Predicting UK Business Cycle Regimes

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Abstract

Following Birchenhall, Jessen, Osborn & Simpson (1999) on predicting US business cycle regimes we apply the same methodology to construct a one-quarter ahead model of classical business cycle regimes in the UK. Birchenhall *et al* used regime data implied by the NBER dating of peaks and troughs. In the UK there is no comparable business cycle chronology and our first task is to date the UK peaks and troughs. Application of a simple mechanical rule to quarterly GDP data from 1963 to 1999 produces a set of acceptable turning points, with one exception that is attributable to the three-day working week in 1974. From this analysis we date three recessions, namely those of 1973-1975, 1979-1981 and 1990-1992. Using a range of real and financial leading indicators, several parsimonious one-quarter-ahead models are then developed for the GDP regimes, with model selection based on the SIC criterion. A number of interesting results emerge from this investigation. A real M4 variable is consistently found to have predictive content. One model that performs well combines this with nominal UK and German short-term interest rates. The role of the latter variable emphasises the open nature of the UK economy and, in particular, its links with Europe.

JEL classification: C22, C32, E32, E44.

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1. Introduction

Both policy makers and private agents have a serious interest in the occurrence of recessions in economic activity and thus show an interest in leading indicators that help in anticipating the onset of recession and recovery. The history of leading indicators dates back to Burns and Mitchell's (1946) discussion of "classical" business cycle phases in the US.

Leading indicators for the US economy were produced by the US Department of Commerce over a long period, with this system now maintained by the Conference Board. This methodology is based on combining a range of individual leading indicators into a single composite indicator. Green and Beckman (1993) discuss the methodology used, but this may be summarised by saying that it depends on averaging across individual leading indicators in order to extract the common predictive signal. Stock and Watson (1991, 1993) have also produced a composite leading indicator for the US using a related, but more sophisticated, methodology. These US leading indicators are traditionally associated with the so-called classical business cycle regimes of recession and expansion in real activity. That is, they are designed to signal in advance periods of decline in overall activity (recessions) in comparison with periods of overall growth (expansions).

In the UK the Office for National Statistics (ONS) had a system of business cycle leading indicators until early 1997[1]. These were designed to lead the growth cycle phase of UK gross domestic product (GDP), where growth cycle phases refer to expansion and contractions relative to a long run trend (Moore, 1993). The OECD also produces composite leading indicators for the growth cycle in many countries (Nilsson, 1987). One important difficulty with any growth cycle analysis is that it is based on a definition of trend and such definitions are essentially arbitrary. It is also arguably the case that policy makers and private agents are more concerned about absolute declines and expansions in activity than in growth cycle measures. For these

[1] These are now being produced by NTC Research, telephone 01491 418625.

reasons, this paper concentrates on classical business cycles for the UK and not growth cycles.

Many papers have analysed the forecasting information contained in the composite indicators mentioned above. A number of recent studies have focused on the role of individual leading indicator variables, in particular financial ones, sometimes comparing the performance of a range of variables. For example, Estrella and Mishkin (1998) utilise a probit model (based on information from financial and real macroeconomic variables, together with composite indicators) to forecast recessions in the US GDP. They find that the best out-of-sample predictor beyond one quarter is the term structure of interest rates (the interest rate on long-term bonds minus the short-term interest rate). Using a more conventional linear approach, Plosser and Rouwenhorst (1994) find strong and positive association between the term structure and subsequent growth in industrial production for the US and Germany. Further empirical evidence by Roma and Torous (1997) suggests that the US term structure is relatively steeper at business cycle troughs and flatter at business cycle peaks. In recent analyses relevant to the UK, Andreou *et al* (2000) examine the role of various financial leading indicators while Camba-Mendez *et al* (1999) adopt an automatic approach to forming composite leading indicators for forecasting the GDP growth of European countries using financial variables.

This paper follows Birchenhall, Jessen, Osborn & Simpson (1999), henceforth BJOS, to construct a composite leading indicator for classical cycles in UK GDP. Our indicator is constructed using a different approach to the composite indicators mentioned above. The numerical value of our indicator is a number lying between zero and one, which can be interpreted as the probability that the economy will be in an expansion next period. Equivalently, one minus the indicator value can be interpreted as the probability that the economy will be in a recession. Its construction is based on logistic regression where the dependent variable is a zero/one dummy variable identifying recessions and expansion regimes in the economy. BJOS had the luxury of a well-established set of dates for peaks and troughs in the US economy, namely those published by the NBER Dating Committee. There is no matching set of dates for the UK and this paper offers a set of dates for the peaks and troughs for the classic cycle in UK GDP before constructing the leading indicator.

The rest of the paper has the following structure. Section 2 discusses the dating of the classical cycle in UK GDP, together with some features of UK post-war recessions. Section 3 then briefly outlines the methodology developed in BJOS to construct the composite indicator. The data used for the construction of the composite leading indicator is then discussed in Section 4, with the one-quarter ahead regime prediction models presented in Section 5. Section 6 offers concluding remarks.

2. Classical Cycles in UK GDP

Business cycle dating is well established for the US, with Boldin (1994) comparing the performance of various approaches. Dating exercises which have been undertaken outside the US based on the concept of the classical business cycle include Artis, Kontolemis and Osborn (1997) for monthly G7 and European industrial production, while Harding and Pagan (1999) date the GDP cycles of the US, UK and Australia. Both of these papers use procedures based on the Bry and Boschan (1971) algorithm. The principle aim of this paper is to provide a UK business cycle leading indicator, not to provide a robust methodology for dating turning points. Therefore, we side-step the dating issue and apply a simple mechanical rule to UK GDP in order to produce a set of acceptable turning points.

Table 1 provides a formal description of the rules we use to identify turning points in UK seasonally adjusted quarterly GDP (this is an index measure at market prices) over the sample 1963 to 1999. In words these rules imply that a peak is identified at t if the value of GDP (the variable Y_t) is strictly greater than the values for the subsequent two quarters t+1 and t+2, while also being at least as large as all values within a year in the past and in the future. Troughs are defined in an analogous manner.

	Peak	**Trough**
1	$\Delta_i Y_t \geq 0$ for i = 1,..,4	$\Delta_i Y_t \leq 0$ for i = 1,..,4
2	$\Delta_i Y_{t+i} \geq 0$ for i = 1,..,4	$\Delta_i Y_{t+i} \leq 0$ for i = 1,..,4
3	$\Delta_1 Y_{t+1} < 0$ and $\Delta_2 Y_{t+2} < 0$	$\Delta_1 Y_{t+1} > 0$ and $\Delta_2 Y_{t+2} > 0$

Table 1: Rules for Dating Peaks and Troughs

Application of the rules results in the turning points in Table 2. These dates are accompanied by the duration of the cycle phase (in quarters) which ends with that turning point[2]. Note the clear (and well known) asymmetry between the duration of expansions and recessions. It should also be remarked at this stage that the rules do not force peaks and troughs to alternate. The one instance of two turning points of the same type being identified by the rules occurs with the troughs identified at 1974 Q1 and 1975 Q3. This case is discussed below.

Date	**Peak or Trough**	**Duration (quarters)**
1973 Q3	Peak	31
1974 Q1	Trough*	
1975 Q3	Trough	8
1979 Q2	Peak	15
1981 Q1	Trough	7
1990 Q2	Peak	37
1992 Q2	Trough	8

* Trough at 74Q1 rejected as a distortion due to 3 day working week

Table 2: UK Classical Turning Points in UK GDP

[2] Note that the first phase duration of 31 quarters is incomplete, since no initial turning point can be identified.

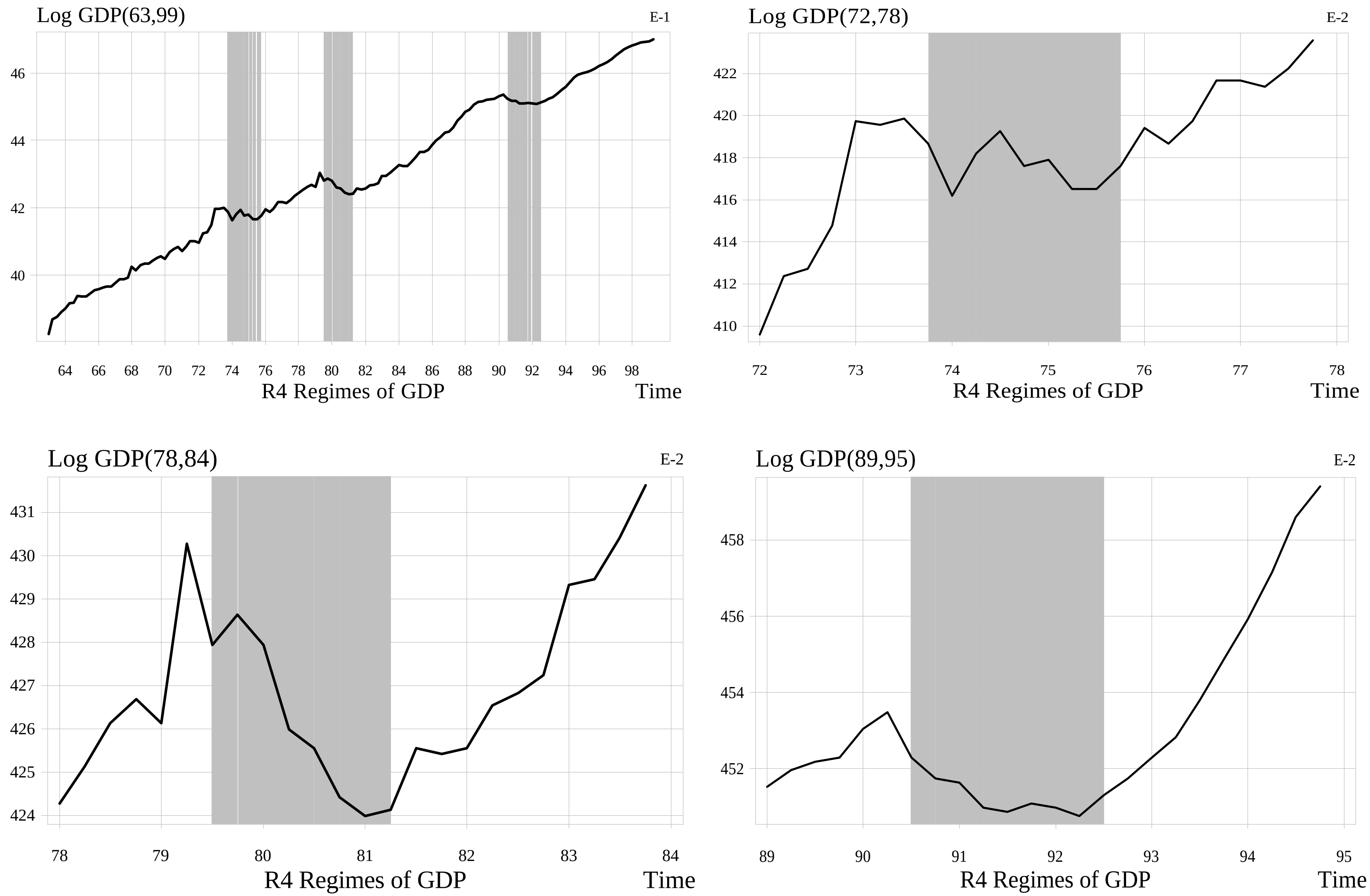

Figure 1: Plots of GDP

Having dated the peaks and troughs, each time period can be classified as either one of expansion or one of contraction. Periods of expansion start with the observation following a trough and run to (and include) the quarter of the subsequent peak. Periods of contraction (or recession) start with the observation following a peak and run to the next trough.

The graphs in Figure 1 show the full sample of the logarithm of UK GDP, together with each of the recession phases identified. Note the vertical axis is the natural logarithm of GDP multiplied by 10 in the first graph and multiplied by 100 in the three sub-period graphs. A word on the line plots and shading is also in order. A point lying on the vertical line marked 79 represents the value of GDP in the first quarter of 1979. That is to say the observation for a variable is plotted at the start of the interval that represents that quarter. The shaded areas represent recessions and thus cover the periods that start in the quarter following a peak up to and including the next trough. For example, the second recession includes the quarters running from 1979 Q3 up to and including 1981 Q1. In the graph for the second recession the shaded area starts at 1979 Q3 and reaches out to 1981 Q2 as this point marks the end of 1981 Q1. By this convention, the value of GDP at 1981 Q2 marks the end of the recession, not the observation at 1981 Q1.

The dating of the first recession is worthy of further discussion. The rule indicates a peak at 1973 Q3, but offers two following trough dates namely 1974 Q1 and 1975 Q3. However, we reject the former on the grounds that the low value of GDP in that quarter, and the subsequent increases in 1974 Q2 and 1974 Q3, reflect the impact of the three-day working week associated with a miner's strike. While this judgement removes the difficulty arising from the two adjacent troughs, it nevertheless suggests that the timing of this recession is not straightforward and some uncertainty remains. In a similar vein the rise in GDP in 1979 Q4 and fall in 1980 Q1 suggest the dating of the onset of the second recession is not entirely clear-cut. Since the construction of our composite indicator assumes that the regimes are known with certainty, these issues need to be kept in mind when assessing the results.

Referring to the authoritative work of Dow (1998) these three recessions are those identified by him as 'major recessions' for the UK. As Dow is essentially looking for growth recessions the precise dating will differ, but the three classical recessions identified above map broadly onto matching recessions in Dow's work. Dow attributes the first two of these recessions at least partly to external events (especially the OPEC oil price rises), whereas the third is viewed as having its origins purely in domestic factors.

The first recession in Britain 1973-75 was preceded by a large injection of government spending into the economy known as the 'Barber Boom' named after the Chancellor of the Exchequer at the time. Dow (1998) describes how between 1972 and 1973 total final expenditure rose by nearly 9% and was accompanied by a boom abroad that led to a rapid rise in exports. The recession followed the boom and was also the reaction to the oil price shock and a rapid tightening of monetary policy that in turn was a reaction to accelerating inflation. The recession was exacerbated at the beginning of 1974 by the effect of the three-day working week, when when the government had to restrict industry to a short working week because a coal strike had reduced coal supplies to power stations at the end of 1973 in the so-called 'winter of discontent'.

The second recession 1979-81 was attributable to the rise in the price of oil at the second OPEC shock, but this was exacerbated by a large exchange rate rise. The latter practically stopped export growth and so was largely deflationary. The 1979 budget was also very deflationary, with cuts in fiscal policy and tightening of monetary policy by the Conservative government as they tried to control the growth of broad money. Broad money was targeted by the government between 1976 and 1986.

The third recession we identify as 1990-92, although Dow dates as longer, namely from 1989-93 when growth was below trend. Dow suggests that the expansion of the 1980s should not simply be attributed to financial deregulation as there was a gap of five years between the removal of lending controls and the time when credit creation started to accelerate. Instead he attributes the credit boom to the growth of pervasive optimism about future prospects and the erosion of prudential standards. Dow concludes that the recession was not due to exogenous shocks, like the previous two recessions, but was entirely due to a reversal of the over-confidence that had been built up in the preceding boom years. This recession was preceded by unsustainable increases in asset prices, property prices and equity prices, which crashed because of a loss of confidence and expectations.

3. Modelling the Probability of Expansion

A fuller account of the methodology used to construct our composite leading indicator is presented in BJOS. A brief outline is presented here to clarify the subsequent discussion of the results.

Let ω_t represent a complete history of all possible information about the state of the economy up to and including period *t*. It is assumed that given ω_t there is no uncertainty in classifying period *t* into one of expansion or contraction. Thus, $p(\omega_t)$ is either 1 or 0, where $p(\omega_t)$ is the probability that period *t* is one of expansion given ω_t. Further, it is assumed that the probability $p(\omega_{t-1})$ of period *t* being one of expansion given the complete history up and including period *t*-1 is always well-defined. A **coincident indicator** of regimes then approximates the true indicator $p(\omega_t)$ based on a model which uses incomplete histories. A **one-period ahead indicator** approximates the true indicator $p(\omega_{t-1})$ using a model based on incomplete histories to period *t*-1.

The present paper concentrates on the task of constructing a one-period ahead indicator. To this end we consider models of the form

$$p_t(x_{t-1}) = lf\,(\beta' \boldsymbol{x}_{t-1}) \qquad (1)$$

where *lf* is the logistic function *i.e.* $lf\,(z) = \exp(z) / [\,1 + \exp(z)\,]$, β is a vector of coefficients and $\boldsymbol{x}_{t-1}$ is a vector of variables observed up to and including *t*-1. The variable y_t indicates the regime at time *t*, so that $y_t = 1$ if period *t* is one of expansion and $y_t = 0$ if period *t* is one of contraction. Given observations y_t on regimes and $\boldsymbol{x}_{t-1}$ on leading indicators for $t = 1,\ldots,T$, then the likelihood function for the binary model is given by

$$L = \Pi_1 lf\,(\boldsymbol{x}_{t-1})\ \Pi_0(1-lf\,(\boldsymbol{x}_{t-1})) \qquad (2)$$

where the first product is taken over all periods for which $y_t = 1$ and the second product is taken over all periods for which $y_t = 0$. Constructing a composite indicator involves choosing $\boldsymbol{x}_{t-1}$ and finding the maximum likelihood estimate of β. The choice of $\boldsymbol{x}_{t-1}$ is crucial, and we achieve this through a prior selection of potential variables followed by an automated search algorithm that aims to minimise the Schwartz Information Criterion (SIC). In this context, SIC is defined by

$$\text{SIC} = (-\,2\log L + n \log T)/T \qquad (3)$$

where *L* is the likelihood value from (2), *n* is the number of estimated parameters and *T* is the number of observations in the sample used for estimation. The advantage of basing model choice on a penalised likelihood function, such as (3), is that they help to guard against "over-fitting" and hence lead to better approximations of true structures than the use of the penalty free likelihood.

The automated search procedure works as follows. We select *a priori* a set of *K* variables $x_{1t}, \ldots, x_{Kt}$. Each potential leading indicator is normalised prior to estimation, by subtraction of its sample mean and division by its sample standard deviation. The algorithm then estimates the full model with K variables and calculates SIC for the sample period. Then all subsets of K–1 variables are examined, from which the one with the lowest value of SIC is selected. This subset is then used in the next stage of the procedure, with the omitted variable excluded from further consideration. Working with the selected K–1 variables the algorithm considers all subsets of K–2 variables and chooses that which gives the lowest SIC value. The omitted variable is excluded. This continues until there is only one variable left. At the final stage the algorithm has K selected subsets (using 1, …, K variables) with associated SIC values. From these it chooses that subset which gives the lowest SIC value.

Although this procedure seems generally to work well in our application, some practical issues should be noted. Firstly, the algorithm is not an exhaustive search of all subsets of all sizes from the original K variables, and hence the final selection is not guaranteed to be that subset which yields the global minimum of SIC. In particular, a variable maybe rejected prematurely. Furthermore, the search procedure is dependent on the initial set of K variables, with the implication that the initial inclusion of one or more specific variables can alter the set which is finally selected even if these variables do not appear in the final selection. A further complication arises from the very real possibility of getting a spurious "perfect" fit in which the model is able to correctly classify all points in the sample set. When such a "perfect" fit occurs for a specified set of initial variables, we modify the set to avoid this problem.

All in all, the selection of the prior set of variables is non-trivial and in practice requires us to draw on prior experience and expectations. In particular, we have found that it is possible to substantially improve SIC values by imposing appropriate restrictions on parameters. For example, the use of "real" variables and the removal of price and inflation variables have proved to be fruitful.

4. Leading Indicator Data

The events outlined in Section 2, which led to the recession eras, were varied in nature and involved the UK operating as an open economy. We therefore analyse a number of domestic and international leading indicators for their performance in predicting the recession for UK GDP.

Essentially we examine a variety of nominal and real variables as the leading indicators in $\boldsymbol{x}_{t-1}$, with these variables being those that previous research finds important for the UK economy.

Relatively few studies have concentrated on the UK experience. Of these, Andreou *et al* (2000) find strong evidence for financial variables having leading properties and Simpson *et al* (1999) investigate financial and other variables for modelling recessions in UK GDP with a Markov-switching model. Furthermore Binner *et al* (1999) find useful leading indicator properties of UK M4 for inflation. Of this range of variables, we consistently found that inflation and a subset of domestic financial variables survived our selection process, with this subset being broad money, stock prices and interest rates. As noted above, we also explicitly acknowledge the open nature of the UK economy by examining international variables. Of the latter, we find strong evidence for US stock prices and German interest rates, with a possible role also for oil prices.

Many variables were considered, all of which are detailed in the Appendix, which includes the abbreviations, variable descriptions, sample dates, sources and transformations used in the modelling. However, many were found to play no role and we omit these from further consideration here. We transform money, stock prices, oil prices and the GDP deflator data by taking logs and then an annual difference to smooth the data[3]. For the interest rate series we analyse the UK Treasury Bill yield (TBY) as the short rate, the 20 year par yield on British Government Securities for the long rate (LR) and the difference between these is the term structure (LR-TBY).

For reference, Figures 2 and 3 graph the leading indicator variables found to play potentially important roles as part of our composite leading indicator for the UK. In each case, the recessions as

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[3] Our experiments investigated the use of one and two-quarter differences, but the annual difference produced better models.

dated in Section 2 are indicated in the graphs by shading. The top panels of Figure 2 shows TBY and the German short-term interest rate series (the FIBOR, or Frankfurt inter-bank offered rate). The lower panels of the figure show the term structure and UKOIL, which is the price per barrel of US oil converted to sterling using the US dollar/pound spot exchange rate.

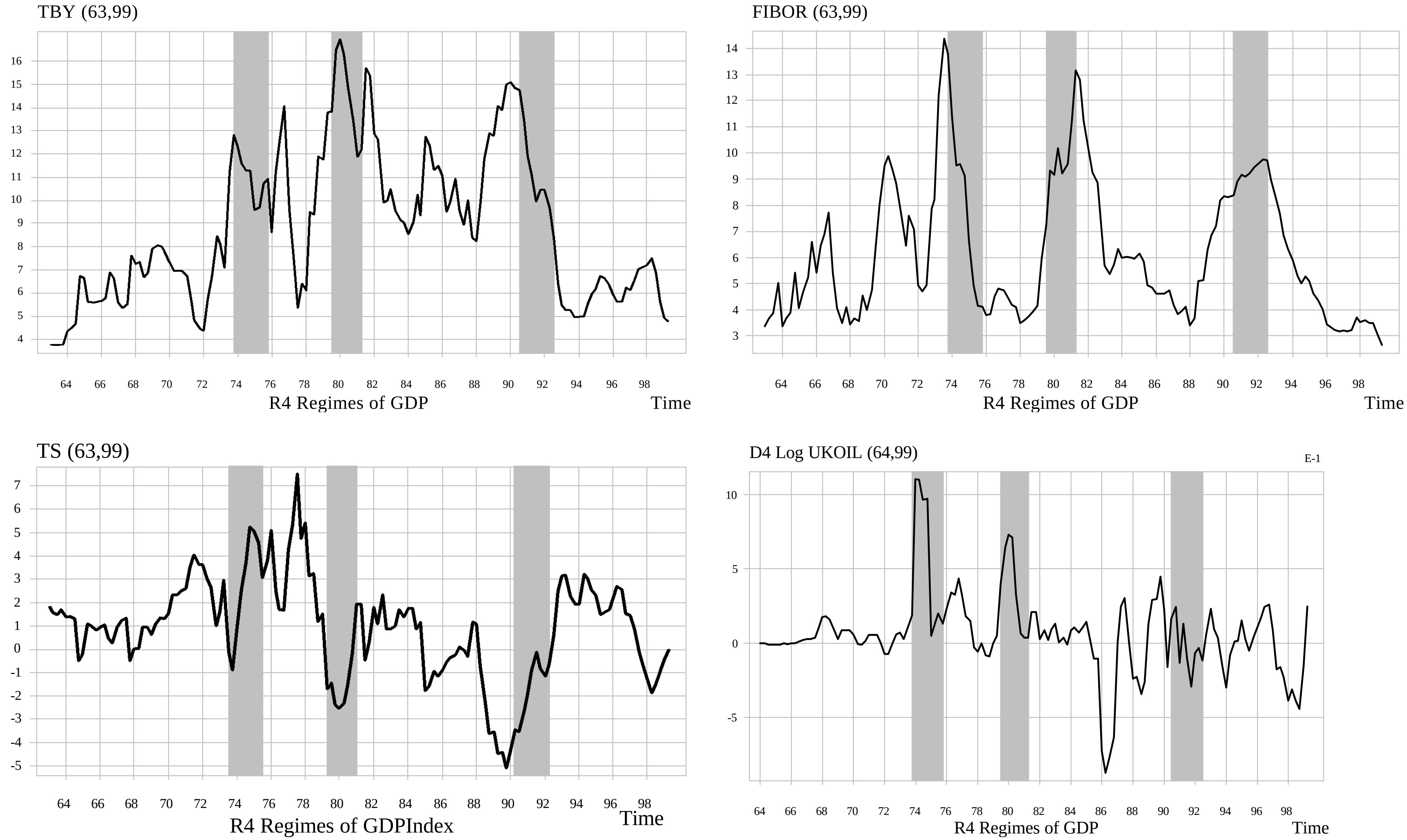

Figure 2: Leading Indicator Plots

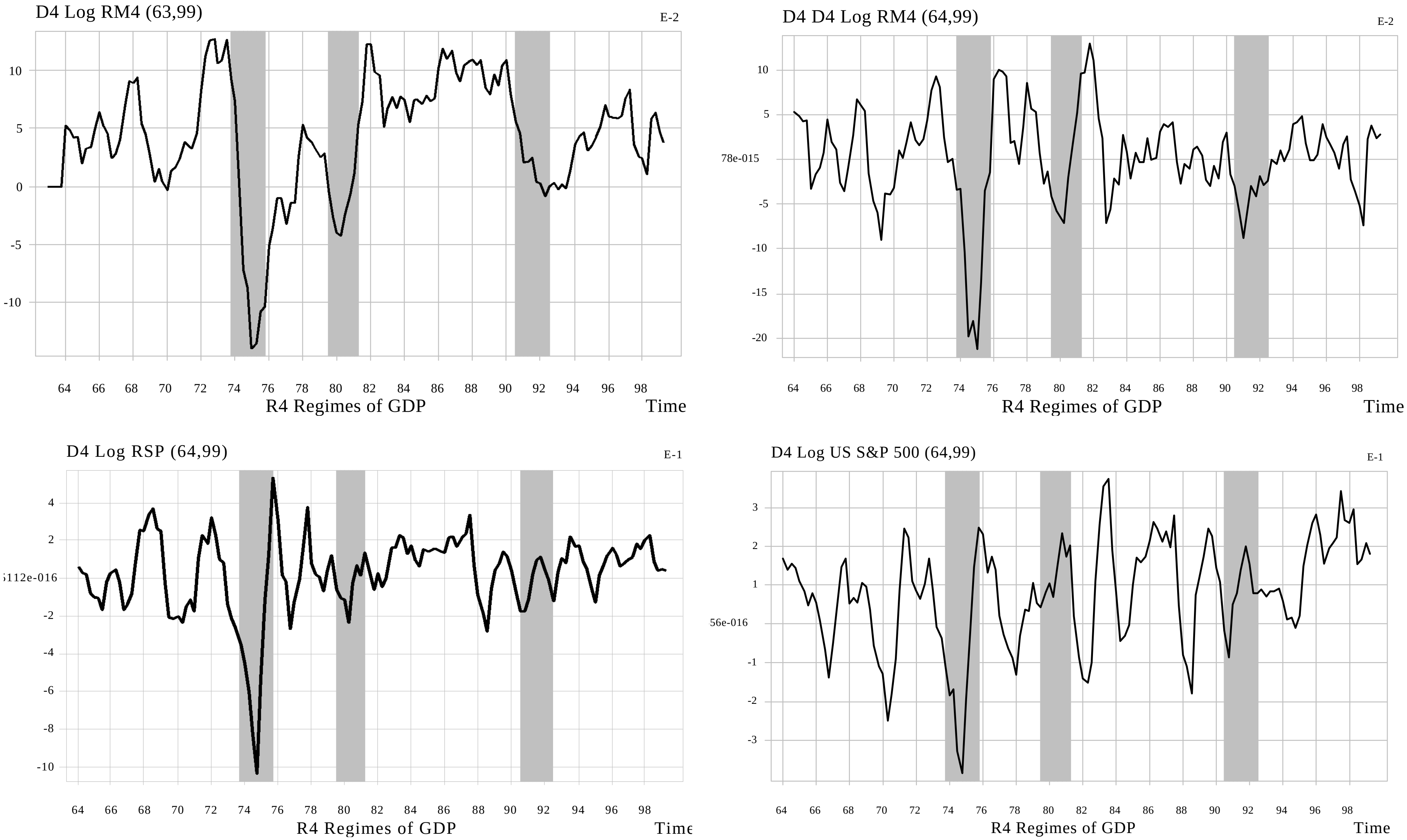

Figure 3: Leading Indicator Plots

Two domestic real variables are included in Figure 3, namely real M4 and real stock prices. These real variables are constructed by dividing the corresponding nominal series by the GDP deflator. The top panel of the figure shows two transformations of real M4, namely the annual difference of its log (D4 Log RM4) and the second annual difference of this series, the latter being found to be important in the Results section. The real stock price index (RSP) and the nominal US stock price index, measured as Standard and Poor's 500 (US S&P 500) common stock index, are both also shown in Figure 3 in the form (annual difference of the log) used in the modelling.

5. Results

5.1 Models Estimated over Three Recessions

A summary of our results are presented in Table 3, based on a sample of 125 quarterly observations running from 1966 Q1 to 1997 Q1. This sample, therefore, includes all three recession regimes identified in Section 2. Although data are available from 1963 Q1, the initial 12 quarters are used for various lag and difference operations. Data from 1997 Q2 to 1999 Q2 are used for the out-of-sample statistics also presented Table 3. We present the estimated coefficients for the normalised variables together with summary statistics (RMSE, –2LogL, SIC) and regime error counts both in and out-of-sample. In each case the error counts are given separately for expansion and contraction periods. In reporting the error count statistics we present the results as percentages in addition to giving the numerical counts. For example, the in-sample error count for Model A1 in Table 3 in expansionary periods is 2% (3/102), which indicates that the (rounded down) percentage of errors is 2%, with 3 out of the 102 sample expansion periods wrongly predicted to be recessions.

To calculate these error counts, the estimated probability $p(\boldsymbol{x}_{t-1})$ is converted into a binary regime forecast. Specifically, an expansion is forecast at time t if $p(\boldsymbol{x}_{t-1}) > 0.5$ and recession if $p(\boldsymbol{x}_{t-1}) \leq 0.5$. Although this "0.5 rule" is natural, there are also arguments to suggest that the rule for expansion prediction should be that $p(\boldsymbol{x}_{t-1}) > \boldsymbol{p}$, where $\boldsymbol{p}$ is the proportion of quarters of expansion in the sample. See BJOS for a discussion of this issue. To reflect the latter, and following BJOS, an estimated probability is considered to fall in the uncertain region when it is greater than 0.5 but less than $\boldsymbol{p}$, with $\boldsymbol{p}$ = 0.816 for this sample period. Therefore, although the reported error counts are based on the 0.5 rule, the uncertain count can be used to indicate the impact of using the $\boldsymbol{p}$-rule. Thus, for example, model A1 in Table 3 yields 8 out of 125 sample values in the uncertain region, so that 8 expansion forecasts may be regarded as uncertain. Since only 3 in-sample errors are made by this model during expansions, these uncertain periods must have been predominantly correct predictions of expansions.

Only a selection of our results are shown, but more detailed results are available from the authors on request. A range of domestic nominal variables were tried one by one in combination with inflation (computed as the annual difference of the log of the GDP deflator). Both the nominal variable and inflation were initially entered with all lags from one to eight inclusive, which allowed the indicators to lead by up to two years. The nominal variables investigated at this stage were M4, stock prices, the term structure and short-term interest rates. Generally the same or close lags were selected for these nominal variables and inflation, with estimated coefficients of similar magnitudes and opposite signs. From this investigation, the nominal series that captured the three recession phases with the lowest SIC was M4 with inflation, which suggested the creation of real M4 (RM4). Nominal stock prices yielded the same selected lag as inflation, thus calling for the real stock price (RSP) series to be created. In contrast, the nominal Treasury Bill yield (TBY) short-term interest rate consistently survived the selection procedure without the inclusion of any inflation variable.

Based on the relatively good performance of real M4, this was included with a combination of other variables. The main surprise from these models was that they generally suffered from spurious perfect fit when lags 1 to 8 were included. To overcome this problem, a number of restrictions were imposed. The variables $\Delta_4\text{Log(RM4)}_{-1}$ and $\Delta_4\text{Log(RM4)}_{-5}$ (the annual difference of real M4 lagged over one and five periods) always came through in the perfect fit models with coefficients which were effectively equal but of opposite signs. This led to the use of the second annual difference of this series, $\Delta_4\Delta_4\text{Log(RM4)}_{-1}$. We also imposed specific lags for variables suggested by other models, for example using real stock prices lagged one period because this was the lag selected in the initial investigations of stock prices and inflation. It is also important to recognise that a full "general to specific" modelling procedure cannot be used in this context due to the problems of perfect fit. Therefore, we typically included a maximum of four separate variables in each initial model, with the lags on one or more of these variables restricted in response to earlier findings.

In addition to the domestic variables, we examined the role of international ones. In particular, the series considered were financial ones, which reflects the international nature of important capital markets. Although both stock prices and interest rate series were considered for the US and Germany, only the US S&P 500 stock returns and German FIBOR interest rates survived the selection process.

Table 3 shows the best models (according to SIC) which emerged from this process. Although they play no role in variable selection, the computed *t*-ratio for each estimated coefficient is shown in parentheses. In any case, these *t*-ratios are unreliable since the residuals may exhibit autocorrelation. Model A1 includes the real

M4 variable, the German short-term interest rates and the oil price. Due to the prior standardisation, the magnitudes of the coefficients can be directly compared, and hence we can conclude that $\Delta_4\Delta_4$Log(RM4)$_{-1}$ is the most important variable in this model in terms of predicting UK recessions. The relatively strong negative coefficient for the FIBOR at a lag of one quarter indicates an important role for German interest rates in this model. In Model B1, real UK stock returns and TBY were initially included at a range of lags (1 to 5). The SIC improves compared to Model A1, but the number of errors in contractions rises by one and there are more also uncertain in-sample expansion predictions than for model A1. Model C1 results from adding the US S&P 500 nominal index (at a range of lags) to the initial variables of Model B1. This US stock price index reflects the open nature of the UK stock market and the potential role of international financial movements. The real UK stock price index retains a role Model C1, but with a longer lag (three as compared to one). Further, US stock returns are selected at a lag of one year and with a negative coefficient. Interestingly, the US variable replaces the longer (five quarter) lag of TBY. While the total number of in-sample errors are very similar to those of Models A1 and B1, with a reduction in the uncetain predictions, Model C1 is the only model in Table 3 which has any error out-of-sample (this model yields an estimated probability of 0.16 for expansion in 1998 Q3).

	Model				
Variable	**A1**	**B1**	**C1**	**D1**	**E1**
Intercept	4.267 (4.25)	4.706 (4.02)	4.582 (4.12)	4.825 (3.99)	8.268 (2.90)
Δ_4Log(RSP)$_{-1}$		2.376 (2.40)		2.343 (2.66)	
Δ_4Log(RSP)$_{-3}$			2.357 (2.63)		
$\Delta_4\Delta_4$Log(RM4)$_{-1}$	3.371 (3.73)	2.978 (3.12)	3.929 (2.96)	4.788 (3.32)	5.584 (2.86)
TBY$_{-1}$		-2.226 (-2.62)	-2.506 (-3.28)		-3.857 (-2.61)
TBY$_{-5}$		-1.619 (-2.45)			
Δ_4Log(UKOIL)$_{-4}$	-1.158 (-2.47)				
FIBOR$_{-1}$	-2.372 (-3.71)				-3.858 (-2.48)
Δ_4Log(USS&P)$_{-4}$			-1.954 (-2.74)		
TS$_{-4}$				2.234 (3.13)	
Δ_4Log(PI)$_{-5}$				-3.297 (-3.37)	
Sample Period Summary Statistics					
RMSE	0.2083	0.2001	0.1915	0.1760	0.1631
–2Log L	37.94	30.90	30.79	28.98	20.38
SIC	0.4580	0.4403	0.4394	0.4250	0.3175
Errors In-Sample					
Expansions	2% (3/102)	1% (2/102)	2% (3/102)	0% (1/102)	1% (2/102)
Contractions	17% (4/23)	21% (5/23)	17% (4/23)	17% (4/23)	17% (4/23)
Uncertain	(8/125)	(9/125)	(6/125)	(8/125)	(7/125)
Errors Out-of-Sample					
Expansions	0% (0/9)	0% (0/9)	11% (1/9)	0% (0/9)	0% (0/9)
Contractions	0% (0/0)	0% (0/0)	0% (0/0)	0% (0/0)	0% (0/0)
Uncertain	(0/9)	(0/9)	(0/9)	(0/9)	(0/9)

Table 3: Results with Forecast of 9 quarters

Model D1 examines real stock prices, the term structure and inflation, in addition to $\Delta_4\Delta_4\text{Log(RM4)}_{-1}$. The surviving variables all have the anticipated signs. Of all the models we investigated which rely entirely on domestic variables, this is the one preferred by SIC. It delivers just one in-sample error during expansion periods, although (in common with the other models of the table) it cannot successfully predict all the recession quarters. However, Model E1 emphasises the important role we find for FIBOR in predicting UK recessions. This specification was obtained by adding the German interest rate (at lags 1 to 8) to the variables of Model C1. It is notable that the introduction of the FIBOR eliminates the effect of both stock market prices compared with C1 and reduces SIC to the lowest value in the table. Both interest rate variables are selected at lag one and both enter with negative coefficients. There is a marginal increase with the in-sample error count for expansions compared with D1, but this is off-set by the reduction in the uncertain predictions.

5.2 Forecasting the 1990s Recession

It may be argued that the models just outlined could be purely statistical artefacts and that we have uncovered no enduring regularities in the prediction of UK recessions. This may be true, but we would like to check the validity of our models by performing a genuine post-sample exercise. It is attractive to consider specifying and estimating models using data which excludes the 1990s recession in order to examine this issue. We attempted to do this by repeating the variable selection and estimation procedure using observations to the end of 1989 and then forecasting the binary business cycle indicator over 1990 Q1 to 1999 Q2. Unfortunately, this was fraught with practical difficulties. In particular, the introduction of a range of lags typically resulted in perfect fit when the initial model was estimated over this shorter sample period. Therefore, we are able to conduct, at best, a restricted post-sample validation exercise.

Table 4 shows the results of this exercise. Each model here can be compared to the corresponding model of Table 3. However, the specifications in Table 4 were arrived at using only a small range of initial lags, which always included the lags actually selected in the Table 3 model. The single exception relates to Model C1, where TBY had to be dropped when the model was investigated over a shorter period, because the inclusion of TBY resulted in perfect fit. Despite these qualifications, the results in Table 4 help us to gauge whether these models could have predicted the 1990s recession. To assist this interpretation, Figure 4 shows the regime predictions generated from each model, with these predictions being post-sample ones from the beginning of 1990 (this is indicated by a vertical line).

Overall, very similar models result in Table 4 compared with Table 3. Indeed, Model E2 is preferred by SIC over its competitors in Table 4, confirming the preference for the corresponding model in Table 3. Further, although the selected lags sometimes differ (for example, only lag 1 of TBY remains in Model B2, compared with two lags in B1), the only case where a variable included in the model of Table 3 drops out entirely in Table 4 is the case of TBY for Model C2 already noted. In general, the corresponding coefficients are also of similar magnitudes. Against these reassuring features, it should be noted that the ranking of models by SIC, beyond the one with the lowest value, does differ between the tables.

Model A2 virtually misses the 1990s recession, with only 2 correctly forecast recession quarters and six errors. For Model B2, the first signal for the 1990s recession arrives a year too early (within the sample period used for estimation) and the signal finishes half way through the actual regime phase. The subsequent expansion is, however, very clearly indicated with the probability of expansion being virtually one throughout this period. It may be said that Model B2 indicates the length of the recession, but not its timing.

Model C2 performs relatively poorly in forecasting, especially in relation to predicting expansion periods, when the signals are erratic (see the third panel of Figure 4) even though they do not lead to any in-sample expansion errors (Table 4). This is, perhaps, not surprising and the loss of the interest rate variable seems to be acutely felt by this model. It should be noted that this model is the worst of those in Table 4 according to SIC, and hence would presumably have been used for forecasting in any case. It is also evident from the third panel of Figure 4 that the 1990s recession is predicted to end earlier than it actually did and that a further recession is predicted in 1997-8. It is noteworthy that although GDP did not fall during this latter period, there was much concern at this time that the UK might be entering a recession. Indeed GDP “flattened off” in the fourth quarter of 1998 and the first quarter of 1999, while industrial production actually fell in these two quarters. The information about this ‘extra’ recession appears to be largely attributable to a “false signal” from the US stock market at that time.

Model D2 predicts the onset of recession on time, but recovery is predicted to occur three quarters too early. Overall, however, the regime predictions from Model D2 are very clear and also generally accurate in timing. In practice, the post-sample error counts from Model E2 are similar to those of D2. However, the onset of recession recession is predicted too early by E2 and also the ending of the recession is too optimistic in timing. The final spike evident in the graph for E2 in Figure 4 towards the end of the recession does not cause the expansion probability to fall below 0.5. Nevertheless, the probability relating to that quarter is an indication of uncertainty about the regime.

	Model				
Variable	**A2**	**B2**	**C2**	**D2**	**E2**
Intercept	3.943 (4.07)	5.927 (2.90)	5.099 (3.51)	4.964 (3.50)	8.546 (2.29)
Δ_4Log(RSP)$_{-1}$		2.482 (2.10)	3.498 (2.33)	3.152 (2.44)	
Δ_4Log(RSP)$_{-3}$			3.371 (2.51)		
$\Delta_4\Delta_4$Log(RM4)$_{-1}$	2.326 (2.81)	2.902 (2.57)	4.362 (2.52)	4.756 (2.83)	5.357 (2.35)
TBY$_{-1}$		-3.949 (-2.42)			-4.51 (-1.89)
Δ_4Log(UKOIL)$_{-1}$	-2.989 (-2.02)				
FIBOR$_{-1}$	-1.801 (-2.73)				-2.918 (-2.12)
Δ_4Log(USS&P)$_{-1}$			-2.865 (-2.47)		
Δ_4Log(USS&P)$_{-4}$			-2.628 (-2.33)		
TS$_{-4}$				1.545 (2.23)	
Δ_4Log(PI)$_{-5}$				-3.416 (-2.97)	
Sample Period Summary Statistics					
RMSE	0.1689	0.1714	0.1685	0.1546	0.1436
–2Log L	23.33	17.58	23.63	19.99	11.85
SIC	0.4332	0.3732	0.5315	0.4459	0.3136
Errors In-Sample					
Expansions	0% (0/81)	1% (1/81)	0% (0/81)	0% (0/81)	1% (1/81)
Contractions	13% (2/15)	20% (3/15)	13% (2/15)	13% (2/15)	13% (2/15)
Uncertain	(6/96)	(7/96)	(5/96)	(6/96)	(6/96)
Errors Out-of-Sample					
Expansions	0% (0/30)	0% (0/30)	20% (6/30)	0% (0/30)	0% (0/30)
Contractions	75% (6/8)	50% (4/8)	37% (3/8)	37% (3/8)	37% (3/8)
Uncertain	(4/38)	(3/38)	(2/38)	(2/38)	(3/38)

Table 4: Results with Forecast of the 1990s Recession

To summarise our results, it appears that the UK short-term interest rate is important for predicting the 1990s recession in the UK, whether this interest rate effect is modelled through the Treasury Bill yield or the term structure. Broad money and inflation play a crucial role over the whole sample, and in combination as real M4 they provide the best single leading indicator of recessions. The German short-term interest rate is the most useful international variable. This may play an important role for the 1990s recession in the UK, since as this time Britain was part of the European Exchange Rate Mechanism (ERM) and the pound was fixed to the DM.

6. Conclusion

In this paper we offer dates for classifying UK GDP into classical cycles of expansion and recession. We also construct a composite leading indicator for this cycle using the methodology developed in BJOS. Not withstanding the difficulties in dating cycles and constructing leading indicators, we believe that the results of our efforts are of interest. In particular, the results suggest that German short-term interest rates complement UK real broad money and the Treasury Bill yield, adding predictive information for regimes in UK GDP compared to that available in domestic variables. The role for German interest rates may relate to evidence in Clarida *et al* (1998), who find the German short-term interest rate to have strong and significant effects for the operation of UK monetary policy.

Although we are unable to undertake a full post-sample forecasting exercise, we are able to verify that our model which is preferred overall by SIC would also be selected among competitors on the basis of information to the end of 1989. Although by no means perfect in its prediction of the timing of the 1990s recession when examined in a post-sample context, the recession signal is clear. It is also notable that a model using only domestic variables (Model D2) also does well in post-sample prediction of this recession. Together, these models may provide a useful basis of further work on the prediction of recessions for the UK.

The role found for domestic short-term interest rates raises the issue of the endogeneity of this variable. This applies especially at the current time, since short-term interest rates are the tool used by the Monetary Policy Committee of the Bank of England to control future inflation. Through the operation of monetary policy, interest rates will be set partly in the light of predicted future output growth. Our models assume, however, that interest rates are exogenous to business cycle phases. Tackling this issue is also a topic for future research.

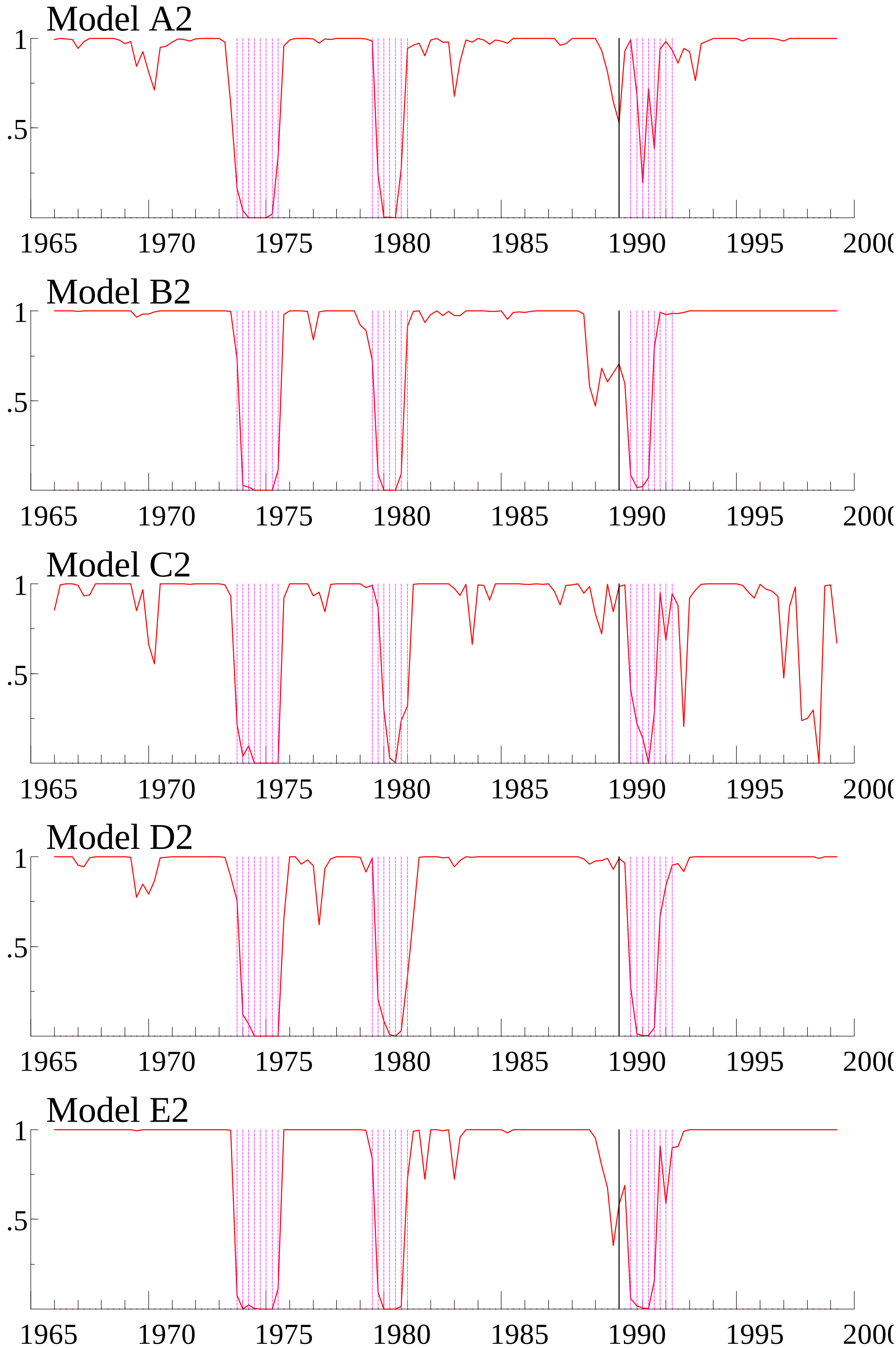

Figure 4: Probability Charts of Models from Table 4

Data Appendix

Variable	Full Name	Sample	Source/ code	SA or NSA*	Transform
GDP	Gross Domestic Product at factor cost: Constant 1995 prices	55q1 – 99q2	ONS/ YBHH	SA	D4 of Log
PI	GDP Gross Value Added at basic prices: Implied deflator1995=100	55q1 – 99q2	ONS/ CGBV	SA	D4 of Log
INF	Inflation Rate	56q1 – 99q2	100*(log(PI)-log(PI(-4)))	SA	-
SP	FT actuaries all share index (10 April 1962=100)	63q1 – 99q3	ONS/ AJMA	NSA	D4 of Log
RSP	Real stock prices	63q1 – 99q3	SP / PI	NSA	D4 of Log
DY	FT actuaries all share index: dividend yield %	63q1 – 99q3	ONS/ AJMD	NSA	None
M4	Money stock M4 (end period): level #m	63q1 – 99q2	ONS/ AUYN	SA	D4 of Log
RM4	Real M4	63q1 – 99q2	M4 / PI	SA	D4 of Log
TBY	Treasury Bills 3 month yield	60q2 – 99q3	ONS/ AJRP	NSA	None
LR	BGS: long-dated (20 years): Par yield - % per annum	57q1 – 99q2	ONS/ AJLX	NSA	None
TS	Term Structure	60q2 – 99q2	LR - TBY	NSA	None
RTS	Real Term Structure	60q2 – 99q2	LR-TBY-INF	NSA	None
US S&P	US Standard & Poor's index of 500 common stocks(monthly average)	60q1 – 99q3	Datastream	NSA	D4 of Log
USFF	US Federal Funds interest rate	60q1 – 99q3	OECD	NSA	None
USXCH	GB/US Dollar Exchange Rate month average / Quantum	60q1 – 99q3	OECD	NSA	-
USOIL	Spot Oil Price: West Texas Intermediate: Prior'82=Posted Price, $/ Barrel	60q1 – 99q3	Federal Reserve	NSA	None
UKOIL	UK oil price	60q1 – 99q3	UKOIL x (1/USXCH)	NSA	D4 of Log
BDSP	German share price index (CDAX), 1995=100	60q1 – 99q3	OECD	NSA	D4 of Log
FIBOR	German Frankfurt inter-bank offered rate	60q1 – 99q3	OECD	NSA	None
CONS	Consumers' Expenditure 1990 Prices	55q1 – 99q2	OECD	SA	D4 of Log
HCPI	CPI Housing / Index publication base	62q1 – 99q2	OECD	NSA	D4 of Log
HS	Housing Starts	57q1 – 98q1	ONS/ CTOZ	SA	D4 of Log
CBIO**	CBI Change in Optimism	59q1 - 71q4	ONS/ DKDK	SA	None
		72q1 – 98q4	Datastream	NSA	

* SA = Seasonally Adjusted and NSA = Not Seasonally Adjusted.
** The CBI Industrial Trend Survey was only conducted three times a year between 1959 and 1971 and the ONS have interpolated these values to give a quarterly series before seasonally adjusting it with X-11. After this the author uses a regression with seasonal dummies to seasonally adjust the data.

Table A.1: Data descriptions with sample period, source and transformations

References

Andreou, E., Osborn, D.R. and Sensier, M. (2000), 'A comparison of the statistical properties of financial variables in the USA, UK and Germany over the business cycle', *The Manchester School*, forthcoming.

Artis, M.J., Kontolemis, Z.G. and Osborn, D.R. (1997), 'Business cycles for G7 and European countries', *Journal of Business*, vol. 70, pp. 249-279.

Binner, J.M., Fielding, A. and Mullineux, A.W. (1999), 'Divisia money in a composite leading indicator of inflation', *Applied Economics*, vol.31, no.8, pp.1021-1031.

Birchenhall, C.R., Jessen, H., Osborn, D.R. and Simpson, P. (1999), 'Predicting US Business-Cycle Regimes', *Journal of Business and Economic Statistics*, vol. 17, no. 3, 313-323.

Boldin, M.D. (1994), 'Dating business cycle turning points', *Journal of Business*, Vol. 67, pp. 97-131.

Bry, G. and Boshcan, C. (1971), *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs*, New York, NBER.

Burns, A.F. and Mitchell, W.C. (1946), *Measuring Business Cycles*, New York, NBER.

Camba-Mendez, G., Kapetanios, G., Smith, R., and Weale, M. (1999), 'An Automatic Leading Indicators of Economic Activity: Forecasting GDP Growth for European Counties', *NIESR Discussion Paper* No. 149.

Clarida, R., Gali, J. and Gertler, M. (1998), 'Monetary policy rules in practice. Some international evidence', *European Economic Review*, vol. 42, pp. 1033-1067.

Conference Board, (1998), Business Cycle Indicators. New York. 2 (February) no.3.

Dow, C. (1998), *Major Recessions: Britain and the World, 1920-1995*, Oxford University Press, Oxford.

Estrella, A. and Mishkin, F.S. (1998), 'Predicting U.S. Recessions: Financial Variables as Leading Indicators', *Review of Economics and Statistics*, vol. 80, pp. 45-61.

Green, G.R. and Beckman, M.A. (1993), 'Business cycle indicators: upcoming revisions of composite leading indicators', *Survey of Current Business*, October, vol. 73, pp. 44-51.

Harding, D. and Pagan, A.R. (1999), 'Dissecting the Cycle', *Melbourne Institute Working Paper* No. 13/99.

Moore B. (1993), 'A Review of CSO Cyclical Indicators', *Economic Trends*, No. 477, July, pp. 99-107.

Nilsson, R. (1987), 'OECD leading indicators', *OECD Economic Studies*, vol. 9, pp. 105-146.

Plosser, C.I. and Rouwenhorst, K.G. (1994), 'International term structures and real economic growth', *Journal Of Monetary Economics*, vol. 33, no. 1, pp. 133-55.

Roma, A. and Torous, W. (1997), 'The cyclical behavior of interest rates', *Journal of Finance*, vol. 52, no. 4, pp. 1519-42.

Simpson P.W., Osborn D.R. and Sensier M. (1999), 'Modelling Business Cycle Movements in the UK Economy', *School of Economic Studies Discussion Paper Series*, University of Manchester, No. 9908. *Economica* forthcoming.

Stock, J.H. and Watson, M.W. (1991), 'A probability model of the co-incident indicators', in G. Moore and K. Lahiri, eds, *Leading Economic Indicators*, Cambridge University Press, pp.63-90.

Stock, J.H. and Watson, M.W. (1993), 'A procedure for predicting recessions with leading indicators: Econometric issues and recent experience', in J.H. Stock and M.W. Watson, eds., *Business Cycle Indicators and Forecasting*, Chicago: University of Chicago Press, pp.95-156.