Applied Financial Economics, 2001, **11**, 403–409

The term spread as a cyclical indicator: a forecasting evaluation

BRYAN L. BOULIER and H. O. STEKLER

Department of Economics, The George Washington University, Washington, DC 20052, USA
E-mail: mortile@gwu.edu

This paper questions whether the spread between long and short-term interests rates is a good cyclical indicator of US economic activity. Probit regressions using the term spread as an independent variable are used to forecast the probability of a recession and the forecasts are evaluated. Using alternative probability thresholds, the turns that were predicted, their timing and the number of recessions that were not forecast were identified and the tradeoff between the number of missed and false predictions is examined. A quantitative measure of the forecast errors is also used to compare the accuracy of probit forecasts with those of two naive standards. Finally, the term spread is evaluated purely as an indicator. It is concluded that this series, by itself, is not a reliable predictor of economic activity.

I. INTRODUCTION

Recently the Conference Board has taken over the calculation and publication of the Index of Leading Series for the United States. An interest rate spread, measured as the difference between the rates of the 90-day T-bill and the 10 year Treasury bond, is now one of the components of this index. This index is a plausible indicator of future economic activity. For example, a decline in the demand for investment will reduce long-term borrowing and thus interest rates on long-term bonds relative to short-run bonds, or tight monetary policy may force up short-run rates relative to long-term rates. More importantly, previous empirical research suggests that the time series of interest rate spreads has been associated to some extent with future levels of economic activity in the USA. (See Bernanke, 1990; Estrella and Hardouvelis, 1991; Friedman and Kuttner, 1998; Lahiri and Wang, 1996; Estrella and Mishkin, 1998).[1]

The conclusions in the existing literature about the value of the spread in predicting real economic activity were derived from several different approaches: (1) regressions of a measure of the economy that is to be predicted on the spread series; (2) probit regressions that yield probabilities that the economy will be in a recession in periods in the future; and (3) filter rules applied to a Markov process that also yield the probability of a recession. The first technique measures the overall quantitative relationship between the leading and coincident series while the other two are primarily concerned with the ability of the spread to predict whether a particular quarter will be a recessionary quarter.

In this paper, the theoretical arguments that make the spread a plausible indicator or predictor of economic recessions are not questioned. The intention is to merely evaluate the term spread to determine whether it is able to forecast turning points without making too many false predictions. Possible quantitative criteria for calling a turning point is therefore identified and then these criteria are used to evaluate the accuracy of the spread in predicting peaks and troughs of the business cycle.

The first section presents the results of previous research obtained from the regression and Markov process approaches and an evaluation of these findings. Since the probit methodology is the one most frequently used to judge the usefulness of the spread as a predictor of business cycle turns, attention is focused on this approach.

[1] Recent studies examining whether an interest rate spread can be used to forecast economic activity in a sample of European countries have reported mixed results (Bernard and Gerlach, 1996; Davis and Fagan, 1997).

Applied Financial Economics ISSN 0960–3107 print/ISSN 1466–4305 online
http://www.tandf.co.uk/journals

Consequently, the subsequent sections present a systematic analysis, including an evaluation of previous studies, of the forecasting properties of probit regressions that are used to calculate the probability of a recession and to determine when these probits predicted cyclical peaks and troughs. Finally, the spread is evaluated purely as an indicator in the same way that previous studies have judged other leading series.

II. PREVIOUS RESEARCH

Regression approach

While there had been evidence that the term structure had predictive power for explaining future movements in both short term interest rates and the future rate of inflation, Estrella and Hardouvelis (1991) were the first to show that there was some relationship between the spread and the future change in economic activity. They regressed real GNP growth rates over a span of k quarters in the future on the average spread, defined as the rate on 10 year Treasury notes minus the rate on 3 month T-Bills, of the current quarter:

$$\mathrm{RGDP}_{t,t+k} = \alpha + \beta\,\mathrm{SPREAD}_t$$

Since the coefficients of the spread variable were significant for large values of k, they concluded that the spread had the ability to predict changes in real economic activity at least 4 quarters ahead and noted that the fits in the 1970s and early 1980s were especially good (p. 561). These results were obtained from the in-sample fit of the regression.

The predictive performance of an indicator can differ substantially beyond the period of fit relative to its record during the sample period. Estrella and Hardouvelis, therefore, used recursive estimation procedures to simulate the forecasts that this regression would have generated, in an *ex ante* sense, in the period 1970.2–1988.4. They fitted the equations to data from 1955 to period $t-1$, then predicted the change in GNP for period $t+4$, included another observation in the regression and repeated the procedure. This approach yielded a set of out of sample forecasts. The root mean square error (RMSE) of these out of sample forecasts was 3.99, only slightly less than the standard deviation of the one quarter growth rate of GNP which was 4.26. Since their analysis was exclusively based on the regression results, they did not examine the timing of the turns, the number of false turns or the leads of the predicted turns over the true cyclical turns. They do point out, however, that the relationship did not work too well during the late 1980s.

Markov process as a predictor

Lahiri and Wang (1996) examine the spread's ability to detect turning points with Hamilton's (1989) two-state Markov switching model and the associated non-linear filter. This procedure estimates the probabilities that in a particular month the economy will fall into a recessionary regime. They show that this approach enables a forecaster to predict turning points. The procedure is tested with a number of different definitions of the spread.

They present results for the difference between (1) the Federal funds and the 10 year bond rates, (2) the rate on 1 year and 10 year Treasury bonds, and (3) the yields on 6 months commercial paper and 6 months T-bills.[2] The criterion for signalling a peak occurred when the probability of a recession was 0.90 or higher. For calling a trough, the critical value was either 0.50 or 0.90, depending on which spread measure was used. The results were mixed. The first of these spreads failed to predict the recessions of 1957 and 1960; the second had a problem with the 1969–1970 cycle, for it had signalled a recession for 62 months, and even at the other peaks the leads were relatively long (from 7 to 19 months); and the spread between commercial paper and T-bills failed to signal the 1990 recession, but the leads at the other peaks were short and not too variable (1–8 months). Some of the spreads failed to signal troughs or did so with lags. With a critical value of 0.50 for calling a trough, only the spread between long and short Treasury bonds predicted every trough contemporaneously with the turn or with a lead.

While these results suggest that using some spread in the Markov two-stage model might provide predictions of turning points, there is a caveat. The Lahiri–Wang analysis was not a true *ex ante* test of this method. The population parameters were estimated from data for the entire period over which the analysis was conducted. (Lahiri and Wang, 1996, p. 300). Recursive methods were not used to determine how well this method would have forecasted on an ex-ante basis.

Quarterly probit predictions

Probit regressions have been the most frequently used technique for analysing the performance of the spread. The probit statistical model is a statistical model relating the probability of the occurrence of discrete random events that take 0,1 values, such as whether or not there is a recession, to a set of explanatory variables. It yields probability estimates of the event occurring if the explanatory variables have specified values. The model is non-linear in parameters in order to assure that the outcome probabilities remain in the (0,1) interval.

[2] The authors indicate that the results for the difference between the 3 month T-bill and 10 year Treasury bond rates do not differ from those of the 1 year and 10 year spread.

Specifically, if we let $Y_{t+k} = 1$ if the period is a recessionary period and $Y_{t+k} = 0$ otherwise, then the probit can be specified as:

$$Prob[Y_{t+k} = 1] = \int_{-\infty}^{\beta' x_t} \phi(z) dz$$

where $\phi(z)$ is the standard normal distribution, x_t is a vector of variables including the spread for period t, and β is a set of parameters to be estimated.

Estrella and Hardouvelis (1991), Bernard and Gerlach (1996), Dueker (1997) and Estrella and Mishkin (1998) have all estimated the probabilities that a particular quarter would be a recessionary period. The term spread (10 year Treasury bonds minus the 3 month T-bill) for the current quarter was used to make these probability predictions for quarter $t + 4$. However, none of these studies undertake a thorough evaluation of the forecasting properties of their probits. There are no tabulations of (1) the highest probabilities that were calculated for each recession, (2) the timing of these predictions relative to the actual turning points, and (3) the probability threshold required for a recession to be predicted or recognized.[3] Moreover, in some cases the probabilities that are graphed in the texts are not true forecasts, for they were calculated from the sample period.[4]

III. EVALUATION OF THE TERM SPREAD AS A CYCLICAL INDICATOR

In this section, the ability of the term spread to predict cyclical economic activity is evaluated. This evaluation of the forecasting ability of the term spread consists of two parts. First, recursive probit equations are estimated relating the occurrence of a recession to the term spread (10 year Treasury bonds minus the 3 month T-bill) lagged four quarters. The estimated probit equations are used to forecast whether a particular quarter will be recessionary. Using various criteria, the accuracy of the predictions is then evaluated. Second, using the results of conventional turning point analysis, it is investigated whether the term spread can be considered a 'good' cyclical indicator.

Probit forecasts

In evaluating the forecasts of the probit model, a longer time period than other studies is used. The time period is extended both backwards and forwards, with the sample including data from 1953.2 to 1997.4. To obtain the recursive estimates, the probit was first fitted to data through 1959.1 using a 4-quarter lag (consistent with other studies), and a forecast was made for 1960.1.[5] The probit equation was then re-estimated with each new data point and new predictions were generated. The recursive probability forecasts include all of the recessions between 1960–1961 and 1990–1991.

Figure 1 shows the actual and forecast quarterly probabilities derived from this procedure. It is next necessary to determine whether these probabilities constituted a prediction of a recessionary quarter. In order to make this determination, a threshold level of these probability estimates must be selected, such that if the forecast probability exceeds this level, a recession is predicted. Then it is possible to determine the number of recessions that were predicted, the number that were not predicted, and the number of times a prediction was made and there was no recession. It is also possible to determine when the recession was predicted relative to when it occurred.

In what follows, thresholds of 0.50 or 0.25 are used for calling a recession.[6] The estimated probabilities (Table 1) never exceeded 0.50 in either the 1960–1961, 1969–1970, or

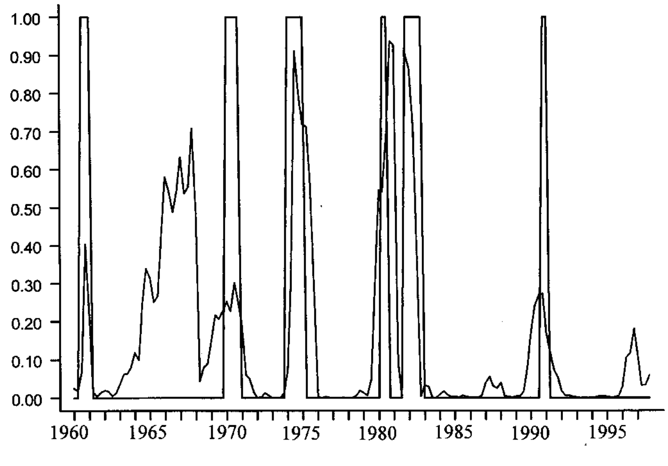

Fig. 1. *Actual and predicted probability of a recession, 1960/1–1997/4*

[3] With each threshold level, there would be a number of turns that were not predicted and a number of turns that were predicted but did not occur.

[4] None of the probabilities of either the Estrella and Hardouvalis and Bernard and Gerlach studies are true forecasts, for they were obtained from the sample period data from which the probit had been estimated. Estrella and Mishkin generated true probability forecasts because they used recursive estimation procedures to calculate the probabilities for the recessions that occurred between 1971 and the middle 1990s.

[5] The pseudo-R^2 for the probit using a 4-quarter lag exceeded that for other lags for the initial period of fit (1953.2–1959.1) as well as the whole of the data set.

[6] On the other hand, when indexes of leading series are used to predict recession, the probability of a recession must exceed 0.90 before a turning point is predicted (see Diebold and Rudebusch, 1991).

Table 1. *Predicted probabilities of recessions near actual recessions*

Recession	Date for which prediction made	Predicted probability	Recession	Date for which prediction made	Predicted probability
1960–1961	1960.2*	0.02	1980–1981	1979.4	0.34
	1960.3[R]	0.07		1980.1*	0.55
	1960.4[R]	0.40		1980.2[R]	0.54
	1961.1	0.22		1980.3[R]	0.69
				1980.4	0.94
1969–1970	1969.4*	0.23		1981.1	0.93
	1970.1[R]	0.25		1981.2	0.09
	1970.2[R]	0.23			
	1970.3[R]	0.30	1981–1982	1981.3*	0.01
	1970.4	0.26		1981.4[R]	0.91
	1971.1	0.19		1982.1[R]	0.87
				1982.2[R]	0.71
1973–1975	1973.4*	0.01		1982.3[R]	0.39
	1974.1[R]	0.07		1982.4[R]	0.01
	1974.2[R]	0.31			
	1974.3[R]	0.91	1990–1991	1990.2	0.24
	1974.4[R]	0.80		1990.3*	0.27
	1975.1[R]	0.72		1990.4[R]	0.27
	1975.2	0.71		1991.1[R]	0.17
	1975.3	0.57		1991.2	0.12
	1975.4	0.30			
	1976.1	0.00			

Note: An asterisk indicates the date when a recession began and an R indicates that the quarter is identified as recessionary.

1990–1991 recessions. Consequently, if the threshold for predicting a recession is that the predicted probability should at least equal 0.50, it is found that the spread failed to predict any of these cycles, although all would have been predicted if a threshold of 0.25 were used. Moreover, the recursive probability forecasts yielded a false signal during the mid-1960s, when the probabilities exceeded 0.50 for all but one quarter between 1966.1 and 1967.4.[7] The predicted probabilities associated with the 1973–75 recession and the two recessions of the 1980s are in the 1990s.

Using the criterion that the predicted probability must be at least 0.50 to signal a recession, it is observed (Table 1) that at the end of 1973.3 a recession was predicted to begin in 1974.3. The National Bureau of Economic Research has identified the cyclical peak as having occurred earlier (in November 1973). While the timing was wrong, the prediction of a recession preceded its occurrence. However, the predicted probability of a recession exceed 0.50 for the middle two quarters of 1975, although neither of these quarters is identified as part of the recession. The timing was correct for the 1980 recession but a quarter too late for the recession of 1981. The probit forecasts for the 1980 recession, like those of the 1973–1975 recession, indicate continued recession for two quarters beyond the true turning point. The probits correctly predict the trough of the 1981–1982 recession (November 1982).

On the basis of these results, it is concluded that, at best, the spread was a good predictor of economic activity only for the three recessions during the time period 1973–1982. It is not just that the spread suddenly failed to predict the 1990–1991 cycle; it had not been a successful indicator prior to the 1973 recession.

These conclusions are based on the assumption that a signal of a recession only occurs when the estimated probability of such an event exceeds 0.50. Estrella and Hardouvelis had argued that every spike in the probability estimates, no matter how low, should have been considered a forecast of a cyclical downturn (Estrella and Hardouvelis, 1991, p. 564). If that criterion were accepted, it is true every recession would have been predicted, but there would have been false predictions during the 1960s and the late 1990s, two periods of unparalleled vigorous economic activity.

Standards for evaluating the probit forecasts

In judging the term spread as a predictor, it is not sufficient to merely count the number of recessions that were predicted or the number of false signals. A more complete evaluation would compare the record of this forecasting method against some standard or benchmark. Two such comparisons are made. One compares the tradeoff between false signals and the failure to predict a recession when different probability thresholds are used to forecast a reces-

[7] Although there was no recession during this period, a mini-recession did occur.

Table 2. *Predicted and actual quarterly recession outcomes by threshold probability, 1960.1–1997.4**

25% Threshold probability				50% Threshold probability			
	Actual recession outcome				Actual recession outcome		
Recession prediction	Yes	No	Total	Recession prediction	Yes	No	Total
Yes	15 (9.87)	23 (5.13)	38 (25.00)	Yes	8 (5.26)	12 (7.89)	20 (13.16)
No	6 (3.95)	108 (71.05)	114 (75.00)	No	13 (8.55)	119 (78.29)	132 (86.84)
Total	21 (13.82)	131 (86.18)	152 (100.00)	Total	21 (13.82)	131 (86.18)	152 (100.00)

Note: Percentages in parentheses.

sion and the other involves a quantitative measure of the errors of the probability forecasts.

Probability thresholds: tradeoff between false predictions and failures to predict. In this section, the trade-offs between making false predictions and failures to predict a recession that occurs are examined. This involves an analysis of the probit's ability to discriminate between recessionary and non-recessionary periods when alternative thresholds are used to predict a recession. That is, if the predicted probability from the probit is greater than a given threshold probability, a recession is called; below the threshold no recession is called. If the estimated probabilities sharply distinguished between recessionary and non-recessionary quarters, then a high threshold would correctly classify the two types of periods. However, if the predicted probabilities are positively correlated with the occurrence of a recession but do not sharply distinguish between the two types of periods, then quarters will be misclassified. If a low threshold probability is selected, the probit will tend to correctly identify recessionary quarters, but will incorrectly classify non-recessionary quarters as recessions.

Table 2 summarizes the distributions of forecasts and outcomes using thresholds of 0.25 and 0.50. When a threshold of 0.25 is used, 80.9% of quarters are correctly classified, including 15 of the 21 recessionary quarters (71%) and 108 out 131 non-recessionary quarters (82.4%). However, using this low threshold probability, there are a substantial number of false signals: of the 38 periods for which a recession is signalled, only 15 of them turned out to be recessionary quarters. When a threshold of 0.50 is used, a higher fraction of quarters (83.5%) are correctly classified, largely because the number of false signals has been reduced. With this high threshold, 91% of non-recessionary quarters are correctly classified, but a recession was only predicted for 8 of 21 (38%) of recessionary quarters. Even with this threshold, when a recession was signalled (20 times), there were more false alarms (12) than correct predictions (8).

Error measure. In this section, an overall measure of the accuracy of the probit predictions of recessionary quarters is provided and the probit predictions are compared to those generated from naive forecasts.

The forecasts generated from the recursive probit regressions are expressed as probabilities. A measure specifically designed to evaluate probability forecasts is then used to determine how well these probit functions predicted the outcomes. For binary (the occurrence or non-occurrence of) events, the overall accuracy measure is the Brier Score:

$$QR = \frac{2\sum_{n=1}^{N}(r_n - d_n)^2}{N}$$

where r_n is the predicted probability that the event will occur on the nth occasion, and $d_n = 1$ if the event occurs on the nth occasion and zero otherwise. Smaller values of QR indicate more accurate forecasts; a value of zero would indicate a perfect prediction. Multiplying the Brier Score by 0.5 yields the mean squared error of the forecast.

Table 3 presents the Brier Scores for the recursive forecasts generated from the probit equations. These are presented for the entire period, 1960.1–1997.4, as well as for each of the four decades of this period. The Brier Scores the forecasts of two naive models that serve as benchmarks or standards of comparison are also shown in Table 3. The first benchmark, called the zero probability forecast, simply assumes that the probability of a recession is zero in each period. The second benchmark, called the recursive naive forecast, predicts that the probability of a recession is equal to the average proportion of quarters that were recessionary from 1954.2 to one year before the forecast date.[8] For

[8] Estrella and Mishkin (1998) evaluate the predictive power of the recursive probit using an index devised by Estrella (1998) that also compares the recursive probit predictions of those of a naive forecast based on the average probability of a recession from the period of fit of the probit. Suppose that recursive predictions are being generated for periods $t+1$ to $t+n$. Let $y_j = 1$ if there is a recession in

Table 3. *Brier scores for quarterly forecasts derived from recursive probits and two naive methods*

		Naive methods	
Period	Recursive probit	Zero probability	Recursive
1960.1–1997.4	0.2054	0.2764	0.2494
1960s	0.2782	0.1500	0.1610
1970s	0.2358	0.4500	0.3800
1980s	0.1924	0.3500	0.2970
1990s	0.0924	0.1250	0.1358

example, the probability of a recession assigned to 1960.1 is the average proportion of quarters that were recessionary during the period of fit, 1953.2 to 1959.1. Over the whole of the sample from 1960.1 to 1997.4, the average value of this recursive naive forecast was 0.17, ranging from a low of 0.12 to a high of 0.25.

For the entire period, the forecasts of the recursive probits are slightly more accurate than either of the benchmark forecasts, with the Brier Score for the probits between 80% and 90% of the scores of the benchmark forecasts. For the 1960s both of the benchmarks are considerably more accurate than the probit.[9] Only for the 1970s and 1980s is the Brier Score of the probit substantially less than those of the benchmarks.

Overall evaluation of the probit forecasts. The results of the evaluation are in conflict. On the one hand, the probits did not predict every cycle and misclassified a substantial number of quarters. On the other hand, the predictions obtained from this procedure were superior to those of simple naive methods (e.g. assuming a zero probability of a recession or assuming that the probability of a recession in a quarter equalled the average probability of a recession), and the quarters that were predicted to be recessionary (non-recessionary) were significantly associated with quarters that were recessionary (non-recessionary).

The spread as an indicator

Since there are conflicting results about the spread's performance as a variable in a probit designed to predict the probability of a recession, its value is also strictly assessed as an indicator. Over the years, economists have developed procedures for evaluating series that are used as cyclical indicators, with an indicator identified as leading if turns in that series precede turns in the economy. In these evaluations, true and false signals are identified and the length of the forecasting leads are calculated. Previous research has shown that there is a tradeoff between the ratio of true to false signals and the length of the forecast lead. This tradeoff depends on the type of ad hoc rule that is used to identify turns in the cyclical indicators (Alexander, 1958;

Table 4. *The spread as an indicator: number of false leads, leads and effective leads at turning points*

	Peaks				Troughs		
Number of false signals	Date of peak	Lead (months)	Effective lead (months)	Number of false signals	Date of trough	Lead (months)	Effective lead (months)
28	1957	6	3	10	1958	−3	−6
	1960	4	1		1961	−7	−10
	1969	4	1		1970	−3	−6
	1973	2	−1		1975	−9	−12
	1980	−2	−5		1980	1	−2
	1981	7	4		1982	2	−1
	1990	13	10		1991	−3	−6

Notes: The effective lead is the true lead in the indicator over the cyclical turning point minus the number of months in the rule used to identify turns. In this study, the rule loses three months.

period j and zero otherwise, F_j be the forecast probability from the probit for period j, and v_j be the forecast probability based on the average probability of a recession over the period of fit. Define $L_u = \prod_{(y_j=1)} F_j \prod_{(y_j=0)} (1 - F_j)$ and $L_c = \prod_{(y_j=1)} \nu_j \prod_{(y_j=0)} (1 - \nu_j)$. Then, the Estrella–Mishkin measure of goodness of fit is

$$1 - \left[\frac{\log L_u}{\log L_c}\right]^{-2/n \log L_c}$$

If the probits perfectly predicted recessionary quarters, then the index would equal 1. If the term structure information included in the probit yielded predictions no different from the average probability of a recession, then the index would equal 0. For the period 1971.1–1995.1, the index for the four-quarter ahead probit forecasts based upon the spread was 0.295, which exceeded the value of the index for other predictors used by Estrella and Mushkin (Table 5, p. 53).

9 This result might be expected, since there had been only a small number of recessionary quarters from which the probit was estimated.

Alexander and Stekler, 1959; Vaccara and Zarnowitz, 1977; Stekler, 1991). These rules are intended to be implicit smoothing devices that reduce both the number of false turns and the average forecasting lead. For the Index of Leading Series (ILS) the most commonly used rule is: a signal of a peak occurs when the ILS declines for three consecutive months. This rule was developed by Vaccara and Zarnowitz (1977).

Even though the spread series is now a component of the ILS, the previous research has not evaluated the cyclical indicator characteristics of the spread. These qualities of the spread were evaluated using *monthly* data. The procedure that was used for identifying turning points was the '3-months up or down' rule, i.e. a peak (trough) was signalled if at least three consecutive observations were below (above) the previous high (low) values of this series (Stekler, 1991). Using this procedure, all the turns were identified and then classified into true and false signals (Table 4). Although the spread predicted all but one of the seven peaks with a lead, this indicator also made an additional 28 false predictions.[10] All seven troughs were forecast but with a lag, ranging from 1 to 2 months up to 12 months. There were also 10 false signals of peaks. Moreover, a closer examination of the behaviour of this series in the vicinity of the true cyclical turns indicated that there were a number of false reversals of the true predictions, i.e. indications that a cyclical turn was not imminent just before it occurred. (Friedman and Kuttner (1998) had shown that this was the case just prior to the 1990 recession. It was also true before other business cycle peaks.)

On the basis of this evidence, it can be concluded that the spread is not a very good cyclical indicator. It does, however, have one advantage over other series that are used as indicators. Unlike the other series, it is never subject to data revisions.

IV. CONCLUSIONS

While previous research had suggested that interest rate spreads were good predictors of future levels of economic activity, these findings are more equivocal. In evaluating the spread as a quarterly predictor of real economic activity, conflicting results were obtained. The probit equations did *not* predict every cycle and misclassified a number of quarters. On the other hand, the probit predictions were somewhat more accurate than those of very simple naive benchmarks. The performance of the term spread as a predictor of recessions varied over time, being relative good in the 1970s and 1980s, but seriously deficient in the 1960s and 1990s. Finally, when the spread was evaluated purely as an indicator, it was found that this series predicted all but one of the peaks, but that it made an extremely large number of false predictions. The overall conclusion is that this series by itself is not a reliable predictor of economic activity.

REFERENCES

Alexander, S. (1958) Rate of change approaches to forecasting – diffusion indexes and first differences, *The Economic Journal*, **68**, 288–301.

Alexander, S. and Stekler, H. O. (1959) Forecasting industrial production – leading series versus autoregression, *The Journal of Political Economy*, **67**, 402–9.

Bernanke, B. S. (1990), On the predictive power of interest rates and interest rate spreads, *New England Economic Review*, **Nov./Dec.** 51–68.

Bernard, H. and Gerlach, S. (1996) Does the term structure predict recessions? The international evidence, Bank for International Settlements, Working Paper No. **37**.

Diebold, F. X. and Rudebusch, G. D. (1991) Turning point prediction with the composite leading index: an ex ante analysis, in *Leading Economic Indicators: New Approaches and Forecasting Records*, (Eds) K. Lahiri and G. H. Moore, Cambridge University Press, Cambridge, pp. 231–56.

Davis, E. P. and Fagan, G. (1977) Are financial spreads useful indicators of future inflation and output growth in EU countries?, *Journal of Applied Econometrics*, **12**, 701–14.

Dueker, M. J. (1997) Strengthening the case for the yield curve as a predictor of US recessions, *Federal Reserve Bank of St. Louis Review*, (**79**) **Mar/Apr**, 41–50.

Estrella, A. (1998) A new measure of fit for equations with dichotomous dependent variables, *Journal of Business and Economic Statistics*, **16**, 198–205.

Estrella, A. and Hardouvelis, G. (1991) The term structure as a predictor of real economic activity, *Journal of Finance*, **46**, 555–76.

Estrella, A. and Mishkin, F. S. (1998) Predicting US recessions: financial variables as leading indicators, *Review of Economics and Statistics*, **80**, 45–61.

Friedman, B. J. and Kuttner, K. N. (1998) Indicator properties of the paper-bill spread: lessons from recent experience, *Review of Economics and Statistics*, **80**, 34–43.

Hamilton, J. D. (1989) A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica*, **57**, 357–84.

Kozicki, S., (1997) Predicting real growth and inflation with the yield spread, *Federal Reserve Bank of Kansas City Economic Review*, **82**, 39–57.

Lahiri, K. and Wang, J. G. (1996) Interest rate spreads as predictors of business cycles, in *Handbook of Statistics*, (Eds.) G. S. Maddala and C. R. Rao, Vol. 14, Elsevier Science B.V., 297–315.

Stekler, H. O. (1991) Turning point predictions, errors, and forecasting procedures, in *Leading Economic Indicators: New Approaches and Forecasting Records*, (Eds.) K. Lahiri and G. H. Moore, Cambridge, pp. 169–81.

Vaccara, B. N. and Zarnowitz, V. (1977) How Good are the Leading Indicators?, Proceedings of the Business and Economics Statistics Section, American Statistical Association, Washington, DC, pp. 41–50.

[10] In an attempt to reduce the large number of false turns, exponential smoothing was applied to the series. The results were not substantially different.