PREDICTING U.S. RECESSIONS: FINANCIAL VARIABLES AS LEADING INDICATORS

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Abstract—This paper examines the out-of-sample performance of various financial variables as predictors of U.S. recessions. Series such as interest rates and spreads, stock prices, and monetary aggregates are evaluated individually and in comparison with other financial and nonfinancial indicators. The analysis focuses on out-of-sample performance from one to eight quarters ahead. Results show that stock prices are useful with one- to three-quarter horizons, as are some well-known macroeconomic indicators. Beyond one quarter, however, the slope of the yield curve emerges as the clear individual choice and typically performs better by itself out of sample than in conjunction with other variables.

I. Introduction

FINANCIAL variables, such as the prices of financial instruments, are commonly associated with expectations of future economic events. Long-term interest rates, for example, are frequently analyzed as weighted averages of expected future short-term interest rates. In this framework, spreads between rates of different maturities are interpreted as expectations of future rates corresponding to the period between the two maturities. Stock prices are similarly interpreted as expected discounted values of future dividend payments, and so incorporate views regarding both the future profitability of the firm and future interest or discounting rates.

In this paper, we examine the usefulness of various financial variables in out-of-sample predictions of whether or not the U.S. economy will be in a recession anywhere between one and eight quarters in the future. Variables with potential predictive content—interest rates, interest rate spreads, stock price indexes, and monetary aggregates—are selected from a broad array of candidates and are examined by themselves and in some plausible combinations. The results are compared with similar exercises involving more traditional macroeconomic indicators, including widely used indexes of leading indicators and their component variables.

The present analysis differs in three important respects from much of the earlier research examining the usefulness of financial variables in predicting future macroeconomic outcomes, including previous work of the authors.[1] First, in contrast to most of the literature, with the exception of Stock and Watson (1993), we focus simply on predicting recessions rather than on quantitative measures of future economic activity. We believe that this is a useful exercise in that it addresses a question frequently posed by policy makers and market participants. There is also empirical evidence (Hamilton (1989), for example) that it makes sense to think of the economy as evolving differently within distinct discrete states. The discrete dependent variable also sidesteps the problem of spurious accuracy associated with quantitative point estimates of, for example, future real gross domestic product (GDP) growth.[2]

Second, the principal criterion of predictive accuracy in this paper is out-of-sample performance, that is, accuracy in predictions for quarters beyond the period over which the model is estimated. In-sample performance can always be improved by introducing additional variables, but in the out-of-sample context more is not necessarily better, as our results will show.[3] Third, new econometric techniques are brought to bear on this question. Preliminary in-sample equations are estimated for the first time using an application of the generalized method of moments, and goodness of fit is measured by an R^2 analogue that facilitates the interpretation of results.

With the existence of large-scale macroeconometric models and with the judicious predictions of knowledgeable market observers, why should we care about the indications of one or a few financial variables? Is such an approach too simplistic?

Policy makers and market participants can benefit in several ways by looking at a few well-chosen financial indicators. First, the indicators may be used to double-check both econometric and judgmental predictions. There is no question that forecasting with macroeconometric models can be quite helpful. Beyond the mere potential accuracy of the forecasts, such models allow the economic analyst to think about the causal relationships that may lead to a specific result, and in the process think about the structure of the economy itself. In many cases, the bottom-line predic-

Received for publication November 18, 1996. Revision accepted for publication April 22, 1997.

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We thank Maria Mendez and Elizabeth Reynolds for excellent research assistance. Any opinions expressed are those of the authors, not those of the Federal Reserve Bank of New York or the Federal Reserve System, Columbia University, or the National Bureau of Economic Research. The data in this paper will be made available free of charge to any researcher who sends us a standard formatted 3½″ diskette with a stamped, self-addressed mailer.

[1] Papers that examine the predictability of future real activity include Palash and Radecki (1985), Harvey (1988), Laurent (1988, 1989), Diebold and Rudebusch (1989), Estrella and Hardouvelis (1990, 1991), Chen (1991), Hu (1993), Bomhoff (1994), Davis and Henry (1994), Plosser and Rouwenhorst (1994), Barran et al. (1995), Davis and Fagan (1994), and Estrella and Mishkin (1997). Papers that examine the predictability of future inflation include Mishkin (1990a,b, 1991) and Jorion and Mishkin (1991).

[2] Stock and Watson (1989), Watson (1991), and Estrella and Hardouvelis (1991) consider, and Stock and Watson (1993) focus primarily on, the prediction of recessions. Boldin (1994), in an alternative approach, models recessions using a regime-switching formulation. In a recent paper, Reinhart and Reinhart (1996), using very different methods than in this paper, find that the best predictors of recession in Canada are the U.S. and Canadian term structure spread, a conclusion that is similar to the one found in this paper.

[3] Stock and Watson (1993) perform some out-of-sample testing of their model, particularly in connection with the prediction of the 1990–1991 recession. Even in that paper, however, the bulk of the analysis is in sample.

tion is not the most interesting or useful part of the modeling exercise. Judgmental forecasts, although not necessarily based on strict statistical analysis, also typically involve thinking about economic relationships and have similar benefits.

A quick look at a financial indicator, however, may quickly flag a problem with the results of more involved approaches. On one hand, if the model and the indicator agree, confidence in the model's results can be enhanced. On the other hand, if the indicator gives a different signal, it may be worthwhile to review the assumptions and relationships that led to the prediction. Of course, the significance one may attach to a particular indicator depends on its historical out-of-sample performance, which is the focus of this paper.

A second reason for looking at simple financial indicators is the potential problem of overfitting. Most econometric models forecast future activity through the use of some sort of statistical regression. These models construct weighted sums of explanatory variables in order to maximize the predictive power of the sum over the sample period. Generally, the more variables a model includes, the better the in-sample results. However, liberal inclusion of explanatory variables in the regression will not necessarily help—and frequently hurts—results when extrapolating beyond the sample's end.

A third reason for looking at financial indicators is that it is quick and simple. Of course, this reason presupposes that the results are accurate. Our analysis should be helpful in determining which particular indicators are worth watching. An additional benefit of the analysis in this paper is that it provides a forecasted probability of a future recession, a probability that is of interest in its own right.

To preview the results, the analysis focuses on out-of-sample performance in predicting whether or not the economy will be in a recession between one and eight quarters ahead. We find that stock prices are useful predictors, particularly one through three quarters ahead. This performance is comparable to that of some well-known macroeconomic indicators, such as the Commerce Department's index of leading indicators and its component series. Beyond one quarter, however, the slope of the yield curve emerges as the clear individual choice: it outperforms other indicators in one-on-one comparisons, and the addition of other variables is generally more likely to hurt at these longer horizons.

In the following section we describe the basic model used to perform the predictive tests and the criteria used to evaluate the results. Next we list and explain the indicators that are included in the tests and discuss some in-sample results that are both illustrative and somewhat useful in model selection. We then present out-of-sample results, the focus of the paper. We conclude with a case study that shows how the indicators would be estimated and applied in practice.

II. Basic Model and Criteria for Evaluation of Results

A. *The Model*

In order to quantify the predictive power of the variables examined with respect to future recessions, we use a probit model. The probit form is dictated by the fact that the variable being predicted takes on only two possible values—whether the economy is or is not in a recession. The model is defined in reference to a theoretical linear relationship of the form

$$y^*_{t+k} = \beta' x_t + \epsilon_t$$

where y^*_t is an unobservable that determines the occurrence of a recession at time t, k is the length of the forecast horizon, ϵ_t is a normally distributed error term, β is a vector of coefficients, and x_t is a vector of values of the independent variables, including a constant. The observable recession indicator R_t is related to this model by

$$R_t = \begin{cases} 1, & \text{if } y^*_t > 0 \\ 0, & \text{otherwise.} \end{cases}$$

The form of the estimated equation is

$$P(R_{t+k} = 1) = F(\beta' x_t) \tag{1}$$

where F is the cumulative normal distribution function corresponding to $-\epsilon$.

The model is estimated by maximum likelihood, with the likelihood function defined as

$$L = \prod_{\{R_{t+k}=1\}} F(\beta' x_t) \prod_{\{R_{t+k}=0\}} [1 - F(\beta' x_t)].$$

In practice, the recession indicator is obtained from the standard National Bureau of Economic Research (NBER) recession dates, that is,

$$R_t = \begin{cases} 1, & \text{if the economy is in recession in quarter } t \\ 0, & \text{otherwise.} \end{cases}$$

B. *Test Criteria*

In this paper we examine many variables with potential predictive power for recessions, and we consider each variable with predictive horizons ranging from one to eight quarters ahead. The volume of output generated by this type of analysis makes it important to summarize the results in a meaningful way. Hence we introduce a few summary measures of the predictive power of a given variable with a given horizon.

The principal measure is a pseudo R^2 developed in Estrella (forthcoming), that is, a simple measure of goodness of fit that corresponds intuitively to the widely used coefficient of determination in a standard linear regression. Denote the unconstrained maximum value of the likelihood function L as L_u and its maximum value under the constraint that all coefficients are zero except for the constant as L_c. The number of observations is n. Then the measure of fit is defined by

$$\text{pseudo } R^2 = 1 - \left(\frac{\log L_u}{\log L_c}\right)^{-(2/n)\log L_c}.$$

The form of this function ensures that the values 0 and 1 correspond to "no fit" and "perfect fit," respectively, and that intermediate values have roughly the same interpretations as their analogues in the linear case. Although the absolute levels of this new measure may differ from measures proposed earlier in the literature, the ordering of alternative models produced by the different likelihood-based measures is the same.

As in the linear regression case, the pseudo R^2 is a useful measure of fit, but it is not sufficient for statistical hypothesis testing. For predicting horizons of two or more quarters, we have an overlapping data problem in that the forecast horizon is longer than the observation interval. As a result, forecast errors are likely to be serially correlated, raising the possibility that the estimates of the significance of individual variables using conventional test statistics may be misstated. Therefore, we calculate t-statistics using standard errors adjusted for the overlapping data problem by applying the Newey–West (1987) technique to the first-order conditions of the maximum-likelihood estimates.

Define

$$F_t \equiv F(\beta' x_t), \qquad f_t \equiv F'(\beta' x_t)$$

and let

$$h_t \equiv \frac{y_t - F_t}{F_t(1 - F_t)} f_t x_t, \qquad h \equiv \sum_{t=1}^{T} h_t.$$

The first-order condition for the probit estimates may then be expressed as $h = 0$. Further, compute the sample autocovariances of h_t,

$$\hat{\Omega}_j = \frac{1}{T} \sum_{t=j+1}^{T} h_t h'_{t-j}$$

and construct an estimator of the covariance of h from

$$\hat{S} = \hat{\Omega}_0 + \sum_{j=1}^{m} \lambda_j (\hat{\Omega}_j + \hat{\Omega}'_j)$$

where $\lambda_j = 1 - j/(m + 1)$. Using the notation $H \equiv (1/T)(\partial h/\partial \beta)$, the variance–covariance matrix of the coefficient estimates is given by

$$V = \frac{1}{T}(H'H)^{-1}H'\hat{S}H(H'H)^{-1}.$$

Estrella and Rodrigues (1997) show that the coefficient estimates are consistent even in the presence of serial correlation and that, therefore, this variance estimator is consistent. They also show that it performs better than the probit standard errors in Monte Carlo simulations, in which both the dependent and the independent variables are serially correlated.

Of particular interest in this paper are the out-of-sample results. We again use the pseudo R^2 measure to assess the out-of-sample accuracy of the forecasts.[4] However, when applied to out-of-sample results, there is no guarantee that the value of the pseudo R^2 will lie between 0 and 1, as is also true in the standard linear regression. Nevertheless, the pseudo R^2 for out-of-sample results is useful as a simple measure of fit and is comparable to the root-mean-square error or R^2 measures in the linear regression case.[5]

[4] Because we estimate the probit model using maximum likelihood, we use the value of the likelihood function as our fundamental accuracy criterion (loss function) for evaluating out-of-sample performance. For ease of interpretation, we rescale the likelihood values into a pseudo R^2, as we did for the in-sample results, as our criterion for out-of-sample forecast accuracy. This criterion is analogous to the use of the mean-squared error or R^2 in the linear regression case with normally distributed errors, in which case the likelihood function reduces to the mean-squared error. Our out-of-sample criterion is direct in that it is based on the objective function used for in-sample estimation, and it is intuitive in that the likelihood function represents the joint probability that the observed values are consistent with the estimated models. An alternative measure used in the literature to assess out-of-sample forecast accuracy is the quadratic probability score, which is a multiple of the mean-squared error (see Diebold and Rudebusch (1989)). Although the above logic suggests that the likelihood-based criterion is superior, Monte Carlo simulations we have performed indicate that it does not always outperform the quadratic probability score if the mean of the indicator variable y is very close to one-half and the fit of the equation is poor. However, in the application here, in which the mean of the indicator y is less than 0.2, Monte Carlo simulations do indicate that our pseudo R^2 is slightly superior to the quadratic score, particularly when the fit of a given equation is good. Note that the basic conclusions about out-of-sample forecasting ability are unaffected by the choice of the accuracy criterion.

[5] In the standard linear regression model within sample and with a constant term, the variance of the dependent variable decomposes exactly into the variance of the fitted values and the variance of the errors. Thus the ratio of the mean-squared error to the variance of the dependent variable may be subtracted from 1 to obtain an R^2 that is always between 0 and 1. Out of sample, the mean-squared error may exceed the variance of the dependent variable, and the resulting pseudo R^2 may be less than zero. Nevertheless, the mean-squared error (or its square root) is frequently used as a measure of out-of-sample fit. A negative R^2 simply indicates a very poor out-of-sample fit. The explanatory variables do such a poor job that they are worse than a constant term by itself. The interpretation of negative values for the pseudo R^2 in this paper is completely analogous. In this case, the likelihood function plays a role similar to that of the mean-squared error in the linear case.

III. Indicators Examined and Data Used

The primary focus of this paper is to test whether simple financial variables are useful predictors of future recessions. Thus we examine such variables as interest rates, interest rate spreads, stock price indexes, and monetary aggregates, both nominal and real. To establish the usefulness of our results, it is necessary to compare them with models based on traditional macroeconomic indicators. We therefore also include as explanatory variables the Commerce Department's index of leading economic indicators and several of its component series, two experimental indexes of leading indicators constructed by Stock and Watson (1989, 1993) in conjunction with the NBER, and also lagged growth in real GDP.[6]

The macroeconomic indicators have an established performance record in predicting real activity. That record is not always subjected to comparison tests, and most of the predictive lead times are not as long as users might prefer. Furthermore, many traditional macroeconomic indicators have been derived by fitting them to the data; that is, their components and the weights for these components have been chosen to maximize the indicators' success in predicting the business cycle within sample. As mentioned earlier, this might lead to an overfitting problem that overstates these indicators' success. The financial series we look at, however, have not been constructed by fitting them to the data and thus may be less subject to the overfitting problem than are traditional macroeconomic indicators.

Another important consideration is the possible lag in the availability of the data for the explanatory variables. Some variables, such as interest rates and stock prices, are available on a continuous basis with no informational lag. In contrast, many monthly macroeconomic series are only available one or two months after the period covered by the data, and GDP has a lag of almost one full quarter. To place all the variables on an equal footing, only observations actually available as of the end of a given quarter are assigned to that quarter.

The recession variable is constructed using the standard NBER dates.[7] Table 1 contains the names and descriptions of the other series, as well as the informational lag used for each variable, in months. More detail on the data, including sources, can be found in appendix B.

The equations are estimated using quarterly data from the first quarter of 1959 to the first quarter of 1995. The precise starting date does not seem to be crucial. The data actually chosen maximizes the availability of comparable data for all series. Results using data for some series that are available earlier in the 1950s are not appreciably different from those presented in this paper. Even though most series are available on a monthly basis, the estimates in this paper are derived from quarterly data for two basic reasons: monthly data are generally too noisy and produce somewhat weaker results, whereas the use of quarterly data guarantees comparability of all series. However, we have found that results derived from monthly data lead to similar conclusions on the usefulness of financial indicators.[8]

TABLE 1.—INDICATOR SERIES AND THEIR INFORMATION LAGS

Series	Description	Information Lag (Months)
	Interest Rates and Spreads	
SPREAD	10-year–3-month Treasury spread	0
CPTB	Commercial paper–Treasury spread (6 months)	0
BILL	3-month T bill	0
BOND	10-year T bond	0
	Stock Prices	
DJIA	Dow Jones industrials	0
NYSE	NYSE composite	0
SP500	S&P 500	0
	Monetary Aggregates	
M0	Monetary base	1
M1	M1	1
M2	M2	1
M3	M3	1
RM0	Monetary base deflated by CPI	1
RM1	M1 deflated by CPI	1
RM2	M2 deflated by CPI	1
RM3	M3 deflated by CPI	1
	Individual Macro Indicators	
GDPG1	Growth in real GDP, previous quarter	3
CPI	Consumer price index	1
NAPMC	Purchasing managers' survey	0
VP	Vendor performance	0
CORD	Contracts and orders for plant and equipment	1
HI	Housing permits	1
CEXP	Consumer expectations (MI)	0
TWD	Trade-weighted dollar	0
MORD	Change in manufacturers' unfilled durable goods orders	1
	Indexes of Leading Indicators	
LEAD	Commerce Department leading index	2
XLI	Stock–Watson (1989) leading index	1
XLI2	Stock–Watson (1993) leading index	1

Notes: Interest rates and spreads are quarterly averages, *MORD* is the quarterly average divided by the level of GDP, and the Stock–Watson indexes are for the last month of each quarter. For other variables, a quarterly growth rate is used.

[6] Stock and Watson (1989) also compute a six-month-ahead probability of a recession that is in some ways comparable to our results. We work with the indexes rather than the probabilities because under our conventions, the latter is only available five months ahead and is thus not strictly comparable to any of our forecast horizons. The performance of the Stock–Watson indexes is comparable to that of their probability for two quarters, where the horizons are closest.

[7] The NBER recession dates are the standard dates used in most business cycle analyses. These dates are not without controversy, however, because the NBER methodology makes implicit assumptions in arriving at these dates.

[8] The equations discussed in the text were also run using monthly data for the same period. Qualitatively, the results were the same: variables were ranked in the same order whether the data were monthly or quarterly. The fit, however, as measured by the pseudo R^2, was better with the quarterly data in the vast majority of cases. This pattern held for both in-sample and out-of-sample results, with only a few exceptions for variables with horizons of one or two quarters.

TABLE 2.—MEASURES OF FIT AND t-STATISTICS FOR PROBIT MODEL VARIABLES BY THEMSELVES, IN SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t})$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD								
Pseudo R^2	0.071	0.211	0.271	0.296	0.256	0.149	0.078	0.031
t-stat	−2.71[a]	−4.21[a]	−4.71[a]	−4.57[a]	−3.87[a]	−4.13[a]	−3.02[a]	−1.63
CPTB								
Pseudo R^2	0.103	0.061	0.026	0.001	0.001	0.001	0.008	0.010
t-stat	2.17[b]	1.57	1.03	0.31	−0.29	−0.36	−1.21	−1.36
RM0								
Pseudo R^2	0.153	0.103	0.156	0.168	0.118	0.072	0.046	0.014
t-stat	−4.00[a]	−3.70[a]	−3.53[a]	−4.06[a]	−3.72[a]	−3.54[a]	−1.89	−0.94
NYSE								
Pseudo R^2	0.174	0.133	0.08	0.043	0.003	0	0.004	0.030
t-stat	−2.75[a]	−3.06[a]	−3.12[a]	−2.65[a]	−0.77	0.09	1.01	3.10[a]
LEAD								
Pseudo R^2	0.236	0.132	0.112	0.018	0.005	0	0.006	0.007
t-stat	−3.01[a]	−2.57[b]	−2.51[b]	−1.48	−0.85	−0.12	0.94	0.70
XLI								
Pseudo R^2	0.387	0.332	0.205	0.103	0.056	0.022	0.006	0.001
t-stat	−6.14[a]	−2.85[a]	−2.28[b]	−2.32[b]	−2.26[b]	−1.54	−0.65	−0.23
XLI2								
Pseudo R^2	0.239	0.091	0.059	0.002	0.008	0.011	0.012	0.017
t-stat	−4.25[a]	−3.54[a]	−2.99[a]	−0.53	1.04	0.82	0.78	0.78
GDPG1								
Pseudo R^2	0.160	0.093	0.008	0.002	0.008	0.007	0.015	0.003
t-stat	−3.02[a]	−3.13[a]	−0.95	−0.62	−0.99	0.70	0.71	0.36

Notes: [a] Significant at the 1% level.
[b] Significant at the 5% level.

IV. In-Sample Results

In-sample results are based on equations estimated over the entire sample period. Their predictions or fitted values are then compared with the actual recession dates. Three types of results are provided: a pseudo R^2, a t-statistic, and indicators of significance at the 5 and 1% levels. Because the focus of the paper is out-of-sample prediction, only a few selected in-sample results are presented with the text. The full in-sample results are provided in appendix A.

The general strategy of the analysis is the following. The probit equation is estimated using each series in table 1. Because the yield curve spread variable (*SPREAD*) produces consistently strong results across all horizons, equations are also run containing the *SPREAD* variable and each of the other variables in turn. Some of the main results are summarized in tables 2 and 3. (The full results are presented in the appendix, tables A.1 and A.2.).[9]

Table 2 contains several of the variables that performed best in sample and for which representative patterns of significance may be identified. Among the nonfinancial (or not strictly financial) variables, the leading indicators and the GDP are clearly strong predictors in the very short run, with the significance generally declining within a year. The significance of the GDP reflects the short-term persistence of economic activity. The leading indicators, however, are constructed from variables that have historically been correlated with future activity. The results we obtain are consistent with those of Koenig and Emery (1991), who show that the predictive horizon for these indicators tends to be short. Among the indexes of leading indicators, the strongest performer is the original Stock–Watson indicator, as seen in table 2.

Among the financial variables, stock prices and the commercial paper spread exhibit a pattern similar to the indexes, although the fit is generally not as good, particularly for the commercial paper spread. Because the commercial paper spread is the difference between two six-month rates, which are presumably forward looking over that horizon, it is not surprising that the predictive power of this variable appears at the very short end. The one-quarter projection is significant at the 5% level.[10]

Stock prices should be more forward looking than the commercial paper spread, at least in principle. Finance theory suggests that stock prices may be interpreted as expected present values of future dividend streams. Although the discounting associated with the calculation of

[9] For a few variables, in-sample results indicate that a second lag of the variable may be significant. For those variables, we also estimated two-lag models with and without the spread and obtained qualitatively similar results. Those results are available from the authors on request.

[10] Evidence of the predictive power of this variable has been provided by Stock and Watson (1989) and Friedman and Kuttner (1993), among others.

present value reduces the effective predictive horizon, the projections should still be focused on the relatively long term. This expectation is confirmed empirically by the results for the New York Stock Exchange (NYSE) index, which are significant up to four quarters.[11]

Changes in monetary aggregates have the potential to affect real activity in the short term. In our results, the real monetary base performs very well within the first year, and its fit is remarkably consistent over quarters one through four. Note, however, that the nominal monetary base has little predictive power, so that most of the predictive power of the deflated monetary base comes from an implicit lagged inflation term (the growth rate of the CPI deflator). In general, the predictive performance of the nominal monetary aggregates is uniformly poor. (See the appendix, tables A.1 and A.2.)

Some of the most significant results in this paper are associated with the yield curve spread variable *SPREAD.* The steepness of the yield curve seems to be an accurate predictor of real activity, especially between two and six quarters ahead. Various factors account for this empirical regularity. One possibility is that current monetary policy has significant influence on both the yield curve spread and real activity over the next several quarters. A rise in the short rate would tend to flatten the yield curve as well as slowing real growth in the near term. Although this relationship is very likely part of the story, it is probably not the whole story. For example, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1997) show that proxies for the stance of monetary policy do not fully account for movements in the yield curve spread, and that the spread retains its predictive power in equations that include such proxies.[12]

The expectations contained in the yield curve spread also seem to play an important role in the prediction of future activity. The *SPREAD* variable corresponds to a forward interest rate applicable from three months to ten years into the future.[13] As explained in Mishkin (1990a,b), this rate can be decomposed into expected real and inflation components, each of which may be helpful in forecasting real growth. The expected real rate may be associated with expectations of future monetary policy. Moreover, because inflation tends to be positively related to activity, perhaps with some lag, the expected inflation component may also be informative about future real growth.

For quarters two and beyond, the *SPREAD* variable produces a better fit than the other variables, with the exception of the Stock–Watson (1989) indicator (*XLI*) in quarter two. Note, however, that the Stock–Watson *XLI* variable includes a yield curve spread as one of its constituent variables, from which it seems to derive much of its out-of-sample predictive power.[14] The *XLI* variable has correlations between 0.6 and 0.7 with *SPREAD, CPTB* (another of its components), *RM0*, and the two other leading indicators, which also have similar correlations with each other. Other than the foregoing pairs, the only other correlation of that level among variables in table 2 is between *SPREAD* and *RM0.* (See table A.5 in appendix A.)

When the yield curve spread is combined with the other variables in the probit model, as in table 3, the results of the single-variable analysis are generally confirmed, although some interesting combinations result. On the one hand, the significance of the *SPREAD* variable is basically undiminished beyond the first two to three quarters. Even within that range, only the real monetary base undoes the significance of the spread at the 5% level, and then only one quarter ahead. On the other hand, the other variables remain strong within two to three quarters, with two exceptions. By including *SPREAD,* both the commercial paper spread and the real base become insignificant beyond one quarter.

The results of the model that combines the yield curve spread with stock prices suggest that these two financial variables, which are readily and continuously available, form a very strong combination across all the horizons examined. The significance at the short end is enhanced by including the stock index, and the significance at the long end is driven largely by *SPREAD.*[15]

V. Out-of-Sample Results

The out-of-sample results are obtained in the following way. First, a given model is estimated using data from the beginning of the sample up to a particular quarter, say the first quarter of 1970. Then these estimates are used to form

[11] We use the quarterly growth rate of the stock price index as a predictor, but other equity-related variables such as the dividend yield or the price–earnings ratio could also be used. In this context, the latter two variables underperform the S&P 500 index growth both in sample (pseudo R^2 at least three percentage points lower) and out of sample. Predictive performance exists only for the price–earnings ratio with a one-quarter horizon.

[12] Proxies for the stance of monetary policy in these papers include real and nominal federal funds rates and monetary aggregates. Estrella (1997) constructs a theoretical model that traces the predictive power of the yield curve to the monetary policy regime rather than the current stance of policy.

[13] We have examined the predictive ability of other yield curve spreads, for example, using the one-year or the ten-year rate as the long rate and the fed funds three-month or six-month rates as the short rate. Among these, the spread between the ten-year and the three-month rates performs best out of sample, although the results with alternative spread variables are similar. We did not use 20- or 30-year rates because of the lack of availability of data for the full sample.

[14] Stock and Watson use the ten-year minus one-year Treasury rate spread. Other financial variables in their model are the commercial paper minus Treasury bill spread (*CPTB* in this paper), the trade-weighted value of the dollar (*TWD*), and the ten-year Treasury rate (*BOND*). The remaining variables are housing permits (*HI*), manufacturers' unfilled orders for durable goods (*MORD*), and the number of people working part time in nonagricultural industries because of slack work (not included here).

[15] Because the dependent variable has only two values, it seems plausible to focus on yield curve inversions, that is, on cases where *SPREAD* is negative. This variable was also examined, but the results are inferior to those for *SPREAD* itself, and are insignificant when *SPREAD* is included. We also tested a lagged dependent variable and the time (number of quarters) since the last recession. These variables were significant with maximum horizons of two and one quarters, respectively. However, this performance is not useful in practice, since the recession dates (and hence the recession variable) are available only with very long lags, possibly a year or more (see Boldin (1994)).

TABLE 3.—MEASURES OF FIT AND t-STATISTICS FOR PROBIT MODEL VARIABLES WITH SPREAD, IN SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t} + \alpha_2 SPREAD_t)$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD[a]								
Pseudo R^2	0.071	0.211	0.271	0.296	0.256	0.149	0.078	0.031
t-stat	−2.71[c]	−4.21[c]	−4.71[c]	−4.57[c]	−3.87[c]	−4.13[c]	−3.02[c]	−1.63
CPTB								
Pseudo R^2	0.142	0.233	0.272	0.307	0.285	0.165	0.102	0.051
t-stat	1.86	1.06	0.32	−1.14	−2.28[d]	−2.25[d]	−2.27[d]	−1.99[d]
t-stat sp[b]	−2.20[d]	−4.71[c]	−5.19[c]	−3.90[c]	−3.37[c]	−4.29[c]	−3.69[c]	−2.06[d]
RMO								
Pseudo R^2	0.154	0.213	0.283	0.309	0.258	0.151	0.081	0.033
t-stat	−3.17[c]	−0.50	−0.90	−1.01	−0.43	−0.54	−0.53	−0.12
t-stat sp	−0.47	−3.26[c]	−3.27[c]	−3.37[c]	−3.65[c]	−3.19[c]	−2.31[d]	−1.60
NYSE								
Pseudo R^2	0.223	0.32	0.321	0.314	0.261	0.159	0.096	0.083
t-stat	−3.54[c]	−4.81[c]	−2.32[d]	−1.57	0.92	1.17	1.71	3.69[c]
t-stat sp	−2.00[d]	−4.01[c]	−5.13[c]	−4.89[c]	−3.77[c]	−3.67[c]	−2.90[c]	−2.09[d]
LEAD								
Pseudo R^2	0.256	0.283	0.331	0.296	0.265	0.16	0.106	0.054
t-stat	−3.11[c]	−2.40[d]	−2.07[d]	−0.08	1.44	1.03	1.48	1.22
t-stat sp	−1.42	−4.16[c]	−4.74[c]	−4.33[c]	−4.07[c]	−3.81[c]	−3.52[c]	−2.57[d]
XLI								
Pseudo R^2	0.43	0.35	0.298	0.297	0.274	0.179	0.106	0.047
t-stat	−4.68[c]	−1.96	−1.21	0.27	1.84	1.57	1.29	0.96
t-stat sp	2.09[d]	−1.18	−2.73[c]	−3.40[c]	−4.62[c]	−3.93[c]	−3.46[c]	−2.48[d]
XLI2								
Pseudo R^2	0.289	0.268	0.298	0.302	0.356	0.21	0.121	0.07
t-stat	−4.25[c]	−2.80[c]	−1.80	0.50	2.95[c]	1.09	1.27	1.20
t-stat sp	−2.51[d]	−4.15[c]	−4.55[c]	−3.70[c]	−4.43[c]	−2.91[c]	−3.96[c]	−2.83[c]
GDPG1								
Pseudo R^2	0.228	0.318	0.275	0.296	0.264	0.160	0.103	0.037
t-stat	−3.54[c]	−3.74[c]	−0.69	−0.07	−0.62	0.60	0.70	0.42
t-stat sp	−2.53[d]	−4.35[c]	−4.84[c]	−4.52[c]	−3.89[c]	−3.92[c]	−3.42[c]	−1.75

Notes: [a] Line repeated from table 2 for reference purposes.
[b] t-stat sp indicates t-statistic for *SPREAD* variable.
[c] Significant at the 1% level.
[d] Significant at the 5% level.

projections, say four quarters ahead. In this case, the projection would apply to the first quarter of 1971. After adding one more quarter to the estimation period, the procedure is repeated. That is, data up to the second quarter of 1970 are used to make a projection for the second quarter of 1971. In this way, the procedure mimics what a statistical model would have predicted with the information available at any point in the past. Data that became available subsequent to the prediction date are not used to estimate or to predict recessions.

This type of procedure leads to a fairer and more realistic test of the predictive abilities of the various models than the in-sample results. It nevertheless has several drawbacks. First, instead of one regression for the whole sample, as in the in-sample case, regressions must be run for each observation following the starting point. Second, the pseudo R^2, which is easily interpretable in sample, is no longer guaranteed to lie between 0 and 1. This is not a consequence of the probit form; it is also true of predictions generated by linear regressions, as explained in footnote 5. Indeed a negative out-of-sample R^2 simply implies a very poor out-of-sample fit; that is, the explanatory variables do such a poor job of forecasting that a model with just the constant term would perform better. Third, statistical tests of significance are no longer available in a strict sense.

We deal with these issues in the following ways. First, we estimate the many required equations, which is time consuming but quite feasible. Second, we present only nonnegative pseudo R^2 values in the results reported in the text because a negative pseudo R^2 indicates a very poor forecasting performance and is not very informative. (The tables in appendix A include the values of the negative pseudo R^2 values for those interested.)

The first data point for which predictions are made is the first quarter of 1971. Although an earlier date would have been possible, we needed to capture some recession observations to arrive at accurate parameter estimates. Because the 1960s were essentially an uninterrupted economic expansion, the sample starts in the early 1970s. Predictions are computed through the first quarter of 1995. The principal

TABLE 4.—MEASURES OF FIT FOR PROBIT MODEL VARIABLES BY THEMSELVES, OUT OF SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t})$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD	0.072	0.236	0.328	0.295	0.155	0.141	—	—
CPTB	—	—	—	—	—	—	—	—
RM0	0.157	0.073	—	0.176	0.101	0.097	—	—
NYSE	0.161	0.077	0.075	0.016	—	—	—	0.028
LEAD	0.121	—	—	—	—	—	—	—
XLI	0.324	0.141	—	0.015	0.067	0.016	—	—
XLI2	0.196	0.028	—	—	—	—	—	—
GDPG1	0.065	—	—	—	—	—	—	—

Note: For each model, pseudo R^2 is shown; — indicates negative value.

results are presented in tables 4 and 5, and full results are given in appendix A, Tables A.3 and A.4.

Table 4 includes results for each of the variables from table 2. The table in general exhibits patterns similar to those described in the previous section, although a few of the results are somewhat surprising. Variables that perform well, confirming expectations, are the yield curve spread, the real monetary base, stock prices, and the indexes of leading indicators. Compared with the in-sample results, the performance of these variables shows some deterioration, in terms of both accuracy and length of the predictive horizon. Nevertheless, the same basic patterns emerge for most of these predictors as in the in-sample results.

For a few variables, the deterioration in performance is substantial. For example, the commercial paper spread (*CPTB*), which was highly significant for one and two quarters in sample, has a negative pseudo R^2 for every predictive horizon out of sample. The Commerce Department's leading indicators also have significantly diminished predictive power compared with the in-sample results. The original Stock–Watson *XLI* index outperforms the other leading indicators, particularly one quarter ahead.

As in the in-sample results, the *SPREAD* variable tends to dominate the results starting with the two-quarter-ahead predictions. Although predictive power at seven and eight quarters is absent, the results for two and three quarters are actually stronger than in sample. No other single variable exhibits this kind of performance, including the traditional macroeconomic indicators. We also note that the model with *SPREAD* is relatively stable over time. For example, we performed an analogous experiment in which we move the out-of-sample period back in time from the first quarter of 1959 to the second quarter of 1953, using data from 1959 to 1995. The results have a different pattern with respect to the predictive horizon when compared to those moving forward from 1971, but are still fairly robust. For instance, the 1955–1959 pseudo R^2 peaks at 19% for a five-quarter horizon, as compared with the out-of-sample forecast results for the 1973–1995 period of 16% for five quarters and 33%, the peak, for three quarters.

When the yield curve spread is included in the model with each of the variables in table 4, the effects are quite dramatic, as illustrated by table 5. One important feature of table 5 is that, with very few exceptions, additional predictive power is absent beyond one quarter when other variables are combined with the yield curve spread. Of course, the variables that do not perform well by themselves remain poor predictors. What is noteworthy, however, is that some variables that do extremely well by themselves, such as the real monetary base and the original Stock–Watson index, are almost completely overshadowed by the spread.

As noted earlier, the Stock–Watson index is partly based on the spread, so that there is little additional information in that measure out of sample. It is more difficult to find a direct link to the reduced significance of the real base, although the empirical results are almost equally striking. More generally, the lesson from table 5 is that parsimonious models work best out of sample. A combination model using two variables, even variables that are good individual predictors, tends to produce worse predictions than does each variable on its own.[16]

It is clear from table 5 that the only variables that truly and consistently enhance the out-of-sample predictive power of the yield curve beyond one quarter are the stock price indexes. With horizons of one, two, three, and five quarters, the results are better with either of the broader market indexes, namely, *NYSE* and the Standard and Poor's 500 (*SP500*).[17] Even for four and six quarters, the reduction in predictive fit is not that large.

[16] This principle also applies to multiple lags of an explanatory variable, as suggested by the results of appendix tables A.5 and A.6 in a working paper version of this paper (Estrella and Mishkin (1995)).

[17] The broad stock indexes are also the only variables for which a second lag has predictive power out of sample, even with the inclusion of the term structure spread. The second lag is helpful with horizons of one, two, and three quarters, as shown in appendix tables A.5 and A.6 in a working paper version of this paper (Estrella and Mishkin (1995)).

TABLE 5.—MEASURES OF FIT FOR PROBIT MODEL VARIABLES WITH SPREAD, OUT OF SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t} + \alpha_2 SPREAD_t)$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD[a]	0.072	0.236	0.328	0.295	0.155	0.141	—	—
CPTB	—	—	—	0.153	0.105	0.140	—	—
RM0	0.127[b]	0.176	—	0.171	—	0.114	—	—
NYSE	0.208[b]	0.316[b]	0.367[b]	0.274	0.161[b]	0.120	—	—
LEAD	0.079[b]	—	0.149	0.254	0.121	0.081	—	—
XLI	—	0.136	0.015	0.192	—	—	—	—
XLI2	0.252[b]	0.270[b]	0.311	0.139	—	—	—	—
GDPG1	0.120[b]	0.186	0.301	0.230	0.047	0.071	—	—

Notes: For each model, pseudo R^2 is shown; — indicates negative value.
[a] Line is repeated from table 4 for reference purposes.
[b] Additional variable improves fit.

We may draw some additional conclusions. First, stock prices provide information that is not contained in the yield curve spread and which is useful in predicting future recessions. Second, a simple model containing these two variables is about the best that can be constructed from financial variables for out-of-sample prediction. Again, it generally pays to be parsimonious. For example, adding GDP to the yield curve spread and the NYSE index increases the fit of the one-quarter prediction dramatically to 0.433, compared with 0.285 without GDP. However, for every other horizon, the results are much worse in the three-variable case.

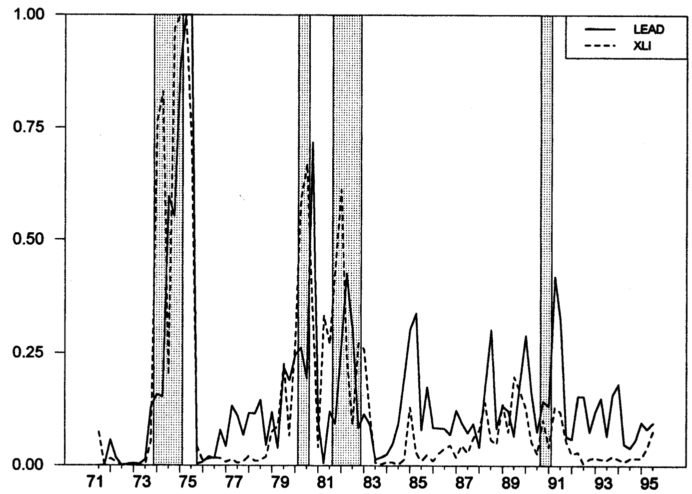
VI. Case Study: An Application of the Approach

Predicting the future is a tricky business. A good example of what may happen is provided by the experience with the Stock–Watson (1989) experimental index of leading indicators. In a very useful piece of postmortem analysis, Watson (1991) and Stock and Watson (1993) describe and analyze the disappointing performance of their indicator in predicting the 1990–1991 recession.

We have shown in this paper how out-of-sample performance may deteriorate significantly with the use of too many explanatory variables. In different ways, the leading indicators of both the Commerce Department and Stock–Watson (1989) are susceptible to this type of overfitting problem. The Commerce Department's measure is based on movements in 11 individual variables, which are combined in a weighted average. The Stock–Watson (1989) indicator uses a fairly complex modeling specification that includes seven individual series, with several lags for each of the series.

Here we examine the performance of two parsimonious models—using *SPREAD* only and using *SPREAD* with *NYSE*—in forecasting the 1990–1991 recession out of sample and compare the results with those from the Commerce and Stock–Watson leading indicators. We examine

FIGURE 1.—PROBABILITY OF RECESSION, TWO QUARTERS AHEAD



forecasting horizons of two and four quarters ahead. We look at two quarters ahead because this is a time horizon considered by Stock and Watson (1989), and at four quarters ahead because this is a more important forecasting horizon in the monetary policy context and is the horizon for which the performance of the *SPREAD* variable is maximized.

Before turning to the 1990–1991 results, consider the earlier performance of the series. For a forecasting horizon of two quarters, all four variables were fairly reliable until the late 1980s. Figure 1, for example, shows the recession probabilities implied by the Commerce (*LEAD*) and Stock–Watson (*XLI*) indicators from 1971 to 1989.[18] Both series produce strong signals that are approximately consistent with the actual recessions up until 1982, but the Stock–Watson measure is superior in timing and accuracy. Our representation of their results is somewhat different from that in their paper. However, comparison of figure 1 with

[18] The probabilities shown in figures 1–4 are forecasts for the contemporaneous quarter, using data from either two or four quarters earlier.

Watson (1991, fig. 4) reveals very similar patterns. The indications of the Commerce variable come too late, are more volatile, and are too high in early 1985. Figure 2 shows the corresponding probabilities using the yield curve spread (*SPREAD*) and the combined spread and stock index (*NYSE*) models. The results are again fairly accurate, with the exception in 1988 of the model using both *SPREAD* and *NYSE* variables, when the stock market crash of 1987 produces a false recession signal.

In the 1990–1991 recession the predictive power of the two leading indicator series broke down, as illustrated in figure 1. This recession, which was associated with unusual events such as the invasion of Kuwait, was particularly hard to predict. Even in 1990, as the onset of the recession approached, there was considerable controversy about the state of the economy. Stock and Watson have documented how their indicator surged too early, declined, and gave a feeble signal within the recession. Our figure shows pretty much the same pattern. The Commerce indicator again was worse. It gave two somewhat strong signals before the recession and a very strong signal after, but it missed the recessionary quarters.

On the other hand, the models using the financial indicators forecast the 1990–1991 recession better than both leading indicators. The model with the *SPREAD* variable does show a rising probability of recession before the 1990–1991 recession, although it peaks a little bit early, whereas the model which also includes the stock index peaks at just about the right time.

When we look at the longer four-quarter forecasting horizon, the dominance of the forecasting models using financial indicators is far more clear-cut. As we can see from figure 3, the leading indicators have essentially no ability to forecast recessions four quarters ahead. Even before the 1990–1991 recession, the recession probabilities using the leading indicator models often reach peaks after the recessions are already over. For the 1990–1991 recession, the leading indicators also completely miss the boat, with no appreciable rise in the recession probabilities during the 1990–1991 recession period.

In contrast, as we can see in figure 4, the models using the *SPREAD* and *NYSE* variables do quite well in forecasting recessions. Before the 1990–1991 recession, the results from these models are fairly accurate, even though the signal in 1973–1974 comes a bit late. In the 1990–1991 recession, the financial indicator models again clearly outperform both leading indicators. Figure 4 shows that the spread by itself was quite informative. It surged a bit prematurely, but less so than the Stock–Watson measure, and the signal was weaker than in some earlier recessions.[19] Nevertheless, it provided a

FIGURE 2.—PROBABILITY OF RECESSION, TWO QUARTERS AHEAD

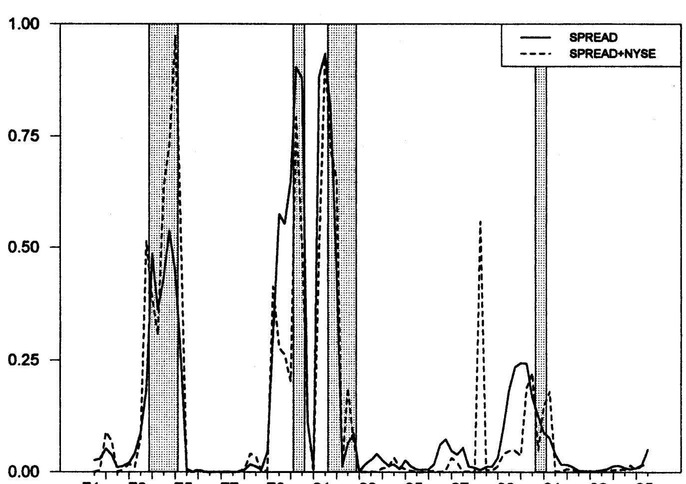


FIGURE 3.—PROBABILITY OF RECESSION, FOUR QUARTERS AHEAD

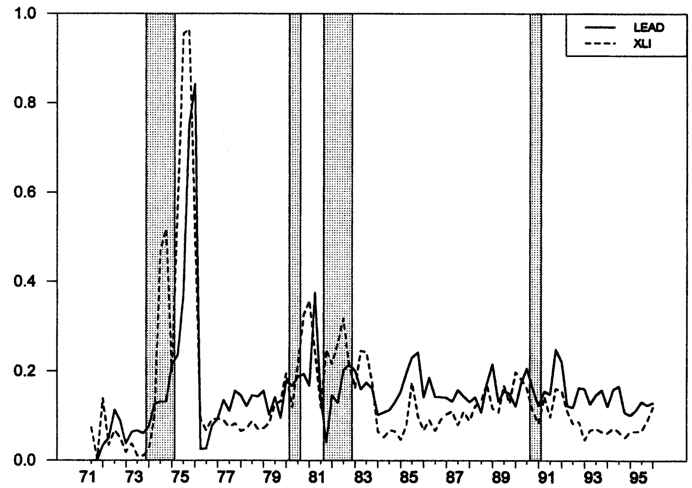
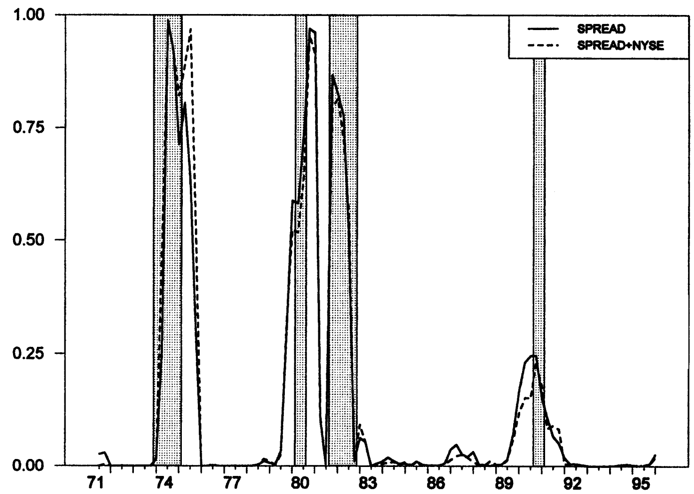


FIGURE 4.—PROBABILITY OF RECESSION, FOUR QUARTERS AHEAD



[19] The signal provided by the yield curve *SPREAD* in the last recession seems weak, but this weakness should be interpreted in relation to the strong signals in the 1980–1981 recessions. In the early 1980s, interest rate cycles exhibited unusually broad ranges. Steep yield curves were steeper than in the rest of the postwar period, and downward sloping curves were more negative. As a result, the signals produced by the yield curve per se were more extreme in both directions. Because the probit approach of this paper compresses one side of the interest rate cycle (large positive values of *SPREAD*) to probabilities close to 0, the increase in the range of

signal that continued to rise into the onset of the recession. The addition of the NYSE index improves the results somewhat in that the probabilities have a similar peak in the recession, but they are not as strong before the recession starts.

The lessons of these out-of-sample forecasting exercises, particularly in 1990–1991, suggest that the simple financial variable models compare favorably with the more complex leading indicators. The results illustrate the dangers of overfitting and the potential benefits of using simple financial variables as indicators. The results are all the more impressive in that the forecasting horizon for which the financial variables do best—four quarters—is a more relevant one for policy making than the shorter two-quarter horizon.

VII. Conclusions

This paper has examined the performance of various financial variables in predicting future U.S. recessions, focusing on out-of-sample results. The results obtained using the yield curve spread and stock prices are encouraging and suggest that these measures can play a useful role in macroeconomic prediction. Of course, we do not propose that these indicators supplant macroeconomic models and judgmental forecasts. Rather, we conclude that the financial variables can usefully supplement the models and other forecasts, and can serve as a quick, reliable check of more elaborate predictions.

Several general principles emerged from our analysis. First, overfitting is a serious problem in macroeconomic predictions. Even when only a few variables are used, the addition of a single variable or another lag of a variable can undermine the predictive power of a parsimonious model. Second, in-sample and out-of-sample performance can differ greatly. A good illustration is the six-month commercial paper–Treasury bill spread, which does very well in sample for one and two quarters, but has no out-of-sample predictive power at any horizon.

A third principle is the importance of determining the optimal out-of-sample horizon for each financial variable. For instance, the yield curve spread shows the best predictive performance across the range of horizons examined. For a one-quarter horizon, however, even though this variable has some power, it is substantially outperformed by a number of other indicators, including the stock price indexes, the Commerce and Stock–Watson leading indicators, and some of the Commerce indicator's components. Other than the yield curve, the indicators we have studied tend to perform best with short horizons, although in some cases (for example, stock prices) the performance extends to two or three quarters.

As to specific conclusions, the yield curve spread and stock price indexes emerge as the most useful simple financial indicators. They may be observed individually over their respective primary horizons, or they may be combined to produce a very reliable simple model. Significantly, this model would have provided some warning of the last recession four quarters ahead, even though that recession, which was connected with unusual events such as the invasion of Kuwait, was particularly hard to predict.

variation looks simply like an increase in the size of the signal in the early 1980s. This explanation may be confirmed by examining probit results that include earlier recessions in the postwar period (see, for example, Estrella and Hardouvelis (1991)). In principle, these changes in the range of variation in the spread may be modeled econometrically, but going to a more complex model does pose the danger of overfitting the data.

REFERENCES

Barran, Fernando, Virginie Coudert, and Benoit Mojon, "Interest Rates, Banking Spreads and Credit Supply: The Real Effects," Working Paper 95-01, Centre d'Etudes Prospectives et d'Informations Internationales (Mar. 1995).

Boldin, Michael D., "Dating Turning Points in the Business Cycle," *Journal of Business* 67 (Jan. 1994), 97–131.

Bomhoff, Eduard J., *Financial Forecasting for Business and Economics* (London: Academic Press, 1994).

Chen, Nai-Fu, "Financial Investment Opportunities and the Macroeconomy," *Journal of Finance* 46 (June 1991), 529–554.

Davis, E. Philip, and Gabriel Fagan, "Indicator Properties of Financial Spreads in the EU: Evidence from Aggregate Union Data," Working Paper, European Monetary Institute (1994).

Davis, E. Philip, and S. G. B. Henry, "The Use of Financial Spreads as Indicator Variables: Evidence for the United Kingdom and Germany," *IMF Staff Papers* 41 (Sept. 1994), 517–525.

Diebold, Francis X., and Glenn D. Rudebusch, "Scoring the Leading Indicators," *Journal of Business* 62 (July 1989), 369–391.

Estrella, Arturo, "Why Do Interest Rates Predict Macro Outcomes? A Unified Theory of Inflation, Output, Interest and Policy," Research Paper 9717, Federal Reserve Bank of New York (May 1997).

——— "A New Measure of Fit for Equations with Dichotomous Dependent Variables," *Journal of Business and Economic Statistics* (forthcoming).

Estrella, Arturo, and Gikas Hardouvelis, "Possible Roles of the Yield Curve in Monetary Analysis," in *Intermediate Targets and Indicators for Monetary Policy* (New York: Federal Reserve Bank of New York, 1990).

——— "The Term Structure as a Predictor of Real Economic Activity," *Journal of Finance* 46 (June 1991), 555–576.

Estrella, Arturo, and Frederic S. Mishkin, "Predicting U.S. Recessions: Financial Variables as Leading Indicators," Working Paper 5379, National Bureau of Economic Research (Dec. 1995).

——— "The Predictive Power of the Term Structure of Interest Rates in Europe and the United States: Implications for the European Central Bank," *European Economic Review* 41 (July 1997), 1375–1401.

Estrella, Arturo, and Anthony P. Rodrigues, "Consistent Covariance Matrix Estimation in Probit Models with Autocorrelated Errors," Working Paper, Federal Reserve Bank of New York (Oct. 1997).

Friedman, Benjamin, and Kenneth Kuttner, "Why Does the Paper–Bill Spread Predict Real Economic Activity?," in James Stock and Mark W. Watson (eds.), *Business Cycles, Indicators, and Forecasting* (Chicago: University of Chicago Press, 1993), 213–253.

Hamilton, James D., "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica* 57 (Mar. 1989), 357–384.

Harvey, Campbell, "The Real Term Structure and Consumption Growth," *Journal of Financial Economics* 22 (Dec. 1988), 305–333.

Hu, Zuliu, "The Yield Curve and Real Activity," *IMF Staff Papers* 40 (Dec. 1993), 781–806.

Jorion, Phillippe, and Frederic S. Mishkin, "A Multi-Country Comparison of Term Structure Forecasts at Long Horizons," *Journal of Financial Economics* 29 (Jan. 1991), 59–80.

Koenig, Evan F., and Kenneth M. Emery, "Misleading Indicators? Using the Composite Leading Indicators to Predict Cyclical Turning

Points," *Federal Reserve Bank of Dallas Economic Review* (July 1991), 1–14.
Laurent, Robert, "An Interest Rate–Based Indicator of Monetary Policy," *Federal Reserve Bank of Chicago Economic Perspectives* 12 (Jan./Feb. 1988), 3–14.
——— "Testing the Spread," *Federal Reserve Bank of Chicago Economic Perspectives* 13 (July/Aug. 1989), 22–34.
Maddala, G. S., *Limited-Dependent and Qualitative Variables in Econometrics* (Cambridge, UK: Cambridge University Press, 1983).
Mishkin, Frederic S., "What Does the Term Structure Tell Us about Future Inflation?," *Journal of Monetary Economics* 25 (Jan. 1990a), 77–95.
——— "The Information in the Longer-Maturity Term Structure about Future Inflation," *Quarterly Journal of Economics* 55 (Aug. 1990b), 815–828.
——— "A Multi-Country Study of the Information in the Term Structure about Future Inflation," *Journal of International Money and Finance* 19 (Mar. 1991), 2–22.
Newey, Whitney, and Kenneth West, "A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica* 55 (May 1987), 703–708.
Palash, Carl, and Lawrence J. Radecki, "Using Monetary and Financial Variables to Predict Cyclical Downturns," *Federal Reserve Bank of New York Quarterly Review* 10 (Summer 1985), 36–45.
Plosser, Charles I., and K. Geert Rouwenhorst, "International Term Structures and Real Economic Growth," *Journal of Monetary Economics* 33 (Feb. 1994), 133–155.
Reinhart, Carmen M., and Vincent R. Reinhart, "Forecasting Turning Points in Canada," mimeo, International Monetary Fund (Mar. 1996).
Stock, James, and Mark Watson, "New Indexes of Coincident and Leading Indicators," in Olivier Blanchard and Stanley Fischer (eds.), *NBER Macroeconomic Annual* 4 (1989), 351–394.
——— "A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Performance," in James Stock and Mark K. Watson (eds.), *Business Cycles, Indicators, and Forecasting* (Chicago: University of Chicago Press, 1993).
Watson, Mark, "Using Econometric Models to Predict Recessions," *Federal Reserve Bank of Chicago Economic Perspectives* 15 (Nov./Dec. 1991), 14–25.

APPENDIX A

Additional Empirical Results

In this appendix we include in-sample results for all the variables listed in table 1 in the text. Results are given for single variables in table A.1 and for single variables with the yield curve spread in table A.2. Full out-of-sample results corresponding to tables 4 and 5 in the text appear in tables A.3 and A.4. Table A.5 contains a correlation matrix of the explanatory variables in tables 2–5.

TABLE A1.—MEASURES OF FIT AND t-STATISTICS FOR PROBIT MODEL VARIABLES BY THEMSELVES, IN SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t})$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD								
Pseudo R^2	0.071	0.211	0.271	0.296	0.256	0.149	0.078	0.031
t-stat	−2.71[a]	−4.21[a]	−4.71[a]	−4.57[a]	−3.87[a]	−4.13[a]	−3.02[a]	−1.63
CPTB								
Pseudo R^2	0.103	0.061	0.026	0.001	0.001	0.001	0.008	0.010
t-stat	2.17[b]	1.57	1.03	0.31	−0.29	−0.36	−1.21	−1.36
BILL								
Pseudo R^2	0.133	0.193	0.177	0.151	0.113	0.064	0.036	0.015
t-stat	3.26[a]	3.73[a]	4.68[a]	4.57[a]	3.92[a]	2.80[a]	1.72	0.95
BOND								
Pseudo R^2	0.077	0.077	0.054	0.036	0.022	0.012	0.007	0.003
t-stat	2.73[a]	2.47[b]	1.97[b]	1.53	1.19	0.88	0.67	0.42
M0								
Pseudo R^2	0	0.001	0.001	0.002	0.006	0	0.001	0.024
t-stat	−0.05	0.36	−0.24	−0.53	−0.81	0.03	0.34	1.78
M1								
Pseudo R^2	0.052	0.021	0.03	0.004	0	0.001	0	0.005
t-stat	−3.47[a]	−2.33[b]	−2.28[b]	−0.78	−0.14	−0.27	0	0.72
M2								
Pseudo R^2	0.022	0.02	0.024	0.002	0.001	0.005	0.004	0.011
t-stat	−1.87	−1.49	−1.52	−0.50	0.37	0.89	0.62	0.96
M3								
Pseudo R^2	0.001	0.002	0.003	0	0.004	0.03	0.031	0.039
t-stat	−0.33	−0.36	−0.36	0.01	0.44	1.39	1.53	1.81
RM0								
Pseudo R^2	0.153	0.103	0.156	0.168	0.118	0.072	0.046	0.014
t-stat	−4.00[a]	−3.70[a]	−3.53[a]	−4.06[a]	−3.72[a]	−3.54[a]	−1.89	−0.94
RM1								
Pseudo R^2	0.209	0.12	0.154	0.092	0.041	0.038	0.023	0.009
t-stat	−3.90[a]	−2.84[a]	−2.59[a]	−2.72[a]	−1.97[b]	−2.71[a]	−1.47	−0.79

TABLE A1.—(CONTINUED)

x_{1t} Variables	$P(R_{t+k}=1)=F(\alpha_0+\alpha_1 x_{1t})$ k = Quarters Ahead 1	2	3	4	5	6	7	8
RM2								
Pseudo R^2	0.172	0.136	0.171	0.103	0.037	0.022	0.017	0.008
t-stat	−3.77[a]	−3.22[a]	−3.82[a]	−4.42[a]	−2.27[b]	−1.76	−0.98	−0.56
RM3								
Pseudo R^2	0.105	0.09	0.117	0.082	0.028	0.005	0.002	0.001
t-stat	−2.91[a]	−3.03[a]	−3.31[a]	−3.20[a]	−1.86	−0.68	−0.30	−0.14
NYSE								
Pseudo R^2	0.174	0.133	0.08	0.043	0.003	0	0.004	0.030
t-stat	−2.75[a]	−3.06[a]	−3.12[a]	−2.65[a]	−0.77	0.09	1.01	3.10[a]
SP500								
Pseudo R^2	0.169	0.134	0.079	0.043	0.003	0.001	0.007	0.031
t-stat	−2.63[a]	−2.87[a]	−2.96[a]	−2.74[a]	−0.72	0.36	1.42	3.13[a]
DJIA								
Pseudo R^2	0.131	0.102	0.065	0.05	0.003	0	0.003	0.013
t-stat	−2.85[a]	−3.02[a]	−2.87[a]	−2.95[a]	−0.82	0.26	1.07	2.16[b]
NAPMC								
Pseudo R^2	0.151	0.04	0.049	0.025	0.006	0.001	0	0.004
t-stat	−4.34[a]	−3.01[a]	−3.02[a]	−2.12[b]	0.93	−0.28	0.17	1.02
VP								
Pseudo R^2	0.074	0.013	0.014	0.006	0.016	0.012	0.006	0.008
t-stat	−2.78[a]	−1.56	−1.61	−0.95	1.87	1.65	1.48	1.32
CORD								
Pseudo R^2	0.084	0.027	0.001	0.001	0.002	0.002	0.003	0
t-stat	−3.99[a]	−3.14[a]	−0.48	−0.62	0.77	0.66	0.66	−0.04
HI								
Pseudo R^2	0.086	0.085	0.171	0.056	0.014	0.003	0	0
t-stat	−2.20[b]	−2.48[b]	−4.94[a]	−2.40[b]	−0.77	−0.77	−0.37	−0.08
CEXP								
Pseudo R^2	0.03	0.047	0.024	0.039	0.001	0	0.005	0
t-stat	−1.41	−2.17[b]	−1.78	−2.28[b]	−0.39	−0.05	−0.71	0.01
TWD								
Pseudo R^2	0.007	0.015	0.006	0.005	0.011	0.003	0	0.003
t-stat	0.90	1.57	0.72	0.49	0.81	0.48	0.20	−0.89
MORD								
Pseudo R^2	0.016	0	0.014	0.044	0.045	0.029	0.016	0.001
t-stat	−0.92	0.05	0.84	1.64	1.69	1.45	1.21	0.40
LEAD								
Pseudo R^2	0.236	0.132	0.112	0.018	0.005	0	0.006	0.007
t-stat	−3.01[a]	−2.57[b]	−2.51[b]	−1.48	−0.85	−0.12	0.94	0.70
XLI								
Pseudo R^2	0.387	0.332	0.205	0.103	0.056	0.022	0.006	0.001
t-stat	−6.14[a]	−2.85[a]	−2.28[b]	−2.32[b]	−2.26[b]	−1.54	−0.65	−0.23
XLI2								
Pseudo R^2	0.239	0.091	0.059	0.002	0.008	0.011	0.012	0.017
t-stat	−4.25[a]	−3.54[a]	−2.99[a]	−0.53	1.04	0.82	0.78	0.78
GDPG1								
Pseudo R^2	0.160	0.093	0.008	0.002	0.008	0.007	0.015	0.003
t-stat	−3.02[a]	−3.13[a]	−0.95	−0.62	−0.99	0.70	0.71	0.36
CPI								
Pseudo R^2	0.172	0.130	0.156	0.147	0.094	0.084	0.062	0.059
t-stat	4.33[a]	3.63[a]	3.86[a]	3.38[a]	3.19[a]	3.73[a]	2.41[b]	2.10[b]

Notes: [a] Significant at the 1% level.
[b] Significant at the 5% level.

TABLE A2.—MEASURES OF FIT AND t-STATISTICS FOR PROBIT MODEL VARIABLES WITH SPREAD, IN SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t} + \alpha_2 SPREAD_t)$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
CPTB								
Pseudo R^2	0.142	0.233	0.272	0.307	0.285	0.165	0.102	0.051
t-stat	1.86	1.06	0.32	−1.14	−2.28[b]	−2.25[b]	−2.27[b]	−1.99[b]
t-stat sp	−2.20[b]	−4.71[a]	−5.19[a]	−3.90[a]	−3.37[a]	−4.29[a]	−3.69[a]	−2.06[b]
BILL								
Pseudo R^2	0.145	0.271	0.305	0.314	0.263	0.153	0.081	0.033
t-stat	2.27[b]	1.69	1.37	1.17	1.00	0.74	0.60	0.38
t-stat sp	−1.04	−2.44[b]	−2.98[a]	−3.36[a]	−3.19[a]	−2.99[a]	−2.36[b]	−1.43
BOND								
Pseudo R^2	0.145	0.271	0.305	0.314	0.263	0.153	0.081	0.033
t-stat	2.27[b]	1.69	1.37	1.17	1.00	0.74	0.60	0.38
t-stat sp	−2.30[b]	−3.16[a]	−3.93[a]	−4.05[a]	−3.70[a]	−3.91[a]	−3.03[a]	−1.66
M0								
Pseudo R^2	0.072	0.216	0.271	0.298	0.257	0.152	0.083	0.066
t-stat	0.37	0.76	−0.17	−0.48	−0.27	0.69	0.91	2.44[b]
t-stat sp	−2.66[a]	−4.28[a]	−4.86[a]	−4.73[a]	−3.77[a]	−4.10[a]	−3.14[a]	−1.92
M1								
Pseudo R^2	0.105	0.215	0.282	0.298	0.272	0.155	0.083	0.047
t-stat	−2.64[a]	−1.02	−1.28	0.57	1.19	0.70	0.71	1.32
t-stat sp	−2.26[b]	−4.10[a]	−4.49[a]	−4.54[a]	−3.97[a]	−4.11[a]	−3.40[a]	−2.11[b]
M2								
Pseudo R^2	0.093	0.231	0.295	0.297	0.281	0.177	0.093	0.055
t-stat	−1.63	−1.17	−1.19	0.31	1.48	1.84	1.21	1.39
t-stat sp	−2.57[b]	−4.11[a]	−4.39[a]	−4.68[a]	−3.81[a]	−4.35[a]	−4.08[a]	−2.40[b]
M3								
Pseudo R^2	0.076	0.223	0.29	0.299	0.259	0.18	0.11	0.074
t-stat	−0.70	−0.98	−0.99	−0.39	0.36	1.39	1.52	1.73
t-stat sp	−2.66[a]	−4.19[a]	−4.24[a]	−4.45[a]	−3.80[a]	−4.10[a]	−3.30[a]	−1.87
RM0								
Pseudo R^2	0.154	0.213	0.283	0.309	0.258	0.151	0.081	0.033
t-stat	−3.17[a]	−0.50	−0.90	−1.01	−0.43	−0.54	−0.53	−0.12
t-stat sp	−0.47	−3.26[a]	−3.27[a]	−3.37[a]	−3.65[a]	−3.19[a]	−2.31[b]	−1.60
RM1								
Pseudo R^2	0.21	0.226	0.294	0.297	0.27	0.15	0.078	0.033
t-stat	−3.40[a]	−1.81	−1.84	−0.21	1.44	0.14	−0.05	−0.01
t-stat sp	−0.41	−3.76[a]	−4.55[a]	−4.36[a]	−4.68[a]	−3.44[a]	−2.69[a]	−1.70
RM2								
Pseudo R^2	0.183	0.242	0.304	0.298	0.271	0.153	0.078	0.033
t-stat	−3.62[a]	−2.08[b]	−2.28[b]	−0.54	1.54	0.72	0.11	−0.04
t-stat sp	−1.33	−4.39[a]	−5.11[a]	−4.72[a]	−4.34[a]	−3.97[a]	−3.38[a]	−1.96
RM3								
Pseudo R^2	0.141	0.239	0.306	0.306	0.258	0.157	0.083	0.035
t-stat	−2.60[a]	−1.91	−1.88	−1.06	0.47	0.78	0.54	0.32
t-stat sp	−2.29[b]	−4.50[a]	−4.77[a]	−4.55[a]	−4.38[a]	−4.26[a]	−4.04[a]	−2.32[b]
NYSE								
Pseudo R^2	0.223	0.32	0.321	0.314	0.261	0.159	0.096	0.083
t-stat	−3.54[a]	−4.81[a]	−2.32[b]	−1.57	0.92	1.17	1.71	3.69[a]
t-stat sp	−2.00[b]	−4.01[a]	−5.13[a]	−4.89[a]	−3.77[a]	−3.67[a]	−2.90[a]	−2.09[b]
SP500								
Pseudo R^2	0.217	0.319	0.319	0.312	0.264	0.165	0.103	0.085
t-stat	−3.39[a]	−4.48[a]	−2.25[b]	−1.59	1.29	1.64	2.26[b]	4.06[a]
t-stat sp	−1.99[b]	−4.03[a]	−5.18[a]	−4.88[a]	−3.72[a]	−3.70[a]	−3.04[a]	−2.18[b]
DJIA								
Pseudo R^2	0.177	0.282	0.303	0.315	0.266	0.166	0.098	0.063
t-stat	−3.39[a]	−3.70[a]	−2.01[b]	−1.75	1.48	1.60	1.92	3.25[a]
t-stat sp	−1.99[b]	−4.20[a]	−4.96[a]	−4.70[a]	−3.99[a]	−3.70[a]	−2.89[a]	−1.99[b]
NAPMC								
Pseudo R^2	0.182	0.217	0.28	0.297	0.343	0.156	0.086	0.046
t-stat	−3.99[a]	−1.18	−1.26	−0.20	4.97[a]	0.71	1.54	2.44[b]

TABLE A2.—(CONTINUED)

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t} + \alpha_2 SPREAD_t)$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
t-stat sp	−1.82	−3.86[a]	−4.37[a]	−4.17[a]	−3.76[a]	−4.04[a]	−3.21[a]	−1.94
VP								
Pseudo R^2	0.119	0.211	0.271	0.297	0.342	0.194	0.099	0.051
t-stat	−2.48[b]	−0.14	−0.09	0.19	3.87[a]	2.90[a]	3.09[a]	2.66[a]
t-stat sp	−2.38[b]	−4.05[a]	−4.39[a]	−4.31[a]	−4.56[a]	−5.08[a]	−3.60[a]	−1.98[b]
CORD								
Pseudo R^2	0.144	0.233	0.271	0.296	0.273	0.156	0.087	0.033
t-stat	−3.91[a]	−2.41[b]	0.50	0.11	1.53	1.35	1.37	0.31
t-stat sp	−2.43[b]	−4.01[a]	−4.81[a]	−4.49[a]	−4.27[a]	−4.20[a]	−3.26[a]	−1.69
HI								
Pseudo R^2	0.113	0.225	0.326	0.297	0.272	0.163	0.086	0.037
t-stat	−1.65	−1.12	−3.29[a]	−0.24	1.10	1.53	1.33	0.97
t-stat sp	−1.90	−3.74[a]	−4.49[a]	−4.06[a]	−4.35[a]	−3.65[a]	−2.80[a]	−1.67
CEXP								
Pseudo R^2	0.088	0.245	0.283	0.322	0.261	0.154	0.078	0.034
t-stat	−0.97	−1.67	−0.96	−1.35	0.54	0.49	−0.15	0.58
t-stat sp	−2.48[b]	−4.01[a]	−4.41[a]	−3.80[a]	−3.98[a]	−3.98[a]	−2.67[a]	−1.54
TWD								
Pseudo R^2	0.111	0.288	0.358	0.374	0.318	0.206	0.121	0.063
t-stat	0.37	0.25	−0.84	−0.75	0.00	−0.29	−0.53	−1.53
t-stat sp	−2.86[a]	−4.37[a]	−4.41[a]	−3.78[a]	−3.72[a]	−4.20[a]	−3.42[a]	−2.03[b]
MORD								
Pseudo R^2	0.143	0.258	0.282	0.296	0.257	0.15	0.079	0.034
t-stat	−2.43[b]	−1.88	−0.89	0.04	0.27	0.29	0.27	−0.29
t-stat sp	−3.18[a]	−3.37[a]	−4.21[a]	−3.96[a]	−3.24[a]	−3.23[a]	−2.16[b]	−1.36
LEAD								
Pseudo R^2	0.256	0.283	0.331	0.296	0.265	0.16	0.106	0.054
t-stat	−3.11[a]	−2.40[b]	−2.07[b]	−0.08	1.44	1.03	1.48	1.22
t-stat sp	−1.42	−4.16[a]	−4.74[a]	−4.33[a]	−4.07[a]	−3.81[a]	−3.52[a]	−2.57[b]
XLI								
Pseudo R^2	0.43	0.35	0.298	0.297	0.274	0.179	0.106	0.047
t-stat	−4.68[a]	−1.96	−1.21	0.27	1.84	1.57	1.29	0.96
t-stat sp	2.09[b]	−1.18	−2.73[a]	−3.40[a]	−4.62[a]	−3.93[a]	−3.46[a]	−2.48[b]
XLI2								
Pseudo R^2	0.289	0.268	0.298	0.302	0.356	0.21	0.121	0.07
t-stat	−4.25[a]	−2.80[a]	−1.80	0.50	2.95[a]	1.09	1.27	1.20
t-stat sp	−2.51[b]	−4.15[a]	−4.55[a]	−3.70[a]	−4.43[a]	−2.91[a]	−3.96[a]	−2.83[a]
GDPG1								
Pseudo R^2	0.228	0.318	0.275	0.296	0.264	0.160	0.103	0.037
t-stat	−3.54[a]	−3.74[a]	−0.69	−0.07	−0.62	0.60	0.70	0.42
t-stat sp	−2.53[b]	−4.35[a]	−4.84[a]	−4.52[a]	−3.89[a]	−3.92[a]	−3.42[a]	−1.75
CPI								
Pseudo R^2	0.173	0.222	0.279	0.301	0.256	0.156	0.091	0.062
t-stat	3.55[a]	1.31	1.07	0.65	0.03	1.08	1.16	1.61
t-stat sp	−0.39	−3.73[a]	−4.14[a]	−3.66[a]	−3.39[a]	−2.87[a]	−1.88	−0.60

Notes: [a] Significant at the 1% level.
[b] Significant at the 5% level.

TABLE A3.—MEASURES OF FIT FOR PROBIT MODEL VARIABLES BY THEMSELVES, OUT OF SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t})$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
SPREAD	0.072	0.236	0.328	0.295	0.155	0.141	−0.052	−0.205
CPTB	−0.121	−0.201	−0.496	−0.087	−0.015	−0.018	−0.085	−0.114
BILL	0.078	0.101	0.070	−0.016	0.004	0.066	0.018	−0.077
BOND	−0.015	−0.041	−0.079	−0.110	−0.104	−0.099	−0.145	−0.182
M0	−0.018	−0.038	−0.078	−0.048	−0.052	−0.043	−0.039	−0.116
M1	0.040	−0.001	−0.048	−0.058	−0.054	−0.128	−0.289	−0.589
M2	−0.075	−0.167	−0.341	−0.196	−0.126	−0.033	−0.031	−0.045
M3	−0.039	−0.179	−1.149	−0.651	−0.278	−0.035	0.006	0.038
RM0	0.157	0.073	−0.173	0.176	0.101	0.097	−0.061	−0.311
RM1	0.169	0.048	−0.340	−0.017	−0.023	0.042	−0.282	−1.152
RM2	0.129	0.061	−0.242	−0.018	−0.058	−0.005	−0.025	−0.169
RM3	0.093	−0.010	−0.323	−0.131	−0.135	−0.069	−0.083	−0.194
NYSE	0.161	0.077	0.075	0.016	−0.022	−0.015	−0.018	0.028
SP500	0.159	0.073	0.068	0.018	−0.018	−0.010	−0.008	0.027
DJIA	0.137	0.036	0.024	0.009	−0.016	−0.017	−0.019	0.001
NAPMC	0.195	0.046	0.005	−0.018	−0.028	−0.029	−0.003	−0.008
VP	0.095	0.007	0.015	−0.019	0.007	0.002	0.001	−0.012
CORD	0.078	−0.006	−0.009	−0.005	−0.011	−0.004	−0.016	−0.014
HI	0.105	0.098	0.205	0.047	−0.056	−0.009	−0.003	−0.021
CEXP	−0.097	−0.201	−0.949	−0.038	−0.128	−0.179	−0.194	−0.068
TWD	−0.056	−0.028	−0.091	−0.269	−1.155	−0.525	−0.313	−0.523
MORD	−0.200	−0.174	−0.100	−0.014	−0.006	−0.008	−0.003	−0.022
LEAD	0.121	−0.328	−0.196	−0.036	−0.024	−0.014	−0.038	−0.097
XLI	0.324	0.141	−0.140	0.015	0.067	0.016	−0.070	−0.200
XLI2	0.196	0.028	−0.030	−0.033	−0.001	−0.132	−0.095	−0.244
GDPG1	0.065	−0.002	−0.015	−0.023	−0.040	−0.032	−0.113	−0.075
CPI	0.153	0.111	−0.181	0.058	−0.231	−0.183	0.015	−0.127

Note: For each model, pseudo R^2 is shown.

TABLE A4.—MEASURES OF FIT FOR PROBIT MODEL VARIABLES WITH SPREAD, OUT OF SAMPLE

	$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 x_{1t} + \alpha_2 SPREAD_t)$							
	k = Quarters Ahead							
x_{1t} Variables	1	2	3	4	5	6	7	8
CPTB	−0.157	−0.088	−0.257	0.153	0.105	0.140	−0.088	−0.362
BILL	0.046	0.101	0.046	0.145	0.095	0.064	−0.224	−0.479
BOND	0.046	0.101	0.046	0.145	0.095	0.064	−0.224	−0.479
M0	0.059	0.223	0.230	0.157	−0.100	0.118	−0.043	−0.418
M1	0.078[a]	0.211	0.249	0.230	0.110	−0.095	−0.257	−1.012
M2	−0.059	−0.002	0.000	0.207	0.114	0.127	0.002[a]	−0.668
M3	0.018	−0.243	−3.239	−0.117	0.081	0.141	−0.002	−0.729
RM0	0.127[a]	0.176	−0.222	0.171	−0.013	0.114	−0.123	−0.755
RM1	0.106[a]	0.199	−0.066	0.201	0.128	0.089	−0.376	−1.716
RM2	0.010	0.131	−0.073	0.225	0.148	0.130	−0.097	−0.670
RM3	0.083[a]	0.031	−19.753	0.181	0.161[a]	0.134	−0.088	−0.753
NYSE	0.208[a]	0.316[a]	0.367[a]	0.274	0.161[a]	0.120	−0.126	−0.501
SP500	0.205[a]	0.314[a]	0.359[a]	0.277	0.161[a]	0.133	−0.097	−0.483
DJIA	0.172[a]	0.248[a]	0.318	0.292	0.153	0.079	−0.167	−0.571
NAPMC	0.205[a]	0.222	0.265	0.233	−0.740	0.090	−0.038	−0.490
VP	0.128[a]	0.212	0.306	0.256	0.190[a]	0.193[a]	−0.022	−0.532
CORD	0.127[a]	0.224	0.322	0.279	0.170[a]	0.148[a]	−0.061	−0.510
HI	0.114[a]	0.237[a]	0.400[a]	0.254	0.126	0.137	−0.079	−0.694
CEXP	−0.044	0.034	−0.593	0.244	−0.195	−0.065	−0.377	−0.733
TWD	−0.003	0.005	−0.048	0.073[a]	−15.160	−0.131	−0.319	−0.752
MORD	−0.137	−0.213	0.030	0.115	−0.010	0.016	−0.170	−0.762
LEAD	0.079[a]	−0.006	0.149	0.254	0.121	0.081	−0.263	−0.792
XLI	−4.427	0.136	0.015	0.192	−0.055	−0.131	−1.029	−0.831
XLI2	0.252[a]	0.270[a]	0.311	0.139	−1.560	−0.973	−1.281	−0.726
GDPG1	0.120[a]	0.186	0.301	0.230	0.047	0.071	−0.618	−0.551
CPI	0.122[a]	0.200	0.021	0.160	−0.162	−0.187	−0.146	−0.576

Notes: For each model, pseudo R^2 is shown.
[a] Additional variable improves fit.

TABLE A5.—CORRELATION MATRIX

	SPREAD	*CPTB*	*RM0*	*NYSE*	*LEAD*	*XLI*	*XLI2*
CPTB	−0.281						
RM0	0.608	−0.232					
NYSE	0.189	−0.330	0.242				
LEAD	0.294	−0.419	0.421	0.392			
XLI	0.611	−0.649	0.602	0.299	0.638		
XLI2	0.158	−0.389	0.285	0.153	0.694	0.639	
GDPG1	0.058	−0.161	0.077	−0.095	0.252	0.353	0.298

APPENDIX B

Description of Data

This section contains a detailed description of the paper's data and data sources. A list of variable descriptions is followed by information about the transformations applied to the basic series.

Interest Rates and Spreads

SPREAD 10-year Treasury bond minus 3-month Treasury bill (*BOND* − *BILL*).
BILL 3-month Treasury bill, market yield, bond equivalent.
BOND 10-year Treasury bond.
CPTB 6-month commercial paper rate minus 6-month Treasury bill rate. The 6-month commercial paper rate is an average of offering rates on commercial paper placed by several leading dealers for firms whose bond rating is AA or the equivalent. The 6-month Treasury bill is market yield, bond equivalent.

Stock Prices

DJIA Dow Jones 30 industrials price index, monthly average dollar price at New York Stock Exchange close.
NYSE New York Stock Exchange composite price index, monthly average price at close.
SP500 Standard and Poor's 500 composite index, monthly average.

Monetary Aggregates

M0 Monetary base, monthly averages of daily figures, seasonally adjusted and adjusted for changes in reserve requirements.
M1 M1, seasonally adjusted.
M2 M2, seasonally adjusted.
M3 M3, seasonally adjusted.
RM0 Monetary base deflated by consumer price index (CPI), seasonally adjusted.
RM1 M1 deflated by CPI, seasonally adjusted.
RM2 M2 deflated by CPI, seasonally adjusted.
RM3 M3 deflated by CPI, seasonally adjusted.

Individual Macroeconomic Indicators

GDPG1 Real GDP, lagged one quarter, seasonally adjusted at annual rates.
CPI Consumer price index, all urban consumers, all items, seasonally adjusted.
NAPMC National Association of Purchasing Managers' Survey composite index, seasonally adjusted.
VP Vendor performance, slower deliveries diffusion index, percent, seasonally adjusted.
CORD Contracts and orders for plant and equipment, seasonally adjusted.
HI Index of new private housing units authorized by local building permits, seasonally adjusted.
CEXP Composite index of consumer expectations (University of Michigan), not seasonally adjusted.
TWD Trade-weighted exchange value of U.S. dollar versus G-10 countries.
MORD Change in manufacturers' unfilled orders, durable goods, smoothed, seasonally adjusted.

Indexes of Leading Indicators

LEAD Commerce Department, composite index of 11 leading indicators, seasonally adjusted.
XLI Stock–Watson (1989) leading index.
XLI2 Stock–Watson (1993) leading index.

All the basic series are monthly except GDP, which is quarterly. Interest rates and spreads are converted to quarterly average levels. Stock price indexes and *TWD* are converted to quarterly averages and then to one-quarter growth rates. *MORD* is the sum of values for three months divided by the previous quarter's GDP level. *XLI* and *XLI2* are the values of the index for the last available month. All other data are lagged according to availability (see table 1) and then converted to one-quarter growth rates. Values for all series are those currently available from the sources listed below.

Data Sources

The three-month and six-month Treasury bill rates and the ten-year Treasury bond rate were obtained from an internal data source at the Federal Reserve Bank of New York. They correspond to constant maturity data published by the Federal Reserve Board. The Stock–Watson leading indexes were obtained from Professor Stock at Harvard University, to whom we are grateful. All other data come from the Haver Analytics Database, US-ECON.