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# Recession Probability Indexes: A Survey

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*Specialized econometric models are designed to measure the likelihood of the occurrence of a recession in the near future. This paper examines a selected group of models that are distinct in terms of their theoretical underpinnings and also in terms of the scope of variables included. The models' performance of predicting the onset of the 1990 recession is mixed. In this case, it appears that what distinguished the models was less the difference in their theoretical underpinnings than whether or not the models included financial variables.*

A wide range of methods is used to forecast recessions. For example, one method is a rule-of-thumb that predicts a recession following three consecutive declines in the Department of Commerce's composite index of leading indicators. At the other extreme are more advanced econometric models. This article will focus on the latter group, and in particular on two advanced econometric models that represent different theoretical approaches: the experimental recession probability index (XRI) model developed by James Stock and Mark Watson at the National Bureau of Economic Research (NBER), and a turning point forecasting model which implements a methodology proposed by Salih Neftci.

The experimental NBER model is theoretically similar to conventional linear regression models that are used for forecasting in general, although it is also unique in terms of the way information is extracted from data and in the information the data provide. Implicit in the NBER's XRI model and in other linear forecasting models is the assumption that expansions and contractions are part of the same stable structure, and that they are responses to random shocks (policy and otherwise).

Neftci-type turning point (TP) models depart from this key assumption of a stable structure. TP models posit multiple behavioral regimes that govern the movements of output over time. Thus, the process that best describes the behavior of output in an expansionary period is fundamentally different from the process describing the behavior of output in a contractionary period. Consequently, forecasting a downturn is equivalent to predicting a switch in the behavioral regime from an expansion to a contraction.

The recession of late 1990 provided the first out-of-sample opportunity to apply these models. The performances of the models in identifying this particular downturn as of late 1990 were mixed, giving probabilities ranging from 14 percent to 98 percent. Interestingly, the differences among the forecasts do not appear to be related to differences in their theoretical underpinnings, but rather to the types of variables used as the signaling source series. The models incorporating several financial variables are associated with low probability forecasts, and the models that rely mostly on nonfinancial variables result in high probability forecasts; that is, financial markets were, in this case, poor forecasters of the recession.

This result is not definitive, however, and must be placed in perspective. By definition, a forecasting model of stochastic outcomes cannot be expected to have a perfect fit repeatedly. One observation hardly provides enough information to judge the overall usefulness of the models. Or, as Aristotle, the father of logic, put it, "One swallow does not a summer make." To judge the accuracy, and thus the reliability, of these models requires a whole series of forecasts.

Brief overviews of different models for estimating the probability of economic downturns are provided in the next three sections: a standard linear regression model (Section I), the NBER's XRI (Section II), and the Neftci turning point forecast models (Section III). An overall assessment of their past within-sample forecasting performances is provided in Section IV, and a discussion of out of sample performance is presented in Section V. Section VI concludes.

## I. FRB San Francisco BVAR Model: A Conventional Regression Model

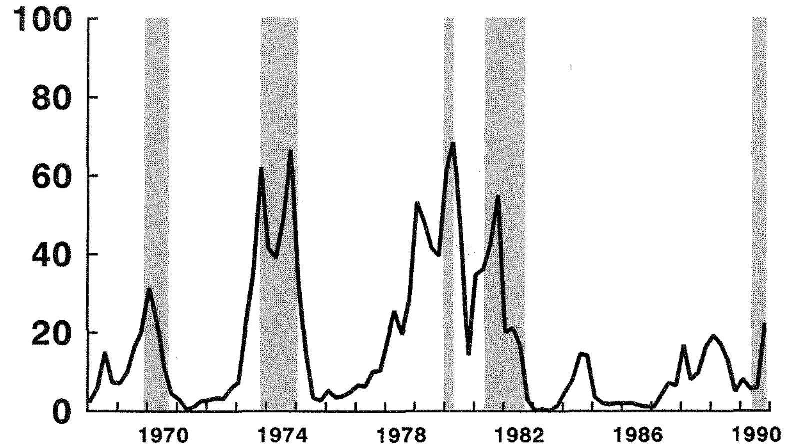
One easy and straightforward way to forecast a recession is to use linear regression models designed to forecast key macroeconomic variables. Any such regression model can be used to forecast a recession once the "operational" definition of a recession is determined in terms of variables in the model. One example is the Bayesian Vector Autoregression (BVAR) model used as a part of the FRB San Francisco in-house staff forecast.[1] The BVAR is designed to forecast growth in real GNP, inflation, and other key macro variables several quarters ahead.[2] The BVAR model is specified in terms of a combination of log and level differences of three real and seven nominal and financial quarterly variables.[3] The Bayesian prior affects this otherwise ordinary VAR system in the form of a priori restrictions on the magnitudes of the coefficients. For example, a simple prior restriction that the real GNP growth rate follows a random walk is imposed on the real GNP equation. Of course, the final estimates would reflect both this prior restriction and the sample information.

Suppose we are interested in finding the probability of a recession occurring within the next three quarters, and that we define a recession as two or more consecutive quarters of negative real GNP growth.[4] The following formula provides the necessary information to calculate the probability in period $t$:

(1) Prob (recession within 3 quarters) = Prob {event (output contracts in periods $t+1$ and $t+2$) $\cup$ event (output contracts in periods $t+2$ and $t+3$) $\cup$ event (output contracts in periods $t+1$, $t+2$, and $t+3$)}.

The actual calculation is in four steps. First, simulate a large number of unconditional forecasts (e.g., 1,000) for the next three quarters based on the model by repeatedly drawing from the stochastic error terms of the system. Second, count the number of simulated forecast triplets that fit any one of the three disjoint events that were defined in (1). Third, calculate the probability measure by dividing the sample numbers obtained from the second step by the total number of simulations. Fourth, the total probability of (1) is the sum of the three probability measures derived in the second step. Actual probabilities calculated this way from the FRBSF BVAR model are presented in Chart 1.

**Chart 1**
**BVAR Recession Index**



## II. The NBER's Experimental Recession Index

The experimental NBER models are also based on the traditional regression method, and thus they share the key assumption that output series over time can be described by a single process. However, the experimental NBER models (Stock and Watson 1989) are more specialized in terms of their scope and of the econometric technique employed.

The NBER XRI is based on two artificial signaling index variables that, in turn, are constructed from sets of actual economic variables. The signaling variables are the experimental indexes of coincident economic indicators and of leading economic indicators.[5]

The experimental index of coincident economic indicators (CEI) is designed to measure the level of current economic activity. It involves a weighted average of four series that are widely perceived to be coincidental: industrial production, real personal income less transfer payments, real manufacturing and trade sales, and employee-hours in nonagricultural establishments. The index is based on a dynamic factor model that measures the change in an unobserved factor that is assumed to be a significant source of movement in all four series (for details, see Sargent and Sims 1977). In terms of both cyclical behavior and historical trend, Stock and Watson's CEI is very close to the CEI released by the Commerce Department, which also was designed to reflect the general state of the economy. The main differences between the two are that Stock and Watson use newer econometric technology to construct the overall index from its components and that Stock and Watson use the employee-hours series, while the Commerce department uses the number of employees.

The experimental index of leading economic indicators (LEI) was designed to provide optimal forecasts of the projected growth in the CEI over the next six months given the information up to period *t*. There are two versions of the LEI, namely, the XLI and the XLI-2, which differ in the variables they use. The XLI uses seven variables—three real and four nominal and financial variables—that were selected after applying multiple sets of tests to a large number of candidate variables. The XLI-2 replaces all nominal and financial variables used in the XLI, except the

### Table 1
### List of Variables

| NBER Experimental Leading Index | | DOC Leading Indicator |
|---|---|---|
| XLI | XLI-2 | |
| 1. New private housing authorized index | 1. New private housing authorized index | 1. Average weekly hours, manufacturing |
| 2. Manufacturers' unfilled orders: Durable Goods Industries | 2. Manufacturers' unfilled orders: Durable Goods Industries | 2. Average weekly initial claims for state unemployment insurance |
| 3. Trade-weighted dollar | 3. Trade-weighted dollar | 3. Manufacturer's new order for consumer goods and materials industries |
| 4. Part-time work in non-agricultural industries because of slack work | 4. Part-time work in non-agricultural industries because of slack work | 4. S&P 500 |
| 5. Yield on constant-maturity portfolio of 10-year Treasury Bonds | 5. Help wanted advertisement | 5. Contracts and orders for plant and equipment |
| 6. Spread between interest rate on 6-month CP and 6-month Treasury Bonds | 6. Capacity utilization rate | 6. New private housing authorized index |
| 7. Spread between variable 5 and the yield on 1-year | 7. Average weekly work hours, manufacturing | 7. Vendor performance, slow deliveries diffusion index |
| | 8. Vendor performance, slow deliveries diffusion index | 8. Changes in sensitive materials prices |
| | | 9. Money supply M2 |
| | | 10. Change in Manufacturers' unfilled orders, durable goods industries |
| | | 11. Index of consumer expectations |

exchange rate, with additional real variables. (See Table 1 for the list of variables. For a detailed econometric description, see Stock and Watson (1989) or Watson (1991, Appendix).)

Two related experimental recession indexes are based on these models, the XRI and the XRI-2. These indexes are designed to measure the probability that the economy (gauged by the CEI) will be in a recession six months hence.[6] Actual probabilities using a stochastic simulation method that is similar to the procedure described in Section I for XRI and XRI-2 are presented in Charts 2 and 3, respectively.

This procedure is valid under a key assumption of linearity in the relationship between the variables involved. That is, the underlying model that describes the behavioral relationship between real GNP (or any variable of interest) and its explanatory variables must remain stable and symmetric across both expansionary and contractionary phases of business cycles. If this linear relationship does not hold, one has to consider some alternative ways to describe the behavioral relationship. Subsequently, calculating the probabilities of the events defined in (1) would become more involved.

Indeed, some economists think that there are fundamental differences in the behavioral patterns of key variables across expansion phases and contraction phases of business cycles. We now turn to a specialized recession probability model that is based on such a view.

**Chart 2**
**NBER Recession Index (XRI)**

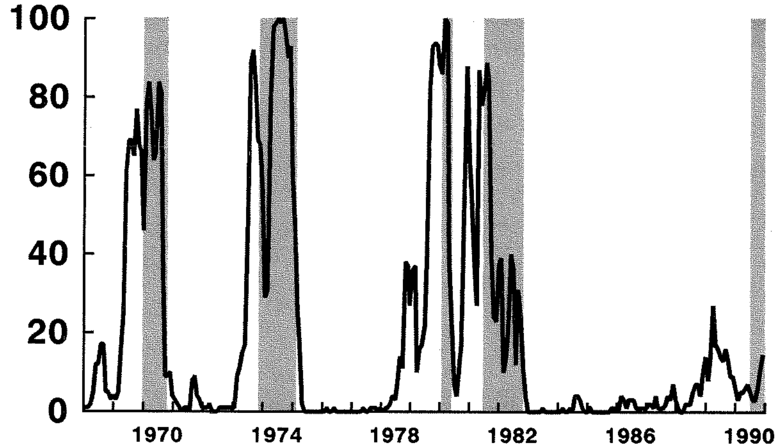
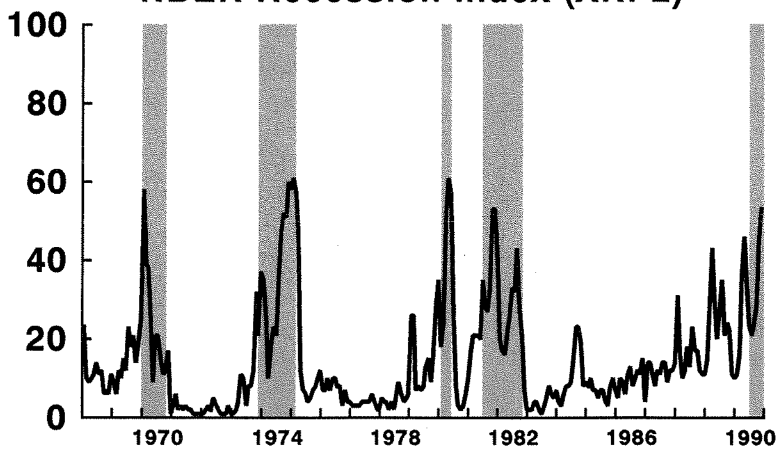



**Chart 3**
**NBER Recession Index (XRI-2)**



## III. Turning Point Recession Index: Process Switching Model

Many economists have observed asymmetric behavior of some key macro variables between economic expansions and contractions. For example, output tends to inch upward during an expansion, but it tends to drop very sharply at the beginning of a contraction. Thus, the behavior of the economy in the two phases is best described as being governed by two distinct stochastic structures instead of by a single underlying structure (Neftci 1982). Consequently, according to these views, forecasting a recession (the onset of a contraction regime) amounts to predicting a behavioral switch in the economy from an expansion to a contraction.

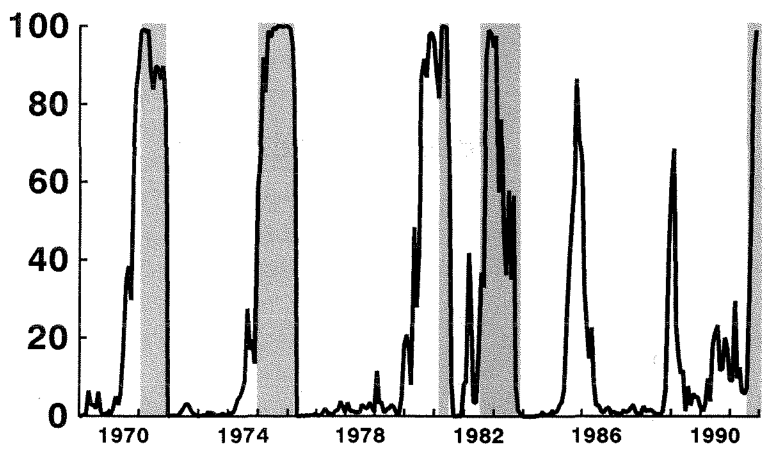
To put this idea into practice, a forecaster needs a signal variable that foretells changes in the behavioral structures. This signal variable must meet several requirements: its behavior should be systematically related to that of the output in the economy; it should have some lead time with respect to changes in output to be useful as a predictor of changes in output; finally, it should be available frequently enough to update the model in a timely manner in terms of key developments that have a bearing on the potential shift in the regime. Both the original turning point model of Neftci (1982) and a model by Diebold and Rudebusch (1989) use the monthly Composite Index of Leading Indicators published by the Department of Commerce (henceforth, DOC LI) as such a signal variable.

The next step is to take the first difference of the series. Then the data characteristics in upturns and downturns are summarized by fitting simple normal distribution functions: first divide the overall historical period into expansionary and contractionary sub-periods using the historical turning point dating in the DOC LI series. Then the DOC LI observations belonging to expansionary and contractionary periods are respectively pooled into two groups of upturn and downturn samples. Finally, two normal distribution functions $N^e(\mu_e,\sigma_e)$, $N^c(\mu_c,\sigma_c)$ (where $\mu$ and $\sigma$ denote the mean and standard deviation) are estimated from the expansion and contraction samples, respectively.

Additionally, determine a prior transitional probability for the signal variable. The transitional probability $\Omega$ is the measure of the likelihood that the signal variable will remain in the current regime at any given time.[7] Consequently, $1-\Omega$ measures the probability of the signal variable switching from the current behavioral regime.

Given this information, one can apply the switching time Bayesian probability formula that was developed by Neftci (1982) as shown in Box 1. With each new observation in the DOC LI, the turning point recession index (TPRI) model calculates the conditional probability that the indicator is in the downturn regime. The probabilities are shown in Chart 4.

**Chart 4**
**Turning Point Recession Index**




## IV. Assessment

Recession probability indexes and turning point models are more sophisticated than rule-of-thumb methods, which typically forecast a recession after three consecutive declines in the DOC LI. They are also more systematic because they account for the magnitude of change as well as the temporal direction of change in the leading indicators, and in general, they substantially outperform the rule-of-thumb predictions.

Stock and Watson (1989, pp. 382) applied a formal econometric method to compare the predictive power of

## Box 1

Denote the signal variable (i.e., DOC LI) at date $t$ as $i_t$ and the date when a switch occurs from one behavioral regime of $i_t$ to another as $Z$. $Z$ will be a random variable that takes integer values. Next denote the collection of the sequential realizations of $i$ up to the present (time $t$) as $I_t$. Then the posterior probability for a turning point occurring at time $t$, given the data $I_t$ can be written as follows:

$$P(Z \leq t \mid I_t) = \frac{P(I_t \mid Z \leq t)}{P(I_t)};$$

or, by denoting $P(Z \leq t \mid I_t)$ as $\Pi_t$, we get

$$\Pi_t = \frac{[\Pi_{t-1} + \Omega(1-\Pi_{t-1})]p_t^d}{[\Pi_{t-1} + \Omega(1-\Pi_{t-1})]p_t^d + (1-\Pi_{t-1})p_t^u(1-\Omega)},$$

where: $\Pi_t$ denotes the conditional probability that the DOC LI is in the downturn regime in period $t$;

$p_t^u$, $p_t^d$ denote the probabilities, obtained from the step described earlier, that the observed $i_t$ came from $N^u(\mu_u, \sigma_u)$ (upturn regime) and $N^d(\mu_d, \sigma_d)$(downturn regime), respectively;

$\Omega$ denotes the unconditional transitional probability of a switch from an upturn regime to a downturn regime.

A new observation on $i_t$ will affect the conditional probability of $\Pi$ through $p_t^u$ and $p_t^d$ because other elements are predetermined. For example, suppose that currently we observe a large positive value for $i_t$. Then it is more likely that it came from the expansionary regime than from the contractionary regime, because on average, the economy grows more during expansions than contractions; that is, $p_t^u > p_t^d$. This large $p_t^u$ will make the second part of the denominator larger relative to both the numerator and the first entry of the denominator. It makes the overall $\Pi_t$ smaller, and thus makes a switch of regimes (from upturn to downturn) in the current period less likely. This consequently reduces the probability that the economy will be in recession in the near future. This formulation works symmetrically for a forecast of a regime switch from downturn to upturn with the proper substitutions of terms.

the rule-of-thumb method and their method, and found their method to be more accurate. They performed regression analyses that related consecutive movements in the DOC LI numbers to actual historical recessions and expansions. For example, the $R^2$ of the regression that related the index to the occurrence of recessions or expansions six months hence was 0.028 using the rule-of-thumb, whereas it was 0.50 for the regression using the experimental NBER XRI. Diebold and Rudebusch (1989) also found a similar relative performance ranking of the rule-of-thumb method compared to different methods, such as the Neftci method.[8]

However, assessing the "goodness of fit" of these models is conceptually difficult, because their forecasts are in terms of probabilities, and "actual" probabilities are not directly observable to evaluate the performance of these models. In fact, low probability recessions may occasionally occur, while high probability recessions may occasionally not occur. Thus, over a limited sample period, simply correlating the probability with the business cycle is not necessarily a good way to judge the accuracy of the models. Of course, the larger the sample, the more appropriate this direct type of evaluation becomes.[9]

One criterion that is often used to gauge reliability is the frequency of false signals, a notorious problem for leading indicators that led to Paul Samuelson's famous remark, "The stock market has predicted nine out of the last five recessions!" The first type of false signal is analogous to the Type II error of the usual hypothesis test; that is, the model forecast of an imminent recession is not followed by an actual recession within a reasonable period of time. For example, suppose we interpret a model as signaling a recession when the probability is above half of the maximum probability (observed over the sample period) of each model. According to this criterion, the TPRI and NBER XRI-2 models each have two instances of false signals for the 1968-1989 sample period (1985 and 1988 for TPRI and 1988 and 1989 for XRI-2); the very striking spikes in the TPRI model in the late 1980s seem to have been reflecting temporary slowdowns in the manufacturing sector during those periods. The NBER XRI and BVAR RI have no false signals.

The second type of false signal is analogous to the Type I error of the usual hypothesis test; that is, the model fails to predict an ensuing recession with some lead time (for example, six months). Using the same cut-off probability as in the first case, the NBER XRI-2 has failed four times (1969, 1973, 1980 and 1982), the TPRI model has failed twice (1974 and 1981), the BVAR RI has failed once (1969), and the NBER XRI has not failed at all. The performance of the TPRI in this regard is most likely related to the fact that it is based on the DOC LI which is notorious for having widely varying lead times with the business cycle peaks and troughs. For the past 30 years, for example, turning points in the DOC LI have led the contractionary turning points of the economy by anywhere from two to twenty months.[10]

## VI. Recent Predictions

As in any of the forecasting models that have been estimated using sample information, an important test of the RPI models' forecasting power hinges on their out-of-sample performance. The only out-of-sample observation we have is the most recent recession, which started in the second half of 1990.

The models' various predictions of the probability of an imminent recession as of the end of November 1990 are 14 percent for the NBER XRI, 21 percent for the BVAR, 53 percent for the NBER XRI-2, and 98 percent for the TPRI. The sharp divergence between the forecasts of the NBER XRI and XRI-2 suggests that different theoretical underpinnings alone do not explain the divergent forecasts. It is natural to ask, then, what the most likely source of such differences is.

One distinguishing feature is that low probability forecasts included a set of financial variables (interest rates and associated spreads) but high probability forecasts did not. This is particularly interesting in light of recent studies on the changing role of financial variables in econometric models of key macro variables.

Bernanke (1990), among others, found that various interest rates and spreads were substantially more useful in explaining and forecasting key macro variables for the pre-1980 sample period than for the post-1980 period. In particular, he examined the spread between the commercial paper rate and the T-bill rate. This spread may reflect the default risk of commercial paper, which, in turn, would be very sensitive to an expected recession. However, if this is the important channel through which the financial variables are useful in forecasting key variables, then they still can be expected to have substantial explanatory power in econometric models.

The spread may also reflect the monetary policy stance, which affects the near-term economic condition by shifting credit conditions. This may be particularly relevant when there are deposit interest rate ceilings and when commercial paper and T-bills are imperfect substitutes as portfolio assets. Monetary tightening would induce an outflow of deposits from banks as market interest rates rise above deposit ceilings. This "disintermediation" creates a "credit crunch" and subsequently an economic contraction. At the same time, bank deposits will flow into T-bills because T-bills can be purchased in relatively small denominations, unlike commercial paper, which is typically in denominations too large for most small deposit holders. This inflow of funds will depress T-bill yields relative to commercial paper rates in periods when the general level of interest rates is higher.[11]

According to this hypothesis, it is relatively easy to explain the diminished role of the spread. Since the early 1980s when deposit rates were deregulated, more alternative financial assets have become available creating closer substitutability among assets.

This conjecture seems relevant in explaining the divergent forecasts of the various models. The yield curve has maintained a positive slope, and few noticeable changes with respect to short-term interest rates and the rate-spread have occurred in late 1990. Thus, the recession forecasts of models that included these financial variables might have picked up mixed signals of the likely conditions of the economy, unlike the models with only real variables. Consequently, according to this conjecture, the probability of recession forecasted by models containing financial variables did not increase as substantially as it did in models relying entirely on real variables.

It is quite possible that the current recession is distinct from preceding ones in terms of both its causes and the way contractionary effects of the causal factors spread across the economy. For example, some economists cite the diminished credit availability which started in 1990 for reasons related to the weakened condition of financial institutions and stricter regulations while others point to the special circumstances associated with the Middle East confrontation, which increased short-term and near-term uncertainties.

The question of whether business cycles are distinct (and hence whether a single modeling strategy is appropriate) is not new. Blanchard and Watson (1986) examined the nature of the sources of impulses behind business cycles using U.S. time series data. Their findings suggest that cycles are not alike; that is, each historical cycle can be associated with several identifiable large single shocks with different origins.

This result, however, does not necessarily make the modeling approaches surveyed here inappropriate. The existing models are still valid and applicable to the designed task if there exist measurable similarities in the way the original shocks propagate or dissipate throughout the economy. Whether or not this is the case is an important empirical issue, one on which we can expect to see more research in the future.

## VII. Conclusion

Representative models designed to forecast prospects of a recession in the near future have been examined. Specifically reviewed were the experimental NBER index models and a model based on the Neftci method. They differ not only in various operational aspects, but also in their conceptual approaches to modeling the behavior of key economic variables, such as output. The experimental NBER models are based on the assumption that output behaves symmetrically across both expansionary and contractionary phases of economic fluctuations, whereas the Neftci method admits a shift in the behavioral regime across the two phases. Whether this assumption of a symmetry in the behavior of the output is empirically appropriate is an issue currently being examined by economists.

The models performed well in terms of within-sample historical predictions. They outperformed the common rule-of-thumb that relies on three consecutive declines in the DOC LI. However, their out-of-sample forecasts were widely divergent, even for those that used the same modeling approach. The distinction is that models with a high probability forecast excluded a set of financial variables while low probability forecasts included financial variables. This seems to reflect the fact that a recession is defined to be a period of contractions in real variables such as orders, sales, output and employment. Although the amount of the lead time may vary, models that rely comprehensively on such real variables will necessarily provide indications of the onset of a serious downturn.

It is likely that the most recent downturn was unusual in that its causal factors differed from the few factors that had frequently been behind past recessions. In that sense, the models that were designed to conform to the general average characteristics of past economic fluctuations did poorly in detecting the most recent economic downturn.

However, it is premature to draw any inferences from this single-sample observation of the current recession; these results need to be considered in the proper perspective. In most situations where we need to draw inferences about an uncertain outcome, more information is preferred to less as a practical principle. This holds true with regard to forecasting business cycle downturns, especially since we do not have a well-understood, widely agreed upon, and operationally feasible framework for describing evolutions of a large set of macro variables.

Such a framework could provide a theoretically well-founded list of variables or a sequence of economic events that could give rise to a "sufficient statistic" about a near-term economic downturn, and would consequently make any additional information redundant. In this context, systematic efforts to reduce our prediction errors involving important aggregate economic variables such as the RPI models can be useful.

The key contribution of the RPI models, however, essentially lies in providing another way to organize and use information contained in the various leading economic indicators. Consequently, their reliability is crucially dependent on the reliability of the leading economic indicators that are used as the sources of information. Thus, any further refinement and improvement of our stock of knowledge on leading indicators will lead to commensurate improvement in the performance of the recession forecasting models.

## ENDNOTES

1. For detailed explanations of this modeling strategy, see Todd (1984) and Roberds (1988). For a more theoretical discussion of this econometric methodology see Doan, Litterman and Sims (1984).

2. This is done by weighing forecast accuracy at the one-year horizon more heavily than the rest of the forecasting horizon. This step is implemented during a model specification selection stage. Following the BVAR modeling practice, a model builder defines a prior matrix of parameters that control the dynamic interactions between variables in each equation of the model. We adjusted these prior parameters selectively to obtain the forecast accuracy configuration across different forecasting time frames. See Roberds (1988) for detailed descriptions.

3. The variables are real GNP, business fixed investment, the unemployment rate, fixed GNP price index, unit labor cost, producer price index, monetary aggregate M2, trade weighted exchange rate, six-month commercial paper, and AAA corporate rates.

4. Applying this rule to post-war U.S. data (1947Q1-1990Q3) we detect six out of the eight recessions that occurred.

5. These indexes were developed as the result of efforts to update the system of indicators that were developed in the 1930s and 1940s at the NBER by Mitchell and others; the latter is still being used at the Department of Commerce.

6. This particular time horizon is related to the way the LEI is constructed. That is, it was specifically designed to give an optimal forecast of the CEI's relative growth over *six months*. A more precise definition of the economy being in a recession is as follows: A month is defined to be in a recession pattern if the monthly growth of the CEI index is either in a sequence of six consecutive declines below a boundary point, or in a sequence of nine declines below the boundary with no more than one increase during the middle seven months.

7. There are different views regarding the question of dependency between the duration of each phase (i.e., expansionary or contractionary) and the probability of transition from one regime to another. For example, in Neftci (1982), the transition probability is treated as dependent on the duration, whereas Diebold and Rudebusch (1989) use a transitional probability matrix that is independent of the duration. For more details on this issue, see Hamilton (1989), Neftci (1984), Diebold and Rudebusch (1990).

8. However, a recent study by Koenig and Emery (1991) found that some relatively simple methods similar to the rule of thumb did as well as the Neftci method when the actual *real time* data that would historically have been available to a forecaster were used, instead of the most recent revised data on the DOC LI. These results point to some potential problems with the DOC LI series, which has gone through major revisions, rather than to a devaluation of the Neftci methodology.

9. Diebold and Rudebusch (1989) propose and examine a set of test statistics that can score a probability forecast model in terms of different attributes such as accuracy, calibration and resolution. Even though these proposed methods are systematic, small-sample observations are still problematic. However, the turning point forecast model seems more appropriate for such an evaluation method, because it generates more observations both in terms of switches from expansions to contractions and vice versa, whereas a simple recession forecast model would count only switches from expansionary to contractionary regimes.

10. Koenig and Emery (1991) give a detail account of the relative performance of the real time DOC LI series in predicting expansions versus contractions. They find the series to be a better predictor of expansions and a poorer predictor of recessions in near future.

11. Financial institutions would have an opportunity to arbitrage by selling T-bills in their portfolio and buying commercial paper in those periods. However, for banks those two instruments are not alike. For example, banks can use T-bills but not commercial paper as collateral for satisfying bank capital adequacy. Thus, due to the imperfect substitutability between T-bills and commercial paper, banks will not arbitrage and offset the widening spread.

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