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Predicting UK Business Cycle Regimes

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ABSTRACT

This paper uses logistic regression to construct a one-quarter ahead prediction model for classical business cycle regimes in the UK. The binary dependent variable is obtained by applying simple mechanical rules to date turning points in quarterly real GDP data from 1963 to 1999. Using a range of real and financial leading indicators, several parsimonious one-quarter-ahead models are developed for the GDP regimes, with model selection based on the SIC criterion. 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 emphasises the open nature of the UK economy.

JEL classification: C22, E32, E37, E40.

Keywords: business cycle dating, financial variables, leading indicators, logistic classification models, regime prediction.

I INTRODUCTION

Much recent interest in theoretical and empirical economics has focused on the role of recessions compared to expansions in economic activity. To emphasise possible differences between them, the literature often refers to expansions and recessions as being the two *regimes* of the business cycle. Policy makers and private agents also have a serious interest in the occurrence of these regimes and, in particular, in models that help in predicting the onset of recession or recovery. This paper empirically studies a class of such models in the context of the UK business cycle.

Many applied studies of business cycle regimes have been undertaken using the Markov-switching model promoted by Hamilton (1989). UK studies based on this approach include Acemoglu and Scott (1994) and Krolzig and Sensier (2000). The Hamilton model is, however, relatively uninteresting from a regime prediction viewpoint because it assumes the regime-switching probabilities are constant over time. Although Filardo (1994) has generalised the approach to permit the regime-switching probabilities to be functions of one or more leading indicators, Birchenhall, Jessen, Osborn and Simpson (1999), hitherto referred to as BJOS, find that US business cycle regimes are better predicted when the leading indicator information is used in the context of a logistic regression model. Thus, while modelling the regime implies a loss of information in comparison with the modelling of observations on GDP growth, it appears that the former yields better predictions when the regime itself is the focus of interest.

In a similar vein to BJOS, Estrella and Mishkin (1998) employ a probit model for US business cycle regime prediction. Both of these papers analyse business cycle regimes defined employing the NBER turning point dates to generate a binary indicator for expansions and recessions. The regime prediction is then a probabilistic statement about the regime at a specified future date, with this probability depending on the values taken by leading indicator variables.

The history of leading indicators dates back to Burns and Mitchell (1946). The usual methodology for producing a composite leading indicator is based on combining a range of individual leading indicators into a single composite indicator, essentially by scaling individual leading indicators and then averaging (see, for example, Green and Beckman, 1993, for the US or Moore, 1993, for the UK). A related, but more sophisticated, methodology is used by Stock and Watson (1991, 1993).

The UK 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 expansions 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 reasons, this paper concentrates on (so-called) classical business cycles for the UK, which are based on absolute expansions and declines in activity, and not growth cycles.

None of the studies mentioned above attempt to build a structural economic model. This is because an empirical model which attempts to predict regimes must focus on statistical relationships which are common across different historical cycles. Therefore, the model must, in one way or another, filter out structural relationships that are specific to individual cycles. In other words, the predictive model will not encompass the rich structural nature of history.

In principle we could consider a structural model that allows for the structural changes across cycles and across regimes within cycles. However, Clements and Hendry (1999) have forcibly argued that, in the presence of structural change, the use of non-structural relationships may significantly improve the performance of forecast models. In common with other analyses, we make no attempt here to construct a structural model of economic activity in the UK, rather we concentrate on identifying stable statistical relationships between leading indicators and business cycle regimes. More specifically, we use the methodology of BJOS to construct a regime prediction model for the UK. The regime prediction probability from this model can itself be interpreted as a composite leading indicator of the UK business cycle.

To specify and estimate the model we need the regimes to be known for our sample period. Unlike the case of the US, there are no well-established dates available for UK classical business cycle turning points. Therefore, our first task is to develop such dates. Note that once the model is estimated we need no further regime information to predict future regimes, since the regime probability then depends only on the values of the leading indicators. The second task is then to select among the available leading indicators. Although we do not conduct an exhaustive search over all possible options, we believe that we have interesting results to offer.

The rest of the paper has the following structure. Section II outlines the BJOS methodology and how it has been further developed for this paper. Section III discusses the dating of the classical cycle for the UK, together with some features of UK post-war recessions. The leading indicator data is then discussed in Section IV, with the one-quarter-ahead regime prediction models presented in Section V. Section VI offers concluding remarks.

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

II MODELLING THE PROBABILITY OF EXPANSION

A fuller account of the methodology used in this paper is presented in BJOS, with a brief outline included here to clarify the subsequent discussion of the results.

Using a data vector $\boldsymbol{x_{t-1}}$ of observed variables up to and including period t-1, we construct a one-period ahead business cycle indicator of the form

$$\boldsymbol{p}_{t-1} = lf\,(\beta'\boldsymbol{x}_{t-1}) \tag{1}$$

where $\boldsymbol{p_{t-1}}$ is the probability that the business cycle regime for at quarter t will be an expansion, based on information up to an including the preceding quarter, t-1. This probability is constructed as a logistic function of the available information, so that lf (z) = exp(z) / [1 + exp(z)], and β is a vector of coefficients. The nonlinear regression used to estimate (1) has the binary regime indicator as the dependent variable (with unity indicating expansion and zero indicating recession), while $\boldsymbol{x}_{t-1}$ consists of leading indicators. Using sample information for t = 1, …, T, the log-likelihood function for this binary model is given by

$$\log(L) = \Sigma_1 \log(\boldsymbol{p}_{t-1}) + \Sigma_0 \log(1 - \boldsymbol{p}_{t-1}) \tag{2}$$

where Σ_1 is the sum over all expansionary quarters and Σ_0 is the sum over all quarters of recession. Constructing our 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. The search aims to minimise the Schwartz Information Criterion (SIC) in the form

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

where L is the likelihood value from (2), k is the number of estimated coefficients and T is the number of observations in the sample used for estimation. Sin and White (1996) show that the use of such penalised likelihood criteria asymptotically select the “best” model from the choice set, in a sense of being closest to the unknown data generating process according to the Kulback–Liebler Divergence, even if all models under consideration are misspecified. Looked at from a different perspective, (3) implies that an additional variable will be included in the model only if increases the term $2 \times \log L$ by more than the penalty for its inclusion, namely $\log(T)$. Essentially variables are retained only if they make a sufficiently strong contribution to likelihood value. In this way, we hope to filter out variables whose contribution to the empirical likelihood is limited or "local" and hence that the selected model will reflect stable relationships in the data. For this interpretation, note from (2) and (3) that a variable will decrease SIC only if its inclusion increases the *average* log-probability by more than $\log(T)/(2T)$. For example, if T=100, the average increase in the probabilities would need to be approximately 2.3%. Any "local" variable that improves only 10% of the probabilities would need to increase those probabilities by some 20% on average if it is to be retained in the model. Nevertheless, we do not rely on only sample period SIC values and we take care to examine out-of-sample performance.

We use two automated search procedures. The first method, *sequential elimination*, 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. 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. This continues, with one variable eliminated at each stage, 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. This method was the basis of model selection in BJOS and has, in spirit, much in common with the general-to-specific approach found to perform well by Hoover and Perez (1999) in the context of the specification of a dynamic linear model.

The second search method we employ is the *n-search algorithm*. As with sequential search we start with a prior set of K variables, but once the set of variables is reduced to a specified number n using sequential elimination, the algorithm considers *all* models with k variables, for $k \leq n$. For this paper, n was set to 7. This choice was based on our experience with sequential elimination in that the largest model selected using that method involved 7 variables.

Sequential elimination has some drawbacks. In principle, a variable may be rejected prematurely and the search procedure is dependent on the initial set of K variables. For example, the inclusion of one or more additional variables in the initial set can alter the selection even if these newly included 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 as expansion or recession periods. When such a "perfect" fit occurs for a specified set of initial variables, we manually adjust the initial choice set to avoid this problem. The n-search algorithm eliminates these difficulties at the cost of not considering all models involving more than n variables and in involving considerably more computational time. Because both algorithms involve a partial search of the possible subsets of the original K variables, the final selection is not guaranteed to be that subset which yields the global minimum of SIC. However, the n-search algorithm employed at the final stage of the analysis in Section V below provides some reassurance in this respect.

III 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 GDP cycles for the US, UK and Australia. Both of these papers use procedures based on the Bry and Boschan (1971) algorithm. The principal 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 set of simple mechanical rules 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 (at factor cost in 1995 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.

TABLE 1: Rules for Dating Peaks and Troughs

	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 $\Delta_2 Y_{t+2} > 0$

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) that 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 1974Q1 and 1975Q3. This case is discussed below.

TABLE 2: UK Classical Turning Points in UK GDP

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		

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. Figure 1 shows the full sample of the logarithm of UK GDP, with the recessions identified by shading.

The dating of the first recession is worthy of further discussion. The rules of Table 1 indicate a peak at 1973Q3, but offer two following trough dates namely 1974Q1 and 1975Q3.

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

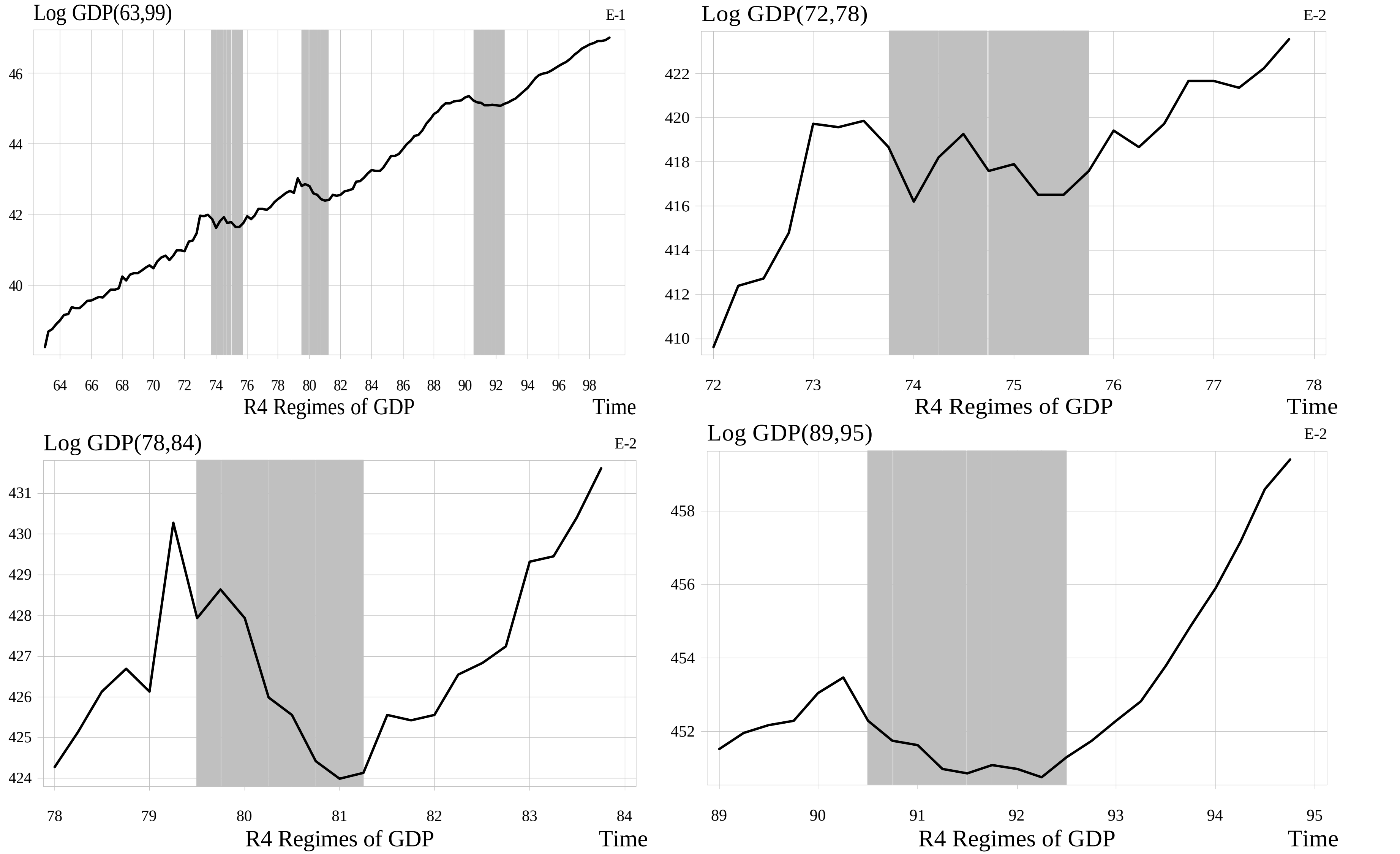

Figure 1: UK GDP (with classical business cycle regimes shaded)

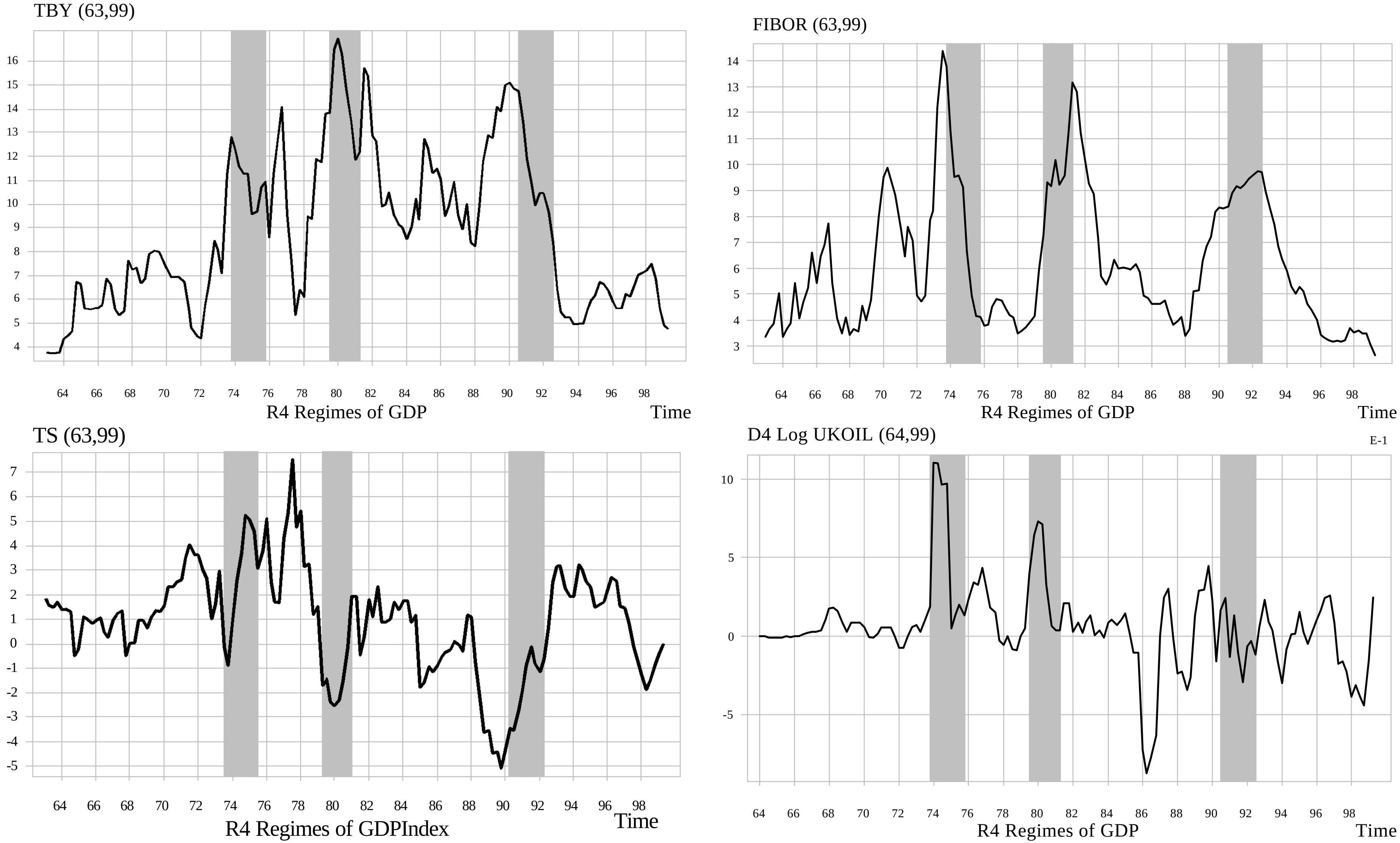

Figure 2: Leading Indicator Plots

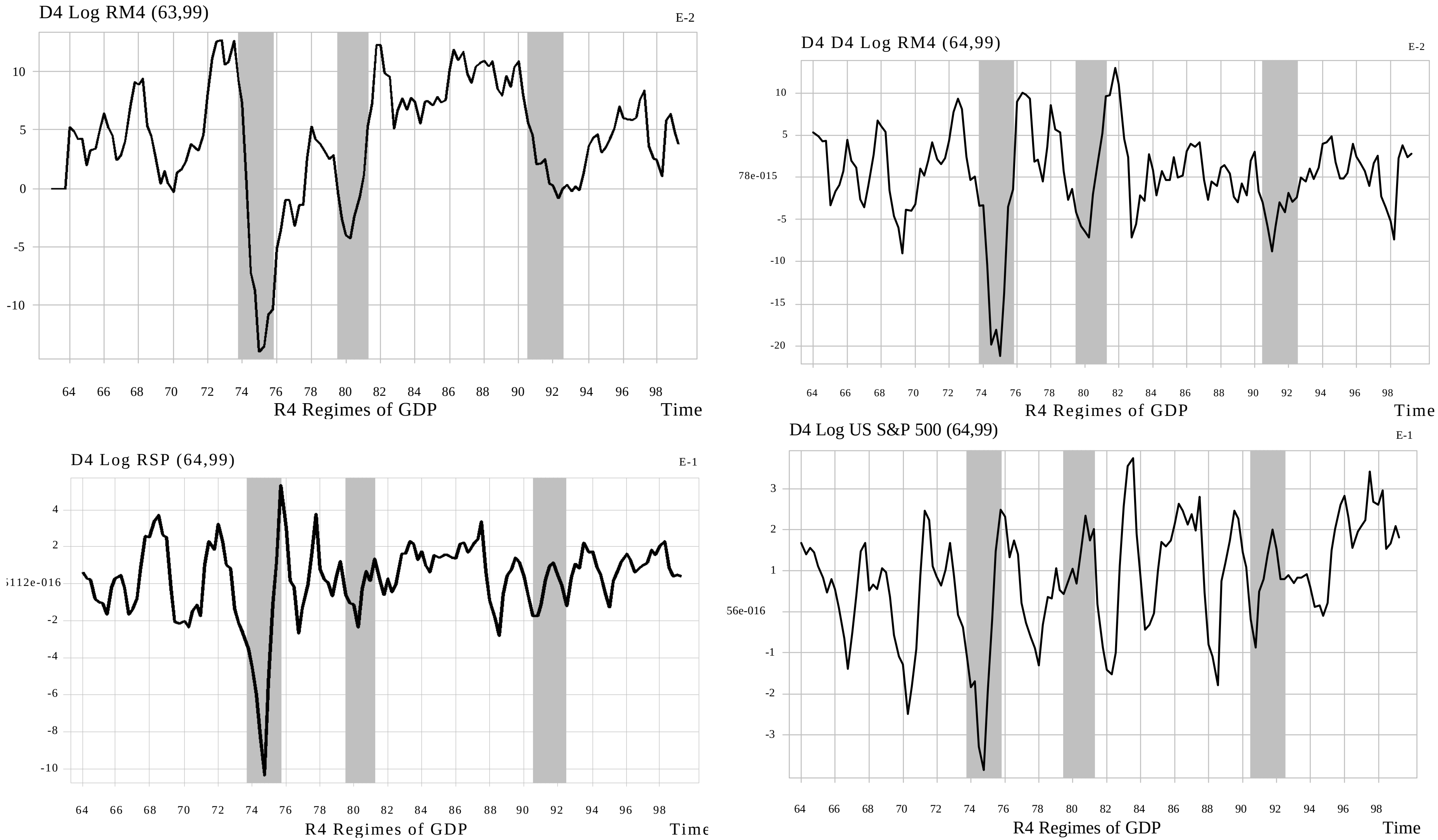

Figure 3: Leading Indicator Plots

However, we reject the former on the grounds that the low value of GDP in that quarter, and the subsequent increases in 1974Q2 and 1974Q3, reflect the impact of the three-day working week associated with a miners' 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 1979Q4 and fall in 1980Q1 suggest the dating of the onset of the second recession is not entirely clear-cut. Dating of the third recession is, however, straightforward.

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.

IV LEADING INDICATOR DATA

Although Stock and Watson (1991, 1993) utilise information in a large number of variables, a number of recent studies have found financial variables and particularly the term structure of interest rates to be important for predicting the US business cycle (for example, Estrella and Mishkin, 1998, Plosser and Rouwenhorst, 1994, Roma and Torous, 1997). Galbraith and Tkacz (2000) examine the link between the term structure and output in G7 countries, while Davis and Fagin (1997) study the predictive content of the term structure for European countries. The general conclusion is that the strong predictive role of this variable for the US does not carry over to other major economies. Analyses specific to the UK are relatively rare, but include Camba-Mendez *et al*. (1999), Andreou *et al.* (2000) and Simpson *et al.* (2000), all of which concentrate on financial series as leading indicators. Furthermore Binner *et al*.

(1999) find M4 to have useful leading indicator properties for UK inflation. The ONS growth cycle leading indicator system also included a number of indicators of real activity.

On the basis of these studies, we considered many variables[3]. These included aspects of real activity (housing starts, consumers' expenditure, the change in optimism from the quarterly CBI survey), as well as financial series. However, these real activity variables were not selected in any model and hence are not discussed below. When a range of domestic variables were considered, we consistently found that inflation and a subset of financial variables survived our selection process, with this subset being broad money, stock prices and short-term interest rates. We also explicitly acknowledge the open nature of the UK economy by examining international financial variables, specifically stock market prices and short-term interest rates for the US and Germany. Of these, we find strong evidence for US stock prices (Standard and Poor's index of 500 common stocks) and German short-term interest rates (Frankfurt inter-bank offered rate), with a possible role also for the UK oil price[4]. The remaining two international financial variables, namely US interest rates and German stock prices, were not selected in any model and hence are not discussed below. Figures 2 and 3 show the full range of leading indicator variables used in the modelling section.

We transform money (M4), the stock market price series, oil prices and the GDP deflator data by taking logs and then an annual difference to smooth the data[5]. The interest rate series are analysed without transformation, except that the term structure is computed as the difference between the UK long and short rates. The UK Treasury Bill yield is used as the domestic short rate and the 20-year par yield on British Government Securities for the domestic long rate.

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[3] For a full list of the variables considered see the data appendix.

[4] The UK oil price is obtained as the West Texas Intermediate posted price, converted from US dollars to sterling using the exchange rate for each quarter.

Of course, business cycle regimes are dynamic and it would be attractive to consider lagged regimes as a potential indicator of the future regime. This is, however, not possible in practice because the current regime is not known with certainty. As indicated by the dating rules used in Section II, the sign of future as well as past GDP growth plays a role in defining the regime. It might also be noted that an alternative approach to the one we adopt would be to combine the individual potential leading indicator series into a single indicator on the basis (say) of principal components or, perhaps, a simple averaging technique. Such techniques are concerned with extracting the common movements across the various series, but do not focus on how well such common movements predict business cycle regimes. The results of BJOS and also Estrella and Mishkin (1998) indicate that regime modelling using a small number of leading indicators can lead to better post-sample regime predictions than employing an indicator based on extracted common movements.

Our model specification procedure is outlined in Section II. Most of our search was based on the sequential elimination algorithm. However, as a check, the n-search algorithm was also applied to the initial variables of the reported models. In almost all cases the *n*-search algorithm, with $n = 7$, selected the same model as sequential elimination. The results reported are based on sequential elimination, with any differences from the *n*-search algorithm noted.

V RESULTS

Our models are initially selected and estimated over the sample period of 125 quarterly observations running from 1966Q1 to 1997Q1 and hence covers the three recessions identified in Section II. Data from 1997Q2 to 1999Q2 are used to generate out-of-sample

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

statistics. However, since no recession occurs during this latter period, the post-sample statistics are not very informative. To examine model stability, we later consider the models which result when selection and estimation is based on data to the end of 1989, which allows prediction of the 1990s recession to be examined.

Although all variables are available from 1963Q1, the initial 12 quarters are used for various lag and difference operations and all estimations commence in 1966Q1. For each normalised variable, we show its the estimated coefficient with the corresponding computed *t*-ratio shown in parentheses. These *t*-ratios play no role in model selection and, in any case, they are unreliable since the residuals may exhibit autocorrelation, and other forms of misspecification. Summary statistics are provided for each model.

The summary statistics within sample are the root mean-square error (RMSE), minus twice the log likelihood ($-2\text{Log}L$) defined by (2), SIC defined by (3) and regime error counts. The regime error counts are also presented for the post-sample period, where this is 1997Q2 to 1999Q2 for the models of Table 3 and 1990Q1 to 1999Q2 for those in Table 4. In each case the error counts are given separately for expansion and contraction regimes. 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, BJOS argue that an alternative rule for expansion prediction is $p(\boldsymbol{x}_{t-1}) > \boldsymbol{p}$, where $\boldsymbol{p}$ is the proportion of quarters of expansion in the sample. This alternative is based on $\boldsymbol{p}$ providing a naive regime prediction, with the leading indicators providing information in the direction of expansion if $p(\boldsymbol{x}_{t-1}) > \boldsymbol{p}$ and in the direction of recession if $p(\boldsymbol{x}_{t-1}) < \boldsymbol{p}$. To reflect the latter view, 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 our 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 this model makes only 3 in-sample errors during expansions, these uncertain periods must have been predominantly correct predictions of expansions.

Models Estimated over Three Recessions

Table 3 provides our principal results for the entire sample period. The results shown reflect the outcome of prior searches. These prior searches initially involved a range of domestic nominal variables being entered 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 the annual growth of broad money (Δ_4LogM4), annual growth of stock prices (Δ_4LogSP), the term structure (TS) and the 3-month Treasury Bill yield (TBY). For each of broad money and stock prices, the same or close lags were generally selected for the nominal variable and inflation, with estimated coefficients of similar magnitudes and opposite signs. Hence, the growth of real M4 (Δ_4LogRM4) and the growth of real stock prices (Δ_4LogRSP) were subsequently used. In contrast, the nominal Treasury Bill yield short-term interest rate consistently survived the selection procedure without the inclusion of any inflation variable and hence TBY is retained as a nominal variable. Of these initial searches, the one involving real M4 and inflation produced the lowest SIC.

TABLE 3: Models Selected using Data to 1997Q1

	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(S&P)$_{-4}$			-1.954 (-2.74)		
TS$_{-4}$				2.234 (3.13)	
Δ_4Log(PRICE)$_{-5}$				-3.297 (-3.37)	
Initial Variables of Search (lags)	UKOIL(1-8), FIBOR(1), RM4(1)	TBY(1-5), RSP(1-5), RM4(1)	TBY(1-5), S&P(1, 4-6), RSP(1-4), RM4(1)	RSP(1), PRICE(3, 5), TS(4, 5), RM4(1)	TBY(1-5), RSP(1-5), FIBOR(1-5), RM4(1)
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)

Based on the initial searches, Δ_4LogRM4 was used with a combination of other variables. The main surprise from these models was that they frequently suffered from perfect fit when all lags 1 to 8 were included. To overcome this problem, a number of restrictions were imposed. The variables Δ_4Log(RM4)$_{-1}$ and Δ_4Log(RM4)$_{-5}$ (lags one and five quarters of Δ_4RM4) 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, $\Delta_4\Delta_4$LogRM4$_{-1}$, which appears in all models reported in Table 3. This second annual difference may be over-differencing in that a single difference renders LogRM4 stationary. However, Clements and Hendry (1999, Chapter 5) show that over-differencing can improve forecasts when the model is subject to structural breaks. It is plausible that our SIC based selection procedure may be suggesting that the relationship between money and real activity changes over the business cycle; different forms of such asymmetry have been investigated for the US by Cover (1992) and by Garcia and Schaller (1995).

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. The starting lags for each model are shown in the tables.

Table 3 shows the best models (according to SIC) that emerged from this process. Model A1 includes the real M4 variable, the German short-term interest rates (FIBOR) and oil price inflation (Δ_4LogUKOIL). Due to the prior standardisation of all indicators employed to zero sample mean and unit sample variance, the magnitudes of the coefficients can be directly compared. Hence we can conclude that $\Delta_4\Delta_4$LogRM4$_{-1}$ is the most important variable in this model, while the relatively strong negative coefficient for the FIBOR at a lag of one quarter indicates an important role for German interest rates. In Model B1, real UK stock prices and TBY were initially included at a range of lags. 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 index (S&P) 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 prices are selected at a lag of one year and with a negative coefficient. Interestingly, this US variable replaces the longer (five quarter) lag of TBY. While the total number of in-sample errors is very similar to those of Models A1 and B1, with a reduction in the uncertain predictions, Model C1 is the only model in Table 3 that has any error out-of-sample (this model yields an estimated probability of 0.16 for expansion in 1998Q3).

Model D1 examines real stock prices, the term structure and inflation (Δ_4LogPRICE), in addition to $\Delta_4\Delta_4$LogRM4$_{-1}$. 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 does not successfully predict all the recession quarters. However, Model E1 emphasises the important role we find for FIBOR in predicting UK recessions. This specification is obtained when the German interest rate is added to the initial variables of either Model B1 or C1. It is notable that, compared with C1, the introduction of the FIBOR eliminates the effect of both the UK and US stock market prices and reduces SIC to the lowest value in the table. Both UK and German interest rates 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 offset by the reduction in the uncertain predictions.

It was noted in the discussion of Section II that our model selection procedure depends on the *a priori* specification of the initial *K* variables to be included in the search. Therefore, the preferred model E1 could be a function of the specific set shown. To guard against this possibility, we defined an encompassing general model as the union of all variables considered in the initial sets for all models of Table 3. Application of the sequential search algorithm again resulted in model E1. This provides assurance that this model is not unduly dependent on the specific initial variables shown for that model in Table 3. In particular, the term structure of interest rates, UK oil prices, UK inflation and US stock prices, which are not included in the initial set for Model E1, are not selected when this initial set is expanded[6].

Forecasting the 1990s Recession

In this section we check the validity of our procedures by performing a post-sample exercise. It is attractive to consider specifying and estimating models using data that 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 1990Q1 to 1999Q2. Unfortunately, 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 (as shown), which usually 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 at any lag resulted in perfect fit. One model in Table 4, namely Model A2, was the only case where the *n*-search produced a different selection from the sequential search. The model selected by *n*-search had a lower SIC and concentrated on the oil price variable and the FIBOR, eliminating real M4. However, this model totally missed the 1990s recession. Given

[6] It is, perhaps, surprising that this expanded initial set of variables did not result in perfect fit.

the role of oil prices in the first recessions and their absence in the third, we have not pursued this model.

TABLE 4: Models Selected using Data to 1989Q4

	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(S&P)$_{-1}$			-2.865 (-2.47)		
Δ_4Log(S&P)$_{-4}$			-2.628 (-2.33)		
TS$_{-4}$				1.545 (2.23)	
Δ_4Log(PRICE)$_{-5}$				-3.416 (-2.97)	
Initial Variables of Search (lags)	UKOIL(1-8), FIBOR(1), RM4(1)	TBY(1, 5), RSP(1), RM4(1)	S&P(1, 4), RSP(1, 3), RM4(1)	RSP(1), PRICE(5), TS(4), RM4(1)	TBY(1), FIBOR(1), RM4(1)
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)

Despite these qualifications, 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, as 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.

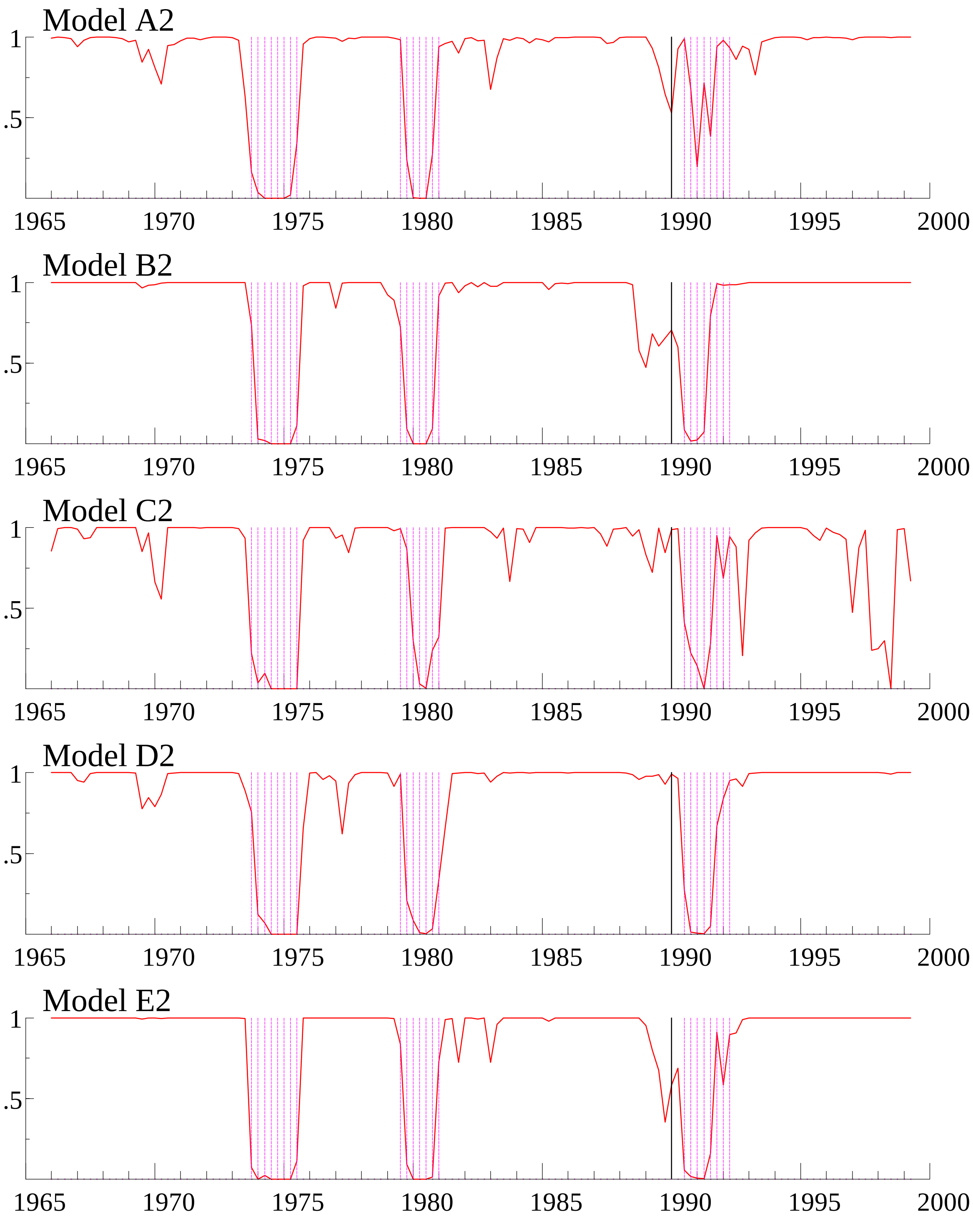

Figure 4: Filter Probability Charts of Models from Table 4

Turning to the post-sample forecasts, Model A2 virtually misses the 1990s recession, with only 2 correctly forecast recession quarters and six errors in this period. All the remaining models predict this recession, but register two or three errors within the eight quarters of recession. Model C2 performs relatively poorly in predicting expansion periods. 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 not have been used for forecasting in any case.

As already noted, Model E2 would be chosen by SIC and this performs well for the post-sample prediction compared with the other models. Figure 4 plots the combined in-sample and out-of-sample estimated probabilities for this model. It predicts the onset of recession too early, with one sample expansion quarter in 1989 incorrectly predicted to be the beginning of recession, and also the ending of the recession is too optimistic in timing. The final spike evident in the graph for E2 in Figure 2 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.

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 (the latter being used in Model D2). 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 due to Britain being part of the European Exchange Rate Mechanism (ERM) at that time. Nevertheless, the results of Table 4 indicate that this variable would be included in a prediction model selected prior to the 1990s.

VI CONCLUSIONS

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 that 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. Although Garcia and Schaller (1995) find that their US results are not sensitive to this issue, tackling this is a topic for future research in the UK context.

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Data Appendix: Data descriptions with sample period, source and transformations

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
PRICE	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	USOIL 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.