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The Predictive Power of the Index of Consumer Sentiment

THE MONTHLY RELEASE of the Index of Consumer Sentiment (ICS) by the Survey Research Center of the University of Michigan is featured in the financial press with much fanfare, especially during periods of economic uncertainty. Yet the conventional wisdom appears to be that although the index by itself has considerable predictive power, when used in conjunction with other readily available economic variables its marginal value is quite small. For example, Christopher Carroll, Jeffrey Fuhrer, and David Wilcox conclude that "consumer sentiment does indeed forecast future changes in household spending. . . . Further, sentiment likely has some (though probably not a great deal) of *incremental* predictive power relative to at least some other indicators for the growth of spending."[1] On the other hand, John Matsusaka and Argia Sbordone find evidence of a qualitatively significant causal relationship between the ICS and GDP: they estimate that between 13 and 26 percent of variations in GDP can be attributed to variations in consumer sentiment.[2]

This paper assesses the predictive power of the ICS, addressing two questions in particular. First, does the index, either alone or in conjunction with other indicator variables, sharpen predictions of recession and recovery? Second, does the index, either alone or in conjunction with other economic indicators, help to predict personal consumption expenditure?

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1. Carroll, Fuhrer, and Wilcox (1994, p. 1401).
2. Matsusaka and Sbordone (1995).

The first question is especially timely in view of the plunge in the ICS in recent months. To answer this question, it is necessary first to define precisely and in quantitative terms what is meant by recession and what is meant by recovery, next to translate the ICS and other indicator variables into a recession signal, and finally to evaluate the accuracy of that signal as a predictor of recession. The next section summarizes the procedure used to carry out these three steps. This procedure is then applied to quarterly values of a set of indicator variables that includes the ICS as well as the spread between long- and short-term interest rates, a composite stock market index, and an index of leading indicators. This procedure is also applied to a model that generates current-quarter estimates of these indicator variables from data for the first, or first two, months of the quarter, to assess the accuracy of high-frequency predictions of recession and recovery.

Finally, the value of monthly indicator data for forecasting personal consumption expenditure is investigated. This question is motivated by the fact that monthly values of the ICS as well as of other indicator variables are available before the corresponding monthly values of personal consumption expenditure are released. An accurate and timely forecast of personal consumption expenditure and its components would be helpful in predicting periods of recession and recovery.

Predicting the Probability of Recession

Definition of Recession

A popular definition of recession is the occurrence of two or more successive quarters of decline in real GDP.[3] This definition, however, corresponds only approximately to the standard reference cycle chronology maintained by the National Bureau of Economic Research (NBER). Recession quarters as identified by the NBER coincide roughly with quarters in which real GDP declines, but the correspondence is not perfect.

A slightly more technical definition of recession that corresponds more closely with the NBER chronology is two or more successive quarters in which a weighted average of the current and immediately preceding and

3. Other definitions of recessionary events have been proposed by Fair (1993) and Stock and Watson (1993).

following quarterly GDP growth rates is negative. In particular, let y_t denote the rate of growth of real GDP from quarter $t - 1$ to t, and let[4]

$$\bar{y}_t = 0.25y_{t-1} + 0.50y_t + 0.25y_{t+1}. \tag{1}$$

According to the average growth rate criterion, a recession is said to begin in quarter t if that quarter is the first of two or more successive quarters for which $\bar{y}_t < 0$. Similarly, a recession is said to end in quarter t if that quarter is the last of two or more successive quarters for which $\bar{y}_t < 0$. This average growth rate series is quite informative about NBER recession quarters. Indeed, as table 1 shows, the correspondence between recession quarters as designated by the NBER and those determined by the average growth rate criterion is remarkable.

Four different types of recession-related event, denoted by E_{kt} for $k =$ 1, 2, 3, 4, are defined for analysis. The event E_{kt} occurs if one of the next k quarters is a recession quarter. Given the definition of recession as two or more successive quarters of negative average growth of real GDP, the event E_{1t} occurs if a recession continues from quarter t, in which case $\bar{y}_t < 0$ and $\bar{y}_{t+1} < 0$, or begins in quarter $t + 1$, in which case $\bar{y}_{t+1} < 0$ and $\bar{y}_{t+2} < 0$. Thus, whether E_{1t} occurs at time t depends on the realized values of $\bar{y}_t$ and $\bar{y}_{t+1}$, or $\bar{y}_{t+1}$ and $\bar{y}_{t+2}$, none of which is known at time t but all of which are known at time $t + 3$. The events E_{kt} for $k = 2, 3, 4$ are defined in terms of $\bar{y}_{t+h}$ in a similar way. Occurrences of these four recession events are taken as the objects to be predicted by the recession signal model.

A Recession Signal Model

A model is needed to translate the indicator variables into recession signals.[5] For this work a vector autoregressive (VAR) model was used, although the same approach could be used with a structural econometric model.[6] The first step is the specification and estimation of a standard VAR model of the following form:

4. This weighted average produces a smoother series than an unweighted average of quarterly growth rates, as can be seen from a comparison of the transfer functions of the weighted and unweighted moving averages.

5. For a survey and comparison of a variety of other procedures for forecasting recessions, see Filardo (1999).

6. See, for example, Adams and Duggal (1976).

Table 1. Comparing Recession Dating Methods, 1960–91

	Quarters in recession	
Period	*NBER*[a]	*Average growth rate*[b]
1960–61	1960:3–61:1	1960:3–60:4
1969–70	1970:1–70:4	1969:4–70:1
1974–75	1974:1–75:1	1974:1–75:1
1980	1980:2–80:3	1980:1–80:3
1981–82	1981:4–82:4	1981:4–82:3
1990–91	1990:4–91:1	1990:3–91:1

Sources: National Bureau of Economic Research and author's calculations.
a. As dated by the National Bureau of Economic Research. A recession begins in the quarter following the month where output reaches its peak and ends in the quarter following the month where output reaches its trough.
b. A recession begins in the first of two or more successive quarters of negative average output growth. A recession ends in the last of two or more successive quarters of negative average output growth.

$$\mathbf{Y}_t = \phi + \sum_{j=1}^{m} \Phi_j \mathbf{Y}_{t-j} + \varepsilon_t, \tag{2}$$

where the vector $\mathbf{Y}_t$ contains two sets of variables: $\mathbf{Y}_{1t}$ and $\mathbf{Y}_{2t}$. The subvector $\mathbf{Y}_{1t}$ includes real GDP (more precisely, the natural logarithm or rate of growth of real GDP) and possibly other fundamental economic variables, and the subvector $\mathbf{Y}_{2t}$ contains one or more indicator variables. The model is used to generate forecasts of the vector $\mathbf{Y}_t$ and of y_t and $\bar{y}_t$ in particular.

Stochastic simulations of the VAR model were used to estimate recession probabilities. To estimate the probability of event E_{kt}, the VAR model was used to generate alternative values of $y_{t+1}, y_{t+2}, \ldots, y_{t+k+2}$, and hence of $\bar{y}_t, \bar{y}_{t+1}, \ldots, \bar{y}_{t+k+1}$ corresponding to alternative realizations of $\varepsilon_{t+1}, \varepsilon_{t+2}, \ldots, \varepsilon_{t+k+2}$. The estimate of the probability of event $E_{kt}, \hat{\mathrm{P}}(E_{kt})$, is the fraction of these realizations that result in the occurrence of E_{kt}. The disturbance terms for the stochastic simulations were drawn from a normal distribution with covariance matrix $\hat{\mathbf{\Omega}}$, the estimated covariance matrix of the disturbance vector ε_t in the VAR model. For each event E_{kt}, 1,000 simulated time paths were used to calculate $\hat{\mathrm{P}}(E_{kt})$ for each time period t.[7]

Scoring the Recession Signal Model

To evaluate the accuracy of these probability forecasts, two methods were used: a visual comparison of the estimated probabilities with the

7. This is the procedure used in Fair (1993) and Howrey (1991a).

actual occurrences and calculation of a quadratic probability score (QPS).[8] The QPS for event E_{kt} is given by

$$QPS_k = \frac{2}{T}\sum_{t=1}^{T}[\hat{\mathrm{P}}(E_{kt}) - \mathrm{R}(E_{kt})]^2, \tag{3}$$

where $\hat{\mathrm{P}}(E_{kt})$ denotes the estimated probability of event E_{kt}, and $\mathrm{R}(E_{kt})$ denotes the realized value of event E_{kt}, which is 1 if E_{kt} actually occurred and 0 otherwise. The highest (worst) score attainable is 2, which occurs if $\hat{\mathrm{P}}(E_{kt}) = 0$ when $\mathrm{R}(E_{kt}) = 1$ and $\hat{\mathrm{P}}(E_{kt}) = 1$ when $\mathrm{R}(E_{kt}) = 0$; the lowest (best) possible score is 0, which occurs if $\hat{\mathrm{P}}(E_{kt}) = 1$ when $\mathrm{R}(E_{kt}) = 1$ and $\hat{\mathrm{P}}(E_{kt}) = 0$ when $\mathrm{R}(E_{kt}) = 0$.

For purposes of comparison with the model-generated predictions of recession, two simple benchmark predictors were considered. First, a constant probability forecast, $\hat{\mathrm{P}}(E_{kt}) = p_k$ for all t, that minimizes the QPS is obtained by setting $\hat{\mathrm{P}}(E_{kt})$ equal to the relative frequency with which the event E_{kt} occurred over the sample period. For the sample period from 1961 to 1999, $p_k = 0.109$ for $k = 1$, 0.141 for $k = 2$, 0.173 for $k = 3$, and 0.205 for $k = 4$. The corresponding QPSs are 0.194 for $k = 1$, 0.242 for $k = 2$, 0.286 for $k = 3$, and 0.326 for $k = 4$. Second, a naïve probability forecast sets $\hat{\mathrm{P}}(E_{kt}) = 1$ if $\bar{y}_{t-1} < 0$ and 0 otherwise. The corresponding QPSs for this naïve predictor are 0.269 for $k = 1$, 0.333 for $k = 2$, 0.397 for $k = 3$, and 0.436 for $k = 4$.

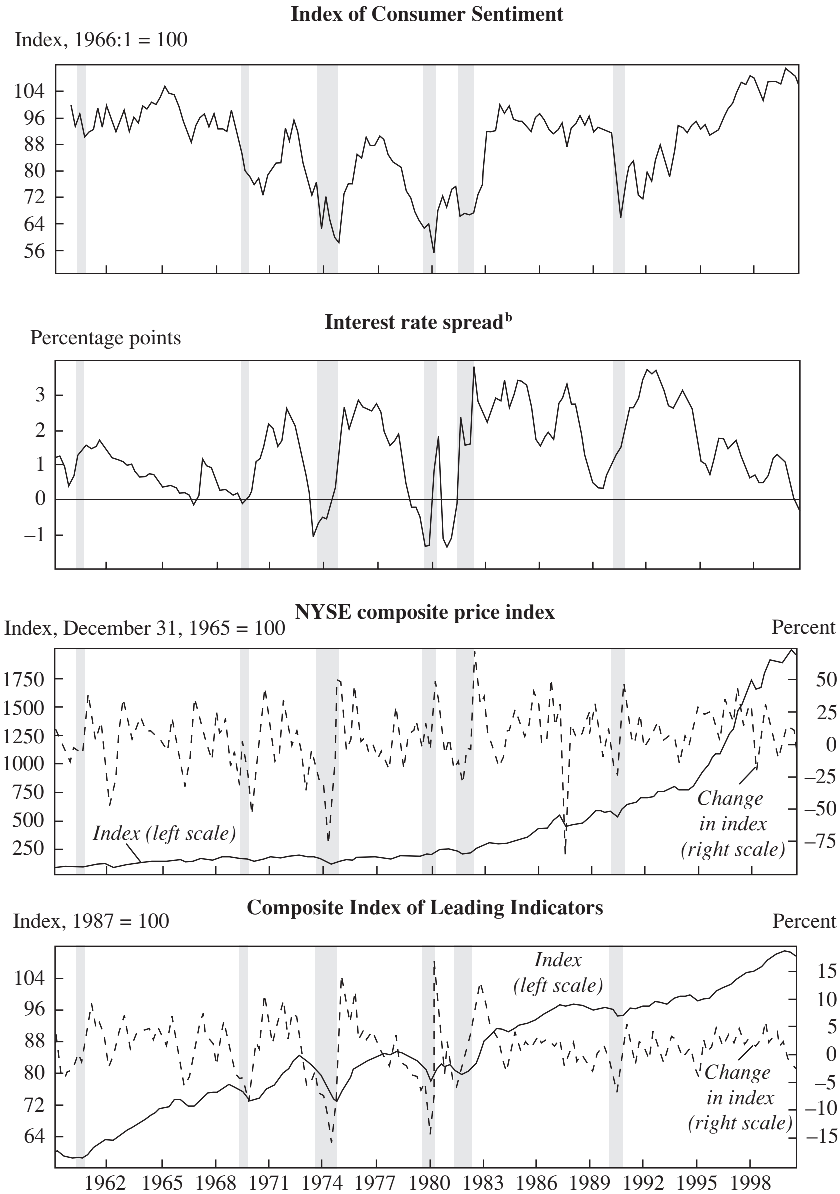
Quarterly Indicators and the Probability of Recession

Four candidate recession indicators were considered: the ICS, the difference in yields (or spread) between the ten-year U.S. Treasury note and the three-month Treasury bill, the New York Stock Exchange (NYSE) composite price index, and the Composite Index of Leading Indicators published by the Conference Board (formerly by the U.S. Department of Commerce).[9] Plots of these four series over the last four decades (figure 1)

8. Diebold and Rudebusch (1989) used the quadratic probability score in their study of the use of leading indicators to predict recessions.

9. The sources for these series are given in the appendix. Estrella and Mishkin (1998) examined a number of indicator variables using a different methodology and concluded that the last three indicators named were among the most promising available for forecasting recessions.

Figure 1. Selected Indicators of Recession, 1959–2000[a]



Source: See appendix for data sources.

a. Shading indicates recessions as identified by the average GDP growth rate criterion (see table 1).

b. Difference in yields between ten-year U.S. Treasury notes and ninety-day Treasury bills.

illustrate both the promise and the potential problems associated with the use of these indicator variables. For example, as others have noted, sharp declines in the ICS preceded the 1969–70, 1973–74, and 1980 recessions. And during the period shown in figure 1, no recession occurred without a sharp decline in the index. However, the lead time from a decline in the index to the arrival of a recession has been highly variable, and the series itself is sufficiently noisy that it is not obvious how to extract a consistent recession signal from the series. Similar observations apply to the yield spread.

An additional problem associated with the use of the NYSE composite price index or the index of leading indicators is that both series exhibit a strong trend. For the analysis that follows, these series were therefore transformed to growth rates, which are shown as the dashed lines in figure 1. Again there is a hint that both series are leading indicators of recession, but a consistent pattern is not readily apparent. That is why a model is needed to translate the information in these four indicators into a recession signal.

Autoregressive (AR) Models

The first set of results is based on a trend-stationary model for GDP:

$$y_t = \alpha_0 + \alpha_1 t + \alpha_2 Y_{t-1} + \sum_{j=1}^{m} \beta_j y_{t-j} + \sum_{i=1}^{r}\sum_{j=1}^{m} \gamma_{ij} x_{it-j} + \varepsilon_t. \tag{4}$$

As before, y_t is the annualized rate of growth of real GDP, Y_t is the natural logarithm of the level of real GDP, and x_i is one of the indicator variables.[10] The index j in this equation indicates the number of quarters the explanatory variable is lagged, and r indicates the number of indicator variables included in the equation (x_i for i from 1 to r). The lag order m, $0 \leq m \leq 8$, was determined by minimizing the value of the Schwartz information criterion (SIC) over the sample period 1962 to 2000.[11]

The results are summarized in table 2. Each row of the table reports results for a version of equation 4 containing one or more, or none, of the indicator variables. The column labeled "Lags" shows the value of m that

10. The ICS and the spread variable were added to the GDP equation as levels, and the NYSE index and the leading indicators index as annualized growth rates.

11. Schwartz (1978).

Table 2. Predicting Recessions with Naïve and AR Models Using the ICS and Other Indicators[a]

					p value				*Predictive accuracy (QPS)*[f]			
Model	*Lags*	$\bar{R}^2$	*Standard error*	*SIC*[b]	*ICS*	*Spread*[c]	*NYSE*[d]	*Lead*[e]	$k = 1$	$k = 2$	$k = 3$	$k = 4$
Naïve									0.269	0.333	0.397	0.436
Average									0.194	0.242	0.286	0.326
AR-01	2	0.13	3.32	1,242					0.128	0.162	0.197	0.226
AR-02	1	0.14	3.29	1,239	0.00				0.121	0.151	0.178	0.218
AR-03	2	0.18	3.22	1,240		0.00			0.112	0.132	0.151	0.183
AR-04	1	0.16	3.27	1,237			0.00		0.118	0.157	0.193	0.237
AR-05	2	0.34	2.90	1,205				0.00	0.115	0.154	0.188	0.233
AR-06	1	0.19	3.21	1,235	0.00	0.00			0.109	0.125	0.139	0.168
AR-07	1	0.19	3.20	1,234	0.01		0.00		0.107	0.141	0.170	0.212
AR-08	1	0.32	2.94	1,206	0.01			0.00	0.107	0.142	0.170	0.213
AR-09	1	0.29	3.00	1,213		0.38	0.00		0.109	0.135	0.160	0.196
AR-10	2	0.34	2.88	1,211		0.14		0.00	0.107	0.141	0.165	0.205
AR-11	1	0.28	3.01	1,214			0.88	0.00	0.112	0.153	0.188	0.235
AR-12	1	0.23	3.11	1,229	0.00	0.00	0.00		0.094	**0.112**	**0.128**	**0.160**
AR-13	1	0.32	2.93	1,209	0.00	0.17		0.00	**0.093**	0.126	0.143	0.178
AR-14	1	0.31	2.95	1,211	0.01		0.89	0.00	0.105	0.141	0.171	0.214
AR-15	1	0.28	3.01	1,218		0.36	0.76	0.00	0.106	0.139	0.162	0.202
AR-16	1	0.32	2.94	1,214	0.00	0.16	0.70	0.00	0.095	0.123	0.138	0.174

a. Estimated using equation 4.

b. Schwartz information criterion. $SIC = T \times \ln \sum_{t=1962:1}^{t=2000:4} \hat{\varepsilon}_t^2 + n \times \ln T$, where n is the number of parameters in the GDP growth rate equation.

c. Yield spread between ten-year Treasury notes and three-month Treasury bills.
d. Composite price index of the New York Stock Exchange.
e. Composite Index of Leading Indicators published by the Conference Board.
f. Quadratic probability scores calculated using equation 3 for t = 1961:1–99:4. Lower scores represent higher accuracy. Boldface type indicates the best score.

minimizes the SIC for the equation. The table also shows the adjusted R^2 and the standard error of the regression, and the p value for a test of the hypothesis that a given indicator variable can be excluded from the equation. Finally, the table reports the QPS for the sample period 1961 to 1999 for $k = 1$ through 4 for each equation. For the model designated AR-01, only the GDP equation itself is needed to calculate the QPS, since lagged GDP is the only indicator. The other models include various combinations of the indicator variables, and a VAR simulation approach was used to calculate the QPS for these models.

Several interesting conclusions emerge from this table. First, each of the four indicator variables when included individually (equations AR-02 through AR-05) is statistically significant at the 1 percent level, and each results in a decrease (that is, an improvement) in the SIC compared with the SIC for model AR-01. The reduction in the standard error of the estimate is minimal, however. When no indicator variables are included in the output equation, the standard error of the regression is 3.32. The best of the single-indicator equations, AR-05, which includes two lags of the growth rate of the index of leading indicators, reduces the standard error of the regression only to 2.90, and for the other equations the reduction is considerably less.

Nevertheless, the QPS for E_1 falls (improves) for all of the single-indicator equations compared with the AR-01 model, and the QPS for E_k falls for all k for the single-indicator equations containing the ICS and the spread variable. The latter produces the best results of the single-indicator equations, a result that is consistent with the findings of Arturo Estrella and Frederic Mishkin.[12]

The next three rows in table 2, those for equations AR-06 through AR-08, show what happens when the ICS is combined with just one of the other three indicator variables. In all three cases the ICS is statistically significant, and its inclusion reduces the QPS. According to the QPSs for E_2, E_3, and E_4, the best of these equations is the one that combines the ICS with the interest rate spread.

The remainder of the table shows what happens when all other possible combinations of the indicator variables are included in the model. The best performer of all of these is AR-12, which includes three of the four indicator variables, excluding only the leading indicators index. The ICS is

12. Estrella and Mishkin (1998).

always statistically significant in these equations, no matter what other indicators are included. In addition, its inclusion in the system always reduces the QPS.

Vector Autoregressive Models

The results obtained so far indicate that the ICS, either alone or in conjunction with other indicator variables, helps to sharpen predictions of the probability of recession. But the question of the marginal contribution of these indicators when the subvector $\mathbf{Y}_{1t}$ in equation 2 includes fundamental economic variables, such as the unemployment and interest rates, remains to be answered. To pursue this issue, a second set of experiments was conducted with four economic variables in the subvector $\mathbf{Y}_{1t}$: the rate of growth of real GDP, the rate of price inflation as measured by the GDP implicit price deflator, the civilian unemployment rate, and the three-month Treasury bill rate. In previous work, forecasts of this four-variable VAR model have been compared with those of the Research Seminar in Quantitative Economics, which are based on the Michigan Quarterly Econometric model of the U.S. Economy.[13] In addition, recession probabilities obtained from the VAR have been compared with recession probabilities generated by the Fair model.[14] In both cases the comparisons were quite favorable. Thus it is of interest to see if even sharper forecasts of the probability of recession can be obtained when indicator variables are added to this four-variable VAR model.

Table 3 summarizes the full set of results, in a format identical to that of table 2. The first striking result is that the ICS retains its statistical significance in the GDP growth rate equation, whereas the spread variable loses its significance, when the inflation rate, the unemployment rate, and the short-term interest rate are added to the system. The best model for predicting recessions two or more quarters in advance is VAR-07, which includes only the ICS and the rate of growth of the NYSE composite index as indicator variables. The differences in probability scores between the AR and VAR models are very small for the one-quarter-ahead forecasts, but the differences become more pronounced as the forecast horizon recedes, with the VAR model having a decided advantage.

13. Howrey (1995).
14. Howrey (1991a).

Table 3. Predicting Recessions with Naïve and VAR Models Using the ICS and Other Indicators[a]

					p value[b]				*Predictive accuracy (QPS)*[b]			
Model	*Lags*	$\bar{R}^2$	*Standard error*	*SIC*[b]	*ICS*	*Spread*	*NYSE*	*Lead*	$k = 1$	$k = 2$	$k = 3$	$k = 4$
Naïve									0.269	0.333	0.397	0.436
Average									0.194	0.242	0.286	0.326
VAR-01	1	0.18	3.22	1,231					0.106	0.123	0.139	0.150
VAR-02	1	0.24	3.09	1,223	0.00				0.097	0.109	0.123	0.135
VAR-03	1	0.18	3.23	1,237		0.96			0.107	0.121	0.137	0.152
VAR-04	1	0.21	3.15	1,229			0.01		0.096	0.113	0.129	0.146
VAR-05	2	0.36	2.93	1,215				0.00	0.085	0.111	0.133	0.154
VAR-06	1	0.24	3.10	1,228	0.00	0.66			0.097	0.108	0.125	0.137
VAR-07	1	0.27	3.05	1,222	0.00		0.02		0.086	**0.102**	**0.116**	**0.132**
VAR-08	1	0.34	2.88	1,204	0.01			0.00	0.084	0.107	0.121	0.135
VAR-09	1	0.21	3.16	1,234		0.69	0.01		0.096	0.113	0.131	0.146
VAR-10	1	0.31	2.95	1,212		0.84		0.00	**0.082**	0.110	0.135	0.157
VAR-11	1	0.31	2.95	1,212			0.83	0.00	0.087	0.112	0.129	0.145
VAR-12	1	0.26	3.06	1,227	0.00	0.92	0.02		0.089	0.103	0.118	0.135
VAR-13	1	0.34	2.89	1,209	0.01	0.86		0.00	0.084	0.107	0.124	0.139
VAR-14	1	0.34	2.89	1,209	0.01		0.82	0.00	0.084	0.105	0.120	0.135
VAR-15	1	0.31	2.96	1,217		0.81	0.80	0.00	0.090	0.115	0.131	0.148
VAR-16	1	0.33	2.90	1,214	0.01	0.88	0.84	0.00	0.083	0.106	0.122	0.137

a. Estimated using equation 2.
b. Variables defined as in table 2.

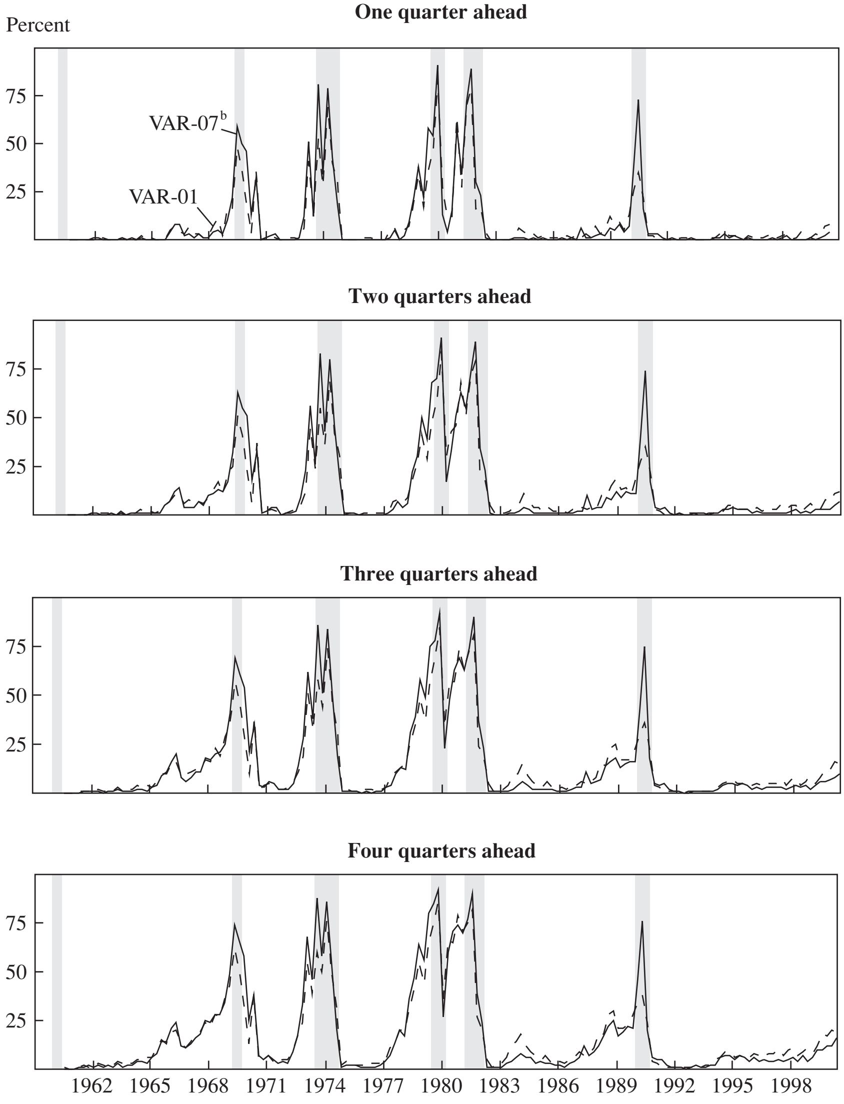
The recession probability forecasts for the VAR-07 model are shown graphically in figure 2. For purposes of comparison, the predictions of the four-variable VAR model (VAR-01) are also shown. It is apparent from figure 2 that the predicted probability of recession increases before and during recessions, although the lead time is not as long or consistent as one might like. There seems to be more advance notice of the 1974–75 recession and the back-to-back recessions of 1980–82 than of the 1969–70 and 1990–91 recessions. For the latter two, the model appears to be better at confirming recessions than at predicting them. Although the VAR-07 model gives better recession probability forecasts, especially two or more quarters in advance, the general pattern is similar for the two models.

The details of the VAR model predictions for each of the recessionary episodes are shown in table 4. Predicted probabilities of recession two quarters before through one quarter after each of the recessions, beginning with the 1969–70 recession, are shown. The shaded rows indicate recessions, determined according to the average GDP growth rate criterion. A perfect prediction of the probability of recession event E_{kt} would have the value 1 for all entries k quarters before and during the recession and 0 for entries elsewhere.

The general pattern is clear: the predicted probability of recession increases before each of these recessions and falls during the last quarter of each recession. Each of the recession episodes has a story to tell, but a couple of events stand out. During the double-dip recessions of 1980–82, the VAR-07 model generated a fairly strong signal that the recovery from the 1980 recession was in trouble. The 1990–91 recession is especially interesting because it was difficult to detect in advance. The VAR-01 model produced a stronger signal of the 1990–91 recession than did the VAR-07 model (which, again, contains the ICS and the NYSE index) just before the recession, but not as strong a confirmation signal once the recession had started.

If the QPS is to be used as a model selection criterion, it is important to know how small a difference in the QPS is statistically significant. Since the QPS is based on estimates of the probability of the events E_{kt} implied by the model, and these probability estimates were obtained by simulation, the QPS is subject to simulation error. Even with 1,000 trials, the standard error of each probability estimate could be as large as 0.016, and so a two-standard-error confidence interval would be ±0.032. To reduce the standard error to 0.005 would require 10,000 simulations of the model.

Figure 2. VAR Model Predictions of Recession, 1959–2000[a]



Source: Author's calculations.

a. Shading indicates recessions as identified by the average GDP growth rate criterion (see table 1).

b. Model VAR-01 excludes, and model VAR-07 includes, the ICS as well as the NYSE price index as explanatory variables.

Table 4. Probabilities of Recession Estimated by VAR Models with and without the ICS and NYSE Index[a]

			Probability of recession in the next one to four quarters							
			Model without ICS and NYSE (VAR-01)				*Model with ICS and NYSE (VAR-07)*			
Quarter	*GDP growth rate (percent a year)*	*Average GDP growth rate (percent a year)[b]*	*One quarter*	*Two quarters*	*Three quarters*	*Four quarters*	*One quarter*	*Two quarters*	*Three quarters*	*Four quarters*
1969–70 recession										
1969:2	1.04	2.64	0.16	0.22	0.29	0.36	0.10	0.17	0.25	0.34
1969:3	2.31	0.95	0.16	0.25	0.35	0.43	0.22	0.32	0.41	0.49
1969:4	–1.89	–0.50	0.48	0.51	0.57	0.62	0.59	0.63	0.69	0.74
1970:1	–0.55	–0.54	0.37	0.41	0.46	0.51	0.50	0.55	0.61	0.66
1970:2	0.83	1.15	0.19	0.23	0.29	0.33	0.46	0.51	0.54	0.58
1974–75 recession										
1973:3	–1.58	1.03	0.41	0.45	0.51	0.55	0.51	0.56	0.62	0.68
1973:4	3.30	0.49	0.12	0.24	0.32	0.39	0.12	0.26	0.38	0.46
1974:1	–3.08	–0.44	0.53	0.55	0.58	0.60	0.81	0.83	0.86	0.88
1974:2	1.08	–1.35	0.28	0.36	0.44	0.50	0.34	0.43	0.51	0.58
1974:3	–4.47	–2.52	0.69	0.69	0.74	0.76	0.79	0.80	0.84	0.86
1974:4	–2.21	–3.51	0.40	0.42	0.47	0.51	0.43	0.46	0.51	0.56
1975:1	–5.15	–2.26	0.30	0.30	0.31	0.32	0.18	0.19	0.19	0.21
1975:2	3.50	2.18	0.01	0.01	0.01	0.02	0.00	0.00	0.01	0.01
1980–82 recessions										
1979:3	2.84	1.81	0.17	0.29	0.34	0.44	0.22	0.39	0.49	0.56
1979:4	1.33	1.70	0.36	0.48	0.57	0.65	0.58	0.68	0.75	0.80
1980:1	1.32	–1.07	0.46	0.58	0.69	0.75	0.54	0.70	0.78	0.85
1980:2	–8.24	–3.94	0.84	0.84	0.85	0.86	0.91	0.91	0.92	0.92
1980:3	–0.62	–0.61	0.27	0.30	0.34	0.36	0.13	0.17	0.23	0.27
1980:4	7.05	5.30	0.12	0.43	0.57	0.66	0.04	0.33	0.48	0.60
1981:1	7.70	4.91	0.12	0.46	0.57	0.65	0.15	0.51	0.63	0.71

1981:2	–2.81	1.70	0.64	0.68	0.74	0.79	0.58	0.63	0.69	0.74
1981:3	4.73	0.48	0.27	0.51	0.63	0.71	0.34	0.55	0.63	0.70
1981:4	–4.75	–2.86	0.70	0.71	0.73	0.75	0.72	0.73	0.74	0.77
1982:1	–6.68	–4.10	0.79	0.79	0.81	0.82	0.89	0.89	0.90	0.90
1982:2	1.72	–1.29	0.16	0.21	0.24	0.27	0.30	0.34	0.37	0.39
1982:3	–1.90	–0.45	0.17	0.18	0.19	0.20	0.23	0.23	0.23	0.24
1982:4	0.28	0.82	0.04	0.05	0.05	0.05	0.01	0.01	0.01	0.01
1990–91 recession										
1990:1	4.96	3.06	0.05	0.10	0.17	0.23	0.04	0.11	0.16	0.22
1990:2	0.92	1.52	0.13	0.19	0.23	0.28	0.07	0.11	0.16	0.21
1990:3	–0.73	–0.96	0.26	0.28	0.30	0.34	0.39	0.41	0.43	0.46
1990:4	–3.30	–2.33	0.35	0.35	0.36	0.38	0.73	0.74	0.75	0.76
1991:1	–1.98	–1.25	0.22	0.22	0.23	0.24	0.16	0.17	0.18	0.20
1991:2	2.24	0.87	0.02	0.03	0.04	0.04	0.03	0.04	0.05	0.06

a. Estimated using equation 2. Shading indicates recessions by the average GDP growth rate criterion (see table 1).
b. Calculated using equation 1.

To assess the impact of simulation error on the QPS values, the VAR-01 model simulation was replicated 100 times. The standard error of the QPS over these 100 replications was less than 0.0013 for all four events. This suggests that differences in the QPS on the order of 0.004 or more can be regarded as meaningful, whereas differences of less than 0.004 could be due to simulation error and should be regarded as negligible.[15]

The results in table 3 are based on a model that was estimated using the full sample (1960 to 2000). In practice, the full sample would not be available; rather, the model would have to be estimated using currently available data. In order to see to what extent recursive estimation of the model would degrade these results, a recursive QPS was calculated. The model was estimated using data through quarter t for t = 1972:1 through 1999:4, and the event probabilities were estimated. Table 5 shows the results for each of the sixteen models.

It is clear from the table that the full-sample estimates of the model overstate the accuracy of recession probability estimates relative to the recursive estimates. When the ICS is added to the VAR model (VAR-02), there is still some improvement in the QPS score, but not as much as with the full-sample estimated model. According to these recursive estimates, the index of leading indicators is the best of the recession indicator variables, whereas the ICS was the best of the recession indicator variables based on the full-sample estimates of the VAR system. The best combination of indicators is that in the VAR-14 model, which includes the ICS, the NYSE index, and the index of leading indicators. Note, however, that the QPS for this model differs from the QPS for the VAR-07 model (which includes only the ICS and the NYSE index) by only a little more than the 0.004 margin of error, so that the differences in the predicted recession probabilities are not that large.

15. The 0.004 margin of error is based on the following calculation. Consider two independent simulations of the QPS with standard deviations equal to σ. If the QPS is normally distributed, the difference between the two simulated values is also normally distributed with variance $2\sigma^2$. A 95 percent confidence interval for the difference between the two QPS values is $\pm 1.96\sqrt{2\sigma^2}$. With $\sigma = 0.0013, 1.96\sqrt{2\sigma^2} = 0.0036,$ and so the margin of error is 0.004.

Table 5. Predictive Accuracy of VAR Models Using Full and Recursive Samples
Quadratic probability score[a]

	Full-sample estimates[b]				*Recursive estimates*[c]			
Model	*k = 1*	*k = 2*	*k = 3*	*k = 4*	*k = 1*	*k = 2*	*k = 3*	*k = 4*
VAR-01	0.128	0.136	0.151	0.162	0.149	0.160	0.175	0.176
VAR-02	0.110	0.114	0.121	0.130	0.138	0.157	0.170	0.172
VAR-03	0.127	0.137	0.151	0.164	0.156	0.176	0.181	0.177
VAR-04	0.111	0.124	0.138	0.153	0.123	0.147	0.176	0.195
VAR-05	0.087	0.114	0.134	0.149	0.108	0.141	0.154	0.161
VAR-06	0.110	0.115	0.125	0.136	0.137	0.164	0.174	0.171
VAR-07	0.096	**0.104**	**0.114**	**0.126**	0.112	0.140	0.154	0.160
VAR-08	0.093	0.111	0.120	0.133	0.106	0.142	0.152	0.155
VAR-09	0.110	0.124	0.138	0.154	0.127	0.153	0.162	0.166
VAR-10	**0.083**	0.112	0.134	0.156	0.115	0.159	0.167	0.168
VAR-11	0.099	0.122	0.135	0.151	0.103	**0.137**	0.149	0.157
VAR-12	0.097	0.106	0.118	0.132	0.113	0.147	0.157	0.158
VAR-13	0.092	0.113	0.126	0.141	0.113	0.159	0.166	0.163
VAR-14	0.090	0.110	0.119	0.133	**0.102**	0.140	**0.148**	**0.154**
VAR-15	0.097	0.123	0.136	0.153	0.112	0.155	0.163	0.166
VAR-16	0.087	0.112	0.121	0.136	0.107	0.155	0.159	0.160

a. Calculated using equation 3 for t = 1972:1–99:1. Boldface type indicates the best score.
b. Estimated over the sample period 1960–2000.
c. Estimated recursively over the sample periods 1960–72, 1960–73, …, 1960–99.

Monthly Indicators and the Probability of Recession

In order to incorporate current monthly values of the indicator variables, the quarterly model must be modified. A number of approaches to combining monthly and quarterly data have been used in the literature.[16] The approach chosen here was to augment the quarterly VAR model by adding a vector of predicted values of variables for the current quarter.[17] This modified model takes the form

$$\mathbf{Y}_t = \phi + \sum_{j=1}^{m} \Phi_j \mathbf{Y}_{t-j} + \Theta \hat{\mathbf{M}}_t + \varepsilon_t, \tag{5}$$

where the vector $\hat{\mathbf{M}}_t$ contains predicted values of quarterly variables based on available monthly observations. For example, the unemployment rate

16. Howrey (1991b) reviews several of these.
17. Miller and Chin (1996) have recently used a similar approach.

for the first month of the quarter is available the first or second Friday of the following month. The predicted average unemployment rate for the quarter can then be obtained from an equation of the form

$$(6) \qquad \hat{M}_t = \hat{\beta}_0 + \hat{\beta}_1 M_{1t},$$

where M_{1t} is the observed value of M for the first month, and the coefficient values are obtained from a regression of historical monthly values M_{1t} on the quarterly values M_t. Similarly, the predicted unemployment rate based on two monthly observations can be obtained from an equation of the form

$$(7) \qquad \hat{M}_t = \hat{\beta}_0 + \hat{\beta}_1 M_{1t} + \hat{\beta}_2 M_{2t},$$

where M_{2t} is the observed value of M for the second month. For variables that enter the system as growth rates, namely, the NYSE index and the index of leading indicators, the forecasting equations take a slightly different form. In this case, the predicted values of the logarithms of the quarterly averages were obtained from equations of the form

$$(8) \qquad \ln(\hat{M}_t) = \hat{\beta}_0 + \hat{\beta}_1 \ln(M_{1t})$$

or

$$(9) \qquad \ln(\hat{M}_t) = \hat{\beta}_0 + \hat{\beta}_1 \ln(M_{1t} + M_{2t}),$$

and the predicted growth rates were calculated in the usual way.

Although more sophisticated procedures could have been used,[18] these simple methods are easy to implement and turn out to be surprisingly accurate. Plots of the actual and predicted values (not shown) for the unemployment rate and the ICS reveal them to be indistinguishable.[19] For the unemployment rate, the regression of the quarterly average on the first month's value produces an adjusted R^2 of 0.992, with a standard error of 0.14. The regression of the quarterly average on the values for the first two months produces an adjusted R^2 of 0.999, with a standard error of 0.06. For the ICS, the regression using the first month has an adjusted R^2 of 0.959, with a standard error of 2.68, and that using the first two months has an adjusted R^2 of 0.989, with a standard error of 1.39.

18. Such as those employed in Howrey, Hymans, and Donihue (1991).

19. Monthly values for the ICS begin in January 1978. Prior to 1978, the actual quarterly value of the index was used.

Table 6 summarizes the results for the GDP growth rate equation in this augmented system. The model VAR-01 is the original four-variable VAR model with current-quarter forecasts of the unemployment and interest rates added as explanatory variables. The inclusion of the current-quarter forecasts reduces the standard error of the GDP growth rate equation from 3.22 to 2.76. Although not shown in the table, the current-quarter predicted value of the unemployment rate is highly significant ($p = 0.00$) in this equation, but the current-quarter predicted value of the interest rate is not ($p = 0.28$). Perhaps not surprisingly, the coefficient of the predicted value of the unemployment rate is negative and nearly equal in absolute value to the coefficient of the lagged unemployment rate, presumably reflecting the relationship described by Arthur Okun between changes in the unemployment rate and in output growth. The remaining entries in the table summarize the p values for inclusion of the current-quarter forecasts of the various indicator variables together with their lagged values in addition to the current-quarter predicted values of the unemployment and interest rates.

The pattern of results in this table is not very different from those in tables 2 and 3. The ICS is always significant no matter what other indicator variables are included. The interest rate spread is not significant in any of the equations. The stock price index is significant by itself or with the spread variable but is not significant in combination with the ICS or the index of leading indicators. The equation with the smallest standard error includes both the ICS and the index of leading indicators. However, no combination of current-quarter indicator variables produces a very large decrease in the standard error of the GDP growth rate equation from that in the model with none of the four indicator variables.

The modified model was used to generate estimates of the probability of recession using the stochastic simulation procedure described previously. The current-quarter-augmented version of the model was used to produce a forecast of the **Y** vector for the current quarter, and these current-quarter predicted values were then used to generate predicted future values using the original quarterly VAR model. This two-step procedure was repeated 1,000 times, and the frequency with which the event E_k occurred was recorded. Table 7 shows the QPS values for each of these models. The best of the models are VAR-07, which includes the ICS and the NYSE index, and VAR-12, which includes the ICS, the spread variable, and the NYSE index. This shows that including the spread variable in the system

Table 6. Significance of Indicator Variables Using Monthly Data to Forecast Current-Quarter GDP Growth Rate[a]

	Forecast from first month's data					*Forecast from first two months' data*					*Full-quarter observation*				
		p value[b]					*p value*[b]					*p value*[b]			
Model	*Standard error*	*ICS*	*Spread*	*NYSE*	*Lead*	*Standard error*	*ICS*	*Spread*	*NYSE*	*Lead*	*Standard error*	*ICS*	*Spread*	*NYSE*	*Lead*
VAR-01	2.76					2.63					2.57				
VAR-02	2.59	0.00				2.50	0.00				2.47	0.00			
VAR-03	2.79		0.70			2.63		0.98			2.58		0.95		
VAR-04	2.69			0.01		2.56			0.01		2.52			0.02	
VAR-05	2.52				0.00	2.41				0.00	2.39				0.00
VAR-06	2.60	0.00	0.58			2.52	0.00	0.91			2.48	0.00	0.84		
VAR-07	2.57	0.00		0.14		2.49	0.00		0.12		2.46	0.00		0.20	
VAR-08	2.46	0.02			0.00	2.38	0.03			0.00	2.35	0.04			0.00
VAR-09	2.71		0.98	0.01		2.58		0.94	0.01		2.54		0.93	0.03	
VAR-10	2.52		0.43		0.00	2.43		0.94		0.00	2.40		0.99		0.00
VAR-11	2.54			0.91	0.00	2.43			0.82	0.00	2.40			0.87	0.00
VAR-12	2.59	0.00	0.84	0.21		2.50	0.00	0.95	0.13		2.47	0.00	0.91	0.22	
VAR-13	2.47	0.02	0.52		0.00	2.39	0.04	1.00		0.00	2.37	0.04	0.99		0.00
VAR-14	2.48	0.02		0.94	0.00	2.39	0.04		0.93	0.00	2.37	0.04		0.92	0.00
VAR-15	2.54		0.47	0.99	0.00	2.44		0.99	0.86	0.00	2.42		1.00	0.87	0.00
VAR-16	2.48	0.02	0.62	0.04	0.00	2.41	0.04	0.99	0.92	0.00	2.38	0.05	0.97	0.91	0.00

a. Estimated using equation 5.
b. Variables defined as in table 2.

Table 7. Predictive Accuracy of Indicator Variables Using Monthly Data to Forecast Current-Quarter GDP Growth Rate

Quadratic probability score[a]

	Forecast from first month's data				*Forecast from first two months' data*				*Full-quarter observation*			
Model	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 1$	$k = 2$	$k = 3$	$k = 4$
VAR-01	0.085	0.121	0.143	0.155	0.089	0.126	0.143	0.157	0.083	0.120	0.140	0.155
VAR-02	0.061	0.091	0.106	**0.118**	0.063	0.094	**0.105**	**0.117**	0.062	0.091	**0.107**	0.121
VAR-03	0.083	0.116	0.140	0.155	0.088	0.124	0.143	0.159	0.083	0.118	0.140	0.157
VAR-04	0.070	0.101	0.128	0.145	0.076	0.109	0.131	0.148	0.074	0.105	0.130	0.147
VAR-05	0.077	0.107	0.134	0.145	0.079	0.109	0.132	0.147	0.070	0.099	0.125	0.143
VAR-06	0.058	0.088	0.105	0.120	0.064	0.094	0.108	0.121	0.064	0.093	0.110	0.124
VAR-07	**0.056**	**0.084**	**0.104**	**0.118**	**0.060**	**0.089**	0.106	0.118	**0.059**	**0.086**	**0.107**	0.121
VAR-08	0.065	0.093	0.114	0.123	0.068	0.096	0.113	0.124	0.061	0.087	0.111	0.124
VAR-09	0.070	0.101	0.126	0.144	0.077	0.111	0.131	0.148	0.075	0.106	0.130	0.147
VAR-10	0.075	0.103	0.131	0.145	0.079	0.108	0.131	0.147	0.072	0.100	0.128	0.146
VAR-11	0.076	0.104	0.132	0.144	0.079	0.109	0.132	0.145	0.072	0.100	0.127	0.143
VAR-12	**0.056**	**0.084**	**0.104**	**0.118**	0.061	**0.089**	0.106	0.117	**0.059**	**0.086**	**0.107**	**0.120**
VAR-13	0.063	0.091	0.113	0.123	0.067	0.095	0.113	0.124	0.060	0.087	0.110	0.124
VAR-14	0.064	0.092	0.113	0.121	0.067	0.096	0.114	0.122	0.060	0.087	0.110	0.121
VAR-15	0.074	0.101	0.130	0.143	0.077	0.106	0.130	0.145	0.071	0.098	0.127	0.143
VAR-16	0.063	0.090	0.112	0.122	0.066	0.093	0.112	0.122	0.060	0.087	0.109	0.122

a. Calculated using equation 3 for t = 1961:1–99:4. Boldface type indicates best score.

does not reduce the accuracy of the predictions of the probability of recessions, but neither does it help. The recession probability predictions based on second- and third-month observations are slightly worse than those using the first month, according to the QPS values, but the differences are within the margin of error of the simulation procedure used to calculate the predicted probabilities of recession.

It seems clear from the results in table 7 that the ICS is a useful recession indicator variable. For purposes of visual comparison, current (as of April 13, 2001) recession forecasts of the VAR-01, VAR-02, and VAR-07 models are shown in figure 3 for the two-quarter forecast horizon event E_{2t}. When the forecast value of the ICS for the first quarter of 2001 is added to the model, the probability of recession spikes up more quickly than when it is not included. The inclusion of stock prices has little additional impact on the recession probability forecasts.

The predicted probabilities of recession from the VAR-07 model, based on currently available quarterly and monthly data as of April 13, 2001, are shown in table 8. It is clear that the probability that one of the four quarters of 2001 will be a recession quarter is not negligible, according to the VAR-07 model. Whether the U.S. economy will be able to avoid a recession in 2001 remains to be seen, but the model is clearly emitting a warning signal, indicating that the probability of recession as of April 2001 was well above the naïve forecast probability.

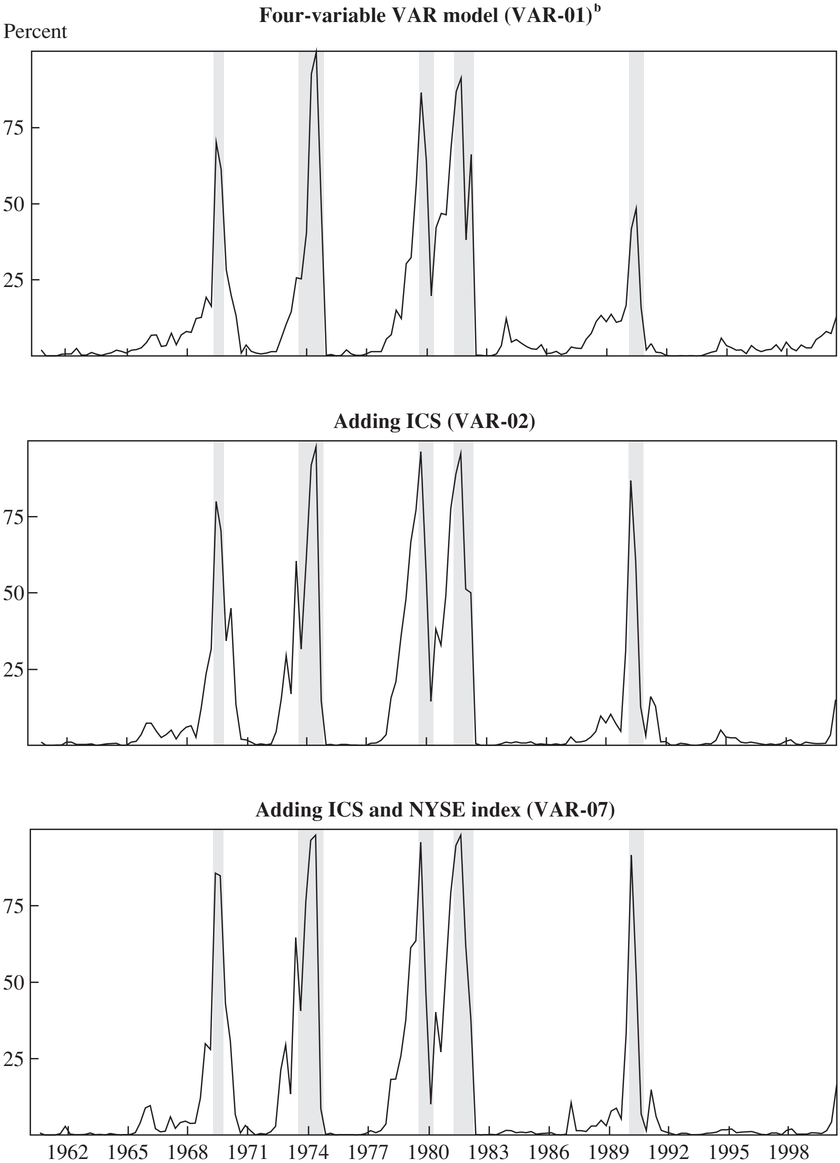
Predicting Personal Consumption Expenditure

Most previous research on the ICS has been concerned more specifically with the index's relationship to personal consumption expenditure.[20] This section looks at the predictive power of the ICS for total personal consumption expenditure, personal consumption expenditure on durable goods, and personal consumption expenditure on motor vehicles and parts.

I begin by asking whether the ICS is useful in predicting the rate of growth of monthly personal consumption expenditure. This question is motivated by the fact that the ICS is announced before the monthly value

20. See, for example, Hymans (1970) and, more recently, Carroll, Fuhrer, and Wilcox (1994) and Bram and Ludvigson (1998). A notable exception is Matsusaka and Sbordone (1995).

Figure 3. Probability of a Recession in the Next Two Quarters, 1959–2000[a]



Source: Author's calculations using equation 5.

a. Shading indicates recessions as dated by the average growth rate criterion (see table 1).

b. Model includes real GDP growth rate, inflation rate, unemployment rate, and three-month Treasury bill rate.

Table 8. Predicted Probability of a Recession, 2000–01[a]

	Probability of a recession in the next one to four quarters			
Date	*One quarter*	*Two quarters*	*Three quarters*	*Four quarters*
2000:1	0.00	0.01	0.02	0.05
2000:2	0.00	0.02	0.04	0.07
2000:3	0.02	0.02	0.07	0.10
2000:4	0.13	0.16	0.19	0.22

a. Using the VAR-07 model and data available as of April 13, 2001.

of personal consumption expenditure is known. For example, the March ICS is announced shortly after the end of March, whereas personal consumption expenditure is known only at the end of April.

An error correction model was used to investigate the relationship between monthly personal consumption expenditure and the ICS. The general form of this model is

$$(10) \qquad \Delta \ln C_t = \beta_0 + \beta_1 \Delta \ln C_{t-1} + \beta_2 \Delta \ln YD_{t-1} + \beta_3 \Delta ICS_t + \beta_4 \ln C_{t-1} + \beta_5 \ln YD_{t-2} + \beta_6 ICS_{t-1} + \varepsilon_t,$$

where C is personal consumption expenditure, and YD is disposable income; an equilibrium relationship among C_t, YD_{t-1}, and ICS_t is implied. In equilibrium, personal consumption expenditure depends on the willingness, as measured by the ICS, and the ability, as measured by disposable income, of consumers to make purchases.

The results shown in table 9 were obtained using monthly data for the period from January 1978 to January 2001.[21] Both the change in the ICS and its lagged level are not only statistically significant but also economically meaningful. Once again, however, the reduction in the standard error of the regression equation is far from impressive: a random-walk model fits the data nearly as well as the error correction model. And this standard error is huge. Thus, although the ICS is statistically significant and economically meaningful in terms of point forecasts of personal consumption expenditure, the relationship between personal consumption expenditure and the ICS is very noisy.

21. January 1978 is the first month for which the ICS is available on a monthly basis.

Table 9. Explaining Personal Consumption Expenditure Using an Error Correction Model, 1978–2001[a]

Independent variable	*Dependent variable:* *Total personal consumption expenditure*	*Personal consumption expenditure on durable goods*	*Personal consumption expenditure on motor vehicles and parts*	$\Delta\, ln\bar{C}_t$[b]
Constant	21.72	–1,030.00	–292.00	9.73
	(35.03)	(301.00)	(249.50)	(16.61)
$\Delta\, ICS_t$	0.33	1.45	2.80	0.21
	(0.10)	(0.56)	(1.10)	(0.05)
ICS_{t-1}	0.19	1.16	2.50	0.12
	(0.04)	(0.27)	(0.55)	(0.02)
$\ln C_{t-1}$[b]	–0.02	–0.13	–0.22	–0.01
	(0.02)	(0.03)	(0.04)	(0.01)
$\ln YD_{t-2}$[c]	0.01	0.19	0.15	0.01
	(0.02)	(0.05)	(0.04)	(0.01)
$\Delta \ln C_{t-1}$[b]	–0.32	–0.24	–0.22	–0.01
	(0.06)	(0.06)	(0.06)	(0.03)
$\Delta \ln YD_{t-1}$	0.01	0.39	0.69	–0.01
	(0.05)	(0.25)	(0.48)	(0.02)
Summary statistic				
Mean	3.26	5.09	3.35	3.22
Standard error	6.10	33.49	65.57	2.88

a. Estimated using equation 10. Data are monthly from January 1978 through January 2001. Standard errors are reported in parentheses. $\Delta \ln x_t = 1{,}200 \times (\ln x_t - \ln x_{t-1})$.

b. C is the personal consumption expenditure measure used as the dependent variable. $\Delta \ln \bar{C}_t = 1/3\, \Delta \ln C_{t+2} + 1/3\, \Delta \ln C_{t+1} + 1/3\, \Delta \ln C_t$.

c. Real disposable personal income, in chained 1996 dollars.

Quarterly average growth rates of personal consumption expenditure can be forecast with somewhat more precision. The last column of table 9 shows the result of a regression in which the rate of growth of personal consumption expenditure averaged over three months is the dependent variable. The ICS retains its statistical significance, and the standard error of the regression is less than half that of the monthly growth rate equation. This provides the motivation for an examination of quarterly growth rate equations.

The results of the empirical work using quarterly data can be summarized as follows. The addition of lagged quarterly values of the ICS to a baseline quarterly consumption function results in coefficient estimates that are statistically significant, but produces only a very modest reduction in the standard error of the regression equation. The first-month value of the index is also statistically significant but again results in a tiny reduction in the standard error of the regression. This first-month effect of the ICS remains statistically significant when first-month values of the unemployment rate, interest rates, and stock prices are added to the regression equation, but the overall effect on the standard error of the regression of all of these first-month values is still very small. When first-month values of consumption expenditure and disposable income are added to the quarterly regression equation, the first-month values of all of the other variables lose their statistical significance. Thus, once the values of consumption and disposable income are known for the first month of the quarter, the other monthly indicators are of no discernible value in predicting quarterly consumption.

The first- and second-month values of the ICS are statistically significant in the equation for total personal consumption expenditure but not significant in the equations for personal consumption of consumer durables or personal consumption of motor vehicles. Again the reduction in the standard error of the equation is minuscule. When the first- and second-month predicted values of consumption expenditure and disposable income are added to the equations, the statistical significance of all the other variables in the total personal consumption expenditure equation is obliterated. In the durables and motor vehicles equations, only the lagged value of consumption expenditure remains statistically significant.

These results are documented in tables 10 and 11. The regression equations on which these results are based are of the form

$$c_t = \phi + \sum_{j=1}^{m} \Phi_j \mathbf{Y}_{t-j} + \Theta \hat{\mathbf{M}}_t + \varepsilon_t, \tag{11}$$

where c_t is the rate of growth of real personal consumption expenditure based on quarterly data, $\mathbf{Y}_{t-j}$ is a vector of lagged quarterly values of the explanatory variables, and $\hat{\mathbf{M}}_t$ is a vector of current-quarter predicted values based on monthly observations for the first or the first and second months of the quarter.

For the results shown in tables 10 and 11, the vector $\mathbf{Y}_{t-j}$ includes lagged values of c, the rate of growth of real disposable income (yd), the civilian unemployment rate (U), the three-month Treasury bill rate (R), the rate of growth of the deflated NYSE composite stock price index ($NYSE$), and the

Table 10. Significance of Lagged and Forecast Variables in Predicting Consumption, Using First-Month Data[a]

			p value											
			Lagged quarterly variable						*Forecast current-quarter variable*					
Model	$\bar{R}^2$	*Standard error*	c[b]	yd[c]	U[d]	R[e]	$NYSE$[f]	ICS	ICS_1	U_1	R_1	$NYSE_1$	c_1	yd_1
PCE-01	0.23	2.51	0.93	0.06	0.01	0.00	0.09							
PCE-02	0.28	2.42	0.19	0.10	0.00	0.00	0.27	0.00						
PCE-03	0.37	2.27	0.18	0.05	0.00	0.00	0.73	0.03	0.00					
PCE-04	0.41	2.19	0.16	0.08	0.02	0.22	0.39	0.24	0.00	0.07	0.61	0.00		
PCE-05	0.76	1.40	0.21	0.55	0.65	0.56	0.73	0.96	0.13	0.94	0.91	0.38	0.00	0.03
PCED-01	0.23	11.59	0.00	0.05	0.00	0.00	0.01							
PCED-02	0.27	11.27	0.00	0.17	0.00	0.00	0.06	0.00						
PCED-03	0.33	10.82	0.00	0.11	0.00	0.00	0.19	0.09	0.00					
PCED-04	0.35	10.61	0.00	0.23	0.00	0.36	0.53	0.21	0.01	0.01	0.78	0.12		
PCED-05	0.71	7.10	0.00	0.75	0.24	0.52	0.34	0.48	0.60	0.64	0.89	0.97	0.00	0.03
PCEM-01	0.23	22.79	0.00	0.12	0.00	0.00	0.02							
PCEM-02	0.24	22.66	0.00	0.27	0.00	0.00	0.06	0.09						
PCEM-03	0.30	21.75	0.00	0.18	0.00	0.02	0.20	0.01	0.00					
PCEM-04	0.30	21.65	0.00	0.29	0.01	0.77	0.38	0.03	0.01	0.06	0.89	0.40		
PCEM-05	0.70	14.22	0.00	0.96	0.38	0.87	0.23	0.82	0.52	0.83	0.89	0.54	0.00	0.04

a. Estimated using equation 11. Regressions PCE-01 through PCE-05 use personal consumption expenditure as the dependent variable, PCED-01 through PCED-05 use personal consumption expenditure on durable goods, and PCEM-01 through PCEM-05 use personal consumption expenditure on motor vehicles and parts.

b. Growth rate of the real personal consumption expenditure measure used as the dependent variable.

c. Growth rate of real disposable income.

d. Civilian unemployment rate.

e. Three-month Treasury bill rate.

f. Deflated composite price index of the New York Stock Exchange.

Table 11. Significance of Lagged and Forecast Variables in Predicting Consumption, Using First- and Second-Month Data[a]

			p value													
			Lagged quarterly variable[b]						*Forecast current-quarter variable*							
Model	$\bar{R}^2$	*Standard error*	c	yd	U	R	$NYSE$	ICS	ICS_2	U_2	R_2	$NYSE_2$	c_1	yd_1	c_2	yd_2
PCE-01	0.76	1.40	0.17	0.74	0.00	0.00	0.32	0.00					0.00	0.03		
PCE-02	0.77	1.38	0.12	0.45	0.00	0.00	0.43	0.53	0.01				0.00	0.03		
PCE-03	0.76	1.39	0.18	0.42	0.72	0.32	0.60	0.73	0.04	0.85	0.95	0.45	0.00	0.03		
PCE-04	0.93	0.75	0.27	0.25	0.47	0.72	0.86	0.39	0.45	0.97	0.59	0.85			0.00	0.17
PCED-01	0.72	7.02	0.00	0.73	0.00	0.01	0.24	0.00					0.00	0.02		
PCED-02	0.72	7.02	0.00	0.64	0.00	0.02	0.27	0.54	0.38				0.00	0.03		
PCED-03	0.71	7.08	0.00	0.71	0.23	0.46	0.26	0.66	0.40	0.65	0.98	0.77	0.00	0.03		
PCED-04	0.91	3.85	0.04	0.46	0.34	0.95	0.37	0.27	0.95	0.79	0.35	0.27			0.00	0.81
PCEM-01	0.71	14.05	0.00	0.98	0.00	0.15	0.24	0.05					0.00	0.03		
PCEM-02	0.71	14.09	0.00	0.94	0.00	0.18	0.26	0.58	0.66				0.00	0.04		
PCEM-03	0.70	14.21	0.00	0.99	0.37	0.77	0.21	0.79	0.53	0.83	0.91	0.48	0.00	0.04		
PCEM-04	0.91	7.71	0.01	0.64	0.39	0.63	0.16	0.48	0.95	0.79	0.26	0.12			0.00	0.83

a. Estimated using equation 11. Regressions PCE-01 through PCE-04 use personal consumption expenditure as the dependent variable, PCED-01 through PCED-04 use personal consumption expenditure on durable goods, and PCEM-01 through PCEM-04 use personal consumption expenditure on motor vehicles and parts.

b. Variables defined as in table 10.

ICS.[22] The $\hat{\mathbf{M}}_t$ vector includes predicted quarterly values of the index of consumer sentiment (ICS_j), the civilian unemployment rate (U_j), the interest rate (R_j), the rate of growth of the real stock price index ($NYSE_j$), the rate of growth of real personal consumption expenditure (c_j), and the rate of growth of real disposable income (yd_j). The subscript j is either 1 or 2, depending on whether the predicted value is based on monthly values for only the first month of the current quarter or the first two months.

To keep these tables manageable, only the adjusted R^2, the standard error of the regression, and p values for the hypothesis that the set of lagged values of each variable can be excluded from the equation are reported. The number of autoregressive lags was determined by examining the SIC for lags $m = 0, 1, \ldots, 8$. For each of the regressions in these two tables, the minimum SIC value occurred at $m = 1$.[23]

Table 10 reports results when the predicted value for the current quarter is based on the first month of the quarter. It shows that the baseline regression for the rate of growth of total real personal consumption expenditure (PCE-01), estimated over the period from 1962 to 2000, has an adjusted R^2 of 0.23 and a standard error of 2.51. The lagged values of disposable income, the unemployment rate, the interest rate, and the real stock price index are all significant at the 10 percent level. When the lagged value of the *ICS* is added to this equation (PCE-02), it displaces the real stock price index as a significant predictor of consumption expenditure. Even though it is statistically significant at the 1 percent level, however, it does not reduce the standard error of the regression, and hence the within-sample, one-quarter-ahead forecast errors, by an appreciable amount. Another small reduction in the standard error of the regression is obtained by introducing the current-quarter value of the *ICS* predicted from its first-month value (ICS_1 in the table; equation PCE-03). Adding predicted current-quarter values of the unemployment rate (U_1), the interest rate (R_1), and the rate of growth of the real stock price index ($NYSE_1$) reduces the standard error by another small increment and leaves ICS_1 statistically significant

22. The variables *c, yd, R*, and *NYSE* were used by Bram and Ludvigson (1998). The inclusion of *U* in consumption functions, particularly purchases of motor vehicles, has a long tradition in macroeconometric models; see, for example, Hymans (1970) and Adams and Duggal (1976).

23. The general pattern of the results is not sensitive to the choice of $m = 1$, however. In particular, a very similar pattern emerges with $m = 4$, the number of lags used by Bram and Ludvigson (1998).

(PCE-04). Finally, adding predicted current-quarter values of the rates of growth of personal consumption expenditure and disposable income (c_1 and yd_1, respectively) to the equation (PCE-05) results in a dramatic decrease in the standard error of the regression and wipes out the statistical significance of all of the other explanatory variables. In fact, once c_1 is available, there is little to be gained from using any of the other variables to forecast the quarterly value of personal consumption expenditure. This same pattern of results also holds for expenditure on durable goods and vehicles.

The results when the first and second months of the quarter are used to predict the value for the current quarter, shown in table 11, are similar to the results using the first month, with one minor, perhaps interesting, exception. The second-month value of the ICS is statistically significant in the equation for total personal consumption expenditure, but not in either the equation for durables or the equation for vehicles. Even so, there is little to be gained in terms of forecast accuracy from the indicators for the second month of the quarter once the values of c and yd for the first month of the quarter are known.

Conclusions

This paper has sought to evaluate the predictive power of the University of Michigan Survey Research Center's Index of Consumer Sentiment. A model and scoring procedure were used to evaluate the accuracy of forecasts using this indicator of the near-term probability of a recession. Four recession indicator series were considered individually and in combination: the ICS, the spread between long- and short-term interest rates, the New York Stock Exchange composite price index, and the Conference Board index of leading indicators. It was found that the ICS, either by itself or in conjunction with one or more of the other indicators, is a statistically significant predictor of the future rate of growth of real GDP. Even though the index produces only a modest reduction in the standard error of one-quarter-ahead forecasts of the real GDP growth rate compared with a model based on lagged GDP only, it does produce a discernible increase in the accuracy of one- to four-quarter-ahead forecasts of the probability of recession.

A procedure for incorporating current-quarter monthly values of the indicator variables was also used to evaluate the predictive power of these recession indicator variables. It was found that current-quarter monthly values of the ICS, either alone or in conjunction with other indicators, are informative about the probability of recession. The second-month value of the index does not appear to provide much improvement in forecast accuracy over the information contained in the first-month value.

Finally, the statistical significance of the ICS for predicting personal consumption expenditure was examined. An analysis of monthly data revealed that the index is statistically significant and economically meaningful in terms of point forecasts of the rate of growth of personal consumption expenditure, but the relationship between monthly values is very noisy. Using quarterly data, it was found that both lagged and current-quarter monthly values of the ICS are statistically significant but result in only a modest reduction of the standard error of forecasts of quarterly consumption expenditure. Once the values of personal consumption expenditure and disposable income for the first month of the current quarter are known, the statistical significance of the ICS disappears. This conclusion holds for personal consumption expenditure on durable goods and on motor vehicles as well as for total expenditure.

Most of these conclusions are based on models that were estimated over the entire sample period. It would be interesting to see whether these results also hold for recursive estimates of the forecasting equations. In addition, no attempt has been made to deal with issues of measurement error and data revision that accompany real-time forecasts.

APPENDIX

Data Sources

Index of Consumer Sentiment

Quarterly and monthly data for the Index of Consumer Sentiment were obtained from the World Wide Web site of the Survey Research Center of the University of Michigan (www.umich.edu/~umsurvey). The procedure used to calculate the index, as described on the website, is as follows:

To calculate the Index of Consumer Sentiment (ICS), first compute the relative scores (the percent giving favorable replies minus the percent giving unfavorable replies, plus 100) for each of the five index questions (see $X_1, \ldots X_5$ listed below). Round each relative score to the nearest whole number. Using the formula shown below, sum the five relative scores, divide by the 1966 base period total of 6.7558, and add 2.0 (a constant to correct for sample design changes from the 1950s).

$$ICS = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{6.7558} + 2.0$$

X_1 = "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are *better off* or *worse off* financially than you were *a year ago*?"

X_2 = "Now looking ahead—do you think that *a year from now* you (and your family living there) will be *better off* financially, or *worse off*, or just about the same as now?"

X_3 = "Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have *good* times financially, or *bad* times, or what?"

X_4 = "Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times *during the next five years* or so, or that we will have periods of widespread *un*employment or depression, or what?"

X_5 = "About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items?"

The Index of Consumer Sentiment is available quarterly from the first quarter of 1960 and monthly from January 1978.

Disposable Personal Income and Personal Consumption Expenditure

Monthly data for disposable personal income and personal consumption expenditure were obtained from the website of the U.S. Department of Commerce's Bureau of Economic Analysis (www.bea.doc.gov) as follows:

Disposable personal income, in chained (1996) dollars
January 1959 to March 2000: hist-pi.exe, Table 209M, line 9
April 2000 to January 2001: nds0171.exe, Table 209M, line 9

Personal consumption expenditure, in current dollars
  January 1959 to June 2000: und-pce.exe, Table 206U, lines 1, 2, and 3
  July 2000 to January 2001: nds0171.exe, Table 206U, lines 1, 2, and 3
Chain-type price indexes for personal consumption expenditure
  January 1959 to June 2000: und-pce.exe, Table 705U, lines 1, 2, and 3
  July 2000 to January 2001: nds0171.exe, Table 705U, lines 1, 2, and 3

Real personal consumption expenditure was obtained by dividing nominal personal consumption expenditure by the chain-type price index.

Other Variables

All other variables were obtained from the Standard and Poor's DRI Basic Economics database:

Gross domestic product (in current dollars)
Real gross domestic product (in chained 1996 dollars)
Unemployment rate, all workers sixteen years and over
Interest rate on ten-year U.S. Treasury bonds at constant maturities (percent a year)
Interest rate on three-month U.S. Treasury bills in the secondary market (percent a year)
New York Stock Exchange composite stock price index (December 31, 1965 = 100)
Composite index of eleven leading indicators (1987 = 100).

Comment and Discussion

Michael C. Lovell: George Katona developed the Index of Consumer Sentiment at the University of Michigan some fifty years ago. Today we are all indebted to Philip Howrey for continuing the great University of Michigan tradition with a fine paper that provides useful information about forecasting business cycles.

Two things about the ICS deserve particular notice. First, Katona did not create the ICS for forecasting purposes, or even to elicit useful information. When he was developing the Survey of Consumer Finances for the Federal Reserve, Katona inserted the five attitudinal questions from which the ICS is calculated in order to loosen up the respondents, so they would be more forthcoming about their income and other personal financial details.[1] Fortunately, Katona tallied the results.

The other interesting—and surprising—thing about the ICS is that, after fifty years, it is still with us. Thirty years ago the ICS was regarded as a relic of the past, an anachronism. Its place on the evening news had been stolen by the forecasts by Lawrence Klein at Wharton Econometrics, by Otto Eckstein at Data Resources Incorporated, and by Michael Evans at Chace Econometrics. Today, however, the findings of the econometric models no longer make it onto the evening news or the front pages of the financial press, and the ICS is stronger than ever in the public's eye. A recent Internet search for "consumer sentiment" produced 46,800 hits. It is fair to say that many regard the ICS as the best one-eyed monster in the valley of the blind. If we believe in the survival of the fittest, we must conclude that consumers know something the econometric forecasters do not.

1. Curtin (1992).

Let us look at how Howrey proceeds to size up the predictive power of the ICS. An advantage that Phil has over earlier investigators is that, with the passage of time, more observations have accumulated: the paper covers about 160 quarters. That is a lot of data, which help generate results that achieve significance at customary levels. On the other hand, over that forty-year period there have been only six recessions, or six opportunities for a forecaster to hit or miss the peak of the business cycle. Of course, one can also make false predictions of recession—a type II error, so to speak. For example, in 1965–66 there was a sharp decline in the ICS of 16.2 percent (top panel of Howrey's figure 1), only slightly less than the recent decline of 19.4 percent that has so spooked the stock market. Yet that decline in the mid-1960s turned out to be a false alarm.

The quadratic probability score (QPS) that Howrey uses to evaluate forecasts is designed to penalize both missed turns and false signals. It is a symmetric index in that it treats both as equally serious. It takes as its input probability statements about the likelihood of recession in each quarter and compares them with what actually happened. A lazy or naïve forecaster might always make the same probability prediction for every quarter, or one could use what happened last time. Howrey finds that the ICS does better than the naïve forecaster, but so do several other indicators.

I found table 2 of Howrey's paper almost overwhelming. He runs the ICS in a race with three other indicators: an interest rate spread (the difference between the ten-year Treasury note and the three-month Treasury bill rate, whose predictive power is related to an inverted Treasury yield curve), the New York Stock Exchange composite price index, and the Conference Board's index of leading economic indicators. He exhaustively considers sixteen alternative autoregressive (AR) models. The first includes none of the indicators; the next four look at the alternative indicators one at a time; the next six consider all possible pairs of the indicators; the next four consider all possible combinations involving three of the four candidate variables; and the last model includes all four candidates. This may seem a bit much, but I much prefer exhaustive to selective reporting, and it allows us to look for results that are robust with regard to specification choices.

The evidence presented in Howrey's table 2 yields three interesting conclusions. First, the usefulness of the ICS and the leading indicators index is clearly established: both appear to be significant at the 1 percent level in every specification in which they are included. In contrast, the results for the interest rate spread and the stock index are far from robust across specifications. Second, in terms of the QPS, all sixteen models do better at forecasting recessions than either the naïve benchmark [$P(E_{kt}) = 1$ if $\bar{y}_{t-1} < 0$, otherwise 0] or simply stating the probability of a recession as the historical average. Third, specifications using several indicators simultaneously rather than any single indicator achieve greater forecasting accuracy as measured by the QPS. I conclude from all this evidence that it is probably best to use all four indicators in forecasting, although one might do marginally better by omitting the leading indicators index. To try to go beyond these three points on the basis of table 2, however, would be to read more into the evidence than is really there. Any further statements would be tenuous and unlikely to survive the additional evidence that the next recession will generate.

I do have a serious reservation about the evidence in table 2. How do we know that the ICS is not just proxying for some other variable or variables that contribute to generating both the business cycle turning points and the ICS itself, rather than containing new information in its own right? The evidence in table 3 helps to resolve this question. There the earlier models are augmented with three additional variables: the inflation rate, the civilian unemployment rate, and the three-month Treasury bill rate. Pao-Lin Tien and I have shown that the ICS may be generated by essentially these same economic variables: inflation, the rate of change in the S&P 500, the growth rate of GDP, and the rate of change in the unemployment rate; dummy variables indicating the party holding the presidency do not matter.[2] So is it not conceivable that the ICS appears to be significant in table 2 only because the same economic variables that generate the ICS are also of direct forecasting value? Might the ICS be no more than a summary of the forecasting information contained in these four augmenting economic variables and the three other indicators considered in table 2? We need to know whether the ICS contains additional, unpredictable information—innovations—that are of direct forecasting value.

How can we test this? A two-step approach would be to take the residuals from a model explaining the generation of the ICS as the innovations and see if they are significant in a forecasting equation (which might also include the same variables generating the ICS). Howrey has not done this.

2. Lovell and Tien (2000).

He does, however, adopt an alternative procedure, which includes both the ICS and the variables that determine it in the forecasting equation; the ICS variable will emerge as significant only if the unpredictable innovations in ICS are important. This alternative strategy, results of which are reported in his table 3, yields a significant ICS in every one of the eight models in which it is included (the leading indicators variable is significant as well). So I think Howrey should claim as a robust result that the ICS is more than just a summary of the economic variables that generate it. Thanks to his table 3, we can conclude that the ICS contains information that does indeed matter in predicting recessions.

Howrey's table 5 presents recursive estimates of models that recognize that in practice a forecaster's information set is limited to data released before the date of the prediction. The table reveals, as one would expect, that forecasts derived from an equation estimated with only currently available information (updated each quarter) are not as accurate as the earlier tables suggested, because these used the entire sample of data in estimating the forecasting equation. Because the results in table 5 do not use all the information now available, if I were deciding what variables to use in a forecasting equation today, I would be inclined to base that decision on the earlier tables rather than table 5.

Howrey's paper contains some other interesting results. For example, he explores the possibility of making more timely forecasts by using observations of explanatory variables for the first month of a quarter to predict what the full-quarter values will be. The procedure works reasonably well, and it is reassuring to find (in his table 6) that the ICS remains significant, at least at the 5 percent level, and is among the variables retained in the best forecasting equations. His table 9 shows that although the ICS is statistically significant in regressions explaining personal consumption, it makes only a trivial improvement in forecasts of consumption.

This paper is almost overwhelming in terms of the number of regressions, tables, and graphs it presents. One therefore hesitates to ask for more, but the following are some questions of interest for future research.

First, how does the Michigan Index of Consumer Expectations (ICE) compare with the ICS as a forecasting tool? It is, after all, not the ICS but the ICE—pioneered by Arthur Burns and Wesley Mitchell, refined by the U.S. Department of Commerce, and currently maintained by the Conference Board—that is included in the official set of leading economic indicators. The ICE focuses only on a forward-looking subset of three of the five questions in the ICS survey that relate to the respondent family's economic prospects over the next year, and the economic prospects for the nation over the next year and the next five years. (The two omitted questions ask whether the respondent is better or worse off than a year ago, and whether the respondent thinks it is a good or a bad time to buy major household items.) It would be a service to the profession if Howrey (or his students) would provide us with a careful evaluation of whether the ICE achieves a better QPS than the ICS within the type of forecasting models he presents in this paper.

A second question is whether we should use real-time (that is, preliminary) data in developing forecasting equations. Howrey mentions this issue in the very last sentence of the paper. We know that much of the data that grab the attention of economic journalists are subject to substantial revision; economic historians look at a very different economic record from that observed by economic agents at the time. The numbers that Howrey used in this paper are the revised numbers. But journalists, the public generally, and professional economic forecasters were looking at preliminary data when they were forming their views about current economic conditions and developing their hunches about future developments. Conceivably, Howrey's appraisal of the relative merits of alternative forecasting procedures might have been different if he had based his analysis on preliminary data rather than the latest revisions available today.

My own view is that using recursive estimation with real-time data might well be a useful and humbling exercise that would help us avoid becoming overly confident about the likely accuracy of our forecasts. It may also be advisable for forecasters to indicate whether they are trying to predict the preliminary estimates or the revised final numbers. But we should appreciate the fact that the compilers of economic data, prompted in part by earlier presentations before this panel, have taken steps over time to improve their procedures so as to make the preliminary data more accurate. To the extent they have succeeded, the change in the structure of preliminary data errors means that the historical gaps between real-time data and the most recent revisions will overstate the errors in future preliminary observations. Partly for this reason, my own inclination would be to use the best evidence we now have—the final data that Howrey uses in this paper—rather than the real-time data in estimating the forecasting equation. But I would like to know Howrey's view on this matter.

The *Stock and Watson Indicator Report*, based on data for January 2001, stated in March that the probability that the economy was in a recession in January was 1 percent, and the probability that it would be in a recession by July is 3 percent or 4 percent.[3] So my third question is, What probability does Howrey himself assign, on the basis of all the evidence in the paper, to the likelihood that the Business Cycle Dating Committee of the National Bureau of Economic Research will eventually conclude that we are currently in a recession? Since Howrey himself evaluates the work of forecasters who make probability statements, I do not think it is unfair to ask him to make such a statement on the basis of his analysis.

General discussion: Some panel participants questioned the relevance of focusing on recessions as opposed to periods of macroeconomic weakness more generally. Robert Gordon argued for trying to predict ups and downs in the growth rate of GDP, especially relative to its trend or potential. The latter would be directly relevant to analyzing unemployment fluctuations, which relate to changes in the gap between actual and potential GDP. Seconding Gordon's proposal, Gregory Mankiw reasoned that it was arbitrary to single out periods when growth crossed the zero threshold, and he questioned the usefulness of the nonlinear transformation that Howrey had devised as a way of focusing on predicting recessions. Mankiw noted that the consumer sentiment index has less extra explanatory power for GDP growth than for the probability of a recession, and he noted the potential for small-sample bias in any analysis that seeks to predict recessions, because there have been so few of them. George Perry agreed that zero growth was a point of no special importance in itself, but he offered two reasons for focusing on recessions nonetheless. First, those are the periods when U.S. unemployment has risen substantially, and second, there is evidence that they are periods when the behavior of the economy has been unusual, as reflected in large residuals in forecasting equations.

Gordon suggested that a study of the determinants of the consumer sentiment index would be useful. He conjectured that such a study would show that consumer confidence has a life of its own and does not simply reflect changes in plausible determinants, such as the stock market and

3. *Stock and Watson Indicator Report* (ksghome.harvard.edu/~jstock.academic.ksg/xri/INDEX.HTM, accessed March 28, 2001).

unemployment. Robert Hall agreed and cited the decline of the index in the late 1970s, when the stock market was generally rising and unemployment falling, as an example of the index departing from such variables at medium frequencies. He concluded that there was independent information in the index and that it would be fascinating to find out what it was and what caused the index to move.

Presumably, whatever does move the index has something to do with the happiness of respondents, and this might have little to do with economic variables. On the basis of her own work in developing countries and that of others for the United States, Carol Graham reported that objective economic conditions and trends seemed to have little effect on happiness. People's answers to questions about their well-being seem to depend mainly on how they are faring economically relative to their neighbors, whether they themselves have had a bad day, or some noteworthy recent event in the news. William Brainard recalled a psychological study in which a dime was surreptitiously placed on the seats of some subjects just before their session with the interviewer. Those who found a dime reported being significantly happier than those that did not.

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