How Reliable Are Recession Prediction Models?

By Andrew J. Filardo

The U.S. economy continues to advance briskly, defying forecasts of more moderate growth. Beginning in March 1991, the current expansion has become the longest *peacetime* expansion on record and is less than a year away from becoming the longest in U.S. history. To the surprise of some observers, economic growth has been particularly robust late in the expansion. In fact, over the last three years growth has averaged 4 percent annually, and indicators of growth for the first half of 1999 show no signs of significant slowing.

Despite these positive signs, few analysts believe the expansion can go on forever. As the expansion continues to age, economists will increasingly be called on to predict the next recession. Recession prediction models may help them gauge the likelihood of imminent recession.

This article examines the reliability of five popular recession prediction models. The first section reviews each model's theoretical strengths and weaknesses in predicting recessions. The second section evaluates how well these models have given advance warning of past recessions. Performance is measured both with recently released data as well as the data originally available to analysts. The article concludes that these models have demonstrated some ability in the past to predict recessions. When judiciously interpreted, the models can help resolve uncertainty about the possibility of future recession.

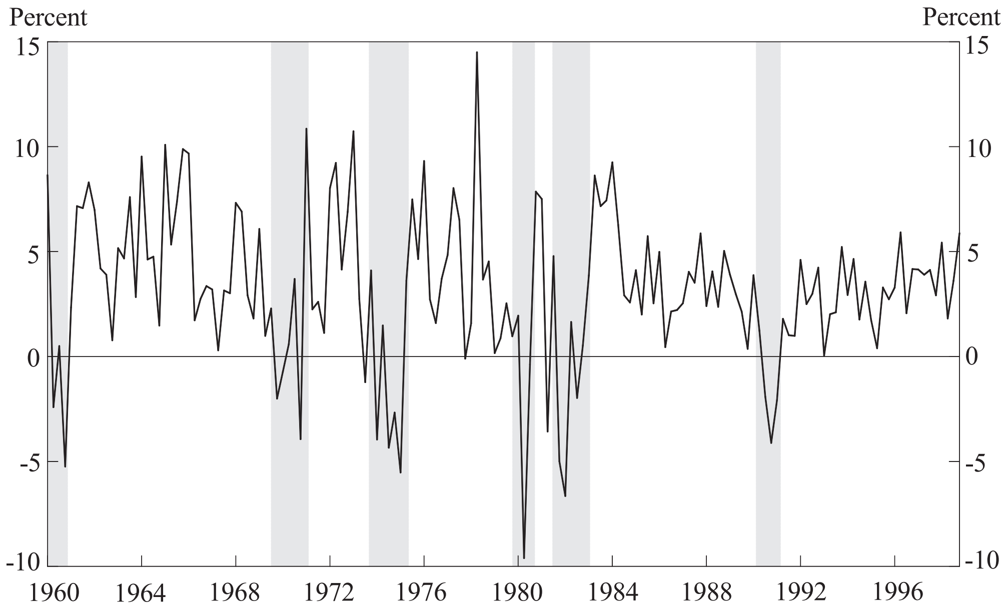
Andrew J. Filardo is an assistant vice president and economist at the Federal Reserve Bank of Kansas City. *The author benefited from conversations with Michael Boldin. The author also thanks John Robertson and Ellis Tallman for their real-time data set. Barak Hoffman, a research associate at the bank, helped prepare the article. This article is on the bank's Website at* ***www.kc.frb.org****.*

I. FIVE RECESSION PREDICTION MODELS

While a recession is commonly understood to be a widespread and prolonged decline in economic activity, using a model to predict recessions requires a more precise definition. One popular definition of recession is a consecutive 2-quarter decline in GDP.[1] The appeal of this definition stems from the fact that GDP is one of the broadest measures of economic activity. It is hard to imagine a widespread decline in economic activity without a decline in GDP.

Another definition of recession comes from the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER), which officially dates the beginnings and ends of U.S. recessions. The Dating Committee defines a

Chart 1
REAL GDP GROWTH AND NBER BUSINESS CYCLE DATES



Note: NBER recessions are indicated by gray bars.

recession as a broad decline in aggregate economic activity (which is measured as a common movement in output, income, employment, and trade), usually lasting from six months to a year, and marked by widespread contractions in many sectors of the economy. The NBER explicitly shuns the GDP definition because it considers GDP to be too narrow a measure of economic activity to reliably date recessions.[2] Nevertheless, declines in GDP are closely correlated to recession periods as denoted by the NBER (Chart 1).

Many analysts use specialized models to predict the onset of recession. These models are useful primarily because the behavior of the economy during periods of transition between expansion and recession is fundamentally different than when recession is not imminent (Hymans). In other words, special times such as turning points in the business cycle call for special models. Moreover, empirical evidence lends support to this view. During expansions when recessions are not a threat, forecasters tend to rely on large-scale econometric models to chart the future of the economy. It is well known, however, that around turning points in economic activity, these models can produce large forecasting errors (Braun and Zarnowitz). As a consequence, when an expansion might be nearing an end, small-scale forecasting models can play a critical, if not a dominant, role in predicting future economic activity (Diebold and Rudebusch 1989).[3] This section describes five of these popular business cycle models: simple rules of thumb using the Conference Board's composite index of leading indicators (CLI), Neftçi's probability model of imminent recession using the CLI, a regression-based model of the probability of recession called a Probit model, a GDP forecasting model, and a recession prediction model recently proposed by Stock and Watson. The appendix provides some technical details.

Simple rules of thumb using the CLI

Simple rules of thumb based on the composite index of leading indicators have long been used to predict recessions. The rules have appeal partly because the CLI has been carefully designed to provide advance warning of recessions.[4] Business cycle researchers, especially those associated with the NBER, have pored over reams of data through the decades to construct an index with the principal purpose of predicting the beginnings and ends of recessions. The ten components of the index have six characteristics that should make them good leading indicators: 1) conformity to the general business cycle, 2) consistent timing as a leading indicator, 3) economic significance based on accepted business cycle theories, 4) statistical reliability of data collection, 5) smooth month-to-month changes, and 6) reasonably prompt publication of the data.[5]

CLI rules of thumb also have popular appeal because they are easy to use and understand. One popular rule signals an imminent recession if the CLI falls in two consecutive months. Another rule requires three consecutive monthly declines. Compared to the 2-month rule, the 3-month rule should provide a stronger warning of imminent recession, thereby producing fewer false signals of recession. False signals arise in a recession prediction model when it signals an imminent recession that does not occur. However, the 3-month rule gives less advance warning.[6]

Philip Klein and Michael Niemira offered a slight refinement to the simple CLI rules of thumb to strengthen the recession signal without increasing the number of consecutive declines. Because it is possible that a few consecutive but small declines in the CLI might falsely signal the onset of recession, Klein and Niemira added a threshold criterion to the simple rule. The modified rules require two or three months of CLI declines of at least 1.3 percent.[7] This extra criterion should help filter out insignificant declines in the CLI, thereby reducing the likelihood of false signals without necessarily lengthening the lead time in correctly identifying recessions.

Neftçi model

Salih Neftçi sought to improve on the simple CLI rules of thumb by developing a formal statistical model of the probability of recession. Neftçi's model converts monthly observations of the CLI into a probability of imminent recession. When the estimated probability of recession exceeds a threshold value, such as 95 percent, the model flashes a signal of an imminent recession.

Neftçi's model may outperform the CLI rules of thumb because it makes better use of past information in the CLI. Neftçi's model provides a way to exploit early, often sporadic, recessionary signals that would not be strong enough to trigger the simple CLI rules of thumb. In other words, advance warning of a recession may become available well before the signal is sufficiently strong to cause the CLI to fall for several consecutive months. As a result, the Neftçi model is potentially able to increase the lead time in spotting recessions. Moreover, by being able to take account of a longer history of CLI data than the CLI rules, the Neftçi model may be able to generate clearer signals of recession and thus reduce the number of false signals.

Neftçi's model offers several other theoretical advantages over the basic CLI rules of thumb. First, Neftçi's model is sufficiently flexible to incorporate different beliefs about how recessions start. For example, if an analyst believes that expansions can die of old age, the analyst can modify the Neftçi model to reflect this belief. Such prior beliefs cannot readily be incorporated into CLI rules of thumb. Second, the Neftçi model can be used to evaluate the ability of variables other than the CLI to predict recession. For example, Giela Fredman and Michael Niemira used this model to evaluate the separate components of the CLI as well as a list of financial variables.[8] Even though Neftçi's model allows some flexibility in assessing various cyclical indicators, the model must evaluate the predictive power of one indicator at a time.

Probit model

The Probit model, recently proposed by Arturo Estrella and Frederic Mishkin, improves on the Neftçi model by allowing an analyst to assess the importance of multiple indicators simultaneously. Using a regression-based framework, the Probit model generates a probability of future recession from information in a set of leading indicators. The closer the probability is to 0, the less likely the economy will be in a recession at some future date; the closer the probability is to 1, the more likely there will be a recession. These probabilities can be easily used to predict the turning point from expansion to recession. When the probability of recession rises above 50 percent, the economy is more likely to be headed toward recession than remaining in expansion; thus a business cycle turning point is signaled. Moreover, the Probit model offers a more precise probability assessment of future recession than the Neftçi model. The Probit model's probability helps predict a recession at a particular forecast horizon, while the Neftçi model simply gives a likelihood of recession sometime in the future.

Because Estrella and Mishkin and others have shown that financial market indicators such as interest rates can be reliable recession predictors, the Probit model used in this article combines both the CLI and financial indicators.[9] In particular, the model includes information on the Treasury yield spread (10-year Treasury bond yield less the 3-month Treasury bill yield), corporate bond yield spread (Aaa bond yield less Baa bond yield), Standard and Poor's 500 stock returns, and the CLI. The Treasury yield spread usually narrows before recessions because it signals relatively poor investment prospects in the future and tighter short-term credit conditions.[10] The credit spread often widens before downturns, reflecting the tendency of risky firms to become disproportionately more risky during periods of weak activity. In addition, investors' tolerances for risk tend to fall as they adjust portfolios toward safer assets. The Standard and Poor's 500 stock return is also in the model because the stock market often falls significantly prior to the onset of recession.[11] Such declines can reflect expectations of lower corporate earnings, higher financing costs of external funds, and less wealth to sustain consumption growth, especially for durable goods. Finally, the CLI is included to incorporate nonfinancial indicators of recessions. To the extent that both the CLI and financial indicators deserve weight in predicting recessions, the Probit model helps to improve on some of the shortcomings of the CLI rules of thumb and the Neftçi model.

The Probit model offers two other advantages over the CLI rules of thumb and the Neftçi model. First, the Probit model allows the analyst to create new composite indexes of leading indicators of recession. The model's regression format can be used to evaluate any group of candidate leading indicators, one at a time or jointly. The estimated regression coefficients are optimal weights for the leading index, where the weights are optimal in the sense that they give the best chance of forecasting future recessions. Second, the Probit model allows the business cycle analyst to identify the most informative set of recession indicators for a given forecast horizon. It is quite possible that some indicators are more useful at short horizons than at long horizons, and vice versa.

The Probit model has two potential drawbacks. First, because the Probit model is designed to predict recessions at a given forecast horizon, the model may miss recessions that exhibit unusual lead times. Historically, the lead times across recessions have been quite variable, raising the possibility that results from the Probit model may be unreliable. Second, as with any regression framework, the Probit model may be subject to the statistical problem of overfitting. If an analyst searches over a large set of variables that in truth have no predictive content for recessions, there is a good chance that some of the variables will spuriously appear to explain the past. A recession prediction model that incorporates such spurious variables will not forecast well.[12]

GDP forecasting model

The GDP forecasting model is also a regression-based framework but tries to predict recessions by forecasting consecutive declines in GDP. The GDP forecasting model is specified as a simple multiequation regression model, more commonly referred to as a vector autoregression, or VAR. In this model, the growth rate of real GDP depends on past growth rates of real GDP, past growth rates of the CLI, past changes in the interest rate spread defined as the 10-year Treasury yield less the 3-month Treasury yield, and past changes in the 3-month Treasury yield. To spot future recessions, the model produces GDP forecasts. A forecast of two consecutive quarterly declines in GDP is taken as a recession signal.

As a regression-based framework, the GDP forecasting model has many of the advantages of the Probit model. Any variable that helps forecast GDP is a potential candidate in the model, and the model can be specialized to focus on any forecast horizon of interest. The GDP forecasting approach may also be attractive because analysts can choose any model that produces forecasts of GDP—not just the particular forecasting model described above.

The GDP forecasting model is not without problems. First, it has some of the unstable lead time and overfitting problems of the Probit model. Second, the GDP forecasting model predicts recessions using a 2-quarter GDP decline definition, which is arguably only an approximation of the NBER's definition of recession.[13] Finally, the GDP forecasting equation used in this article can be viewed as a small-scale version of a large-scale forecasting model. Like large-scale models, the GDP forecasting model may be susceptible to a degradation in forecasting performance around turning points in the business cycle.

Stock-Watson model

James Stock and Mark Watson (1989) developed a recession prediction model that tries to capture the institutional process of the NBER's Business Cycle Dating Committee. The difficulty in mimicking the Dating Committee's decision process is that the Committee shuns simple numerical rules for dating recessions, but a model that produces probabilities of recession must have numerical rules. Stock and Watson compensate for the model's need for rules by formulating elaborate rules that may be sufficiently flexible to capture the behavior of the Dating Committee.

The Stock-Watson model is similar in spirit to the GDP forecasting model but differs in two important ways. First, instead of GDP, the model uses a broader measure of economic activity. Specifically, Stock and Watson use a coincident index of economic activity which is a weighted average of industrial production, real personal income less transfer payments, real sales in manufacturing and trade, and total employee-hours in nonagricultural establishments. This index is forecast with seven leading indicators: new private housing building permits, durable goods industries' unfilled orders, trade-weighted exchange rate, part-time employment because of slack work, 10-year constant maturity Treasury bond yield, credit interest rate spread, and term interest rate spread. Second, a recession probability measure, called the Experimental

Recession Index, is produced by comparing the forecasts from the model with an elaborate up-and-down pattern that could be consistent with what the NBER might actually define as a recession.[14] The published index measures the probability that the economy will be in recession in six months.[15]

The model has experienced growing appeal in the 1990s, reflecting several attractive aspects of the model. First, like the Probit model, the Stock-Watson model puts considerable weight on financial variables, reflecting the view that financial variables such as interest rates provide useful forward-looking macroeconomic information.[16] However, the Stock-Watson model uses the financial variables in a different way than the Probit model. Rather than directly predict turning points from expansion to recession, the Stock-Watson model uses the variables to predict future economic activity. Second, the Stock-Watson model was developed on the basis of a state-of-the-art and exhaustive specification search. The choice of model specification, including the selection of variables, has been subject to a search across hundreds, if not thousands, of alternatives. Finally, an up-to-date version of the recession index is readily available through the NBER. Stock and Watson regularly update their model as new data become available and publish the results in a monthly newsletter.

The key drawback of the published recession index is its narrow focus. The published index represents the probability that the economy will be in recession in six months, not one to five months or longer than seven months. While, in theory, the model could be modified to produce implications about recessions at different horizons, there is no simple way for analysts to evaluate the given model at different horizons. Moreover, the sophistication of the model has been a formidable hurdle for analysts who want to check its robustness. As a result, ongoing research on the model has been limited, thus leaving unresolved a fair amount of uncertainty about its potential.

II. EMPIRICAL EVIDENCE

The previous section described how the five business cycle models—simple rules of thumb using the CLI, Neftçi's model, Probit model, GDP forecasting model, and Stock-Watson model—offer different ways to predict recessions. No matter how sound the theoretical justification of the models, their value comes from their ability to accurately predict recessions with sufficient advance warning. This section assesses each model's historical forecast performance using two different kinds of data sets that interest business cycle analysts and policymakers. The first data set consists of the recently published data series, which in many cases have been revised substantially over time. The second data set—a real-time data set—includes the originally published versions of the data series. This data set reflects information that policymakers had at the time decisions were made. This section concludes by evaluating what the models are now saying about the possibility of imminent recession.

Measures of forecasting performance

The forecasting performance of each model is examined using two measures: timeliness and accuracy. *Timeliness* measures how far in advance a model signals the start of a recession—in particular, the number of months or quarters between the time of a signal and the onset of recession. A long lead time is preferred to a short one.[17]

Accuracy measures how well predictions from the model match actual outcomes. A model is accurate if it predicts an imminent recession and one occurs, or if it correctly predicts a continuation of expansion. While conceptually simple, the criterion is quite complicated in practice due to two types of prediction errors. The model errs if it predicts a continuation of expansion and recession begins (missed signal), or if it predicts imminent recession and none occurs (false

Table 1
TIMELINESS AND ACCURACY OF VARIOUS CLI RULES OF THUMB

	Advance warning of recession (in months)			
Start of recession	2-month rule	2-month rule with threshold	3-month rule	3-month rule with threshold
May 1960	10	10	9	9
January 1970	7	7	6	6
December 1973	8	8	7	4
February 1980	14	14	13	2
August 1981	7	7	6	6
August 1990	14	-1	-1	-2
Mean (lead time)	10	7	7	4
	Number of episodes without an onset of recession			
False signals	9	4	4	2

Notes: The *k*-month rule requires the CLI to decline for *k* consecutive months before a recession signal is sent. The threshold adds the criterion that each consecutive decline must each be of sufficient size. The episodes of false signals correspond to periods in which one or more monthly false signals were sent without the onset of recession. These periods were typically less than six months in duration.

signal). Whether one type of error is more important than the other depends on how the models are used.

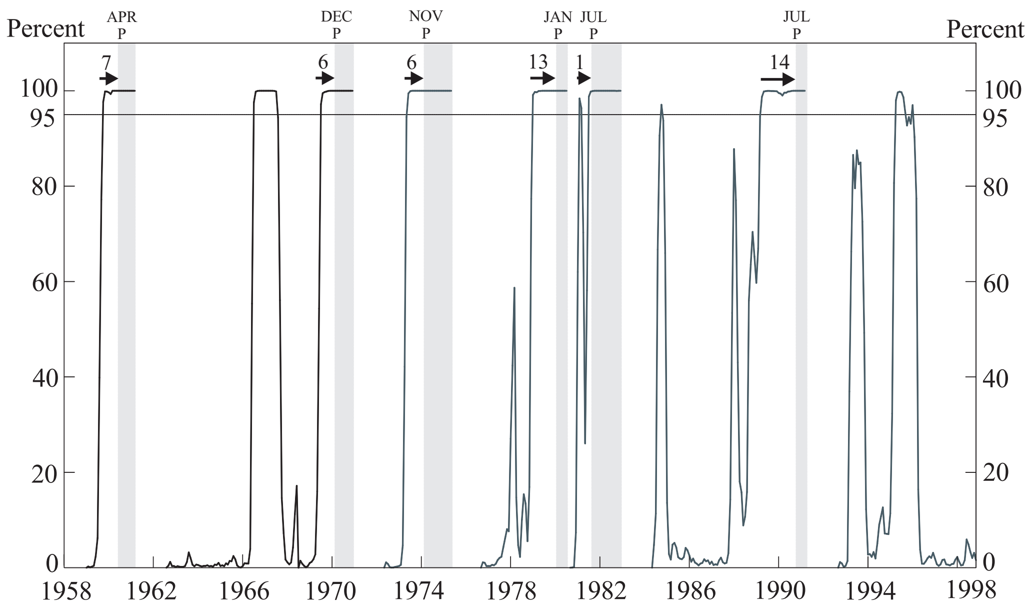
In a monetary policy context, missed signals are certainly costly because accurate advance warning of recession allows policymakers to ease monetary conditions to mitigate the severity and duration of recessions. Advance warning is particularly important because monetary policy affects the economy with long and variable lags. False signals are more difficult to assess than missed signals because some false signals may not be viewed as a blemish on a model's performance. In fact, some false signals of recession may indicate successful policy. For example, a signal of imminent recession may spur policy actions that pull the economy from the brink of recession. Distinguishing signals of recessions which were avoided from those signals that are simply false requires some consideration of the economic conditions surrounding the signal.

Historical performance using the recently revised data

Using the recently revised data, the five models show some ability to provide advance warning of recession.

CLI rules of thumb. The CLI rules of thumb tended to predict recessions one-half year prior to their onset, highlighting the usefulness of the model (Table 1). On average, the basic 2-month rule had the longest lead time of ten months, while the more conservative 3-month rule with threshold spotted recessions with the shortest advance warning of four months; the 2-month rule with threshold and basic 3-month rule both averaged seven months.[18] Lead times across rules and across recessions were quite variable, though, complicating any rule's use in policymaking. For example, prior to the 1980 recession, the 2-month rule gave advance notice of 14 months,

Chart 2
PROBABILITY OF IMMINENT RECESSION—NEFTÇI MODEL



Note: Number next to arrowheads denotes advance warning (in months) of recession. See appendix for details of model.

while the 3-month rule with threshold only gave two months of advance warning.[19] Over the past recessionary periods, the difference between the longest and shortest lead times for any one rule was roughly a year.

The CLI rules of thumb also appear to be fairly accurate at predicting recessions. The rules correctly predicted the onset of most or all of the recessions but had mixed success in screening false signals. In fact, the rules that correctly predicted actual recessions better than other rules also tended to produce more false signals. For example, the 2-month rule was sufficiently sensitive to predict every recession but produced at least twice as many false signals as the other rules. The other rules with their shorter lead times issued fewer false signals but missed the 1990-91 recession.[20]

Neftçi model. The Neftçi model offered only marginal forecasting improvement over the CLI rules, despite its theoretical advantages. The model's lead-time and variability were comparable to the CLI rules. On average, the Neftçi model sent an 8-month advance signal of recession, similar to the average of the CLI rules. In addition, the model's lead times showed considerable variation, with the advance warning from the Neftçi model fluctuating between 1 month (for the 1981-82 recession) and 14 months (for the 1990-91 recession).

The Neftçi model appeared to predict recessions somewhat more accurately than the CLI rules. Chart 2 clearly shows that the Neftçi model provided advance warning for all the recessions, unlike many of the CLI rules. Moreover, its accuracy in spotting actual recessions

Table 2

TIMELINESS AND ACCURACY—PROBIT MODEL

Forecast horizon	Missed recessions	False signals of recession
1	1960	1966, 1983, 1988
2	1960	1966, 1983, 1988
3	1960	1966, 1983, 1988
4	1960, 1990	1966
5	1960, 1990	1966
6	1960, 1990	1966
7	1960, 1990	1966
8	1960, 1990	1966
9	1960, 1990	None
10	1960, 1970, 1990	None
11	1960, 1970, 1990	None
12	1960, 1970, 1990	None

was achieved with, arguably, fewer false signals than the CLI rules. To be sure, Chart 2 shows four false signals, but only one of them truly stands out as false. The 1966 false signal was clear and persistent, reflecting the pause in economic growth. In fact, the NBER almost called this period a recession (Hall). The three false signals that occurred in 1981, 1984, and 1995 were weak and short- lived. Discounting these three minor signals, a business cycle analyst might reasonably conclude that, when compared with CLI rules of thumb, the Neftçi model tended to provide relatively long lead times of actual recessions while sending fewer false signals.[21]

Probit model. The Probit model by design can be specified to predict recessions at any particular forecast horizon, and thus did not provide lead time information that compares with the CLI rules of thumb and Neftçi's model. The Probit model results, however, show how predictive accuracy varies with the forecast horizon (Table 2). At short forecast horizons (one to three months), the model yielded advance warning of each recession, except for 1960-61. However, the model sent false signals in 1966, 1983, and 1988. At midrange horizons (four to nine months), the model experienced a degradation of predictive power, as might be expected with a lengthening of the forecast horizon. Despite producing only one false signal, the model failed to spot the 1960-61 and 1990-91 recessions. Part of the drop in accuracy was due to the deterioration in the statistical and economic significance of the CLI in the model at the longer horizons. At long horizons (10-12 months), the results from the Probit model confirmed those from earlier research by Estrella and Mishkin and Lamy. The Treasury spread was the only statistically significant predictor at these horizons. Even though the model made no false signals, it flashed no advance warning of the 1960, 1970, and 1990 recessions. These Probit model results also suggest that business cycle analysts should carefully choose the variables for each forecast horizon of interest.

As with the Neftçi model, further analysis of

Table 3
ADVANCE WARNING OF RECESSIONS—GDP FORECASTING MODEL

Beginning of recession	Early warning (quarters)[a]	First estimate of recession start date[b]
1960:Q2	4	1960:Q1
1970:Q1	3	1969:Q4
1974:Q1	5	1973:Q4
1980:Q1	5	1979:Q4
1981:Q3	3	1982:Q1
1990:Q3[c]	None	None

[a] The number of quarters corresponds to the difference between the start date of the recession and the date at which the GDP forecasting model predicted an imminent recession.
[b] The third column reports the initial estimate of the recession's start date when the model first signals an imminent recession. The estimate becomes updated when subsequent data become available.
[c] The GDP forecasting model did not spot the 1990-91 recession.

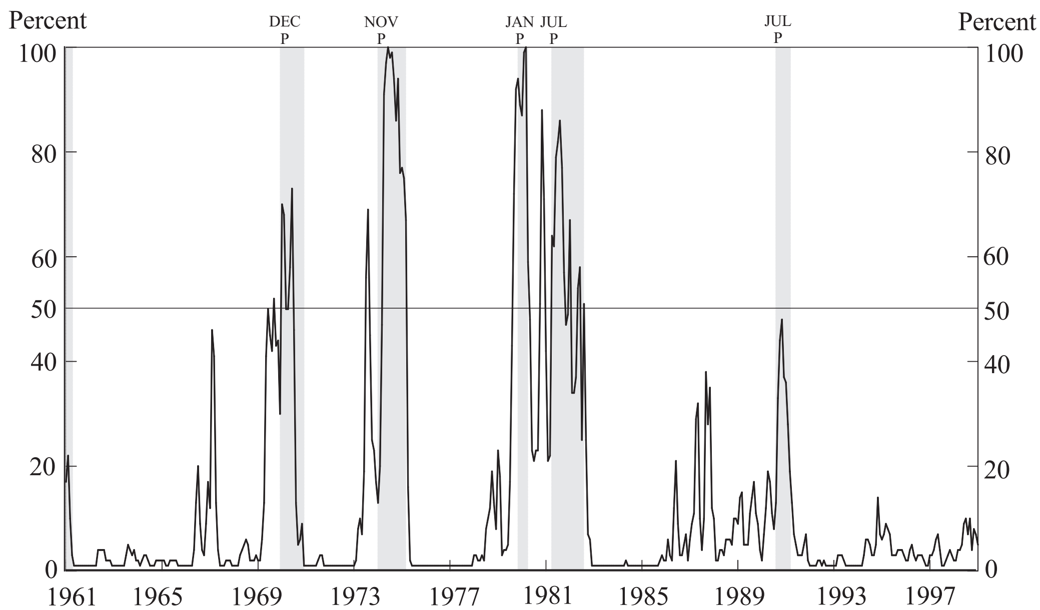
false signals suggests that distinguishing the strong signals from the weak ones can help improve the accuracy of recession predictions. For the Probit model, the false signals exhibited qualitatively different behavior than true signals. The false signals were typically short-lived (usual about one month long), weak, and associated with periods of economic weakness. While the 1966 false signal was fairly strong, the other two false signals came during growth slowdowns in the 1980s. In contrast, the probabilities of recession prior to actual recessions were sustained and strong.

GDP forecasting model. The GDP forecasting model showed some success in forecasting recessions. Table 3 indicates that the model had the ability to signal imminent recessions roughly three to five quarters in advance. Because this model not only signaled imminent recessions but also provided estimates of a recession's starting date, accuracy in predicting the correct starting date can be assessed. In general, the early estimates of a recession's starting date were usually premature. Table 3 shows that when the model first flashed a signal of imminent recession, the model tended to predict that the recession would start one quarter earlier than it actually did. As more information became available, the GDP forecasting model tended to home in on the actual starting date of the recession.

The accuracy of the GDP forecasting model shares some of the same weaknesses of some of the other models. While the model's false signals were limited to 1962 and to late 1996, its failure to anticipate the 1990-91 recession at any forecast horizon raises concerns. To its credit, the model did predict a GDP decline in the fourth quarter of 1990, but the 1-quarter decline was not sufficient to trip the 2-quarter GDP recession definition.

Stock-Watson model. The Stock-Watson model generated the shortest average lead times for the

Chart 3
STOCK-WATSON RECESSION INDEX



Source: NBER.

models considered in this article (Chart 3). Even though the recession index is designed to identify recessions six months in advance, the index in general signaled recessions four to five months in advance of their onset. In addition, the recession index usually followed an intuitively plausible pattern prior to recessions. Typically, the recession index tended to rise well before the onset of recession. When the economy was about to enter recession or was in recession, the recession index was typically near or above the 50 percent probability threshold. In contrast, during periods when recession was not imminent, the recession index stayed fairly close to 0.

When the model sent signals of imminent recession, the signals tended to be fairly accurate. Arguably, the only false signal was a minor one that occurred prior to the 1981-82 recession. In October 1980, the recession index signaled the beginning of recession in April 1981; however, the recession did not begin until August of that year. As for missed signals, the model gave no advance warning of the 1990-91 recession. The probability of recession did not jump until four months into the recession, and even then the probability came close to but did not exceed the 50 percent threshold. Overall, the forecast performance demonstrated the model's ability to mimic NBER business cycle dating practices.

Historical performance using real-time data

Using the recently published data series, the previous section presented a favorable assessment of the five models. These results, however, may exaggerate the predictive power of the

Table 4

REAL-TIME ADVANCE WARNING—CLI RULE OF THUMB AND NEFTÇI MODEL

Beginning of recession date	Variation is estimates of lead times with real-time data (in months)			
	3-month CLI rule		Neftçi model	
	Shortest	Longest	Shortest	Longest
May 1960	1	8	5	7
January 1970	2	7	1	12
December 1973	-4	8	-5	5
February 1980	5	5	5	14
August 1981	-3	12	-2	6
August 1990	-3	12	-1	14
Average	-1	9	1	10

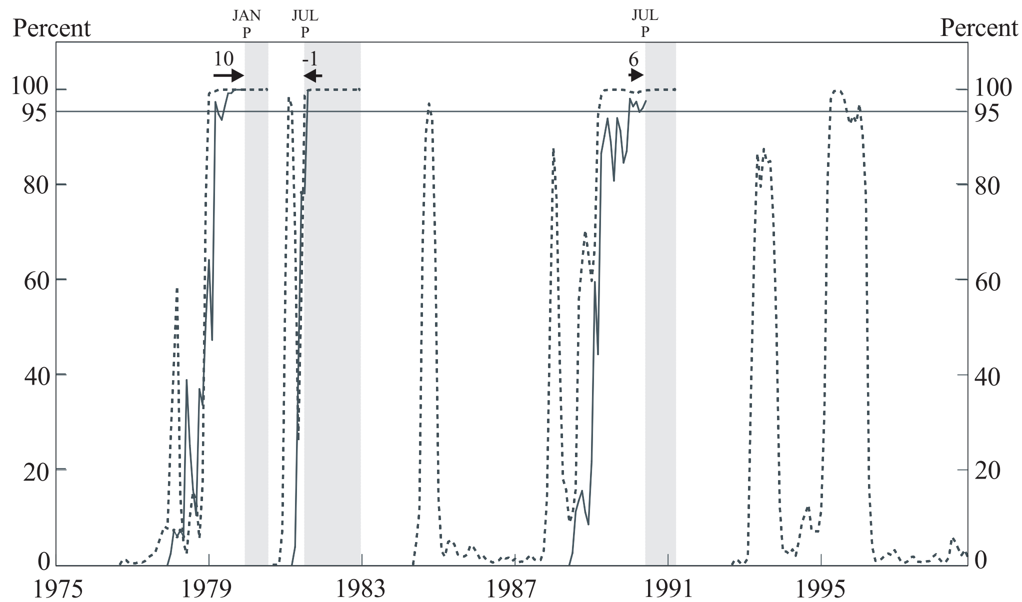
Notes: The entries in this table are the shortest and longest lead times estimates for the 3-month CLI rule of thumb and the Neftçi model. The variation in the lead times is caused by CLI revisions in the real-time data set.

recession models because the recently published data can give the impression that an imminent recession was obvious when, in fact, data available at the time would have given a much more ambiguous picture of economic conditions.[22] This section examines the robustness of the models' predictive performance by evaluating each model with a real-time data set. The real-time data set in this article contains data series that were originally published in each month from January 1977 to April 1998. For example, the data set includes the 256 CLI series that were published during the period. By convention, the first series in the data set is called the January 1977 vintage, the second is called the February 1977 vintage, and so on.[23]

CLI rules of thumb. The CLI rules of thumb were quite sensitive to revisions in the CLI data. This sensitivity should not be too surprising because the CLI is typically subject to considerable revision; the CLI data are revised not only as each component series is revised over time but also as the number and types of leading indicators that make up the CLI are changed to better fit the recession chronology.[24] In terms of forecast performance, both the lead times and number of false signals varied widely as the data were revised. For example, Table 4 shows how the revisions caused the average lead time for the 3-month rule to vary from zero to nine months. In terms of false signals, revisions to the CLI data often caused the number of false signals to decline, thus giving the impression that the model was more accurate than it was in real-time. Overall, the results are consistent with the growing body of research that revisions to the CLI cause it to appear to be a much better predictor of recessions than suggested by the originally published data.[25] These results should make analysts wary about using CLI rules of thumb.

Neftçi model. The Neftçi model also showed

Chart 4
PROBABILITY OF IMMINENT RECESSION—NEFTÇI MODEL: REAL-TIME ANALYSIS



Notes: Number next to arrowheads denotes advance warning (in months) of recession. See appendix for details of model.

sensitivity to CLI data revisions. Table 4 illustrates how data revisions caused the model's estimates of lead times to vary widely. For example, data revisions caused the model to produce anywhere from a 1-month lag to a 14-month lead for the 1990-91 recession. The deterioration in performance can be more clearly seen in Chart 4, which shows the estimated probabilities from the Neftçi model using real-time and recently revised data. The dark lines represent the probabilities from the model using real-time data. The model gave much shorter lead times when using the real-time data than when using the most recently revised data (light line). In sum, the sensitivity of the Neftçi model and CLI rules of thumb raise serious doubts about their ability to reliably predict recessions.

Probit model. In contrast, the Probit model's performance using the real-time data was fairly robust to data revisions. This result should not be too surprising because the financial market variables included in the model were not revised or updated. The revisions in the CLI data could cause the Probit model results at various horizons to be sensitive to the real-time data. However, the effect of the revisions on the performance of the Probit model at midrange and long horizons was modest largely because the CLI played a minor statistical role in the estimated model. Even at short horizons, the CLI revisions did not significantly change the recession prediction results. The robustness of the Probit model to data revisions makes the model attractive.

GDP forecasting model. The GDP forecasting model as specified in this article also appeared to be fairly robust to data revisions. The model had roughly the same lead time and accuracy with real-time data as with the recently published data. However, with real-time data the model did send false signals of recession in the early 1980s. Those signals were subsequently eliminated when the GDP and CLI data were revised. In addition, these results do not necessarily contradict earlier research that found important sensitivities of GDP forecasting to data revisions (Runkle). The earlier work focused on accuracy in forecasting GDP magnitudes rather than forecasting recessions.

Stock-Watson model. Evaluation of the Stock-Watson model's performance is complicated because data limitations preclude direct verification of its performance in the face of data revision. A real-time analysis would require about a dozen different real-time series, which are not readily available. An alternative approach to testing the performance in real time is to see how well the model predicted the last recession. The behavior of the model in the last recession is particularly important because Stock and Watson created the model in the 1980s, and as a result the model faced its first recession test during the early 1990s.

The model failed to call the recession 1990-91 recession in advance of its onset. The failure prompted mixed reviews of the model. On the one hand, the failure confirmed the suspicions of some critics of the model.[26] On the other hand, and to be fair, many other recession prediction models missed the last recession. At the very least, the model sent a confirmatory signal in November 1990. By that time, the model showed an 80 percent likelihood that the economy was in recession.

In response to the model's performance, Stock and Watson (1993) published a detailed analysis of their model's real-time performance in 1990-91. They found that the yield curve spreads and exchange rate indicators gave optimistic (and thus faulty) signals before the recession. Part of the failure of the financial variables to predict the downturn was attributed to the fact that monetary policy was not particularly tight during the period. The miss prompted Stock and Watson to develop an alternative index to improve predictions in the future.[27] Thus, the jury is still out on how well the model will perform in the future.

What are the recession models predicting now?

Although all the models provide useful information about imminent recessions, none of them is foolproof. The real-time analysis in particular showed that some models, such as the CLI rules of thumb and Neftçi's model, can be unreliable. But it is also true that every recession has been preceded by signals of imminent recession from at least one of the models—and most recessions have been accompanied by many of the models flashing an advance warning of imminent recession.

Currently, all the models are sending the same clear signal—no imminent recession. The CLI rules of thumb and GDP forecasting model are not picking up any hint of imminent recession; moreover, the Neftçi, Probit, and Stock-Watson models estimate the probability of imminent recession to be close to 0. For example, the recent probability reading from the Stock- Watson model is 3 percent, which indicates only a 3 percent probability that the economy will be in recession later this year.

III. CONCLUSION

The extraordinarily long expansion in the 1990s has raised the inevitable question: when is it going to end? This answer is not only of interest to policymakers, but to anyone who would be hurt by such developments. This article offers a simple answer: not soon. Moreover, this article provides an approach to address such questions in the future. All five recession prediction models can provide reliable information about future recession. To be sure, some of the models have missed spotting some past recessions, some have sent more false signals than others, some were more accurate at certain forecast horizons, and some were more robust to real-time data than others. So, analysts must carefully interpret the signals from the models. But, there seems to be strength in numbers. While each model has its own idiosyncratic tendencies, recession signals are clearest when all the models are in agreement.

However, it is important to remember that past successes do not guarantee future performance. These models, like all models, are not perfect. The best way to improve their reliability is to continue monitoring their performance, learning more about when they are likely to predict correctly and when they are likely to err. Ultimately, the only way to truly increase the reliability of the models is to test them further. Those models that accurately warn of future recessions deserve more weight in the prediction. But, if we are fortunate enough to avoid future recessions, we may never know which model is best.

APPENDIX

This appendix describes technical details of the estimated recession prediction models other than the CLI rules of thumb, which were described in the text, and the Stock-Watson model, which was not estimated. Stock and Watson (1989, 1991, and 1993) describe their model in detail.[28]

Neftçi model

The Neftçi model of the probability of recession can be written as a simple recursive equation. Recursion means that the probability at time *t* is a function of the probability at time *t-1* plus other relevant information about the probability of imminent recession. The probability of imminent recession can be calculated by the following equation:

$$P_t = \frac{[P_{t-1} + \pi^r (1 - P_{t-1})]F^r}{[P_{t-1} + \pi^r (1 - P_{t-1})]F^r + (1 - P_{t-1})(1 - \pi^r)F^e},$$

where P_t is the probability of imminent recession at time *t*, P_{t-1} is the probability of imminent recession at time *t-1*, π^r is the average transition probability of the economy entering a recession at time *t* under the assumption that the economy was in expansion at *t-1*, and F^e and F^r are the likelihood functions that the latest CLI observation came from an expansionary phase or recessionary phase, respectively.

Following Diebold and Rudebusch (1989), the transition probability from expansion to recession, π^r, is assumed to be independent of the time elapsed in the phase and set to 0.02 (implicitly consistent with results from Hamilton).[29] The probability distribution functions of the CLI data, F^e and F^r, are modeled as being normally distributed around mean growth rates of the 3-month moving average of the CLI during expansionary and recessionary periods. The 3-month moving average of CLI smooths the wiggles, or noise, in the CLI data.

To use this model to predict recessions, the estimated probability of recession, P_t, is compared to a prespecified threshold. Following Diebold and Rudebusch (1989), the threshold is assumed to be 95 percent, which by convention for this model represents a reasonable burden of proof that a recession is imminent. Once the model's probability exceeds the threshold, a recession is signaled. Then the recursion is reinitialized to search for another recession. In practice, the model was reinitialized 18 months after the trough and a year after a false signal.

Probit model

Following Mishkin and Estrella and Lamy, the Probit model is a nonlinear regression model that translates information contained in leading indicators of recession into a probability of recession. The specification in this article uses the change in the term spread (*TS*), change in the corporate spread (*CS*), S&P500 return (*SP500*), and growth of the CLI (*CLI*) as leading indicators of recession. To predict a recession *k* months ahead, the model is estimated using lagged information as represented in the vector

$$X_{t-k} = \{TS_{t-k}, CS_{t-k}, SP500_{t-k}, CLI_{t-k}\}.$$

In other words, the nonlinear regression to assess the probability *k* steps ahead is

APPENDIX - continued

$$P(recession \mid X_{t-k}) = F(\beta_0 + \beta_1 TS_{t-k} + \beta_2 CS_{t-k} + \beta_3 SP500_{t-k} + \beta_4 CLI_{t-k}).$$

This equation states that the probability of recession is equal to a function of the four explanatory variables. If the probability is less than 50 percent, an expansion is more likely than a recession; if the probability is above 50 percent, a recession is more likely.[30]

GDP forecasting model

The GDP forecasting model is a 4-variable vector autoregression (VAR). The first equation in the system is the real GDP equation. Real GDP growth is a function of lags of GDP growth, changes in the 3-month Treasury bill rate, the core CPI inflation rate, and the growth rate of the CLI:

$$RGDP_t = \mu_0 + \sum_{j=1}^{4} \mu_j^{RGDP} RGDP_{t-j} + \sum_{j=1}^{4} \mu_j^{R} R_{t-j} + \sum_{j=1}^{4} \mu_j^{CPI} CPI_{t-j} + \sum_{j=1}^{4} \mu_j^{CLI} CLI_{t-j} + \varepsilon_t .$$

The three other equations in the system describe the dynamics of the interest rate, inflation, and CLI data. The explanatory variables for these equations are the same as in the RGDP equation. The forecasted values from these three equations are used in the RGDP equation to forecast future values of GDP.

The procedure to predict recessions requires two steps. First, the VAR is estimated using standard regression methods, and forecasts are made. This is called the *estimation and forecasting step*.[31] Second, the patterns of the GDP forecasts at various horizons are examined for their conformity with two consecutive quarterly declines in GDP. This second step is called the *pattern recognition step*. The quarterly business cycle dates were chosen to be consistent with the NBER monthly business cycle chronologies. The timing of the signal assumes that the GDP data are known at the end of the quarter for which they are reported. In practice, the advance, preliminary, and final releases considerably lag the end of the quarter.

ENDNOTES

1 This definition can be traced back to early work by Julius Shiskin, one of the pioneers of empirical business cycle research associated with the NBER. As Klein and Niemira note, Shiskin's definition is more elaborate than the 2-quarter GDP definition because it also includes duration, amplitude, and diffusion criteria. His definition was based on consecutive declines in industrial production and GDP, a threshold size of GDP and payroll employment declines and of unemployment rate increases, and widespread sectoral employment declines.

2 The NBER deems the GDP definition too sensitive to special factors to be reliable. The GDP definition is more likely to be affected by temporary events than the NBER definition of economic activity. For example, labor strikes, natural disasters, unseasonable weather, and shifts in spending patterns across the year can cause GDP to swing downward. Such temporary swings, however, are not what analysts would consider a recession. In addition, the GDP definition tends to be more sensitive to data revisions than the NBER definition. For example, McNees pointed out that by the GDP criterion "the 1980 recession is in danger of extinction; a relatively small upward revision of real growth in 1980:Q3 would eliminate it." Also see Grimm and Parker, Moore (1983) and Hall. GDP measures all final goods and services purchased in a quarter. While broad, it

fails to measure certain important types of economic activity such as employment or intermediate products such as wholesale trade (Moore and Zarnowitz).

[3] While turning point periods are special in a statistical sense, they also have an important human side. The "large errors" associated with forecasting models are often associated with dire conditions for workers, investors, and consumers. Recessions are periods of acute turmoil, often accompanied by unemployment, bankruptcy, and social unrest. The possibility of reducing the human costs associated with recessions motivates the study of recession prediction models. While some recessions in the past may have been unavoidable, others might have been avoided or at least might have been made less severe if advance warning of their onset were known. With such timely information, policymakers might be able to implement more effective countercyclical policies, corporations might be able to moderate production and employment swings, and consumers might be able improve their balance sheets by saving more, thereby cushioning the ill effects of recessions.

[4] The CLI is a weighted average of ten leading indicators: average weekly hours in manufacturing, average weekly initial claims for unemployment insurance, manufacturers' new orders for consumer goods and materials, vendor performance measured by slower deliveries diffusion index, manufacturers' new orders for nondefense capital goods, building permits for new private housing units, stock prices (S&P 500 common stocks), M2 money supply, 10-year Treasury bond yield less federal funds rate, and index of consumer expectations. Boshan and Zarnowitz, Zarnowitz, and recent issues of *Business Conditions Indicators* provide further information.

[5] The index is periodically revised to improve its ability to track the business cycle. In its last major revision, the Conference Board used these criteria to justify modifications to the index. The new index dropped the change in sensitive materials prices and change in unfilled orders for durable goods, and added the interest rate spread between the 10-year Treasury bold yield and the federal funds rate. This new index "differentiates slowdowns in the economy from true recessions better than the old leading index" (*Business Cycle Indicators*, January 1997).

[6] For example, if the CLI began to decline five months prior to the onset of recession, a 2-month rule would provide three months of advance warning; a 3-month rule would provide only two months of advance warning. In practice, because the CLI data are released with about a one-month delay, the 3-month rule would give policymakers about a one-month lead; the 2-month rule would provide a two-month lead.

[7] The threshold represents a decline of at least ½ of a standard deviation below the CLI's average growth rate.

[8] Some analysts believe a better leading indicator than the CLI would include a larger set of variables, different variables, or alternative ways of combining component series. Neftçi's model could easily be modified to compare the predictive power of alternative leading indexes with the CLI. For example, Fredman and Niemira find that certain financial market variables can outperform the CLI. Also see Palash and Radecki.

[9] Using this model, Estrella and Mishkin explored the importance of financial market variables in signaling future recessions and generally found that interest rate spreads, such as the yield difference between the 10-year Treasury bond and the 3-month Treasury bill, provide reliable information at fairly long horizons. Analysts have also found other useful financial variables, such as corporate bond yield spreads and stock market returns.

[10] See Kozicki for a more extensive discussion of the role of the yield spread in explaining economic activity.

[11] The relationship between stock market performance and business cycle turning points is notoriously imprecise. As Paul Samuelson has often been quoted as saying, "the stock market has predicted nine out of the last five recessions."

[12] To some extent, this article guards against overfitting by evaluating the forecast performance of the model.

[13] The 2-quarter GDP rule is far less accurate than the popular press has suggested. GDP-based peak dates do not coincide with the NBER dates. For example, the GDP rule indicates a peak in May 1974 during the 1973-5 recession, roughly half a year later than the official NBER date. The NBER date was missed largely because GDP grew in an up-down pattern earlier. Such a pattern evades detection under the 2-consecutive-decline rule. This same up-down pattern shows up in the early 1960s when the GDP rule missed the 1960-61 recession. Clearly, the GDP rule is not perfect, but it is also true that GDP has not declined two-consecutive quarters without a recession occurring—suggesting that the GDP forecasting model might be quite conservative in recession prediction.

[14] See Stock and Watson (1993) for detailed discussion of their pattern recognition algorithm. Instead of a 2-quarter rule, they use a variant of a 17-month rule.

[15] Stock and Watson also offer an alternative experimental recession index. It replaces the interest rate and part-time work variables with the help-wanted index, average hourly hours of production workers in durable goods industries, vendor performance, and manufacturing capacity utilization rate. The alternative index is consistent with a traditional approach that emphasizes quantity rather than financial variables in predicting recessions.

[16] Stock and Watson empirically demonstrated the importance of interest rate spreads as cyclical indicators. To some extent, Stock and Watson's research has helped to persuade the Conference Board to include an interest rate spread in the CLI.

[17] Both the NBER and GDP dating conventions suffer from considerable lags in identifying recessions. By construction, the GDP definition has a 2-quarter lag in recognition. In practice, the lag is somewhat longer because reports on GDP are released at least a month after the end of the quarter. The NBER Dating Committee need not wait for the GDP data to call a recession, but they do not call a recession until a recession is well under way. Historically, the timing of announcements from the NBER Dating Committee and of confirmation from GDP reports roughly coincides. The lags imply that a recession prediction model which calls the start of a recession with less than a two-quarter delay still provides useful information.

[18] Experiments using a 4-month rule showed a significant degradation in advance warnings of recession.

[19] The CLI acted somewhat out of character in the period prior to the 1990-91 recession. During the period, the CLI was fairly flat, thus complicating the dating with the CLI rule.

[20] The CLI rules sent the following false signals: 1962, 1966, 1984, 1985, 1987-88, 1991, 1992, 1993, 1995 for the 2-month rule; 1962, 1966, 1989, and 1995 for the 2-month rule with threshold; 1966, 1987, 1988, 1993, and 1995 for the 3-month rule; and 1966 and 1995 for the 3-month rule with threshold.

[21] Closer examination of the results for the 1990-91 recession shows when the Neftçi model tends to outperform the CLI rules. In the 18 months prior to the July 1990 peak, the 2-month CLI rule with threshold and 3-month rules of thumb did not send a signal of imminent recession despite the fact that the CLI did decline during four out of five months in early 1989. By contrast, the four out of five CLI declines were sufficient to signal imminent recession using the Neftçi model.

[22] Some analysts suggest that real-time data analysis is more revealing than analysis using the most recently revised data. To be sure, the real-time data were available to policymakers. However, policymakers might have been able to forecast the future revisions because policymakers typically know more about economic conditions than a small set of data series would suggest. In such cases, the revised data would provide a more accurate picture of what was more generally known at the time than the real-time data.

[23] Robertson and Tallman provide more details about the real-time data set.

[24] See, for example, *Business Conditions Indicators*, June 1997. The Conference Board compares various vintages of the CLI and draws implications for business cycle dating.

[25] These results build on the work of Diebold and Rudebusch (1991, 1992), Hamilton and Perez-Quiros, Robertson and Tallman, Swanson, and Ghysels, and Callan, and Emery and Koenig (1991, 1993) who warn against using the revised CLI data to assess predictive accuracy.

[26] Zarnowitz (1992, pp. 352-53) raised concerns about the methodology and the ultimate choice of leading indicator series. He voiced doubts about the importance of financial variables, especially interest rate variables, in the Stock-Watson index. In the past, these measures have been less reliable than other variables found in the CLI to predict recessions. For further comments, see Sims, Braun, and Zarnowitz (1989), and Huh. However, Zarnowitz also qualifies his comments by noting that most business cycle models failed to predict the 1990-91 recession. He suggests that this poor performance may have been due to the influence of the Iraqi invasion of Kuwait. The event disrupted world oil markets and adversely affected consumer confidence, thereby aggravating and accelerating the economic downturn in August 1990.

[27] Stock and Watson examined many alternative financial and nonfinancial indicators to improve the forecasting performance of their index. Most alternative financial indicators only marginally improved the out-of-sample performance. However, alternative indicators such as housing starts, weekly employment hours, help wanted advertising, stock prices, and consumer sentiment improved the out-of-sample performance. Despite out-of-sample improvement, the in-sample performance of the alternative was disappointing. A recession index based on these alternative indicators is published monthly with the Stock-Watson index.

[28] The five popular recession prediction models can be lumped together into two broad categories: intrinsic and extrinsic business cycle models. The CLI rules of thumb, Neftçi, and Probit models are intrinsic models, and the GDP forecasting and Stock-Watson models are extrinsic models. Intrinsic models treat the relationship between economic activity and business cycle phases differently than extrinsic models. In intrinsic models, economic activity and its responses to changing economic conditions depend on the phase of the business cycle. In other words, the economy reacts differently in expansions than in recessions. Extrinsic models, by contrast, treat economic activity and its responses to changing economic conditions as being unrelated to the business cycle phase. Recessions and expansions are merely labels to describe when conditions are weak and strong.

The two types of models have important modeling differences. Intrinsic models typically rely on nonlinear estimation methods to capture the complex interrelationship between economic activity and the phase. The extrinsic models do not distinguish between economic activity across phases, usually making the estimation much simpler. But these models require an extra step to convert the phase-independent estimation results into phase-dependent implications for expansions and recessions. Filardo and Gordon (1999) explore the differences between extrinsic and intrinsic models.

[29] Neftçi originally specified the model with transition probabilities from expansion to recession that varied with the length of the expansion. Diebold and Rudebusch (1990) report evidence supporting their assumption.

[30] In general, all four variables in the model are statistically significant.

[31] Technically, the parameters are estimated by minimizing the mean of the squared errors over the sample period. It is well known that a model fit to the sample may be a poor predictor of turning points. Conversely, a good model of turning points may not do well at forecasting nonturning point periods. See Kling, Steckler, and Wecker for more details.

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