the  $c_t$ s to the probability of a recession. Figure 1 suggests that this is easy to do: your eye can naturally pick out recessionary patterns from a graph of  $c_t$ . Recessions are the periods of sustained and significant declines in the index. The specification of the probability of recession given the  $c_t$ s that Stock and I use captures this simple notion. Unfortunately, carefully specifying a pattern recognition algorithm that mimics what your eye does naturally requires the introduction of much notation and many additional equations. This will not be done here, but the interested reader can see this detailed in Stock and Watson (1991b). It is sufficient to say that the specification assigns a high probability of a recession to periods of time in which  $c_t$  undergoes a sustained sequence of declines.

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#### Footnote

<sup>1</sup>These models are discussed in any good econometrics textbook. A detailed discussion can be found in Maddala (1983).

indexes designed to track and forecast the macroeconomy. The first is the NBER Experimental Coincident Index (the XCI). This is the series plotted in Figure 1; we saw that expansions and contractions in the series coincided with NBER business cycle reference dates. The second index is the NBER Experimental Leading Index (the XLI), which forecasts the growth in the XCI over the next six months. The final index is the NBER Experimental Recession Index (the XRI), which shows the probability that the economy will be in recession six months hence. The framework used to compute the XCI, XLI, and XRI is described in the Box, and a more technical description is offered in the Appendix.

The variables that are used to construct the XCI, XLI, and XRI are listed in Table 2. The coincident indicators are fairly standard; with one exception (total employee hours), they are the same variables used in the Department of Commerce's index of coincident indicators. Some of the leading indicators are standard (housing authorizations and manufacturers' unfilled orders); while others are not. For ex-

ample, we use two interest rate spreads (a yield curve spread and a commercial paper/Treasury bill spread). The set of leading indicators was chosen from a systematic investigation of over 250 candidate series, which is documented in Stock and Watson (1989).

The XRI focuses on six month ahead prediction, but the statistical framework allows us to calculate recession probabilities over any horizon. Figures 2-4 show the recession probabilities computed for three different forecasting horizons from January 1962 through April 1991 computed from the model. Figure 2 shows the coincident recession indicator: the probability that the economy is in recession at time  $t$  constructed from data available at time  $t$ . Figure 3 shows the three month ahead recession indicator: the probability that the economy will be in a recession at time  $t+3$  given information available at time  $t$ . Finally, Figure 4 shows the six month ahead recession predictor; this predictor is the NBER's Experimental Recession Index (XRI). The series are plotted so that date  $t$  corresponds to when the forecast was made. For example, the six month ahead predictor

**TABLE 2**

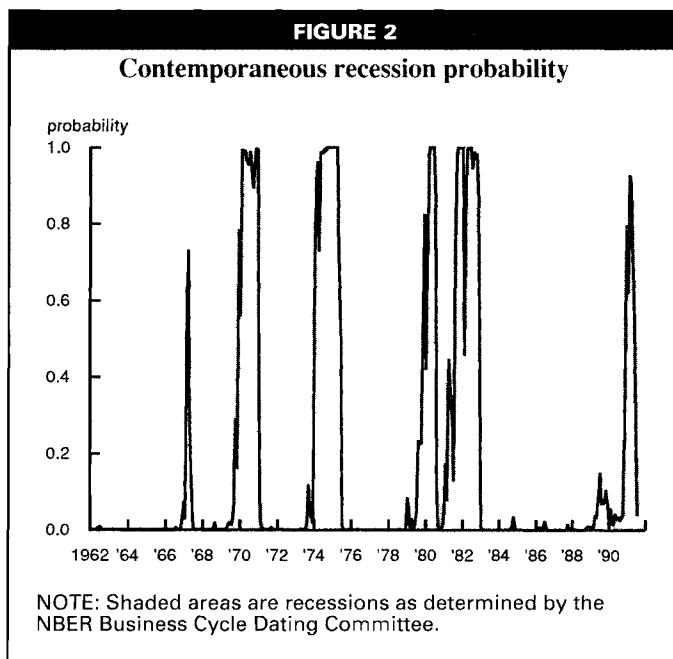
**Coincident and leading indicators**

**Coincident indicators**

1. Industrial production.
2. Personal income, total, less transfer payments, 1982\$.
3. Manufacturing and trade sales, total 1982\$.
4. Total employee hours in nonagricultural establishments.

**Leading indicators**

1. Housing authorizations (building permits): new private housing.
2. Manufacturers' unfilled orders: durable goods industries, 1982\$ (smoothed).
3. Trade-weighted index of nominal exchange rates between the U.S. and the U.K., West Germany, France, Italy, and Japan (smoothed).
4. Number of people working part-time in nonagricultural industries because of slack work (smoothed).
5. The yield on a constant maturity portfolio of 10 year U.S. Treasury bonds (smoothed).
6. The spread (difference) between the interest rate on 6 month commercial paper and the interest rate on 6 month U.S. Treasury bills.
7. The spread (difference) between the yield on a constant maturity portfolio of 10 year U.S. Treasury bonds and the yield on 1 year U.S. Treasury bonds.



should tend to increase six months before the onset of each recession and decrease six months before the recession ends.

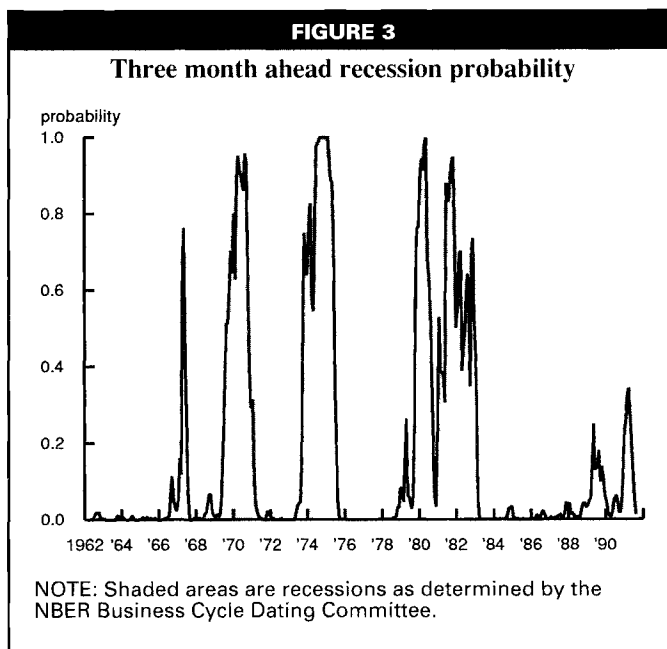
Looking first at Figure 2, the coincident recession indicator seems quite reliable. The major exceptions are the growth recession of 1967 and the beginning of the current recession. Keep in mind that coincident "prediction" is more difficult than it would appear; it was not until the end of April 1991 that the NBER determined that the economy had peaked in July 1990. Taken together, the Figures show that the ability to forecast a recession declines as the forecast horizon increases; the coincident recession predictor is more accurate than the three month ahead predictor, which in turn is more accurate than the six month ahead predictor. But, at least for the 1970, 1973-1975, 1980, and 1981-1982 recessions, predictions as far as six months ahead were reasonably accurate. The forecasting performance of the model for the current recession, particularly at the six month ahead horizon, was significantly worse than for the previous recessions.

There are several possible reasons for the failure of the model;

each is carefully analyzed in Stock and Watson (1991b). In the next section I will mention them all and discuss the most interesting in detail. First, here is some background.

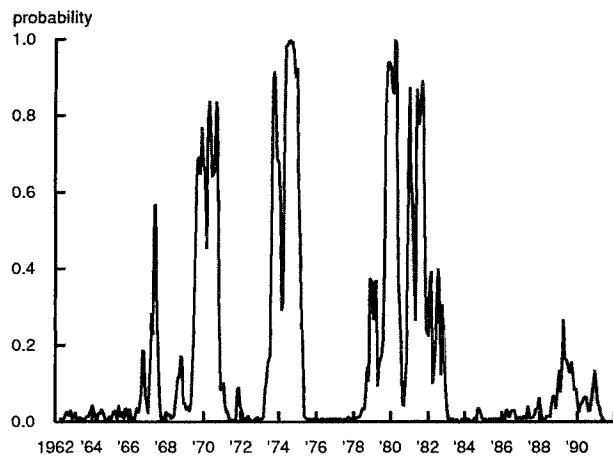
The NBER experimental leading indicator model was constructed using historical data from January 1959 through September 1988. All results after September 1988 are out-of-sample. Figure 1 shows that the XCI continued to be an accurate coincident indicator in the out-of-sample period: the XCI peaked in July 1990, precisely the peak chosen by the NBER's Business Cycle Dating Committee, and fell nearly 4 percent from July 1990 through April 1991. Figures 5 and 6 show the forecasting performance of the leading indicators over the out-of-

sample period. These Figures show how well the indicators predicted growth in the XCI three and six months ahead. The forecasts tracked the actual data reasonably well until the middle of 1990. The indicators correctly predicted the slowdown that occurred in 1989 and the subsequent rebound in early 1990. But, as data from the fall of 1990 became available, it was clear that the model was off track.



**FIGURE 4**

**Six month ahead recession probability**



NOTE: Shaded areas are recessions as determined by the NBER Business Cycle Dating Committee.

**What went wrong?**

Four possible reasons are analyzed in Stock and Watson (1991b). First, the statistical model may have been poorly determined, in the sense that the parameters were poorly estimated and the model “overfit.” That is, the model may have been fit to match patterns in the historical data that did not persist into the future. Second, the model may have been correct, but the data subject to large revisions. Third, the XCI may have become an unreliable coincident indicator. Finally, the set of leading indicators used in the model may have behaved differently than in past recessions. In Stock and Watson (1991b), we present a variety of evidence suggesting that the first three possible reasons were not important. However, the final reason—the unusual behavior of some of the indicators, relative to their behavior in past recessions—was important. Three of the seven leading variables were primarily responsible for the index’s optimism as the recession began: the spread between the yield on commercial paper and Treasury bills; the spread between the yield on 10 year government bonds and 1 year government bonds; and the exchange rate. The difference be-

tween the historical behavior of these variables and their behavior in the current recession is the key to understanding why the index failed and why the current recession is unique in the postwar historical record.

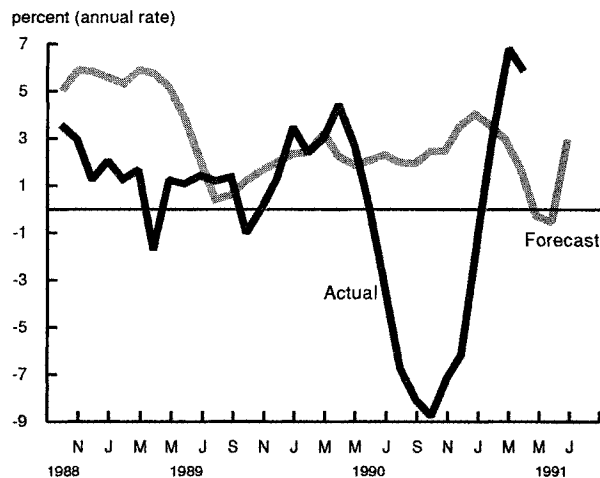
Table 3 documents the behavior of the interest rate spreads prior to the 1960 and subsequent recessions. During the 1959-1990 period, the spread between commercial paper and Treasury bills averaged 57 basis points and increased sharply prior to each of the 1960-1981 cyclical peaks. In contrast, coming into the current recession, the spread was essentially flat, averaging only 41 basis points during the first eight months of 1990.

The slope of the Treasury yield curve, measured as the yield spread

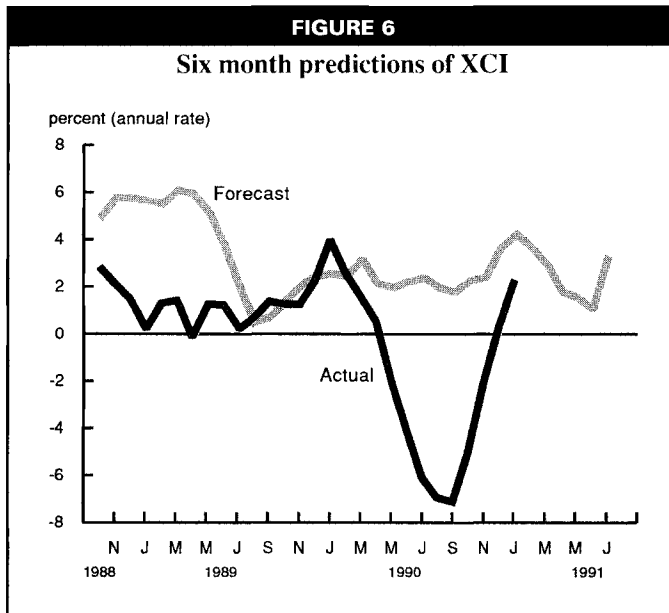
between 10 year and 1 year government bonds, also behaved differently than in past recessions. Over the 1959-1990 period, the yield curve usually sloped upwards; the average yield curve spread was 54 basis points. But, before each recession in the sample, the yield curve inverted and this spread became negative. From January 1990 to July 1990 the yield curve spread remains essentially constant, averaging +38 basis points. This was a slightly negative reading by this indicator, but nowhere near

**FIGURE 5**

**Three month predictions of XCI**







significant enough to suggest a recession. Just as important, in August and September of 1990, the yield curve steepened significantly; the spread increased to 97 basis points in August and to 113 basis points in September. Typically, such a steepening of the yield curve is associated with an increase in economic activity.

As the recession began, exchange rates also served as a positive indicator. In general, as the dollar weakens, U.S. goods fall in price relative to foreign goods, so that, controlling for the other indicators in the model, a depreciation in the dollar is a positive indicator. While the value of the dollar was essentially flat during the first seven months of 1990, it fell by 11 percent from July to November, suggesting an increase in future demand for domestically produced goods.

While the financial indicators behaved perversely during 1990, the real indicators used in the model behaved qualitatively as they had in earlier recessions. Building permits were weak. The number of workers involuntarily moving from full-time to part-time work increased. Manufacturers' unfilled orders slowed. While these indicators provided negative signals, these signals were not large enough to forecast the recession.

#### **Could the recession have been predicted?**

The answer to this question is clearly yes: some analysts *did* accurately predict the recession.

(An interesting question is how many of these forecasters also predicted recessions in 1987 and 1989.) Standard econometric models and the consensus business forecaster did not. For example, in May 1990 only 19 percent of the forecasters surveyed by the *Blue Chip Economic Indicators* expected the recession to begin in 1990. In mid-1990 the consensus forecast called for 2.3 percent growth in real GNP over the 1990-1991 period. Variables that are typically used to predict economic activity did not point to a recession. This raises the question of what variables could have been used to help forecast this recession.

It is always easy in hindsight to find a single variable that would have predicted a specific event. To be useful for forecasting, a variable must not only have predicted this recession, but also predict future recessions. Statistical procedures search for such variables by asking whether they have consistently predicted past recessions. In Stock and Watson (1991b), a careful statistical search for such variables is documented. We found that the most important variables omitted from our original model appear to be stock prices, help-wanted advertising, average weekly hours in manufacturing employment, and consumer sentiment. Interestingly, if the variables are added to our original list of indicators and the model is re-estimated, only marginal improvements are realized. The interest rate spreads predict the previous recessions so well that they get much of the weight in the statistical fit; the new variables receive little weight. The new variables lead to improved prediction only if the spreads are dropped from the model; in this case the new variables receive enough weight to be useful in the most recent recession. While this modified model performs better during the current recession, the original model performs better during previous recessions. The challenge is to construct a new model, including the entire list of indicators, and perhaps more, that will perform well during the next recession.

**What does this tell us about the current recession?**

These results suggest tentative conclusions about the nature of the current downturn. First and foremost is that it differs from the recessions of the 1960s, 1970s, and 1980s. This difference has been documented by other researchers, notably Strongin (1990) and Strongin and Eugeni (1991). In the present context, the most obvious symptom of this difference is the unusual behavior of the interest rate spreads relative to their behavior in past recessions. To understand what this difference suggests about the nature of this recession, it is important to understand why the interest rate spreads have traditionally been reliable indicators. This question has motivated much recent research [see Cook and Lawler (1983), Friedman and Kuttner (1990 and 1991b), Bernanke (1990), and Kashyap, Stein, and Wilcox (1991)], and a variety of explanations have been offered. The most reasonable seems to go as follows.

It is widely (although not universally) accepted that a tightening of monetary policy leads, in the short run, to a slowdown in aggregate economic activity.<sup>2</sup> A tightening of monetary policy is accompanied by a rise in short term interest rates and a tightening in bank lending. The increase in short term interest rates relative to long term rates leads to an inverted yield curve. The tightening in bank lending leads some firms to raise capital by issuing new commercial paper. This increases the stock of commercial paper, which raises the commercial paper rate relative to the rate on Treasury bills.

This explanation suggests that monetary policy, important for the recessions of the 1960s, 1970s, and 1980s, was less important during the current recession.

An alternative explanation is that monetary policy played a major role in the current recession but that structural changes in financial markets changed the relation between monetary policy and the interest rate spreads. This explanation is not convincing: the commercial paper/Treasury bill spread *did* widen significantly

**TABLE 3**

**Behavior of interest rate spreads prior to recessions**

**A. Commercial paper—Treasury bill spread (basis points)**

Cyclical peak	Months prior to cyclical peak			
	9	6	3	0
4/60	-7	3	88	107
12/69	120	114	84	133
11/73	62	106	160	101
1/80	65	140	96	147
7/81	185	78	113	101
7/90	51	38	43	51

**B. 10 year Treasury bond—1 year Treasury bond spread (basis points)**

Cyclical peak	Months prior to cyclical peak			
	9	6	3	0
4/60	-32	-45	23	79
12/69	-10	-85	-75	-35
11/73	-18	-126	-61	-43
1/80	-66	-151	-159	-307
7/81	-204	-59	-139	-120
7/90	12	24	38	113

before this recession, and the yield curve *did* invert. But this occurred in early 1989 when worries of inflation led the Fed to tighten policy. By the middle of 1990 the interest rate spreads had returned to normal levels, consistent with a more neutral monetary policy.

In the introduction, I noted that econometric methods are well suited for prediction over forecast periods with characteristics similar to those found in the sample. Many characteristics of the current recession are unique; the most obvious is the sudden outbreak of hostilities in the Middle East and coincident increase in uncertainty and fall in consumer sentiment. These could not have been predicted by any reasonable model. Thus, one can argue that this was a recession that *should not* have been predicted by an econometric model and that XRI passed this specification test. While there are elements of both truth and “cop out” here, I am not too concerned by the XRI’s failure to predict the recession. What is of more concern is the XRI’s failure to reflect the increased pessimism in the fall of 1990, by which time it was clear that the model was off track. Future research will focus on making the model more adaptive to changing circumstances.

APPENDIX

The probability model underlying the XCI is a dynamic factor model of the form:

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

$$(2) \quad D(L)u_t = \varepsilon_t,$$

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

where  $x_t$  is a 4 x 1 vector of coincident indicators,  $c_t$  is the scalar unobserved "state of the business cycle,"  $u_t$  and  $\varepsilon_t$  are unobserved shocks, and  $\gamma(L)$ ,  $D(L)$ , and  $\phi(L)$  are polynomials in the lag operator  $L$ ; so, for example,  $\gamma(L)\Delta c_t$  represents a distributed lag of  $\Delta c_{t-i}$  with weights  $\gamma_i$ . The coincident indicators in  $x_t$  include industrial production, real personal income, total employment (hours), and manufacturing and trade sales. They are precisely defined in Table 2. It is assumed that the matrix polynomial  $D(L)$  is diagonal, so that  $D(L) = \text{diag}[d_{ii}(L)]$ , and  $\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^3, \varepsilon_t^4$ , and  $\eta_t$  are mutually uncorrelated Gaussian white noises. These assumptions imply that  $c_t$  explains all of the comovement between the indicators, but that each indicator may move independently from the other because of innovations in its "uniqueness"  $u_t^i$ . Thus,  $c_t$  is a natural index of co-movement or covariation in the coincident variables and provides an index of aggregate cyclical activity. For three of the variables,  $\gamma(L) = \gamma_t$ , and this fixes the timing of  $c_t$ ; movements in  $c_t$  are coincident with industrial production, personal income, and manufacturing and trade sales. Since employment is slightly lagging, lagged values of  $c_t$  enter its equation. The XCI, plotted in Figure 1, is the minimum mean square error estimate of  $c_t$ , constructed from current and lagged values of  $x_t$ .

Leading indicators are added to the model to help predict future values of  $c_t$ . The complete model, including leading indicators, is (1) and (2) together with the vector autoregression:

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

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

where  $y_t$  is a vector of leading indicators and  $v_t' = (v_{ct}' \ v_{yt}')$  is NIID(0,  $\Sigma_v$ ) and independent of  $\varepsilon_t$ .

The definition of the leading indicators used in our analysis is given in Table 2; Stock and Watson (1989) provides a detailed discussion of the selection of variables, the estimated model and diagnostic tests.

Equations (1)-(2) and (4)-(5) provide a complete probability model for the index  $c_t$  and its relation to the coincident and leading indicators. Forecasts of  $c_t$  can be constructed in a straightforward way. The NBER's experimental index of leading indicators (XLI) are the forecasts of  $c_t$  over the next six months, that is,  $E_t(c_{t+6} - c_t)$ .

The model can be used to construct the probability distribution of past, current, and future values of the index, conditional on the observed data, that is,  $F_t(\dots, c_{t-1}, c_t, c_{t+1}, \dots)$ . Given the assumptions made about the disturbances in Equations (1)-(2) and (4)-(5), this conditional distribution is multivariate normal with a mean and covariance matrix that is easily calculated using standard prediction formulae. The recession prediction problem is simplified by the following assumption which captures the single index notion in this context:

$$(6) \quad \begin{aligned} P[R_{t+j} = 1 | \{c_\tau\}_{-\infty}^\infty, z_t, z_{t-1}, \dots] = \\ P[R_{t+j} = 1 | \{c_\tau\}_{-\infty}^\infty], \text{ for all } t \text{ and } j. \end{aligned}$$

Thus,  $z_t$  provides no information about a recession at time  $t+j$  that is not included in  $\{c_\tau\}$ . Interpreting  $z_t$  as the leading and coincident indicators in the model implies:

$$(7) \quad \begin{aligned} P(R_{t+j} = 1 | z_t, z_{t-1}, \dots) = \\ \int P[R_{t+j} = 1 | \{c_\tau\}_{-\infty}^\infty] dF_t(\dots, c_{t-1}, c_t, c_{t+1}, \dots); \end{aligned}$$

so that the probability of a recession at time  $t+j$ , given information through time  $t$ , can be calculated in two steps. In the first step, the probability of a recession at date  $t$  is calculated, given the entire history of the index  $\{c_\tau\}$ , that is,  $P[R_{t+j} = 1 | \{c_\tau\}_{-\infty}^\infty]$  is formed. In the next step, these probabilities are averaged using the probability distribution of the index  $\{c_\tau\}$ , conditioned on the observed data, that is, the integration is performed. This simplification is utilized to calculate  $P_{t+6|t}$ , which is the NBER's Experimental Recession Index or XRI.

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## FOOTNOTES

<sup>1</sup>This is an ongoing project, and our progress to date is summarized in three papers: Stock and Watson (1989), (1991a), and (1991b).

<sup>2</sup>The most thorough documentation of the relation between aggregate activity and the supply of money is Friedman and Schwartz (1963).

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