International Journal of Forecasting 17 (2001) 383–401
international journal of forecasting
www.elsevier.com/locate/ijforecast

Predicting US recessions with leading indicators via neural network models

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Abstract

This paper examines the relevance of various financial and economic indicators in predicting US recessions via neural network models. We share the view that business cycles are asymmetric and cannot be adequately accommodated by linear constant-parameter single-index models. We employ a novel neural network (NN) to recursively model the relationship between the leading indicators and the probability of a future recession. The out-of-sample results show that via the NN model indicators, such as interest rate spread, Department of Commerce leading index, Stock and Watson index, and S&P500 index are useful in predicting US recessions, including the most recent one in the early 1990s. Furthermore, when the out-of-sample forecasting period is divided into three subperiods, we find that the relevance of various leading indicators may change from time to time.

Keywords: Recession; Business cycle; Leading indicators; Forecasting; Neural networks

1. Introduction

Despite of its obvious importance, prediction of recessions continues to be a tough task with limited success in economic analysis. Although new developments have emerged in the field of business cycles and economic indicators[1], none of the existing models is foolproof.

The dynamic single-index model is a linear time-invariant model and the selection and weighting of leading indicator variables is likewise based on linear regression methods. Whereas Sims (1989) expresses disappointment at the use of a model without time-varying coefficients, Wallis (1993) expresses reservation concerns its linearity. These are related since a linear approximation to a nonlinear model in general has time varying (or more precisely, state-dependent) coefficients. Moreover, in statistical modeling of the business cycle, it has been well established that the cycles are asymmetric. Therefore, it is doubtful that linear constant-parameter models can adequately accommodate the business cycles. It is also com-

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[1]See Auerbach (1982); Gordon (1986); Kling (1987); Koch and Rasche (1988); Diebold and Rudebusch (1989); Hamilton (1989); Klein (1990); Zarnowitz (1992); Lahiri and Wang (1994); and Estrella and Mishkin (1998), to name just a few.

0169-2070/01/$ – see front matter
PII: S0169-2070(01)00092-9

monly noted that the models need to be extended from the univariate to the multivariate settings since the business cycle is about comovements in a broad range of macroeconomic aggregates.

To avoid the aforementioned pitfalls of the widely used linear constant-parameter models, in the present study we adopt a novel modeling technique, neural networks (NNs), to forecast business cycles. NNs can provide a flexible functional mapping between variables, thus have the potential to fundamentally change the way various indicators are used to predict future business cycles.

Due to their powerful pattern recognition ability, neural networks have been widely used in science, engineering, medical, and business applications. Proposed primarily outside the fields of statistics and econometrics, NN models have attracted more and more attention from statisticians and econometricians in recent years[2]. Generally speaking, NNs are nonlinear nonparametric models that can flexibly and accurately approximate almost any functional forms. This property makes them an ideal modeling tool for studies in which there exists very little a priori knowledge about the appropriate functional representation of the relationship under investigation. While NNs have demonstrated success in several financial applications[3], there are very few economic studies that utilize neural networks. Swanson and White (1995, 1997a,b) find that nonlinear neural networks are useful in economic time series forecasting. The time series variables they investigated include interest rate, unemployment, GNP, etc.

While there has been a fairly large amount of research completed in the area of NNs, as well as of leading indicators and business cycle forecasting. Up to now, there has been only one study by Vishwakarma (1994) that uses a neural network to recognize business cycle turning points[4], in which the dates of business cycle peaks and troughs identified by a state space neural network agree closely with the official chronology. However, Vishwakarma (1994) is essentially an in-sample model fitting exercise with no out-of-sample prediction results. Moreover, his choice of the four key indicators is ad hoc without including any interest rates, monetary aggregates or financial market indices that have been found important in recent literature. No one has yet used neural networks to study, in a systematic way, the relevance of various leading indicators for predicting the US business cycles out of sample. Given that NNs have shown success in many areas of applications, and the limited success of the traditional models in the business cycle literature, we try to fill this gap in the current literature. Since little is known about the true underlying functional form through which various leading economic indicators are related to economic recessions, NN models seem to be appealing. A brief technique description of NN models will be given in the methodology section.

Using NNs, we examine the usefulness of various financial and economic variables in predicting the US recessions in a flexible nonlinear setting. We experiment with eight forecasting horizons from 1 to 8 quarters, and with a wide array of candidate variables: interest rates

[2]See, for example, Ripley (1994) surveys neural networks and related methods for classification; Kuan and White (1994) discuss NNs and their applications in economics; Qi (1996) reviews some financial applications of NN models.

[3]See, for example, option pricing (Hutchinson et al., 1994; Garcia & Gencay, 2000), stock market prediction (Gencay, 1998; Qi, 1999; Qi & Maddala, 1999), and exchange rate forecasting (Gencay, 1999).

[4]We thank one anonymous referee for providing the reference to Vishwakarma (1994).

and spreads, stock price indexes, monetary aggregates, individual macro indicators, indexes of leading indicators, both by themselves and in some plausible combinations. In contrast to most of the literature except for Stock and Watson (1993); Lahiri and Wang (1994, 1996); Estrella and Mishkin (1998); and Birchenhall et al. (1999), we aim at predicting recessions rather than on quantitative values of future economic variables. We focus on out-of-sample rather than in-sample performance because the latter can always be improved by including more variables or employing more complex models. To allow for possible structural change, when making ex ante predictions all models are updated quarterly. Our research design is somewhat ad hoc in that the data and experimental design are intended to be the same as in Estrella and Mishkin (1998) except that we use the NN model instead of their probit. The present study thus offers an opportunity to assess the robustness of their results, as well as to evaluate the forecast performance of NN models compared to the more traditional probit model[5]. Furthermore, we divide the entire out-of-sample period into three subperiods to evaluate the relative performance of various indicators from time to time.

To summarize our empirical results up front, we find that among the 27 indicators investigated, the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill is the single best predictor of the US economic recessions. It generates the smallest out-of-sample mean squared forecast errors at 2- to 6-quarter forecast horizons. When other indicators, such as Stock and Watson (1989) leading index, commercial paper–treasury spread, the S&P500 index, Department of Commerce leading indicator, real money supply, and NYSE index, etc., are combined with the spread, the out-of-sample performance can be improved further. Moreover, we find that the best predictors of the recessions in the 1970s or 1980s may not still be the best in the 1990s. This may help explain the failure of some of the existing business cycle models in predicting the most recent recession in the early 1990s, since these models try to use the same set of variables to predict all recessions.

The remainder of this paper is organized as follows. In the next section, we describe the NN model used to generate the predictions and the measurement to be employed to evaluate the performance. Section 3 lists and describes the indicators that are investigated in this study. In Section 4 we report the out-of-sample prediction results. Concluding remarks and further discussions are offered in Section 5.

2. Methodology

Since NN is a relatively new modeling approach, we briefly explain it in Subsection 2.1. Subsection 2.2 describes the design of the forecasting experiment and the performance measure used in the comparison of out-of-sample prediction performance.

2.1. Neural networks

NNs are a class of flexible nonlinear models inspired by the way in which the human brain processes information. Given an appropriate number of hidden-layer units, NNs can approximate any nonlinear (or linear) function to an arbitrary degree of accuracy through the composition of a network of relatively simple

[5]Of course, limiting the number and combinations of explanatory variables is likely to hinder the potential of any forecasting models. As stated in Section 5, we can expand the number of explanatory variables, and experiment with more combinations in future studies.

functions (see Hornik et al., 1989; and White, 1990, among others). The flexibility and simplicity of NNs have made them a popular modeling and forecasting tool across different research areas in recent years.

A variety of different NN models have thus been developed, among which the three-layer feedforward network is the most widely used and is adopted in the present study. Let f be the unknown underlying function (linear or nonlinear) through which a vector of explanatory variables $X = (x_1, x_2, \ldots, x_k)'$ relates to the dependent variable y, i.e., $y = f(X)$. Then f can be approximated by a three-layer NN model. Fig. 1 depicts a typical three-layer feedforward NN.

The NN model can be written as two layers of logistic functions:

$$f(X) = g\left[\alpha_0 + \sum_{j=1}^{n} \alpha_j g\left(\sum_{i=1}^{k} \beta_{ij} x_i + \beta_{0j}\right)\right] + \varepsilon \tag{1}$$

where n is the number of units in the hidden layer, k is the number of explanatory variables, g is a logistic transfer function defined as $g(a) = 1/(1 + e^{-a})$, $\{\alpha_j,\ j = 0,1, \ldots, n\}$ represents a vector of parameters from the hidden- to the output-layer units, $\{\beta_{ij}, i = 0,1, \ldots, k, j = 0,1,..,n\}$ denotes a matrix of parameters from the input- to the hidden-layer units, and ε is the error term. The error term ε can be made arbitrarily small if sufficiently many explanatory variables are included and if n is chosen to be large enough. However, if n is too large, the model may overfit in which case the in-sample errors can be made very small but the out-of-sample errors may be large. The choice of n depends on the number of explanatory variables and the nature of the underlying relationship between y and X. Because the number of explanatory variables in each of our NN models is never greater than 2, we fix n to be 3.

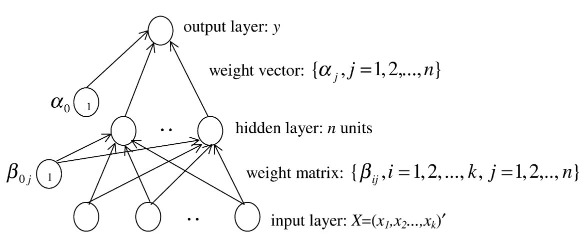

Fig. 1. A three-layer feedforward neural network.

The parameter values in Eq. (1) are chosen to minimize the sum of squared errors, $\Sigma\varepsilon^2$. In general there is no analytical solution to this minimization problem and the parameters have to be estimated numerically. Because the Levenberg–Marquardt algorithm is by far the fastest algorithm for moderate-sized (up to several hundred free parameters) feedforward NNs, we use it to estimate the parameters. Due to the relatively large number of parameters and the nonlinearity inherent in the NN model specification, the objective function is unlikely to be globally convex and thus can have many local minima. To insure that the global minimum is obtained, at the beginning of each recursive estimation the NN model is estimated 10 times based on 10 sets of initial values. The model that generates the smallest sum of square errors is used to make out-of-sample forecasts, and its parameter estimates are used as initial values in the recursive estimation that follows. Finally, the initial values of the parameters are generated with Nguyen and Widrow's (1990) method in which the initial values are assigned such that the active regions of the layer's units are roughly evenly distributed over the range of the explanatory variable space. The benefit is that fewer units are wasted and that the network converges faster compared to purely random initial parameter values.

2.2. *Ex ante out-of-sample forecast and performance measure*

For a given data set with T observations, the out-of-sample forecasts for a given horizon h

are constructed by first estimating the NN model (1) with data up through date $t_0 < T$, so that the last observation used is (y_{t_0}, X_{t_0-h}). Let $(\hat{\alpha}^h_{t_0}, \hat{\beta}^h_{t_0})$ be the parameters estimated with these observations. The first h-horizon forecast is computed from[6]

$$\hat{y}_{t_0+h} = g\left[\hat{\alpha}^h_{0,t_0} + \sum_{j=1}^{3} \hat{\alpha}^h_{j,t_0} g\left(\sum_{i=1}^{k} \hat{\beta}^h_{ij,t_0} x_{i,t_0} + \hat{\beta}^h_{0j,t_0} \right) \right] \quad (2)$$

This procedure is repeated for $t_0 + 1$, $t_0 + 2, \ldots, T - h$, thus yielding N forecasts, where $N = T - t_0 - h + 1$. Our sample starts from the second quarter of 1967 to the first quarter of 1995, a total of 112 quarterly observations ($T = 112$). The indicators are used to predict whether the US economy is going to have a recession 1 to 8 quarters in the future ($h = 1, 2, 3, \ldots, 8$). For all forecasting horizons and for all indicators, the out-of-sample forecasts begin in the first quarter of 1972 and end in the first quarter of 1995, yielding a total of 93 forecasts ($N = 93$). This time frame is the same as that in Estrella and Mishkin (1998) where a probit model is used to predict US recessions.

For dichotomous dependent variable (DDV) models, many goodness of fit measures have been proposed. Estrella (1998) gives a comprehensive list of nine different measures that can be categorized into two broad categories: probability based, and moment based. For the former, the measures are based on the maximum likelihood statistics. For the latter, they are based on the first and second moments of the actual and fitted values of the dependent variable, y and $\hat{y}$. In our model, the unconstrained likelihood is occasionally zero, rendering the log-likelihood and log-likelihood based goodness of fit measures undefined. Therefore, we simply use a moment-based measure of fit, mean squared forecast errors (*MSFE*) as in Hamilton and Perez-Quiros (1996)[7]:

$$MSFE = N^{-1} \sum_{t=t_0+h}^{T} (y_t - \hat{y}_t)^2 \quad (3)$$

A simple benchmark prediction of the recession probability can be easily constructed by letting $\hat{y}$ be a constant equal to the historical fraction of quarters for which the economy was in a recession: $\hat{y}_t = N^{-1}\Sigma_{t=t_0+h}^{T} y_t$. A forecasting model can be considered as successful at identifying turning points if its *MSFE* beats the benchmark prediction.

3. Data

The standard National Bureau of Economic Research (NBER) recession dates are used to determine the values of y, the recession dummy that equals 1 (recession) or 0 (otherwise). The whole sample consists of quarterly data from the second quarter in 1967 to the first quarter in 1995, a total of 112 observations, among which there are 18 recessions[8]. To make our NN results comparable to those of the probit model

[6] Granger and Teräsvirta (1993) contain a good discussion on the advantages and disadvantages of five alternative ways of producing multi-step forecasts from nonlinear models. These include naïve, exact, Monte Carlo, bootstrap, and direct methods. The one used here is the direct method that is fairly easy to use but it does involve building a new model for each forecasting horizon. Moreover, with the direct method, the forecasting error is not usually a white noise but may have temporal relationships. Nevertheless, this is not a problem in the present study since we do not make any statistical inference based on the forecasting errors.

[7] We thank an anonymous referee for suggesting this measure to us.

[8] We would like to thank Arturo Estrella for his kindness in providing all the data used in the present study.

of Estrella and Mishkin (1998), our out-of-sample forecasts also start from the first quarter of 1972 and end in the first quarter of 1995, a total of 93 predictions that include 14 recessions.

The primary goal of this paper is to investigate what financial or economic variables (if any) are useful predictors of future recessions through a flexible nonlinear NN model. Thus we study an extensive list of all the 27 indicators examined in Estrella and Mishkin (1998) that consists of 4 interest rate and spread variables, 3 stock price indices, 8 monetary aggregates, 9 individual macro indicators, and 3 indices of leading indicators. While some variables, such as interest rates and stock prices, are available instantly, many macroeconomic variables are available 1 or 2 months after the sample quarter, and GDP has a lag of almost 1 quarter. To make forecasts in an ex ante fashion, only observations actually available at the end of a given quarter are used for that quarter. The data have the same definitions, informational lags, and sources as those given in Estrella and Mishkin (1998). Table 1 lists the names, codes, informational lags, as well as descriptions for all the indicators.

4. Empirical results

The out-of-sample forecasts are made in a recursive fashion to capture possible structural changes in the economy. First, a NN model is estimated using data from the beginning of the sample up to a particular quarter, say, 1971.IV. Then the parameters are used to make the prediction for 1972.I for the 1-quarter horizon prediction, or the 1972.II for the 2-quarter prediction horizon, and so on. Next, one more observation is added to the sample, i.e., the data up to 1972.I are used to reestimate the NN model. Then the parameters are used to make prediction for 1972.II for the 1-quarter horizon prediction, for 1972.III for the 2-quarter horizon prediction, and so on and so forth. Although time consuming, the recursive procedure generates predictions in a real time fashion in that information that becomes available after the prediction date is not used to estimate the model parameters or predict the recession. Subsection 4.1 reports the out-of-sample results for the entire forecasting period from 1972.I to 1995.I. Subsection 4.2 compares the relevance of various leading indicators in three subperiods: 1970s (1972.I to 1979.IV), 1980s (1980.I to 1989.IV), and 1990s (1990.I to 1995.I). Finally, Subsection 4.3 discusses a few cases of out-of-sample predictions.

4.1. Out-of-sample results in the entire forecasting period

Table 2 reports the out-of-sample *MSFE* for each of the individual indicators listed in Table 1, 1–8 quarters in the future. The first column gives the ranking, and the second and third columns give the codes of the indicators and their corresponding *MSFE*s (sorted in an ascending order) for the 1-quarter horizon prediction. Columns 4 and 5 give the codes of the indicators and their corresponding *MSFE*s for the 2-quarter horizon prediction, and so on and so forth. There are a number of interesting findings based on the *MSFE*s reported in this table. First, across all eight forecast horizons, while the recessions are more predictable 1–4 quarters ahead by some individual indicators, 5–8 quarters ahead, none of the individual indicators seems to be able to beat the benchmark prediction, the *MSFE* of which is 0.1279. Second, while x_{24}, the Stock and Watson (1989) leading index (*XLI*, the coding is listed in Table 1) is the best individual predictor at 1 quarter horizon (the out-of-sample *MSFE* is 0.098), x_1, the *SPREAD* variable tends to dominate 2–6

Table 1
Summary information about indicator variables

Indicator	Code	Lag (month)	Description
			Interest rates and spreads
SPREAD	1	0	10-year treasury bond rate – 3-month treasury bill rate
CPTB	2	0	6-month commercial paper rate – 6-month treasury bill rate
BILL	3	0	3-month treasury bill, market yield, bond equivalent
BOND	4	0	10-year treasury bond
			Monetary aggregates
M0	5	1	Monetary base, monthly averages of daily figures, seasonally adjusted (SA)
M1	6	1	M1, SA
M2	7	1	M2, SA
M3	8	1	M3, SA
RM0	9	1	Monetary base deflated by CPI, SA
RM1	10	1	M1 deflated by CPI, SA
RM2	11	1	M2 deflated by CPI, SA
RM3	12	1	M3 deflated by CPI, SA
			Stock prices
NYSE	13	0	New York Stock Exchange composite index
SP500	14	0	Standard and Poor's 500 composite index, monthly average
DJIA	15	0	Dow Jones 30 industrials index, monthly average at close
			Individual macro indicators
NAPMC	16	0	Purchasing Managers' Survey composite index, SA
VP	17	0	Vendor performance, slower deliveries diffusion index, SA
CORD	18	1	Contracts and orders for plant and equipment, SA
HI	19	1	New private housing permits, SA
CEXP	20	0	Consumer expectations (MI), NSA
TWD	21	0	Trade-weighted dollar vs. G-10 countries
MORD	22	1	Change in manufacturers' unfilled durable goods orders, SA
CPI	26	1	Consumer price index, all urban consumers, all items, SA
GDPG1	27	3	Growth in real GDP, lagged 1 quarter, SA
			Indexes of leading indicators
LEAD	23	2	Commerce Department composite index of 11 leading indicators, SA
XLI	24	1	Stock and Watson (1989) leading index
XLI2	25	1	Stock and Watson (1993) leading index

quarters ahead. These two observations largely agree with those of Estrella and Mishkin (1998) although a probit model rather than a flexible NN model was used in their study[9]. Third, within 1- to 4-quarter horizons, only 10 out of the 27 indicators can generate a smaller MSFE than the benchmark prediction. These are *SPREAD* (2–4 quarters ahead), Department of Commerce leading indicator, NYSE index, and S&P500 index (1 and 3 quarters ahead), Stock and Watson (1989) leading index, *CPTB*, *RM3*,

[9]Note, however, that a different performance measure was used in Estrella and Mishkin (1998).

Table 2
Out-of-sample *MSFE* of individual indicators (x_i, $i=1, 2, \ldots, 27$), 1–8 quarters ahead, 1972.I to 1995.I[a]

Rank	$h=1$		$h=2$		$h=3$		$h=4$		$h=5$		$h=6$		$h=7$		$h=8$	
	i		i		i		i		i		i		i		i	
1	24	**0.098**	1	**0.115**	1	**0.100**	1	**0.097**	1	0.138	1	0.172	21	0.151	4	0.151
2	14	**0.100**	10	**0.127**	23	**0.122**	24	0.144	21	0.150	17	0.172	4	0.162	19	0.161
3	23	**0.108**	24	0.129	13	**0.122**	10	0.154	19	0.156	16	0.182	11	0.179	27	0.177
4	13	**0.109**	2	0.130	14	**0.124**	14	0.155	15	0.183	21	0.183	25	0.194	18	0.186
5	2	**0.116**	3	0.133	2	0.137	2	0.158	22	0.194	25	0.187	2	0.203	17	0.194
6	12	**0.118**	26	0.133	26	0.137	13	0.188	16	0.204	9	0.194	13	0.226	23	0.210
7	25	**0.122**	19	0.134	24	0.140	15	0.190	8	0.204	10	0.210	27	0.229	26	0.215
8	18	**0.123**	15	0.138	18	0.144	12	0.198	5	0.205	13	0.215	18	0.230	16	0.226
9	26	0.131	13	0.146	3	0.145	27	0.202	13	0.212	8	0.247	1	0.237	10	0.226
10	27	0.133	23	0.147	27	0.152	9	0.214	14	0.222	5	0.250	7	0.237	12	0.237
11	11	0.134	6	0.150	19	0.153	5	0.215	27	0.231	18	0.255	15	0.250	25	0.241
12	3	0.144	18	0.151	16	0.154	18	0.228	10	0.238	23	0.266	23	0.258	8	0.250
13	9	0.144	14	0.151	17	0.158	25	0.237	24	0.258	19	0.269	16	0.258	24	0.255
14	22	0.146	25	0.152	11	0.161	16	0.249	2	0.263	24	0.284	17	0.265	13	0.269
15	15	0.147	27	0.157	15	0.171	23	0.250	6	0.280	7	0.305	10	0.269	11	0.277
16	10	0.148	16	0.165	7	0.174	6	0.266	26	0.285	6	0.313	6	0.301	2	0.281
17	16	0.148	22	0.166	20	0.177	19	0.267	20	0.302	11	0.319	9	0.301	7	0.291
18	19	0.149	5	0.169	25	0.181	7	0.269	25	0.312	22	0.323	24	0.333	6	0.301
19	17	0.152	8	0.173	9	0.181	22	0.275	9	0.340	14	0.359	19	0.366	1	0.301
20	1	0.153	9	0.175	10	0.186	26	0.284	23	0.357	2	0.411	3	0.380	15	0.301
21	21	0.157	4	0.179	6	0.194	4	0.290	7	0.429	27	0.430	22	0.409	9	0.323
22	6	0.157	7	0.183	22	0.195	11	0.301	18	0.430	26	0.451	20	0.430	5	0.355
23	7	0.169	12	0.184	4	0.197	8	0.323	17	0.471	20	0.452	8	0.462	3	0.387
24	5	0.170	11	0.184	8	0.201	20	0.344	12	0.500	15	0.538	14	0.462	14	0.419
25	8	0.170	20	0.186	5	0.207	3	0.419	3	0.548	12	0.546	5	0.548	21	0.433
26	4	0.183	17	0.202	12	0.218	17	0.450	11	0.548	3	0.602	26	0.559	20	0.495
27	20	0.187	21	0.222	21	0.238	21	0.518	4	0.828	4	0.839	12	0.645	22	0.516

[a] Note: The bold numbers are smaller than the *MSFE* of the benchmark prediction made based on the ex post probability of the recession (0.1279).

Stock and Watson (1993) leading index, and *CORD* (1 quarter ahead), and *RM1* (2 quarters ahead). Finally, based on *MSFE*, among all the 27 individual indicators and across all the 8 forecast horizons, the US recessions are most predictable 4 quarters ahead by *SPREAD*, with a *MSFE* of 0.097.

Since *SPREAD* is the best single indicator for most forecasting horizons, we include it in the NN model together with one other indicator listed in Table 1. The results of the two-indicator NN models are given in Table 3. The structure of Table 3 is the same as that of Table 2 except that it shows the *MSFE* of the two-variable NN models (one of the two indicators is always *SPREAD*). The results are summarized below. First, when the yield curve spread is combined with other indicators, at forecast horizons of 1 through 4 quarters, power losses are common and gains are rare. In particular, at 1-quarter horizon none of the indicators gains predictive power when combined with *SPREAD*. At 2-quarter horizon, only two indicators (*XLI* and *CPTB*) when combined with

Table 3
Out-of-sample *MSFE* of *SPREAD* and another indicator (x_i, $i=2, 3, \ldots, 27$), 1–8 quarters ahead, 1972.I and 1995.I[a]

Rank	***h*=1**		***h*=2**		***h*=3**		***h*=4**		***h*=5**		***h*=6**		***h*=7**		***h*=8**	
	1, *i*		**1**, *i*		**1**, *i*		**1**, *i*		**1**, *i*		**1**, *i*		**1**, *i*		**1**, *i*	
1	13	**0.119**	24	**0.095**	14	**0.108**	23	**0.086**	9	**0.108**	17	**0.118**	19	**0.125**	24	0.166
2	2	0.140	2	**0.108**	17	**0.118**	11	**0.086**	17	**0.109**	23	0.140	2	0.168	18	0.169
3	26	0.153	19	**0.118**	19	**0.118**	14	**0.097**	14	**0.118**	5	0.142	9	0.204	20	0.169
4	19	0.154	22	**0.118**	23	**0.118**	7	**0.097**	18	**0.118**	24	0.154	27	0.211	9	0.172
5	20	0.158	27	**0.118**	24	**0.118**	27	**0.100**	5	**0.118**	18	0.161	14	0.215	14	0.172
6	27	0.160	14	0.140	8	**0.118**	13	**0.101**	3	0.129	25	0.162	16	0.215	21	0.246
7	9	0.161	9	0.140	7	**0.125**	17	**0.108**	4	0.129	19	0.172	25	0.215	2	0.247
8	24	0.161	23	0.140	15	0.129	6	**0.108**	26	0.129	6	0.182	18	0.224	13	0.247
9	21	0.172	10	0.151	2	0.129	22	**0.108**	27	0.129	4	0.183	3	0.226	27	0.249
10	17	0.183	16	0.161	10	0.129	2	**0.108**	13	0.129	16	0.183	23	0.226	3	0.260
11	22	0.183	17	0.161	16	0.129	24	**0.117**	19	0.139	14	0.192	4	0.226	22	0.268
12	14	0.193	13	0.166	27	0.129	3	**0.118**	16	0.141	13	0.194	5	0.237	17	0.301
13	16	0.204	18	0.183	13	0.129	12	**0.118**	6	0.145	3	0.194	8	0.237	4	0.301
14	11	0.226	7	0.183	26	0.137	18	**0.118**	8	0.147	7	0.194	26	0.242	11	0.301
15	5	0.226	8	0.204	5	0.140	21	**0.118**	2	0.151	9	0.194	12	0.247	12	0.301
16	25	0.229	5	0.215	11	0.151	9	**0.119**	24	0.158	26	0.197	20	0.247	6	0.312
17	6	0.297	25	0.215	12	0.151	8	**0.119**	22	0.159	12	0.200	6	0.247	25	0.312
18	15	0.305	15	0.226	18	0.151	16	**0.121**	7	0.162	8	0.204	7	0.247	23	0.312
19	23	0.311	26	0.226	25	0.151	4	**0.125**	23	0.183	22	0.204	13	0.247	8	0.312
20	10	0.327	11	0.257	9	0.154	15	0.129	10	0.196	2	0.209	24	0.247	19	0.312
21	18	0.361	12	0.257	22	0.162	25	0.129	21	0.204	10	0.215	22	0.258	26	0.312
22	4	0.366	20	0.280	6	0.169	19	0.140	11	0.216	15	0.226	10	0.260	7	0.313
23	7	0.667	6	0.301	4	0.194	5	0.151	25	0.245	27	0.226	11	0.269	5	0.319
24	3	0.688	3	0.366	20	0.215	26	0.151	15	0.247	21	0.333	17	0.269	15	0.344
25	8	0.699	4	0.366	21	0.247	10	0.151	12	0.312	20	0.376	21	0.291	16	0.475
26	12	0.713	21	0.495	3	0.250	20	0.177	20	0.387	11	0.537	15	0.516	10	0.480

[a] Note: The bold numbers are smaller than the *MSFE* of the benchmark prediction made based on the ex post probability of the recession (0.1279).

SPREAD, generate smaller *MSFE* than *SPREAD* along. At 3-quarter forecast horizon, only *S&P* 500 index, when combined with *SPREAD*, get better fit than *SPREAD* or *S&P* 500 index along. At the 4-quarter horizon, except for *LEAD* and *RM2*, the rest of the indicators, when combined with *SPREAD* show no improvement in the out-of-sample fit of the individual indicators. This may be because *SPREAD* alone already does very well at these horizons. Moreover, as pointed by Estrella and Mishkin (1998), the Stock–Watson index and Department of Commerce leading index are partly based on *SPREAD*, so that there is little additional information in these measures out of sample. This suggests the importance of the parsimonious principle. A combination model using two redundant variables even variables that are good individual predictors, may produce worse predictions than does each variable on its own.

Second, at the horizons of 5–8 quarters, none of the individual indicators beats the benchmark *MSFE*, however, when combined with the yield curve spread, a minimum of 6 (at 6-quarter horizon) to a maximum of 10 (at 5- and 8-

quarter horizons) paired indicators show improvement of different degrees. And more importantly, at 5- to 7-quarter horizons, at least one pair of indicators beats the benchmark prediction. Third, it should be noted that although at the 8-quarter horizon when combined with *SPREAD* 10 indicators show some gain in the out-of-sample accuracy, none of them beats the benchmark prediction. Therefore, recessions are still largely unpredictable at the 8-quarter horizon by either the individual or paired indicators considered in this study. Finally, from 1972.I to 1995.I, across all forecasting horizons and among all individual and paired indicators, recessions are most predictable 4 quarters ahead by *LEAD*/*SPREAD* and *RM2*/*SPREAD*, the *MSFE* of both pairs (0.086) is the smallest.

4.2. Out-of-sample results in the three subperiods

Although the results reported in the previous subsection may indicate the relevance of various indicators in the entire forecasting periods, it does not provide direct information on whether and how the importance of various indicators change over time. Therefore, we report in Tables 4 and 5 the *MSFE* and the rankings of various predictors in three subperiods: 1970s, 1980s, and 1990s. Since none of the individual indicators seems to be able to beat the benchmark prediction at 5- to 8-quarter horizons, to economize on space we only report the results for 1- to 4-quarter horizons. Each table has three panels to represent the three subperiods[10]. The *MSFE* of the simple benchmark prediction in the three subperiods are 0.1318, 0.1488, and 0.0554, respectively.

Table 4 gives the *MSFE* and the rankings of all individual indicators. From Table 4, we observe the following. First, the out-of-sample forecasting accuracy of various indicators tends to change from subperiod to subperiod. For example, at the 1-quarter forecast horizon, Stock and Watson (1989) index (x_{24}) ranked No.1 in the entire forecasting period and in the 1st subperiod, it ranked the 5th and 9th in the 2nd and 3rd subperiods, respectively. The ranking changes even more dramatically for *SPREAD* at 2-quarter forecast horizon. At the 2-quarter forecast horizon, though *SPREAD* is the best in the entire out-of-sample forecast period and ranked the 2nd in the first subperiod, it failed to beat the benchmark in the 1980s and 1990s. Though *SPREAD* is the best in the entire forecasting period at horizons of 2–6 quarters, it is the best only at 4-quarter horizon in the 1970s and 1980s.

Second, even at the same forecasting horizon, the best predictors in the three subperiods are rarely the same. For example, at the 1-quarter horizon, Stock and Watson (1989) index is the best in the 1970s, but Department of Commerce leading index takes its place in the 1980s, and in the 1990s, they both give way to the *S&P500* index.

Third, although certain indicators can beat the benchmark prediction at all four horizons in certain subperiods or at certain horizons in all three subperiods, none of them beats the benchmark at all four horizons and in all three subperiods. For example, Stock and Watson (1989) index beats the benchmark at all four horizons but only in the 1980s, and *NYSE*, *S&P500*, and Stock and Watson (1989) indices beat the benchmark in all three subperiods but only at the 1-quarter horizon.

Similar patterns are observed with Table 5 where the *MSFE* and rankings of the two-indicator NN model are reported. The implication of these findings is that the best predictor of the US recessions at one time or one forecasting horizon may not necessarily be the best at other

[10]We thank one anonymous referee for suggesting this way of organizing tables.

Table 4
Out-of-sample *MSFE* and rankings of individual indicators (x_i, $i=1, 2, \ldots, 27$), 1–4 quarters ahead, in three subperiods[a]

x_i	Panel A. 1972.I to 1979.IV								Panel B. 1980.I to 1989.IV								Panel C. 1990.I to 1995.I							
	h=1		**h=2**		**h=3**		**h=4**		**h=1**		**h=2**		**h=3**		**h=4**		**h=1**		**h=2**		**h=3**		**h=4**	
	MSFE	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank
1	0.166	17	**0.081**	2	**0.047**	2	**0.094**	1	0.155	12	0.162	10	0.155	6	**0.114**	1	0.122	25	0.059	9	0.059	6	0.059	5
2	**0.093**	3	**0.073**	1	**0.110**	4	0.169	5	0.155	13	0.201	23	0.183	14	0.179	6	**0.054**	10	**0.055**	6	0.066	8	0.085	9
3	0.164	16	0.138	6	**0.100**	3	0.312	20	0.173	20	0.164	12	0.212	22	0.591	27	**0.029**	3	**0.045**	3	0.059	5	0.176	16
4	0.25	27	0.199	19	0.220	20	0.281	17	0.175	21	0.204	24	0.231	25	0.250	14	0.076	17	0.078	13	0.067	9	0.412	20
5	0.193	24	0.198	18	0.217	19	0.313	21	0.190	24	0.191	21	0.229	24	0.205	10	0.076	16	0.058	8	0.129	22	0.059	6
6	0.164	15	0.194	16	0.261	24	0.341	23	0.173	19	**0.142**	4	0.201	19	0.268	16	0.105	22	0.089	15	**0.050**	1	0.118	12
7	**0.088**	2	**0.086**	3	0.156	11	0.156	3	0.242	27	0.246	27	0.221	23	0.295	18	0.133	26	0.201	26	0.084	14	0.412	21
8	0.164	13	0.151	11	0.139	8	0.156	4	0.195	25	0.175	16	0.183	15	0.364	23	0.118	23	0.208	27	0.362	27	0.529	26
9	0.155	11	0.259	24	0.222	21	0.303	19	0.167	17	0.156	8	0.177	13	0.210	11	0.065	13	0.067	12	0.114	20	0.059	7
10	0.224	26	**0.122**	5	0.150	9	0.198	8	**0.137**	9	0.168	13	0.250	27	0.166	4	**0.034**	4	**0.028**	1	0.088	16	**0.041**	2
11	**0.098**	4	0.228	23	**0.118**	5	0.250	15	0.172	18	0.189	20	0.208	21	0.364	24	0.104	21	0.090	16	0.123	21	0.235	18
12	**0.099**	5	0.169	14	0.274	25	0.219	10	0.159	14	0.223	26	0.206	20	0.190	9	**0.048**	8	0.112	21	0.145	24	0.176	14
13	**0.104**	6	0.141	8	0.134	7	0.216	9	**0.145**	10	0.169	14	**0.133**	4	0.216	13	**0.023**	2	0.096	19	0.073	12	0.062	8
14	**0.104**	7	0.171	15	**0.124**	6	0.175	6	**0.129**	6	0.170	15	**0.113**	1	0.157	3	**0.013**	1	0.067	11	0.154	26	0.111	10
15	0.185	22	0.164	13	0.172	13	0.233	14	0.162	16	0.152	7	0.198	18	0.211	12	**0.038**	6	**0.051**	4	0.099	18	**0.052**	3
16	0.164	14	0.195	17	0.189	15	0.181	7	0.160	15	0.186	19	0.156	7	0.299	20	0.087	18	**0.054**	5	0.082	13	0.244	19
17	0.169	19	0.308	27	0.195	17	0.433	26	0.184	23	0.181	18	0.165	9	0.387	25	**0.037**	5	0.056	7	0.068	10	0.645	27
18	0.151	10	0.141	7	0.153	10	0.315	22	**0.123**	4	0.180	17	0.169	12	0.184	8	0.068	14	0.095	18	0.062	7	0.176	15
19	0.158	12	0.151	10	0.247	23	0.256	16	0.180	22	**0.142**	3	**0.123**	2	0.329	21	**0.048**	7	0.079	14	**0.052**	3	0.125	13
20	0.183	21	0.272	25	0.229	22	0.281	18	0.227	26	**0.149**	5	0.166	10	0.341	22	0.091	20	0.122	23	0.106	19	0.471	25
21	0.219	25	0.291	26	0.314	27	0.665	27	**0.147**	11	0.210	25	0.239	26	0.451	26	0.069	15	0.123	24	0.094	17	0.415	22
22	0.192	23	0.205	21	0.305	26	0.383	25	**0.116**	2	0.160	9	0.167	11	0.280	17	0.137	27	0.108	20	0.058	4	0.059	4
23	**0.125**	9	**0.094**	4	**0.029**	1	0.133	2	**0.116**	1	0.198	22	0.185	16	0.253	15	0.056	11	0.116	22	0.134	23	0.464	24
24	**0.083**	1	0.156	12	0.205	18	0.229	13	**0.128**	5	**0.135**	2	**0.128**	3	**0.125**	2	**0.049**	9	0.065	10	**0.050**	2	**0.034**	1
25	**0.107**	8	0.150	9	0.191	16	0.226	12	**0.135**	8	0.163	11	0.187	17	0.170	5	0.119	24	0.129	25	0.146	25	0.432	23
26	0.167	18	0.205	22	0.167	12	0.353	24	**0.133**	7	**0.121**	1	**0.141**	5	0.298	19	0.059	12	**0.029**	2	0.071	11	0.117	11
27	0.174	20	0.201	20	0.180	14	0.222	11	**0.121**	3	0.150	6	0.157	8	0.181	7	0.088	19	0.090	17	0.084	15	0.218	17

[a] Note: The bold numbers are smaller than the *MSFE* of the benchmark prediction made based on the ex post probability of recession in the corresponding subperiod (0.1318, 0.1488, and 0.0554, respectively, in the three subperiods).

Table 5
Out-of-sample *MSFE* and rankings of *SPREAD* and another indicator (x_i, $i=2, 3, \ldots, 27$), 1–4 quarters ahead, in three subperiods[a]

x_1, x_i	Panel A. 1972.I to 1979.IV								Panel B. 1980.I to 1989.IV								Panel C. 1990.I to 1995.I							
	***h*=1**		***h*=2**		***h*=3**		***h*=4**		***h*=1**		***h*=2**		***h*=3**		***h*=4**		***h*=1**		***h*=2**		***h*=3**		***h*=4**	
	MSFE	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank	*MSFE*	Rank
2	**0.063**	1	**0.063**	2	**0.125**	10	**0.125**	10	0.227	12	0.159	4	**0.136**	2	**0.114**	9	0.059	6	0.059	1	0.118	24	0.060	23
3	0.656	26	0.188	10	0.219	23	**0.125**	11	0.818	26	0.614	25	0.345	26	**0.136**	14	0.412	23	0.059	2	0.061	23	0.059	4
4	0.406	21	0.188	11	0.219	24	**0.125**	12	0.455	22	0.614	26	0.227	23	**0.149**	19	0.059	7	0.059	3	0.059	2	0.060	24
5	0.313	15	0.219	15	**0.094**	4	0.156	20	0.227	13	0.273	20	0.205	17	0.182	21	0.059	8	0.059	4	0.059	3	0.059	5
6	0.396	19	0.250	19	**0.063**	1	0.156	21	0.227	11	0.341	22	0.290	24	**0.091**	1	0.294	21	0.293	25	0.059	4	0.059	6
7	0.531	23	0.281	21	**0.112**	9	**0.094**	6	0.659	23	0.159	5	0.159	7	**0.114**	6	0.941	25	0.062	20	0.059	5	0.059	7
8	0.531	24	0.219	14	0.156	20	**0.125**	13	0.727	25	0.205	15	**0.114**	1	**0.137**	18	0.941	26	0.176	23	0.059	6	0.059	8
9	0.188	6	**0.062**	1	**0.125**	11	**0.125**	19	0.182	3	0.227	16	0.212	19	**0.137**	17	0.059	9	0.059	5	0.059	7	0.059	9
10	0.419	22	0.188	12	0.156	19	0.156	22	0.341	19	0.159	6	**0.136**	3	0.182	24	0.118	18	0.059	6	0.059	8	0.059	10
11	0.375	17	0.219	16	**0.125**	12	**0.094**	1	0.182	4	0.361	23	0.205	18	**0.091**	2	0.059	10	0.059	7	0.059	9	0.059	11
12	0.596	25	0.500	26	0.188	22	**0.125**	14	0.711	24	0.157	3	0.159	8	**0.136**	15	0.941	24	0.059	8	0.059	10	0.059	12
13	**0.075**	2	0.250	20	**0.094**	8	**0.094**	2	0.197	7	**0.146**	2	0.182	15	**0.127**	11	**0.002**	1	0.059	9	0.059	11	**0.046**	3
14	0.206	11	**0.125**	7	**0.063**	3	**0.125**	8	0.236	15	0.182	11	0.159	9	**0.091**	3	0.059	5	0.059	10	0.059	12	0.059	13
15	0.350	16	0.219	17	0.156	18	**0.094**	5	0.308	18	0.227	17	**0.136**	4	0.182	22	0.211	20	0.235	24	0.059	13	0.059	14
16	0.219	12	0.156	9	**0.125**	13	0.156	23	0.250	16	0.182	12	0.159	10	**0.115**	10	0.059	11	0.118	22	0.059	14	0.068	26
17	0.156	5	0.188	13	**0.125**	14	**0.125**	9	0.250	17	0.182	13	**0.136**	5	**0.114**	7	0.059	12	0.059	11	0.059	15	0.059	15
18	0.274	13	0.283	22	**0.094**	5	**0.125**	15	0.406	21	0.159	7	0.227	20	0.159	20	0.409	22	0.059	12	0.059	16	**0.000**	2
19	0.198	10	**0.094**	4	**0.094**	6	0.187	24	0.175	2	0.159	8	0.159	11	**0.136**	13	**0.015**	2	0.059	13	0.059	17	0.059	16
20	**0.124**	3	0.375	24	0.187	21	0.188	25	0.197	8	0.296	21	0.227	21	0.213	26	0.118	17	0.059	14	0.235	26	0.062	25
21	0.188	7	0.500	25	0.219	25	**0.125**	16	0.205	10	0.523	24	0.295	25	**0.136**	16	0.059	13	0.412	26	0.176	25	0.059	17
22	0.188	8	**0.094**	5	0.220	26	**0.125**	17	0.227	14	0.159	9	0.159	12	**0.114**	8	0.059	14	0.059	15	0.059	18	0.059	18
23	0.406	20	**0.125**	8	**0.063**	2	**0.094**	3	0.341	20	0.182	14	0.182	16	**0.091**	4	0.056	4	0.059	16	0.059	19	0.059	19
24	0.188	9	**0.088**	3	**0.125**	15	**0.125**	18	0.182	5	**0.115**	1	**0.136**	6	**0.133**	12	0.059	15	0.059	17	0.059	20	0.059	22
25	0.385	18	0.233	18	**0.094**	7	**0.094**	4	0.182	6	0.250	19	0.227	22	0.182	25	0.059	16	0.091	21	0.059	21	0.059	20
26	0.283	14	0.313	23	**0.125**	16	0.188	26	**0.109**	1	0.227	18	0.178	14	0.182	23	**0.021**	3	0.059	18	**0.051**	1	**0.000**	1
27	**0.125**	4	**0.094**	6	**0.125**	17	**0.118**	7	0.201	9	0.159	10	0.159	13	**0.104**	5	0.118	19	0.059	19	0.059	22	0.059	21

[a] Note: The bold numbers are smaller than the *MSFE* of the benchmark prediction made based on the ex post probability of recession in the corresponding subperiod (0.1318, 0.1488, and 0.0554, respectively, in the three subperiods).

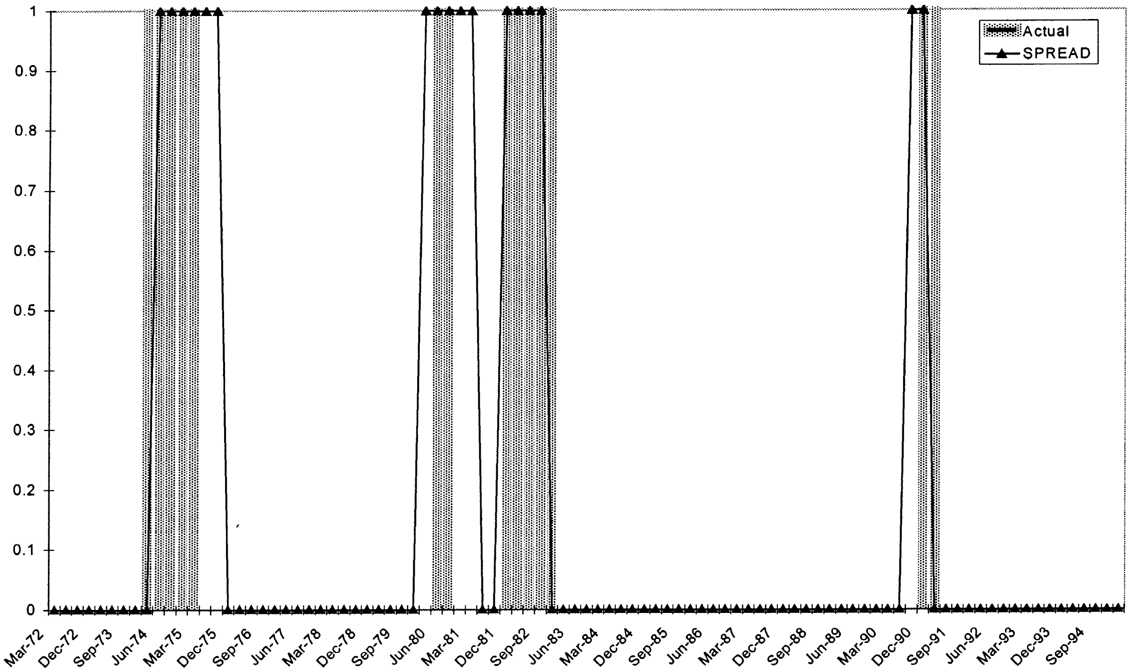

Fig. 2. Probability of recession, 4 quarters ahead, *SPREAD*, 1972.I to 1995.I.

times or other forecasting horizons. It may be unrealistic for people to believe the existence of a single model that will work the best at all times and at all forecasting horizons. Researchers should always take the effort to check on the possible structural change in the economy.

4.3. Case study on the out-of-sample prediction

To get a feel about the performance of various individual indicators and indicator pairs, we plot the out-of-sample predicted probabilities of a recession over time. Due to the space limit, we show only the cases of 4- and 5-quarter horizon predictions by *SPREAD*, *LEAD*, and *S&P500* index[11]. In Figs. 2–5, the shaded bars indicate the recessions that happened in the US economy and the black triangles represent the predicted probabilities of a recession. From these figures, it is obvious that unlike the probabilities often obtained from some other models, such as the probit model (see, for example, Figs. 1–4 in Estrella and Mishkin (1998)), or the Markov switching model (e.g., Figs. 2 and 4 in Lahiri and Wang (1994), and Fig. 2(b) and (d) of Birchenhall et al. (1999)), the NN predicted probabilities almost always take values of either 0 or 1. Consequently, if we were to make a prediction on whether a recession or an expansion is likely to happen in the future, it would not be very sensitive to the choice of cutoff values. Therefore, we would not face a big trade-off between the type I and type II errors when choosing the cutoff value. As can be seen from these figures, there are a total of four recession periods in our prediction period. The first one began in 1974.I

[11]Interested readers can email the author to request the results of other indicators and at other forecasting horizons.

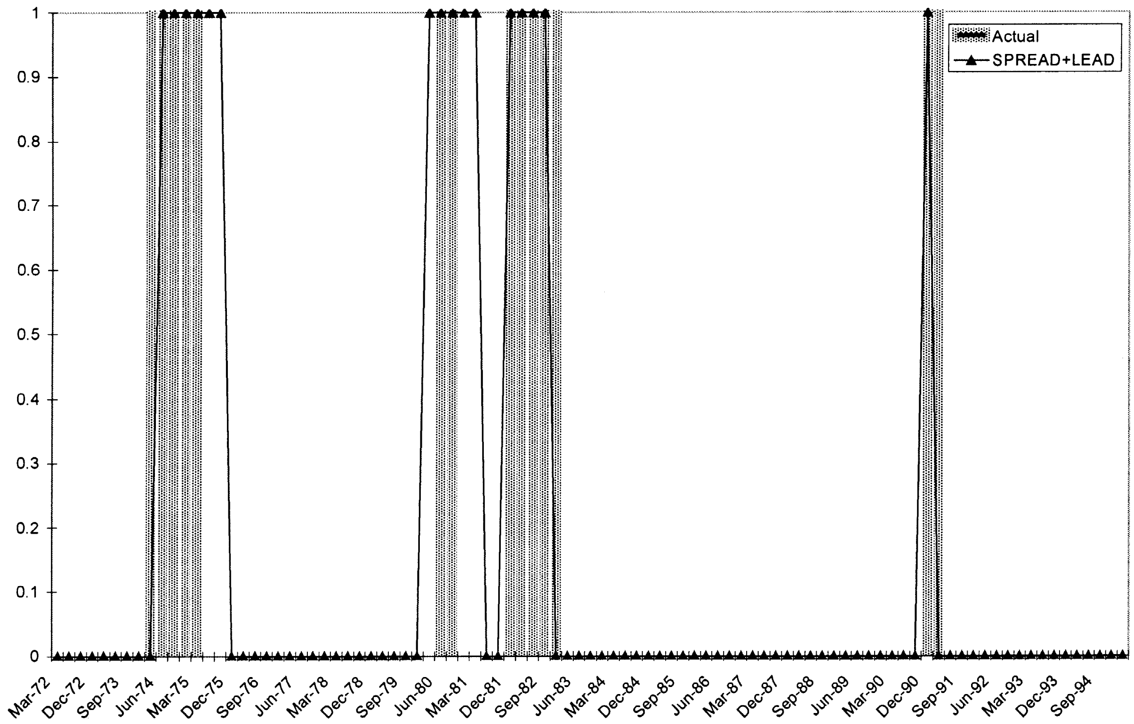

Fig. 3. Probability of recession, 4 quarters ahead, *SPREAD* and *LEAD*, 1972.I to 1995.I.

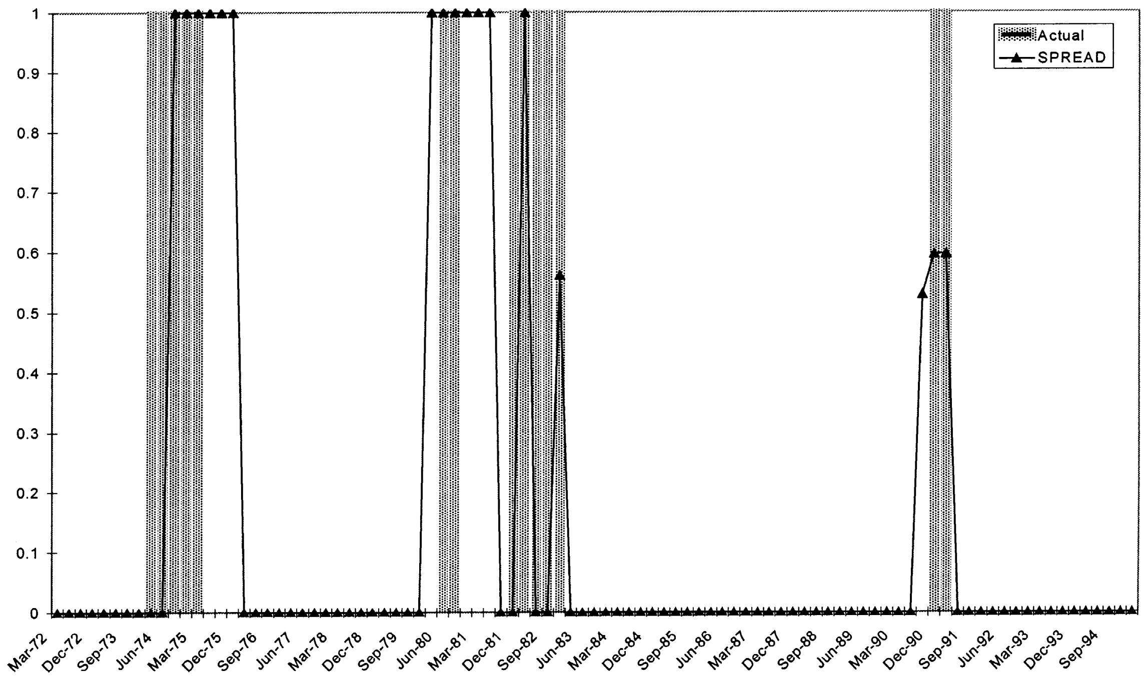

Fig. 4. Probability of recession, 5 quarters ahead, *SPREAD*, 1972.I to 1995.I.

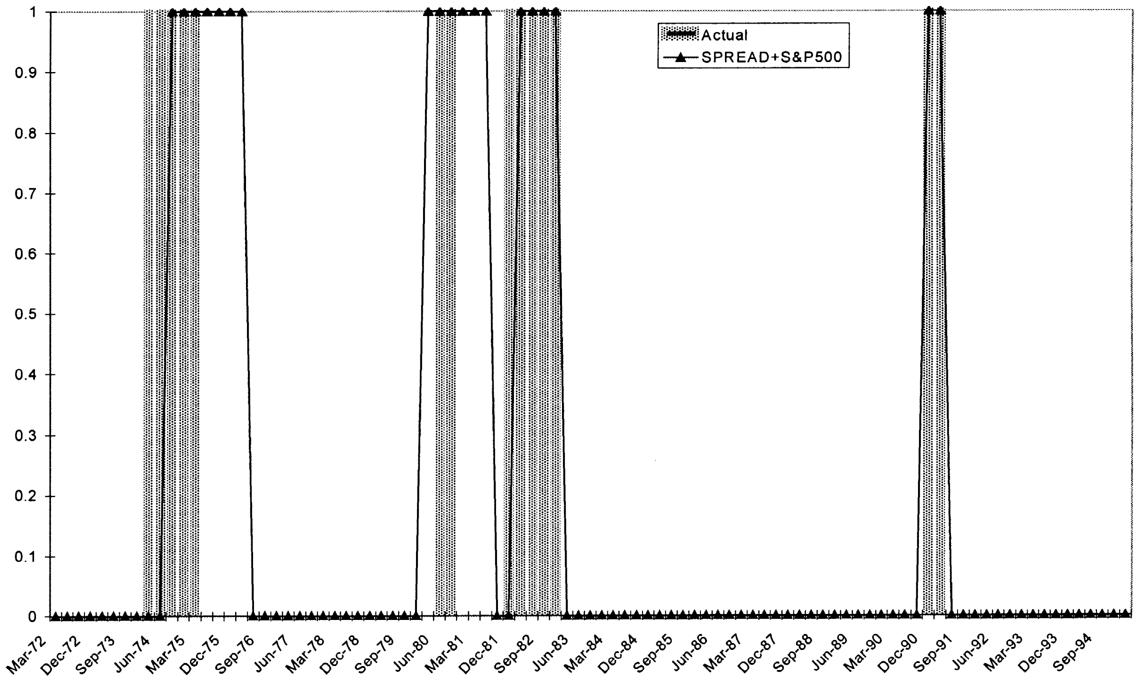

Fig. 5. Probability of recession, 5 quarters ahead, *SPREAD* and *S&P500*, 1972.I to 1995.I.

and ended in 1975.I. The second one happened briefly in 1980.II and 1980.III. The third recession happened one year after the second and lasted until 1982.IV. Finally, the last recession stroke briefly between 1990.IV and 1991.I.

Fig. 2 gives the 4-quarter horizon out-of-sample prediction by *SPREAD* itself. For the five consecutive quarters of the first recession period from 1974 to 1975, *SPREAD* can correctly predict it with a lag of only 1 quarter. It is commonly agreed that the recession in this period can be divided into two distinctive phases: November 1973 to September 1974, and October 1974 to April 1995. In the first phase, employment continued to grow and industrial production decreased only slightly. It was in the second phase that most of the decline in real economic activity actually took place. Therefore, *SPREAD* gives a closer signal to the outbreak of this second phase of the severe recession. For the brief recession period in 1980 (the second recession in our prediction period), *SPREAD* correctly predicts it with a lead of only 1 quarter. For the five consecutive quarters of recession from 1981 to 1982 (the third recession in our prediction period), *SPREAD* correctly predicts the first 4 quarters. Finally, for the most recent recession in the sample (from 1990 to 1991), *SPREAD* predicts with a lead of 1 quarter. The results are noteworthy because the 1990–1991 recession was associated with unusual events such as the invasion of Kuwait and was particularly difficult to predict. Most of the existing studies including Estrella and Mishkin (1998), Stock and Watson (1993) fail to predict it. Since our data set is the same as that in Estrella and Mishkin (1998), these results clearly demonstrate the relative richness of NN model over the usual probit model.

At the same horizon when the Department of Commerce leading index is combined with *SPREAD* (Fig. 3), it reduces the lead time by 1 quarter for the last recession, and the rest of the predicted probabilities are the same. Because the *LEAD*/*SPREAD* pair generates less false signals for recession than *SPREAD* along, the overall accuracy is improved.

Fig. 4 shows the predicted probability of recession at 5-quarter horizon by *SPREAD* along. It signals the first recession with a lag of 2 quarters, indicating that it successfully signaled the outbreak of the second phase of this severe recession. As with the 4-quarter horizon prediction, *SPREAD* predicts the second recession with a 1-quarter lead. For the third recession, however, it predicts with a lag of 1 quarter and missed 2 quarters thereafter. For the last recession in the 1990s, it correctly predicts it with a lead of 1 quarter. In Fig. 5, the results for the *S&P500*/*SPREAD* combination are shown. As can be seen when the *S&P500* index is included, the prediction accuracy has been greatly improved for the third and the fourth recession. The pair correctly predicts 4 out of 5 quarters of recession in the third recession period, and predicts the last recession perfectly.

From Figs. 2–5, we find that our NN model performs reasonably well in that it can predict all the four recessions occurred during the entire out-of-sample period with reasonable leads and lags. We also find that the prediction accuracy can be further enhanced when other indicators, such as *LEAD* or *S&P500* index, are combined with *SPREAD*.

5. Conclusion and discussion

It is commonly agreed among economists that business cycles are asymmetric and cannot be adequately accommodated by linear constant parameter single-index models. NNs are a class of flexible nonlinear models. Given enough data, they can approximate almost any functions arbitrarily close. Because there is little a priori knowledge about the true underlying function that relates financial, economic and composite indicators to the probability of future recessions, the NN models are an ideal choice for modeling these relationships. We employ NN to investigate the predictability of the US recessions, 1–8 quarters in the future, using a wide array of candidate variables including interest rates and spreads, stock price indexes, monetary aggregates, individual macro indicators, composite leading indexes, both by themselves and in some plausible combinations.

The out-of-sample results indicate that among the 27 indicators we investigated, the interest spread is the single best indicator of the US recessions 2–6 quarters in the future, based on the mean squared forecast errors. When other indicators, such as the Department of Commerce leading index, Stock and Watson (1989) index, real money supply, and S&P500 index, are combined with the spread, the out-of-sample prediction can be further improved. Using these indicators, the NN model can predict all the four recessions that occurred during our prediction period fairly well. The NN model is noteworthy in that it can correctly predict the most recent recession in the early 1990s, which was missed in most of the existing studies except Lahiri and Wang (1996) and Filardo (1999). Another feature of NN demonstrated in this study is that it can generate very clear signals of recessions and expansions. This makes the decision less sensitive to the choice of cutoff values. Therefore, we conclude that the flexible nonlinear NN models can be considered as a valuable addition to the toolbox of business cycle studies.

When the entire out-of-sample forecast period is divided into three subperiods, we find that the relevance of various indicators tends to change from time to time. In the three subperiods we investigated, the rankings of indicators rarely stay the same in the 1970s, 1980s, and 1990s across all the four forecasting horizons we looked at. The best predictor in certain subperiod and at certain forecasting horizon is unlikely to be the best in other subperiod or at other forecasting horizons. This finding suggests that researchers should at least be cautious when choosing the variables to predict recession in a particular period or at a particular horizon even if the same model is used. Particularly, since March 1991, the current expansion has become the longest on record in US history. It is not yet clear what impact this phenomenon will have on business cycle theory. Will the same model and the same set of indicators that worked in the past correctly predict the next recession?

Although our results are encouraging, the present study is still limited in many ways and can be extended in future work. First, we only use up to two indicators, and one of them is always the interest rate spread. From this point, the NN used in the present study is better considered as an alternative to the popular probability predicting models such as probit or Markov switching. More indicators can be experimented in the future. This is particularly important if we want to investigate whether NN could be an alternative to the dynamic factor models that typically rely on more than two variables. Second, in the present study, the number of hidden layer units is fixed at 3, overfitting may not be a serious problem because the number of indicators used in each model is either one or two. In future work, if more indicators are to be included in an NN model, certain cross validation procedures can be used to select the best model which has the optimal number of hidden layer units and contains the best set of indicators.

Acknowledgements

I thank Arturo Estrella for providing all the data used in this study. I am grateful to Barbara Craig, Michael Y. Hu, Kajal Lahiri (the editor), G.S. Maddala, Murali Shanker, Kathy Wilson, the two anonymous referees, and the participants of a seminar at University of Akron and a session of the 60th Annual Meeting of the Ohio Association of Economists and Political Scientists, for comments, suggestions, and discussions. I acknowledge with thanks the financial support from the Kent State University Research Council and College of Business Administration. Any remaining errors are my own responsibility.

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