Turn, Turn, Turn: Predicting Turning Points in Economic Activity

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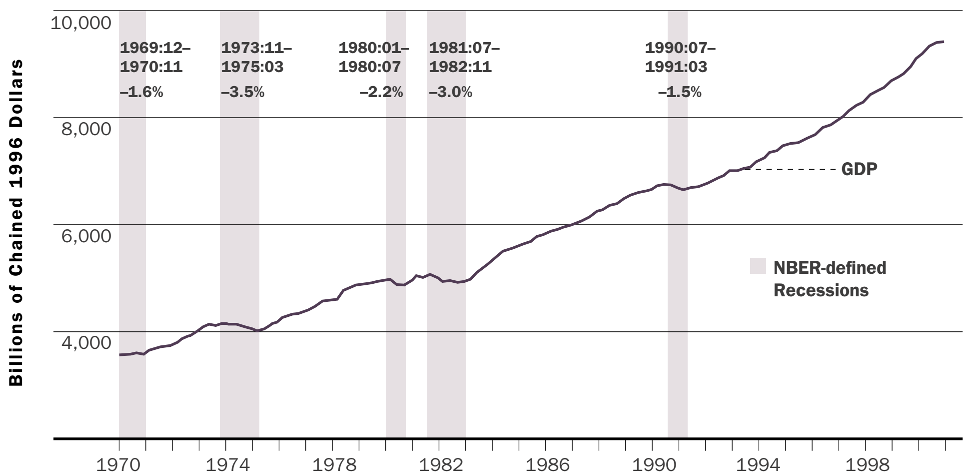
JULY 31, 2000: THE PRELIMINARY DATA FOR SECOND QUARTER REAL GROSS DOMESTIC PRODUCT (GDP) SHOW THAT THE ECONOMY IS GROWING AT A RATE OF ALMOST 6 PERCENT. THE LONGEST POSTWAR EXPANSION MARCHES ON. "NEW ECONOMY" PROPHETS CELEBRATE THE DEATH OF THE BUSINESS CYCLE—NAMELY, THE SEQUENCE OF UPS AND DOWNS, UNEVEN IN strength and duration, that have, so far, characterized economic activity.

January 31, 2001: Preliminary real GDP growth for the fourth quarter is barely above 1 percent, more than 4 percentage points below what is was only two quarters before and about 7 percentage points below its level in the third quarter of 1999. Much of the press, and some forecasters, predict that the first quarter of 2001 may be the beginning of a recession. Whether this is the case or not is on the minds of many policymakers while this article is being written.

The current state of the economy, not to mention the stock market, is certainly a far cry from what it was a few months ago. The recent gyrations in the economy and in the stock market remind us that the business cycle may not be dead—yet. They also remind us that economic conditions may change fast and somewhat unpredictably. This article focuses on providing some evidence on econometric models' ability to forecast these sudden changes in the business cycle, also called turning points.

A model that can correctly predict turning points would clearly be useful to the business community and the general public. Investment decisions are made with an eye toward future economic conditions. The clearer the crystal ball, the wiser the decision. Policymakers would also benefit from the ability to forecast turning points. As late as May 2000 the Fed raised interest rates by 50 basis points to 6.5 percent, the last of a sequence of federal funds rate increases, totaling 1.75 percent, that started in June 1999. The increase in target rates at that time was justified by the strength of the economy and the dangers posed by a potential comeback in inflation.[1] Without in any way implying that such a policy move has "caused" the current slowdown in activity, one could reasonably argue that policymakers might have behaved differently then had they known what was to come. These suppositions bring us to the main question of this article: How good is the state of the art in turning point forecasting?

CHART 1 Real GDP Growth 1970–2000



Notes: Percentages are declines in real GDP during the recessions.

Sources: GDP data from the Bureau of Economic Analysis, U.S. Department of Commerce; recession dates from the National Bureau of Economic Research (NBER)

The first section of the article discusses the definition of turning points in economic activity. The article then describes different approaches to turning point forecasting and their relative advantages and disadvantages. Next, the article assesses the performance of the Atlanta Fed Bayesian vector autoregression (BVAR) model in terms of forecasting turning points relative to a well-known alternative. The Atlanta Fed research department uses its BVAR model as a tool for forecasting and policy analysis. The model appears to be moderately successful, relative to other models, in forecasting real activity (see Robertson and Tallman 1999). However, as discussed later in this article, predicting particular events—like turning points—is not necessarily the same as day-to-day forecasting. The Atlanta BVAR model is geared toward the latter task. If the model turns out not to be adequate for the former task, it may be appropriate to supplement the BVAR model with a model that is specifically designed to forecast turning points.

Defining Turning Points

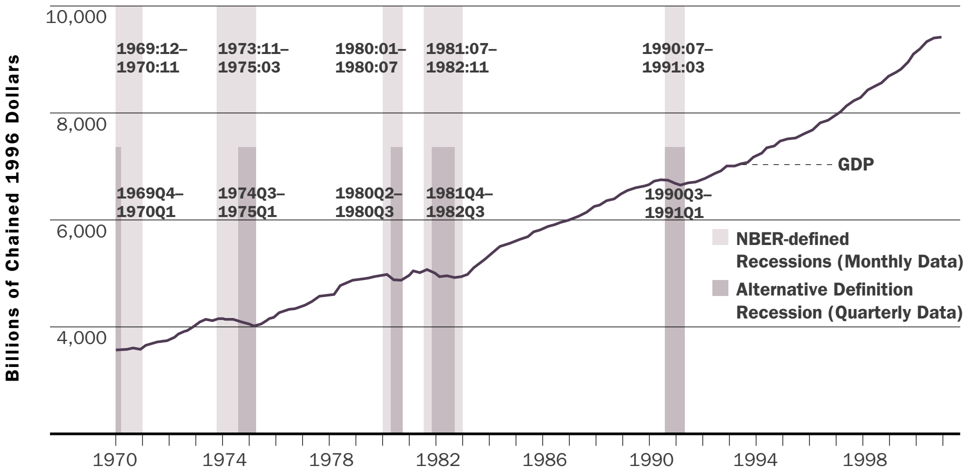
Everybody knows, roughly speaking, what a recession is. Not everybody knows what a turning point in real GDP is. The two are in fact closely related. According to a rule popularized by Arthur Okun and widely used in the press, the beginning of a recession (the end of an expansion) is defined as the first of two consecutive quarters of decline in real GDP. By analogy, the end of a recession (or the beginning of an expansion) is marked by the first of two consecutive quarters of real GDP growth (see Harding and Pagan 1998). The beginning and end of a recession are turning points in real GDP: the beginning represents a *peak* in real GDP while the end represents a *trough*.

Chart 1 illustrates this pattern. The chart plots real GDP from 1959 to the present as well as the National Bureau of Economic Research (NBER) recessions (shaded areas). In July 1990, at the beginning of a recession, real GDP starts to decline. Since real GDP is going down, its value in July 1990 is the highest attained for the next few quarters—a peak in real GDP. The chart shows that real GDP declines until March 1991. After that month, the recession ends and real GDP starts rising again. The value of GDP attained in March 1991 is lower than its value in any quarter of the preceding recession or the following expansion, so March 1991 is referred to as a trough in real GDP.

To be precise, the definition of recessions and expansions used by the NBER is not as simple as the one given above. The NBER recession and expansion dates are determined by the NBER Business Cycle Dating Committee. The members of the committee are guided in their decision by the widely quoted Burns and Mitchell definition of business cycles:

> Business cycles are a type of fluctuation found in the aggregate economic activity of nations

CHART 2 Real GDP Growth 1970–2000



Sources: See sources for Chart 1; alternative recession dates calculated by the Federal Reserve Bank of Atlanta

> 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 amplitudes approximating their own. (1946, 3)

Burns and Mitchell's definition emphasizes three important business cycle characteristics, known as the three Ds: duration, depth, and diffusion. A recession has to be sufficiently long (duration); it has to involve a substantial decline in output (depth); and it has to affect several sectors of the economy (diffusion). Faithful to the generality and complexity of Burns and Mitchell's definition, the NBER committee eschews numerical rules like the "two quarters of decline in real GDP" rule given above. Nonetheless, Chart 2 shows that after 1970 the recession and expansion dates determined using the "two quarters" rule are a good approximation of the NBER recession and expansion dates. The only difference is that NBER-defined recessions tend to be longer than recession defined using the two quarters rule. The NBER considers months of stagnant or very moderate growth as belonging to recessions rather than to expansionary periods. However, for practical purposes, turning points defined using the popular two quarters rule and NBER-defined turning points are not too far apart.

Predicting Turning Points: The Leading Indicators

The most well known predictors of turning points in economic activity are the series known as Leading Economic Indicators (LEI). The leading indicators were originally proposed in 1938 by Burns, Mitchell, and their colleagues at the NBER on the basis of their tendency to lead the cycle, as their name suggests (see Mitchell and Burns 1983). Until December 1995, the Leading Economic Indicators were produced by the Bureau of Economic Analysis at the Department of Commerce. Since that date, they have been produced by The Conference Board, a private, nonprofit organization.[2]

The box lists the series that are currently part of the LEI. The current list has changed from that originally proposed by Burns and Mitchell. Over

1. A May 16, 2000, press release from the Federal Open Market Committee (FOMC) stated, "Against the background of its long-term goals of price stability and sustainable economic growth and of the information already available, the Committee believes the risks are weighted mainly toward conditions that may generate heightened inflation pressures in the foreseeable future."
2. The Conference Board also produces a list of Coincident and Lagging Economic Indicators as well as the Consumer Confidence Index.

B O X

Index of Leading Economic Indicators

(1) Average weekly hours, manufacturing

(2) Average weekly initial claims for unemployment insurance

(3) Manufacturers' new orders, consumer goods and materials (in 1996 dollars)

(4) Vendor performance, slower deliveries diffusion index

(5) Manufacturers' new orders, nondefense capital goods (in 1996 dollars)

(6) Building permits, new private housing units

(7) Stock prices, 500 common stocks

(8) Money supply, M2 (in 1996 dollars)

(9) Interest rate spread, ten-year Treasury bonds less federal funds

(10) Index of consumer expectations

Source: The Conference Board

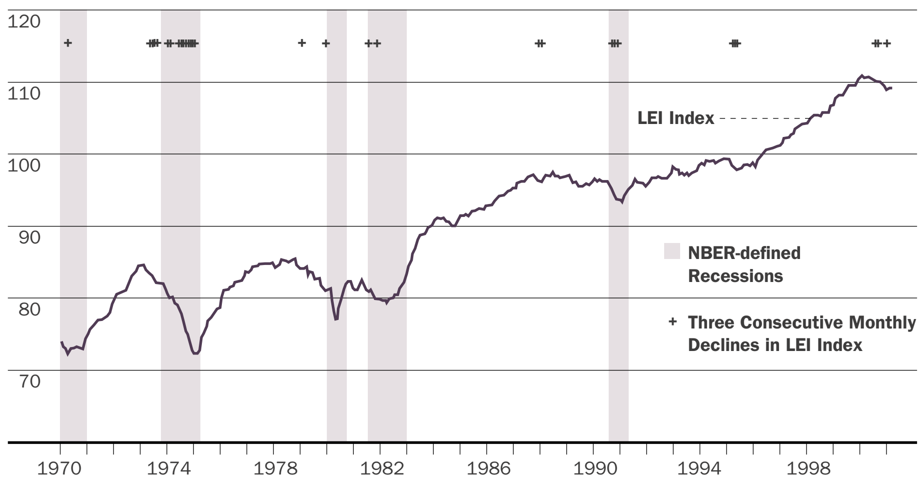
time, as new information about turning points has become available, series have been added or dropped out. A leading indicator that has recently received much attention in the press is the Index of Consumer Expectations, produced by the University of Michigan, which measures consumers' optimism and their willingness to spend and invest. This indicator has recently made the headlines because the sharp fall in consumer sentiment toward the end of 2000 and the beginning of 2001 raises the question of whether the beginning of a recession is imminent.

Policymakers, the press, and the public analyze the leading indicators series to gauge whether a recession is forthcoming. Leading indicators have an advantage over more complex econometric models: the index can be readily understood and interpreted. Popular discussion often neglects the fact that the leading indicators suffer from some of the very same problems as the more complex econometric models. The series representing the leading indicators were chosen on the basis of their ability to predict past recessions. Using the econometric lingo, they were chosen on the basis of their *in-sample* performance—that is, their ability to predict, with hindsight, recessions that have already occurred. Whether the leading indicators are able to predict future recessions (*out-of-sample* performance) is a different matter. Indeed, one of the reasons the Leading Economic Indicators list is periodically revised is that each new recession shows that some of the series were not good predictors after all (see Moore 1983 and Conference Board 1997 for a history of the revision process). For example, the only two series that have survived the test of time from the original Mitchell and Burns list of indicators are "average weekly hours, manufacturing" and the "S&P 500 Index."[3] All other series from their original list have been discarded.[4] Of course, some of the series that are in the current list may at some point share the same destiny.

In fairness to the Leading Economic Indicators, some literature shows that they have predictive power, not only in-sample but also out-of-sample (see Moore 1983; Zarnowitz and Braun 1988). However, such predictive signals coming from the leading indicators are hard to decipher, just like the pronouncements of the Delphic oracle.[5] For starters, leading indicator series often give conflicting signals. For example, in the last few months consumer sentiment has been plummeting, but building permits for new houses have been quite strong. Which indicators should one trust?

To avoid this problem, forecasters often rely on the Leading Economic Indicators Index, which is a weighted average of all leading indicators. Forecasters pay particular attention to turning points in the index: by the very nature of leading indicators, turning points in the index should anticipate turning points in economic activity. Still, turning points in the index are not always easy to recognize. Chart 3 plots the LEI Index along with the NBER recessions (shaded areas).[6] One can see that the 1973 recession is the only case in which a peak in the index clearly leads to a peak in economic activity. It is much harder to recognize turning points in the index prior to the 1981 or 1990 recessions. A rule often used to identify turning

CHART 3 Index of Leading Economic Indicators



Sources: Conference Board; NBER

points in the index is the so-called three-consecutive-declines rule: three consecutive declines in the LEI Index signal a turning point, suggesting that a downturn in economic activity may be imminent. The plus (+) signs in Chart 3 designate the third month in each sequence of three consecutive declines in the index. The patterns in the chart suggest that the three-consecutive-declines rule was helpful in predicting the 1973 recession, gave mixed signals prior to the 1980 recession, and was not helpful at all prior to the 1981 and 1990 recessions. In addition, the rule gave false signals in 1987 and 1995.

Other rules may perform better than the three-consecutive-declines rule. Diebold and Rudebusch (1989) use a more sophisticated approach to capture turning points in the index (also see Neftci 1982). This approach uses a regime-switching model to compute at each point in time the probability of a turning point in the index. Since in each period the probability is updated using the most recent index data release, this method is called the sequential-probability-of-turning-point approach. Diebold and Rudebusch find that this approach performs reasonably well, and certainly better than the three-consecutive-declines rule, in predicting postwar U.S. recessions.

In summary, the evidence suggests that leading indicators may be useful in predicting recessions. At the same time, the emphasis placed by the press on the latest LEI figures seems to be exaggerated. Like a Delphic oracle, leading indicators give valuable signs. However, interpreting those signs is less clear-cut than it would appear from reading the press. Additional tools may be needed to refine the accuracy of turning point prediction.

Predicting Turning Points: Econometric Models

An alternative approach to forecasting turning points in economic activity is to use econometric models. Within this approach, there are two different ways of tackling the problem of predicting turning points. One way is to rely on statistical models that are built to predict future values of economic variables, one of which is real GDP. The other way is to build a model that focuses directly on predicting the event of interest—in this case, turning points. For the first category of models, predicting turning points is a by-product of day-to-day forecasting. For the second category, it is the

3. To be precise, Mitchell and Burns's original list used a different index of stock prices—the Dow-Jones index of industrial common stock prices (see Moore 1983).
4. For instance, "change in sensitive material prices and change in unfilled orders for manufactured goods . . . were finally deleted in 1996. Each of these deletions followed the recognition that the component was not as reliable a leading indicator as originally thought" (Conference Board 1997, 5).
5. "The lord whose is the oracle at Delphoi neither utters nor hides his meaning, but shows it by a sign" (Heraclitus, Fragment 93, Diels-Kranz numeration).
6. The series for the LEI Index was obtained from Haver.

very goal of the model. This section describes the merits and faults of the two approaches and briefly discusses their underpinnings in the history of economic thought.

Econometric models are widely used to produce forecasts of economic time series. These models differ substantially from one another in terms of their econometric methodology, the variables that are being forecast, and the importance of judgmental factors. Some well-known examples of econometric models are the structural models in the Cowles Foundation tradition. These models usually employ a large number of equations, with each block of equations representing a specific aspect of economic behavior (household behavior, firm behavior, and so forth).[7] Several commercial forecasting models, like the Penn-MIT model, the Fair model, and the Macro-Advisors model, belong to this category. Another set of models commonly used for forecasting is vector autoregression (VAR) models (often Bayesian VARs, in the Litterman 1980 tradition), like the one currently in use at the Atlanta Fed. VAR models differ from structural econometric models in several ways, but mainly in their identifying assumptions (see Sims 1980 and Stock and Watson forthcoming for a discussion of VARs).[8] Finally, a third set of econometric models used in forecasting is the dynamic factor models, pioneered by Sargent and Sims (1977). In particular, Stock and Watson (1989) use a dynamic factor model to create indexes of the coincident and leading indicators that capture the information present in the Coincident and Leading Economic Indicators already mentioned.

The evidence suggests that leading indicators may be useful in predicting recessions. At the same time, the emphasis placed by the press on the latest LEI figures seems to be exaggerated.

All these various models embody, implicitly or explicitly, a so-called extrinsic view of business cycles. According to this view, the underlying structure of the economy does not change from a recession to an expansion. The underlying structure is stable and can be described, or at least approximated, by a linear probabilistic model. From the extrinsic point of view, the main difference between recessions and expansions lies in the sign (negative or positive), and possibly in the size and duration, of the shocks that hit the economy (see Stock and Watson 1989 and Diebold and Rudebusch 1996 for a discussion of this point). In contrast, traditional business cycle research tends to view recessions and expansions as being intrinsically distinct; according to this "intrinsic" view, turning points represent shifts in the economic behavior of agents and are not simply the result of a large negative shock in economic activity.[9] In terms of forecasting, one implication of the intrinsic view is that day-to-day forecasting and predicting turning points may be different businesses altogether.

While there is no systematic record of the ability to predict turning points for all existing structural models and VARs, the common wisdom is that most of these models share a dismal record in predicting recessions.[10] Perhaps in response to this poor performance, a different approach to turning point forecasting, pioneered by Estrella and Hardouvelis (1991) and then followed by Estrella and Mishkin (1998) and Chin, Geweke, and Miller (2000), was recently developed.[11] This approach recognizes that the set of variables that helps predict "routine" ups and downs in output may not necessarily be of much use in predicting recessions. Likewise, statistical models that are used in forecasting future values of economic time series may not be too useful in predicting a specific event, like a recession.[12] Instead of using a linear regression model, the above-mentioned authors directly model the probability of a recession using a *probit* model. In a probit model the variables included in the model and their respective coefficients are chosen not on the basis of their ability to track past movements in real GDP but on the basis of their ability to indicate the likelihood of past recessions.

The main strength of this approach is that it is geared specifically toward predicting turning points. The very strength of the approach, however, is also its main weakness. The probit model focuses on recessions, and recessions are rare events. Econometric models aimed at tracking real GDP have numerous observations at their disposal. Models aimed at pinning down recessions have only a handful.

Probit models suffer an additional disadvantage relative to econometric models when it comes to policy analysis. As emphasized in the press and in the policy debate, policymakers' actions may affect the likelihood of a recession. Policymakers need to assess how their actions change the probability that the economy may encounter a recession a few quarters down the road. Unfortunately, these issues cannot be addressed quantitatively in the context of probit models, which do not distinguish between policymakers' actions and shocks coming from elsewhere in the economy. Identified econometric models like the VAR, however, allow for such a distinction. Within the framework of identified models one can ask the question, If the Fed had lowered interest rates by an additional 50 basis points in March, would the likelihood of a recession be significantly lower (see Leeper and Zha 2001)? The reliability of the answer, of course, depends on how good the underlying identification assumptions and the forecasting ability of the model are. Yet the capability to perform such important thought experiments gives identified econometric models an edge over probit models and leading indicators.

A Comparison of Techniques

The ultimate test for all forecasting models lies in their out-of-sample accuracy. This section compares the predictive ability of the Atlanta Fed BVAR model with that of both the Leading Economic Indicators Index and the turning point model proposed by Estrella and Mishkin.

The Atlanta Fed model is a Bayesian VAR that incorporates six variables: the federal funds rate, the consumer price index (CPI), M2, oil prices, unemployment, and real GDP.[13] All these variables are available since 1959 and enter the model in logarithms, with the exception of the unemployment rate and the fed funds rate, which enter in levels. All the variables except GDP are available on a monthly frequency; monthly GDP is computed by interpolating quarterly GDP. Following the Bayesian tradition, the model uses priors (that is, it combines prior information with sample data to estimate equation parameters) to deal with the large number of coefficients and the issue of nonstationarity (see Robertson and Tallman 1999 for a detailed description of the model, the priors, and the data).

Chart 4 plots the probabilities of a recession in the next eight quarters computed from January 1970 to March 2001 using the Atlanta Fed Bayesian VAR model. Chart 4 also shows the Leading Economic Indicators Index. Plus (+) signs indicate the third month for each sequence of three consecutive declines in the index. As discussed above, the three-consecutive-declines rule is often used to detect turning points in the index.

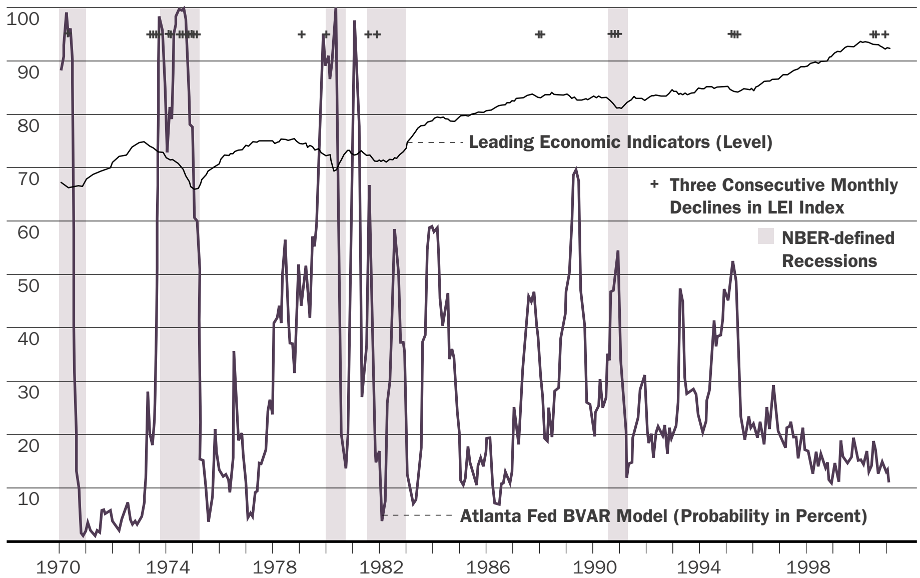
The probabilities shown in Chart 4 are out-of-sample probabilities of a recession. The probability of a recession in the next eight quarters computed for, say, January 1970 is computed by performing the following steps:

(1) estimating the model using only the data that were available in January 1970;[14]
(2) using a Monte Carlo procedure, generating 2,000 draws from the probability distribution of the forecasts of future real GDP (the draws are obtained by randomly sampling from the joint distribution of forecast errors);
(3) for each draw, determining whether a recession (defined as two consecutive quarters of negative real GDP growth) will occur in the next eight quarters or not; and
(4) computing the percentage of draws for which a recession occurs, thus providing an estimate of the probability of a recession.

Relative to turning point models, like the one proposed by Estrella and Mishkin, the Atlanta Fed BVAR model is far less precise in indicating the exact timing of a recession.

7. See Fair (1994) for a discussion of the Cowles Foundation tradition.
8. In structural econometric models an identification problem can arise in estimating simultaneous equations when it is impossible to distinguish from the data which equation is being estimated. To eliminate this problem, structural models often impose the restriction that variables factored into one block of equations—say, the household block—not be used in other blocks, either contemporaneously or with lags. The proponents of VARs claim that these restrictions have little or no ground in modern general equilibrium theory and prefer models with fewer variables but also fewer restrictions.
9. Regime-switching models (see Hamilton 1989) somewhat bridge the extrinsic and intrinsic views: these models recognize that the parameters describing the economy may change from a recession to an expansion; at the same time, the models assume a linear probabilistic structure within regimes. Bayesian turning point models also bridge the two views as they assume linearity with time-varying parameters (see Zellner and Hong 1988).
10. For example, Stock and Watson (1992) discuss how their model missed the 1990 recession.
11. This approach has an antecedent in the "experimental recession index" developed by Stock and Watson (1989, 1992).
12. Chin, Geweke, and Miller, also proponents of this approach, state that "An unwritten rule of forecasting is that accuracy is enhanced by forecasting directly what is of interest—in this case turning points" (2000, 3).
13. The model was originally designed by Tao Zha (Zha 1998).
14. The probabilities are computed starting in 1970 because prior to that date too few data are available for the estimation.

CHART 4
Probability of a Recession in the Next Eight Quarters



Sources: Conference Board; NBER; BVAR model from the Federal Reserve Bank of Atlanta

It is important to remark two features of this procedure. First, the model is estimated using only the data available up to that month. For instance, from January to March 1970 the model uses only the series for real GDP up to the fourth quarter of 1969 because the real GDP figures for a given quarter become available only in the month after the end of that quarter. The model uses the most recent vintage of revised data, not the data that were actually available in January 1970, but the experiment tries to duplicate "real-time" forecasting as closely as possible.[15]

The second important feature of the procedure is that it estimates the probability of a recession occurring in any of the next eight quarters, including the current quarter. There are two reasons for estimating the probabilities this way. First, it allows comparison of the accuracy of the signals from the BVAR model with those from the Leading Economic Indicators Index. Chart 3 shows that the timing of turning points in the LEI Index relative to turning points in economic activity varies considerably from recession to recession. In other words, a turning point in the index signals that some time in the near future a recession may be starting but does not give a precise signal of when it may begin. To make a fair comparison, the same leeway is allowed for the BVAR model in terms of the timing of recessions. Second, from the perspective of policymakers, determining the precise timing of a recession is, arguably, less important than determining the likelihood of a recession in the near future.

The patterns in Chart 4 suggest that the predictive ability of the BVAR model, both in absolute terms and relative to the LEI, is less dismal than one would expect given that the model is not geared toward predicting recessions and that it includes only one of the LEI series (M2) among its variables. The BVAR signals ahead of time both the 1973 and 1980 recessions. The probability of the 1973 recession rises above 50 percent only a few months prior to the beginning of the recession while the signal from the LEI is more timely. For the 1980 recession, the warnings from the BVAR appear more clear-cut than the warnings from the index.[16] For the 1981 recession, the BVAR sends a very clear signal at the beginning of the year while the index sends none. However, the BVAR signal is not steady in that the probability decreases below 50 percent immediately prior to the recession. Finally, both the BVAR and the index miss the 1990 recession. The recession probability computed by the BVAR rises to 70 percent in 1989 but then declines below 30 percent and rises again only well into the recession. In terms of false signals, the BVAR and the three-consecutive-declines rule are roughly at the same level. The probability of a recession computed by the BVAR rises, incorrectly, above 50 percent in 1984 and in 1995. The three-consecutive-declines rule sends false signals in 1987 and 1995.

While visible patterns in the data are helpful, forecasters would like to have a more quantitative measure to compare predictive abilities. Diebold and Rudebusch (1989) provide two such measures. The first, called a quadratic probability score (QPS), is computed as follows:

$$QPS = 1/T \sum_{t=1}^{T} 2(P_t - R_t)^2,$$

where P_t is the probability assigned by the model and R_t is an indicator function equal to 1 if a recession is occurring within the next eight quarters and equal to 0 otherwise.[17] If the forecasting model is right all the time, in the sense that the model assigns a probability of 1 when a recession is going to occur and of 0 otherwise, the QPS takes a value of 0. If the forecasting model is wrong all the time, in the sense that the model assigns a probability of 0 when a recession is going to occur and of 1 otherwise, the QPS takes a value of 2. The second measure is called the log probability score (LPS) and is computed as follows:

$$LPS = -1/T \sum_{t=1}^{T} [(1 - R_t)\ln(1 - P_t) + R_t \ln(P_t)].$$

While the QPS penalizes small and large forecasting errors proportionally—a model that makes several small mistakes may have the same score as a model that makes few very large mistakes—the LPS penalizes large mistakes more heavily.

In order to compare the predictive ability of the BVAR model to that of the LEI Index, the three-consecutive-declines rule must be transformed into recession probabilities. Following Diebold and Rudebusch, this transformation is accomplished in two ways. The first transformation, denoted as 3CD, associates a value of 1 to P_t (a 100 percent probability of a recession) whenever a plus (+) appears on Chart 4 and a 0 otherwise. The second transformation, denoted as 3CDa, is just like the first except that a linear decay method is added. Values of P_t equal to 1 are followed by values of P_t equal to 0.8, 0.6, 0.4, and 0 (unless another plus [+] occurs, in which case P_t returns to 1). Table 1 shows the QP and the LP scores for the BVAR model and the two transformations of the three-consecutive-declines rule.[18] The table shows that the BVAR model has a better forecasting ability than the three-consecutive-declines rule, regardless of the transformation, for both the QPS and the LPS.

TABLE 1
Comparison in Forecasting Scores: Probability of a Recession within the Next Eight Quarters (1970–98, Monthly)

	QPS	LPS
BVAR	.37	.59
3CD	.67	2.32
3CDa	.56	1.82

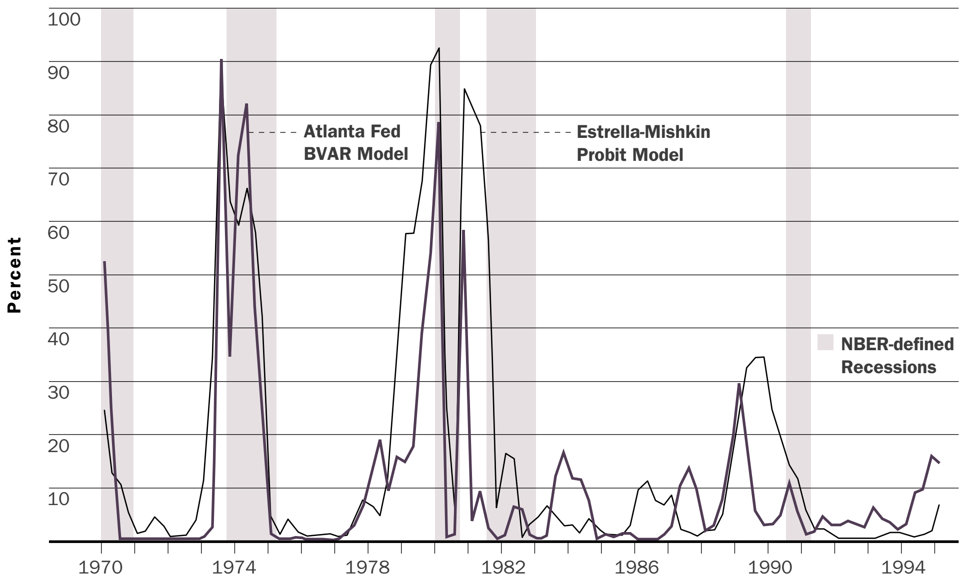
Note: The table compares the forecasting accuracy in terms of assessing the likelihood of a recession within the next eight quarters for the Atlanta BVAR model and for two variants (3CD, 3CDa) of the "three-consecutive-months-decline" rule. The forecasting accuracy is assessed using both the quadratic probability score (QPS) and the logarithmic probability score (LPS). The scores are computed using the sample 1970:01–1998:12.

The three-consecutive-declines rule is a naive rule for signal extraction. A more sophisticated use of the information from the LEI Index, like the sequential-probability-of-turning-point approach described in Diebold and Rudebusch (1989) and mentioned above, may well lead to a better predictive ability than the one obtained using the naive rule. The patterns revealed in charting the results from the sequential-probability-of-turning-point measure of Diebold and Rudebusch (379) suggest that its performance is comparable to that of the BVAR model. The Diebold and Rudebusch model predicts more timely the 1973 recession, behaves similarly to the BVAR's probability prior to the 1980 recession, and fails to predict the 1981 recession.[19]

Estrella and Mishkin (1998) focus on their probit model's ability to forecast recessions exactly k quarters ahead (where k ranges from one to eight) as opposed to assessing the likelihood of a recession occurring in any of the next k quarters. For the sake of comparing the two models, the probabilities of a recession exactly k quarters ahead are also computed using the BVAR model. Chart 5 shows the probabilities of a recession four quarters ahead computed

15. See Filardo (1999) for a comparison of different turning point prediction models using "real-time" data.
16. The recession probability computed by the BVAR rises steadily as the recession approaches while the three-consecutive-declines rule posts only two plus signs: one well before the recession and one immediately prior to it.
17. In essence, R_t is a time series of 1's and 0's indicating whether a recession is beginning within the next eight quarters (1) or not (0).
18. The scores are computed using the sample 1970:01–1998:12.
19. Diebold and Rudebusch's sample stops in 1988, so the two models cannot be compared for the 1990 recession. Also, Diebold and Rudebusch use the LEI Index available in 1988, which is different from the current index.

CHART 5 Probability of a Recession Four Quarters Ahead



Sources: NBER; probabilities calculated by the Federal Reserve Bank of Atlanta

according to both models.[20] The probabilities are computed at a quarterly frequency for both the Estrella-Mishkin and the BVAR model. Specifically, for the BVAR the probability of a recession four quarters ahead was computed using only the data available at the end of each quarter, which is roughly the same information set used in Estrella and Mishkin. From Chart 5 it appears that the Estrella-Mishkin model outperforms the BVAR, especially in terms of predicting the timing of the recession. For all recessions after 1970, the signal from the Estrella-Mishkin model is more timely and more precise than that from the BVAR, particularly for the last three recessions.

Table 2, which gives the QP and LP scores for the BVAR and Estrella-Mishkin models during the 1970:1–1995:1 period, shows that the Estrella-Mishkin model compares favorably to the BVAR. Over shorter horizons, like two quarters, the BVAR's performance worsens considerably relative to that of the Estrella-Mishkin model.

To improve the forecasting ability of the BVAR model, the six-variable version was augmented with an extra variable chosen from those economic series that should, at least in principle, have predictive content. These forward-looking series are the stock market index (S&P 500), the University of Michigan Consumer Sentiment Index, and the spread between a ten-year bond and a three-month Treasury bill (see Estrella and Mishkin 1998 for a discussion of why this spread is a useful predictor of recessions). Interestingly, none of these variables was found to add noticeably to the BVAR model's predictive ability in turning point forecasting.

In summary, it appears that the BVAR model compares favorably with respect to the LEI Index in turning point forecasting, especially when relatively naive rules like the three-consecutive-declines rule are used to extract information from the index. The BVAR compares unfavorably to the Estrella-Mishkin model in terms of predicting the exact timing of future recessions. In providing early signals of recessions beginning sometime within the next two years, the BVAR model seems to hold its ground although its signals are less precise and less timely than those from the Estrella-Mishkin model.[21]

Conclusion

This article first examines the concept of turning points in economic activity and discusses them in relation to the better-known concepts of "recession" and "expansion." The study then describes different approaches to turning point forecasting and analyzes their relative advantages and disadvantages. Specifically, the article focuses on the Leading Economic Indicators and on econometric models, including turning point models, and assesses their out-of-sample accuracy in predicting recessions.

The article finds that the Atlanta Fed's BVAR model forecasts contain information on future recessions that appears superior to that embodied in the LEI Index (at least when simple rules like the three-consecutive-declines rule are used to extract information from the

TABLE 2
Comparison in Forecasting Scores: Probability of a Recession Four Quarters Ahead (1970–95, Quarterly)

	QPS	LPS
BVAR	.31	.95
Estrella-Mishkin	.19	.32

Note: The table compares the forecasting accuracy in terms of assessing the likelihood of a recession four quarters ahead for the Atlanta BVAR model and for the Estrella-Mishkin model. The forecasting accuracy is assessed using both the quadratic probability score (QPS) and the logarithmic probability score (LPS). The scores are computed using the sample 1970:1–1995:1.

index). Since the outcome of the naive rules is what usually makes headlines, one implication of these results is that it may not be wise to rely too much on the latest LEI number, as filtered by the press.

Relative to turning point models, like the one proposed by Estrella and Mishkin, the Atlanta Fed BVAR model is far less precise in indicating the exact timing of a recession. In general, the quality of the warning signals from models that are specifically designed to forecast turning points appears to be better than that from the BVAR model. This conclusion suggests that it is worthwhile to supplement the BVAR with a turning point model.[22]

To determine whether these conclusions are valid one simply has to wait for more evidence. The next recession should provide some clues.

20. Estrella and Mishkin's paper shows the results for two and four quarters ahead. The four-quarter horizon is perhaps more relevant for policymakers than the two-quarter horizon given the lags with which monetary policy operates. For this reason, Chart 5 focuses on the results for the four-quarter horizon.

This study tried to replicate Estrella and Mishkin's results using a different software. By and large this attempt was successful, as can be seen by comparing Chart 5 with Figure 4 in Estrella and Mishkin (1998, 54). Nonetheless, some small disparities remain. Also, the timing convention in Chart 5 is different than that used in Estrella and Mishkin's Figure 4. Chart 5 plots the probabilities for the quarter in which the forecasts are produced. Figure 4 plots the probabilities for the quarter that is being forecast.

21. Coming from an Atlanta Fed economist, this conclusion may remind some readers of the Neapolitan proverb, "Pure o scarrafone è bello a mamma suia" (Even the cockroach looks beautiful to his mother).
22. By using both models policymakers can exploit the benefits from the "portfolio diversification" of forecasts.

REFERENCES

BURNS, ARTHUR F., AND WESLEY C. MITCHELL. 1946. *Measuring business cycles.* New York: National Bureau of Economic Research.

CHIN, DAN M., JOHN GEWEKE, AND PRESTON J. MILLER. 2000. Predicting turning points. Federal Reserve Bank of Minneapolis Staff Report Number 267, June.

CONFERENCE BOARD. 1997. A look at historical revisions to the leading index. *Business Cycle Indicators*, June.

DIEBOLD, FRANCIS X., AND GLENN D. RUDEBUSCH. 1989. Scoring the leading indicators. *Journal of Business* 62, no. 3:369–91.

———. 1996. Measuring business cycles: A modern perspective. *Review of Economics and Statistics* 78, no. 1:67–77.

ESTRELLA, ARTURO, AND GIKAS HARDOUVELIS. 1991. The term structure as a predictor of real economic activity. *Journal of Finance* 46 (June): 555–76.

ESTRELLA, ARTURO, AND FREDERIC S. MISHKIN. 1998. Predicting U.S. recessions: Financial variables as leading indicators. *Review of Economics and Statistics* 80, no. 1: 45–61.

FAIR, RAY C. 1994. *Testing macroeconometric models*. Boston: Harvard University Press.

FILARDO, ANDREW J. 1999. How reliable are recession prediction models? Federal Reserve Bank of Kansas City *Economic Review* 83 (Second Quarter): 35–55.

HAMILTON, JAMES D. 1989. A new approach to the economic analysis of non-stationary time series and the business cycle. *Econometrica* 57 (March): 357–84.

HARDING, DON, AND ADRIAN R. PAGAN. 1998. Knowing the cycle. Photocopy.

LEEPER, ERIC, AND TAO ZHA. 2001. Modest policy interventions. Federal Reserve Bank of Atlanta. Manuscript.

LITTERMAN, ROBERT B. 1980. A Bayesian procedure for forecasting with vector autoregressions. Massachusetts Institute of Technology Department of Economics Working Paper.

MITCHELL, WESLEY C., AND ARTHUR F. BURNS. 1983. Statistical indicators of cyclical revivals. In *Business cycles, inflation, and forecasting,* 2d ed., edited by Geoffrey H. Moore (Cambridge Mass.: National Bureau of Economic Research). First published in National Bureau of Economic Research Bulletin 69 (1938).

MOORE, GEOFFREY H. 1983. The forty-second anniversary of the leading indicators. In *Business cycles, inflation, and forecasting,* 2d ed., edited by Geoffrey H. Moore (Cambridge Mass.: National Bureau of Economic Research). First published in *Contemporary economic problems*, edited by William Fellner (Washington, D.C.: American Enterprise Institute, 1979).

NEFTCI, SALIH. 1982. Optimal predictions of cyclical downturns. *Journal of Economic Dynamics and Control* 4 (August): 225–41.

ROBERTSON, JOHN C., AND ELLIS W. TALLMAN. 1999. Vector autoregressions: Forecasting and reality. Federal Reserve Bank of Atlanta *Economic Review* (First Quarter): 4–18.

SARGENT, THOMAS J., AND CHRISTOPHER A. SIMS. 1977. Business cycle modeling without pretending to have too much a priori economic theory. In *New methods in business cycle research*, edited by C. Sims et al. Minneapolis: Federal Reserve Bank of Minneapolis.

SIMS, CHRISTOPHER A. 1980. Macroeconomics and reality. *Econometrica* 48 (January): 1–48.

STOCK, JAMES H., AND MARK W. WATSON. 1989. New indexes of coincident and leading indicators. In *National Bureau of Economic Research Macroeconomic Annual 4*, edited by Olivier Blanchard and Stanley Fisher. Cambridge, Mass.: National Bureau of Economic Research.

———. 1992. A procedure for predicting recessions with leading indicators: Econometric issues and recent experience. National Bureau of Economic Research Working Paper #4014, March.

———. Forthcoming. Vector autoregressions. *Journal of Economic Perspectives*.

ZARNOWITZ, VICTOR, AND PHILLIP BRAUN. 1988. Comment to Stock and Watson's new indexes of coincident and leading indicators. In *National Bureau of Economic Research Macroeconomic Annual 4*, edited by Olivier Blanchard and Stanley Fisher. Cambridge, Mass.: National Bureau of Economic Research.

ZELLNER, ARNOLD, AND CHANSIK HONG. 1988. Bayesian methods for forecasting turning points in economic time series: Sensitivity of forecasts to asymmetry of loss structures. In *Leading economic indicators: New approaches and forecasting records,* edited by K. Lahiri and G. Moore. Cambridge: Cambridge University Press.

ZHA, TAO. 1998. A dynamic multivariate model for use in formulating policy. Federal Reserve Bank of Atlanta *Economic Review* 83 (First Quarter): 16–29.