The University *of* Manchester

Discussion Paper Series

Domestic and International Influences on Business Cycle Regimes in Europe

By
Marianne Sensier[†], Michael Artis[*], Chris R. Birchenhall[†] and Denise R. Osborn[†]

[†]Centre for Growth and Business Cycle Research, School of Economic Studies, University of Manchester, Manchester, M13 9PL, UK
[*]EUI, Florence, Italy and CEPR

April 2002
Number 011

THE UNIVERSITY *of* MANCHESTER

Domestic and International Influences on Business Cycle Regimes in Europe

by

Marianne Sensier†, Michael Artis*, Chris R. Birchenhall†
And Denise R. Osborn†

*EUI, Florence, Italy and CEPR

†Centre for Growth and Business Cycle Research
School of Economic Studies
University of Manchester, Manchester, M13 9PL, UK
e-mail: Marianne.Sensier@man.ac.uk
web address: http://www.ses.man.ac.uk/cgbcr/

April 2002

This paper is preliminary. Please do not quote without permission from the authors.
The authors would like to thank the Leverhulme Trust for financial support under the project "International Growth and Business Cycles" and ESRC grant L138251002.

Domestic and International Influences on Business Cycle Regimes in Europe

ABSTRACT

This paper examines the roles of domestic and international variables in predicting classical business cycle regimes in Germany, France, Italy and the UK over the period 1970 to 2001. A range of real and financial variables are used as leading indicators in domestic models, with these variables predicting regimes in Germany relatively well, followed (in order) by the UK, Italy and France. Consideration of foreign variables leads to important roles for the composite leading indicator for France, together with German and US interest rates. The relative importance of these variables differs over countries, but overall they confirm the importance of international influences in the business cycles of these European countries. Three-months ahead forecasts are given for each country, with those for Germany indicating that this country will follow the US into recession in 2001.

JEL classification: C22, E32, E37, E40.

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

1. Introduction

Understanding the nature of the links among the countries of the European Union is a central issue for the success of the EU. This is especially important since the launch of the Single European Currency, with interest rates for the participating countries now being set by the European Central Bank. A number of studies have found that German interest rates play an important role in leading interest rates for other leading countries; examples include Artis and Zhang (1998) and the recent study of Barassi, Caporale and Hall (2000). There are, however, relatively few studies of the links between economic activity in the countries of the EU. An important exception is Artis and Zhang (1997, 1999), who use correlation analysis to compare the synchronisation of business cycles of European countries with the US and Germany before and after the introduction of the Exchange Rate Mechanism (ERM) in Europe.

The purpose of this paper is to contribute to the literature on links between the economies of the EU. More specifically, our approach is to examine empirically the importance of links between Germany, France, Italy and the UK in the transmission of business cycle regimes between these countries. In this context, the two business cycle regimes of interest to us are recessions and expansions in economic activity. Policy makers and private agents have a serious interest in the occurrence of these business cycle regimes and, in particular, in the prediction of the onset of recession or recovery. Consequently, there has been a great deal of recent research concerned with models that predict such regimes, with the majority of the work relating to the US. Examples include Birchenhall, Jessen, Osborn and Simpson (1999), or BJOS hereafter, Chauvet and Potter (2001), Estrella and Mishkin (1998), Camacho and Perez-Quiros (2002), while Birchenhall, Osborn and Sensier (2001) consider regime prediction models for the UK. Indeed, in the short time since these studies were undertaken, interest in business cycle regime changes has gained renewed momentum due to the onset of a recession in the US that has been dated by the National Bureau of Economic Research (NBER) to have begun in April 2001.

This paper uses leading indicator data to estimate logistic regression models that deliver probabilities of future business cycle regimes for the four European countries. However, our purpose is not simply to build regime prediction models, but also to examine the relevance of foreign variables, particularly those from other European countries. Therefore, we consider the additional information supplied by such variables for business cycle regime prediction, and hence examine the channels through which regime changes to expansions or recessions are transmitted between these countries. Due to the importance of the US in the world economy, and also in the light of the recent debate about whether the US recession would be transmitted to Europe, the role of key US variables is also considered for these European business cycle regimes. Recent discussion of business cycle linkages (e.g. International Monetary Fund 2001) has directed attention to the importance of *financial* channels of transmission of business cycles, an emphasis with which the findings of the present study are consistent.

The business cycle prediction framework employed in this paper is similar to that set out in BJOS[1]. That study concludes that US business cycle regimes are better predicted when the leading indicator information is used within a logistic regression model, rather than in the context of a Markov switching model as used by Filardo (1994) or Simpson, Osborn and Sensier (2001). Therefore, the present study also adopts the logistic model approach[2].

The rest of the paper has the following structure. Section 2 presents the business cycle regime information for the European countries and outlines the methodology we use. The leading indicator data are discussed in Section 3. Section 4 presents the results along with forecasts for the three-months ahead regime prediction models for each country. Section 5 offers some concluding remarks.

2. Classical Business Cycle Dates and Methodology

To specify and estimate the model we need the business cycle chronologies to be known for our sample period. Our interest is in recessions versus expansions, since we believe that policy makers and private agents are more concerned about absolute declines and expansions in activity than in growth cycle measures. In any case, an important difficulty with any growth cycle analysis is that it is based on a definition of trend and such definitions are essentially arbitrary. Therefore, the chronologies we require are for the so-called classical business cycle and not the growth cycle. In the case of the US, the NBER chronology for the classical business cycle is available over

---

[1] The usefulness of this approach was confirmed by a real time update of the BJOS study that predicted onset of recession in the US from the beginning of 2001. This update can be found on the Centre for Growth and Business Cycle Research (CGBCR) web site (http://www.ses.man.ac.uk/cgbcr/).

[2] Camacho and Perez-Quiros (2002) come to a different conclusion. However, the US models they compare contain only a single explanatory variable (the composite leading indicator) and it is unclear whether their results will carry over when a richer set of such variables are considered. Indeed, the consideration of many potential explanatory variables, as in our study, points to the use of a relatively simple regime prediction method such as the logistic model.

the last century, but no such history is available for other countries. Nevertheless, the Economic Cycle Research Institute (ECRI) uses NBER-style procedures to date classical cycle turning point for various countries and their chronology for the US is identical with those of the NBER. We adopt the ECRI turning points dates for our economies, with these shown in Table 1.

Given the expansion and recession regimes defined from the ECRI turning points, our business cycle phases are simply represented as zero/one binary series, with periods of expansion taking the value unity[3]. Our aim is to predict the probability that a specific future period will be within an expansion, with the recession probability then being one minus the expansion probability. 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 observed values of the leading indicators.

Table 1: ECRI Classical Business Cycle Turning Point Dates 1970-2001

Peak or Trough	Germany	France	Italy	UK
Peak			1970 m10	
Trough			1971 m8	
Peak	1973 m8	1974 m7	1974 m4	1974 m9
Trough	1975 m7	1975 m6	1975 m4	1975 m8
Peak	1980 m1	1979 m8	1980 m5	1979 m6
Trough		1980 m6		1981 m5
Peak		1982 m4		
Trough	1982 m10	1984 m12	1983 m5	
Peak	1991 m1	1992 m2	1992 m2	1990 m5
Trough	1994 m4	1993 m8	1993 m10	1992 m3
Peak	2001 m1			

Source: http://www.businesscycle.com/research/intlcycledates.asp

We now turn to a description of the methodology we use. A lengthier account can be found in BJOS.

3 Harding and Pagan (2001) point out that the business cycle regime is a constructed variable, but that this is ignored in analyses (such as logistic regression) that take the regime as the dependent variable. We acknowledge this point, and further research is warranted on its practical importance.

Using a data vector $\boldsymbol{x}_{t\text{-}h}$ of observed variables up to and including period t-h, we construct a h-period ahead business cycle regime predictor of the form

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

where $\boldsymbol{p_t}$ is the probability that the business cycle regime for at quarter t will be an expansion, based on information up to an including the previous period t-h. In practice, we use monthly data with $h = 3$, so that we model the probability at a horizon of three months. 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 for periods within expansion regimes and zero for periods within recession regimes), while $\boldsymbol{x}_{t\text{-}h}$ consists of leading indicators. Using sample information for $t = 1, \ldots, T$, the log-likelihood function for this binary model is given by

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

where Σ_1 is the sum over all expansionary months and Σ_0 is the sum over all months of recession. Our modelling problem involves choosing $\boldsymbol{x}_{t\text{-}h}$ and finding the maximum likelihood estimate of β.

The choice of the components in $\boldsymbol{x}_{t\text{-}h}$ is crucial, and we achieve this through a prior selection of potential variables followed by the application of 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. Thus, (3) implies that an additional variable will be included in the model only if it 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.

We use two automated search procedures. The first method, *sequential elimination*, works as follows. We select *a priori* a set of K variables $x_{1t}, \ldots, x_{Kt}$. 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 an initial set of K variables, but the algorithm simply considers from this initial set *all* subsets of k variables, for $k = 1, \ldots, n$ and where n is specified in advance. For this paper, n was set to 9. This choice was based on our experience with sequential elimination in that the largest model selected using that method involved 9 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 themselves 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 (with estimated expansion probability of one or zero, as appropriate) all points in the sample. 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 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. Nevertheless, the use of both procedures provides some reassurance in this respect.

It needs to be emphasised that the procedures of hypothesis testing play no role in our model selection procedure, and, indeed, such procedures would have to be applied with some care in our context. This is because the overlapping forecast horizons that apply when $h > 1$ imply that serial correlation is virtually certain to be present in the residuals of our model. Nevertheless, Sin and White (1996) show that the use of penalised likelihood criteria, such as (3), asymptotically select the "best" model from the choice set, in the sense of being closest to the unknown data generating process according to the Kulback–Liebler Divergence criterion, even if all models under consideration are misspecified.

It may be noted that our models are not dynamic in the sense that we do not explicitly model time series autocorrelation in the binary dependent variable. Chauvet and Potter (2001) find that modelling such autocorrelation can be important for regime prediction; see also Harding and Pagan (2001). However, our approach with many explanatory variables considered makes an approach of this type impractical. Also, as argued in BJOS, we allow dynamics to enter through the lags (or here differencing intervals) considered for each explanatory variable.

A fundamental task is to select from among the available leading indicators. An important purpose of this paper is to use the prediction context as one in which to examine the role of international variables. In this way we aim to cast light on the extent to which business cycle regimes in each country are imported through financial or other linkages. This purpose influences both the set of variables we consider and also the way the modelling procedure is implemented in practice.

3. Leading Indicators

A large number of studies have used leading indicator data to help predict the business cycle; the history of work of this kind 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, Stock and Watson, 1991 and 1993 for the US). The OECD produces composite leading indicators for the growth cycle in many countries (Nilsson, 1987), but not for the classical cycle examined here.

In principle we could consider a structural model that allows for structural changes across cycles and across regimes within cycles. However, Clements and Hendry (1999) have 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 Europe, rather we concentrate on identifying stable statistical relationships between leading indicators and business cycle regimes. The regime prediction probability from this model can itself be interpreted as a composite leading indicator of the business cycle regime for each country.

Stock and Watson (1991, 1993) investigate a large number of variables, as leading indicators for the US, but 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, Hamilton and Kim, 2002, Plosser and Rouwenhorst, 1994, Roma and Torous, 1997). Davis and Fagan (1997) find that the spread leads to an improvement in the forecasting performance of output for the UK, Belgium and Denmark, while Galbraith and Tkacz (2000) find this to be the case for all G7 countries apart from Japan.

Our analysis of business cycle regime predictors draws from this academic literature, but it also includes a composite leading indicator for each country, namely the OECD series (http://www1.oecd.org/std/licomp.htm). Although the OECD series are constructed to lead the growth cycle, they provide a convenient composite indicator for each country that may provide relevant information in our context of classical business cycles. We also analyse a range of financial variables, specifically narrow money expressed in real terms by dividing the nominal series by the consumer price index, stock market prices, short-term and long-term interest rates. Real activity is represented by the index of industrial production and retail sales (both expressed as real variables). The range of international variables considered covers stock prices, short-term interest rates, the composite leading indicators and industrial production for each country. These variables are considered for each of the four European countries of our study, plus the USA. We also consider a possible role also for the oil price (oil prices are obtained as the West Texas Intermediate posted price, converted from US dollars to the appropriate European currency using the exchange rate for each month). For the full list of variables used in this study see the Data Appendix.

The data we use are monthly and the in-sample period we model is from January 1970 to December 1996. We retain the data for January 1997 to December 2001 for a genuine out-of-sample forecast and predict the probability of expansion for each of the first three months of 2002. As already mentioned above, our models are fitted three months ahead, so we use information dated t-3 and earlier to forecast whether the regime will be in expansion in month t. Our initial analysis also considered one-month ahead prediction models, but the broad pattern of results was similar to the three-months ahead models presented here. Three-months is preferred because it allows for realistic time lags in the availability of data (especially for real series, including industrial production) and for lags in the response of agents to economic information, both domestic and international.

We transform the majority of series by taking logs and then a range of differences over 3, 6, 9 and 12 months to smooth the data. The interest rate series are analysed without these transformations, with the term structure computed as the difference between the long and short rates. As we are estimating the three-months ahead model we use lag three of the differences. For the interest rates intermittent lags are used up to a year (3, 6, 9 and 12 months). Outliers are removed for a number of series and these are generally associated with events that do not relate to the business cycle, e.g. strikes. A table of the adjustments performed on the data is given in the appendix. After all other transformations, each series is standardised to zero mean and unit variance. Thus the magnitudes of the coefficients in the estimated models can be compared as an indication of the relative strength of the effect of the respective leading indicator on the binary dependent variable for the regime.

4. Results

Two tables of results are presented. The first contains the best model for each country with domestic variables only and the second is obtained by considering both domestic and international variables. The specific models shown are the outcome of the *n*-search algorithm outlined in Section 2. Identical or very similar models were obtained using sequential elimination.

For the domestic models, two initial sets of variables were considered. In one case both long and short interest rates were used and the term structure excluded, with the second included the term structure but not the separate rates. Otherwise, all domestic variables were included in the initial set[4]. In the case of the international models, sequential elimination was conducted with each of the same two initial sets of domestic variables except retail sales (which was never selected in any domestic model) and each international variable entered one by one. The international variables relate to the other three countries and the US. The two models with lowest SIC values were taken as indicating two potentially relevant international variables. The *n*-search algorithm was then applied, with all domestic variables (excluding retail

[4] Initially we also considered unemployment for each country, apart from Italy, but this did not improve fit. Employment was not used, as a consistent monthly series is not available for each country.

sales) and the two international variables included as the initial set. All four lags or differences, as appropriate, of the variables were always included in the initial set.

Information in the tables includes, in addition to the SIC and log likelihood values, the conventional sample period root mean-square error (RMSE) for the binary dependent variable. Further the prediction errors are shown as percentages of the number of observations classified as within expansions and recessions, with the numbers of errors in parentheses. As usual in the regime prediction literature, estimated probabilities are converted to binary regime predictions using the "0.5 rule", so that an estimated expansion probability over 0.5 is considered to be a prediction of expansion while one less than 0.5 is a recession prediction. However, we also follow BJOS as identifying as "uncertain" any month where the estimated expansion probability is between 0.5 and the sample proportion of expansion months. Corresponding regime prediction error information is provided for the post-sample period to the end of 2001.

Table 2 shows the best three-months ahead models for each country with domestic variables. From the table it can be seen that there a number of patterns common across countries in terms of selected variables and their signs, but there are also important differences.

The OECD composite leading indicator (CLI) enters the model in each case, with the single exception of the UK where it apparently adds no predictive information compared with the other variables considered. Although retail sales growth does not survive the selection procedure for any country, growth in the index of production (IOP) remains for Germany and the UK. Real narrow money (RM1) is important for all countries apart from Germany, although sometimes with negative coefficients. Domestic stock market prices (SP) enter, except for Italy, again with differing signs and lengths of differences. The importance of interest rates is clear, with the effects being predominantly negative. For Germany, France and the UK, the effect of the short rate (SR) is felt even at the short horizon of three months, although there is also a contrasting coefficient for the long rate (LR) at this horizon for France and the UK. There are separate negative effects of the long rate at longer lead times for the UK, but the long rate at three months is the only interest rate variable that enters for Italy. In no case is a model incorporating the term structure preferred to the separate use of the short and long rates.

Table 2: Three-Months-Ahead Domestic Models for

Prediction of Expansion

Variables:	**Germany**	**France**	**Italy**	**UK**
Intercept	3.412	3.059	3.062	5.543
$\Delta_6\log(CLI)_{-3}$		2.973		
$\Delta_9\log(CLI)_{-3}$	2.346			
$\Delta_{12}\log(CLI)_{-3}$		-2.539	3.504	
$\Delta_6\log(IOP)_{-3}$	-2.291			
$\Delta_9\log(IOP)_{-3}$				1.605
$\Delta_{12}\log(IOP)_{-3}$	2.895			
$\Delta_6\log(RM1)_{-3}$				1.414
$\Delta_{12}\log(RM1)_{-3}$		0.831	-0.802	-4.013
$\Delta_6\log(SP)_{-3}$	-1.140	-1.320		
$\Delta_9\log(SP)_{-3}$				1.646
$(SR)_{-3}$	-4.574	-2.602		-3.734
$(SR)_{-12}$		-2.155		-2.993
$(LR)_{-3}$		1.678	-1.546	3.496
$(LR)_{-9}$				-3.621
Summary Statistics:				
RMSE Sample	0.2028	0.2874	0.2835	0.2229
Log Likelihood	-44.86	-85.24	-84.88	-48.90
SIC	124.4	216.7	192.9	149.8
Errors In-Sample:				
Expansion	3% (8/229)	5% (14/253)	4% (12/246)	4% (11/268)
Contractions	12% (12/95)	35% (25/71)	24% (18/78)	23% (13/56)
Uncertain	15/324	47/324	33/324	24/324
Errors Out-of-Sample:				
Expansion	0% (0/49)	(0/60)	(0/60)	(0/60)
Contractions	100% (11/11)	(0/0)	(0/0)	(0/0)
Uncertain	0/60	0/60	0/60	0/60
Prediction:				
Forecast 2002m1	0.9976	1	0.9718	0.9997
Forecast 2002m2	0.9987	1	0.9906	0.9998
Forecast 2002m3	0.9987	1	0.9904	0.9999

Notes: In sample data set: 1970m1-1996m12 and out of sample data set: 1997m11-2001m12.

In considering the extent to which business cycle recessions and expansions are domestic or international phenomena, the summary statistics are the most interesting part of Table 2. The model that provides the best fit to the observed regimes is that for Germany, whether this is judged according to SIC or the number of in-sample errors (a total of 20 prediction errors for expansions and contractions). Indeed, the clear classifications provided by this model is also indicated by the relatively small number of predictions that fall within the uncertain region. According to these fit criteria, Germany is followed by the UK, then Italy and finally France. Indeed, 35 percent of recession months in France are not predicted by the model, even within the sample period.

Therefore, it appears that domestic variables are able to predict business cycle regimes well in Germany and reasonably well in the UK, but not so well for Italy and, still less, France. At the two extremes, it appears from the evidence of Table 2 that business cycles are not purely domestic phenomena in France, whereas they are much more domestic events in Germany. Figures 1-4 illustrate the estimated expansion probabilities for each country for the entire period (including the post-sample period of 1997 to 2001), with ECRI recession periods shaded. These diagrams reinforce the comments just made, with the contrast between the performance of the prediction models for Germany and France in Figures 1 and 2 being especially notable.

The domestic models for all four countries continue to predict expansion through the out-of-sample period and (with estimated probabilities close to one) predict that the first three months of 2002 will be in expansion. The German domestic model performs poorly in the post sample as it does not predict the 2001 recession.

Table 3 presents the results for the best three-months ahead models for each country when international variables are also considered. Figures 5-8 show the sample period estimated expansion probabilities computed using these Table 3 models. Compared with Table 2, the models change substantially, with only a sub-set of the domestic variables previously selected surviving. In particular, domestic industrial production drops out, except for the annual growth rate for Germany, and (with the single exception of the UK, where its sign is negative) domestic real money growth is also eliminated. The term structure improves the fit of the German model compared to when the short and long-term interest rates are used separately. Important roles for domestic interest rates remain for all countries, except Italy. Where domestic stock market prices are included (for Germany, France and Italy), these price changes have a negative effect on the expansion probability.

Table 3: Three-Months-Ahead Expansion Prediction Models with International Variables

Variables:	Germany	France	Italy	UK
Intercept	6.859	3.409	6.901	6.732
$\Delta_6\log(CLI)_{-3}$		2.198		
$\Delta_{12}\log(CLI)_{-3}$			5.820	
$\Delta_{12}\log(IOP)_{-3}$	2.694			
$\Delta_{12}\log(RM0)_{-3}$				-3.918
$\Delta_6\log(SP)_{-3}$	-1.479			
$\Delta_9\log(SP)_{-3}$		-2.355		
$\Delta_{12}\log(SP)_{-3}$			-2.324	
$(TS)_{-3}$	6.300			
$(TS)_{-12}$	1.428			
$(SR)_{-3}$		-3.468		-4.941
$(SR)_{-6}$		-1.496		
$(SR)_{-12}$				-3.476
$(LR)_{-3}$				3.465
$(LR)_{-9}$				-4.838
$(FIBOR)_{-3}$			-1.787	
$(FIBOR)_{-9}$		3.556		
$(FIBOR)_{-12}$		-3.100	-5.148	
$(USTB)_{-6}$		2.464		
$(USTB)_{-9}$				2.410
$\Delta_{12}\log(FRCLI)_{-3}$	5.411		-2.125	3.686
Summary Statistics:				
RMSE Sample	0.1579	0.2386	0.1599	0.1896
Log Likelihood	-27.25	-67.33	-29.27	-36.93
SIC	89.2	180.9	93.2	120.1
Errors In-Sample:				
Expansion	1% (4/229)	2% (8/253)	2% (5/246)	2% (6/268)
Contractions	6% (6/95)	25% (18/71)	8% (7/78)	17% (10/56)
Uncertain	12/324	29/324	13/324	20/324
Errors Out-of-Sample:				
Expansion	0% (0/49)	(0/60)	(0/60)	(0/60)
Contractions	36% (4/11)	(0/0)	(0/0)	(0/0)
Uncertain	0/60	0/60	0/60	0/60
Prediction:				
Forecast 2002m1	0.0967*	1	1	0.9998
Forecast 2002m2	0.0892*	1	1	0.9998
Forecast 2002m3	0.3048*	1	1	0.9998

Notes: In sample data set: 1970m1-1996m12 and out of sample data set: 1997m11-2001m12. * Indicates a warning of recession, as the forecast probability is less than 0.5.

The OECD composite leading indicator for France (FRCLI, or simply CLI in the French model) is important for all countries. The annual difference of this variable is strongly positive for Germany and the UK, but is negative for Italy. It is noteworthy that this French leading indicator series comprises mainly French domestic variables, but it also includes the US composite leading indicator so that US economic activity is embedded in this measure. However, it is also worth noting that the US CLI itself was considered, but was not selected for any country. The negative sign for FRCLI for Italy in Table 3 is not anticipated, and may reflect the different business cycle regime dates for Italy in comparison with France in Table 1.

The other striking international effects evident in Table 3 operate through interest rates. Short interest rates in Germany (the Frankfurt inter-bank offered rate, FIBOR) influence business cycle regimes in both France and Italy, while short interest rates in the US (USTB) influence regimes in France and the UK. Foreign interest rates have mixed effects. The German short-term rate affects the Italian economy negatively at both short and long lags, while it has effects of mixed signs for the French economy. For both France and Italy, the introduction of FIBOR apparently dominates the roles ascribed to domestic long interest rates in the models of Table 2. The role of the German interest rates in the three other countries, together with the fact that no role for foreign interest rates is detected in Germany, substantiates the literature on the German leadership hypothesis (GLH) where German interest rates are found to play a role in leading other European interest rates; see, for example Artis and Zhang (1998) and, more recently Barassi et al (2000). The results obtained in the latter and more recent study support a weaker version of the GLH than the former and do not exclude that US interest rates are also important for European economies. Table 3 implies positive effects for the US interest rate at 6 and 9 months later for France and the UK respectively. This backs up the evidence in the literature that the UK cycle is more closely related to the US economy than to Europe, Artis and Zhang (1997, 1999). Also Kim (2001) has shown that expansionary US monetary policy shocks (through instruments like the short-term interest rate) lead to booms in the remaining G7 countries.

In contrast with the roles found for foreign interest rates, no international stock market variables appear in Table 3. Indeed, the overall role of stock market prices is muted relative to that of interest rates, pointing to the possibility that the primary effects of international financial variables on business cycles in these countries operate through interest rates rather than stock prices.

Comparing these two tables, and due to our model selection procedure, the model fit is necessarily improved in terms of SIC in each case by the introduction of international variables. Nevertheless, the in-sample error statistics for Germany and the UK are relatively little changed, indicating that foreign variables have made only fairly marginal improvements to the corresponding domestic models of Table 2. For France, the inclusion of foreign interest rates improves the prediction of recessions and reduces the number of uncertain classifications, although around a quarter of recession months are still not forecast by the model of Table 3. The most dramatic improvement for any country is that for Italy, where both SIC and RMSE drop very substantially, with regime prediction errors during contractions being little more than a third of the corresponding values in Table 2.

One noteworthy result in Table 3 concerns the out-of-sample prediction errors for Germany. Although the models were estimated on data up to the end of 1996, the model has correctly estimated a recession for that country beginning in June 2001, slightly later than the February 2001 recession start estimated by ECRI. The predictions for the first three months of 2002 are for continuation of this recession. Despite noting above that international variables had relatively little impact on the sample period fit of the model for Germany, the model that results from their introduction has very different implications for that economy in the latter part of 2001 and early 2002.

5. Conclusions

This paper uses logistic regression to construct three-months ahead prediction models for classical business cycle regimes (expansions and contractions) in Germany, France, Italy and the UK for the sample 1970 to 2001. Our results indicate that, at least over much of the period, domestic variables are able to predict the business cycle of Germany relatively well, but with less success for the corresponding models for the UK, Italy and (especially) France. When international variables are considered, we detect important roles for two types of variable, namely the composite leading indicator for France and foreign short-term interest rates for Germany and the US.

The role detected for the French composite leading indicator for all other countries is surprising in the context of the relatively poor performance of the domestic model for France. It is plausible that it is the components of that indicator relating to the US and to financial variables that might give this series an international role, and this issue is worthy of further investigation.

In general, our results emphasise that business cycle regimes in these European countries are strongly influenced by international events. Even in the case of Germany, where the domestic model generally performs relatively well, the introduction of international variables (specifically the composite leading indicator for France) is important in the context of predicting recession for late 2001 and early 2002, an event that appears to be taking place in practice.

REFERENCES

Artis, M.J. and Zhang, W. (1997), "International business cycle and the ERM: is there a European business cycle?", *International Journal of Finance and Economics*, vol. 2, pp. 1-16.

Artis, M.J. and Zhang, W. (1998), "The linkage of interest rates within the EMS", *Weltwirtschaftliches Archiv,* 134, 1, 117-32.

Artis, M.J. and Zhang, W. (1999), "Further evidence on the international business cycle and the ERM: Is there a European business cycle?", *Oxford Economic Papers* vol. 51, pp. 120-132.

Barassi, M.R., Caporale, G.M. and Hall, S.G. (2000), "Interest rate linkages: a Kalman filter approach to detecting structural change", Imperial College Management School Working Papers, 5 (June).

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, pp. 313-323.

Birchenhall, C. R., Osborn, D. R. and Sensier, M. (2001), "Predicting UK business cycle regimes", *Scottish Journal of Political Economy*, vol. 48, pp. 179-198.

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

Camacho, M. and Perez-Quiros, G. (2002), "This is what the leading indicators lead", *Journal of Applied Econometrics*, vol. 17, pp.61-80.

Chauvet, M. and Potter, S. (2001), "Forecasting recessions using the yield curve", Staff Report number 134, Federal Reserve Bank of New York.

Clements, M.P. and Hendry, D.F. (1999), *Forecasting Non-Stationary Economic Time Series*. Cambridge, Massachusetts: The MIT Press.

Davis, E. P. and Fagan, G. (1997), "Are financial spreads useful indicators of future inflation and output growth in EU countries?", *Journal of Applied Econometrics*, vol. 12, pp. 701-714.

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

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.

Filardo, A.J. (1994), "Business cycle phases and their transitional dynamics", *Journal of Business and Economic Statistics*, vol. 12, pp.299-308.

Galbraith, J. W. and Tkacz, G. (2000), "Testing for asymmetry in the link between the yield spread and output in the G-7 countries", *Journal of International Money and Finance*, vol. 19, pp. 657-672.

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

Hamilton, J. D. and Kim, D. H. (2002), "A Re-examination of the Predictability of Economic Activity using the Yield Spread", *Journal of Money, Credit and Banking*, vol. 34, pp. 340-360.

Harding, D. and Pagan, A. (2001), “Extracting, analysing and using cyclical information”. Mimeo.

Hoover, K. D. and Perez, S. J. (1999), “Data mining reconsidered: encompassing and the general-to-specific approach to specification search”, *The Econometrics Journal*, vol. 2, pp. 167-191.

International Monetary Fund (2001), *World Economic Outlook*, October.

Kim, S. (2001), “International transmission of U.S. monetary policy shocks: Evidence from VAR’s”, *Journal of Monetary Economics*, vol. 48, pp. 339-372.

Nilsson, R. (1987), “OECD leading indicators”, *OECD Economic Studies*, 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, pp. 133-55.

Roma, A. and Torous, W. (1997), “The cyclical behavior of interest rates”, *Journal of Finance*, vol. 52, pp. 1519-42.

Simpson, P.W., Osborn, D.R. and Sensier, M. (2001), “Modelling business cycle movements in the UK economy”, *Economica*, vol. 68, pp. 243-267.

Sin, C. Y. and White, H. (1996), “Information criteria for selecting possibly misspecified parametric models”, *Journal of Econometrics*, vol. 71, pp. 207-225.

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: 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.

Figure 1: Expansion Probabilities from Domestic Model for Germany

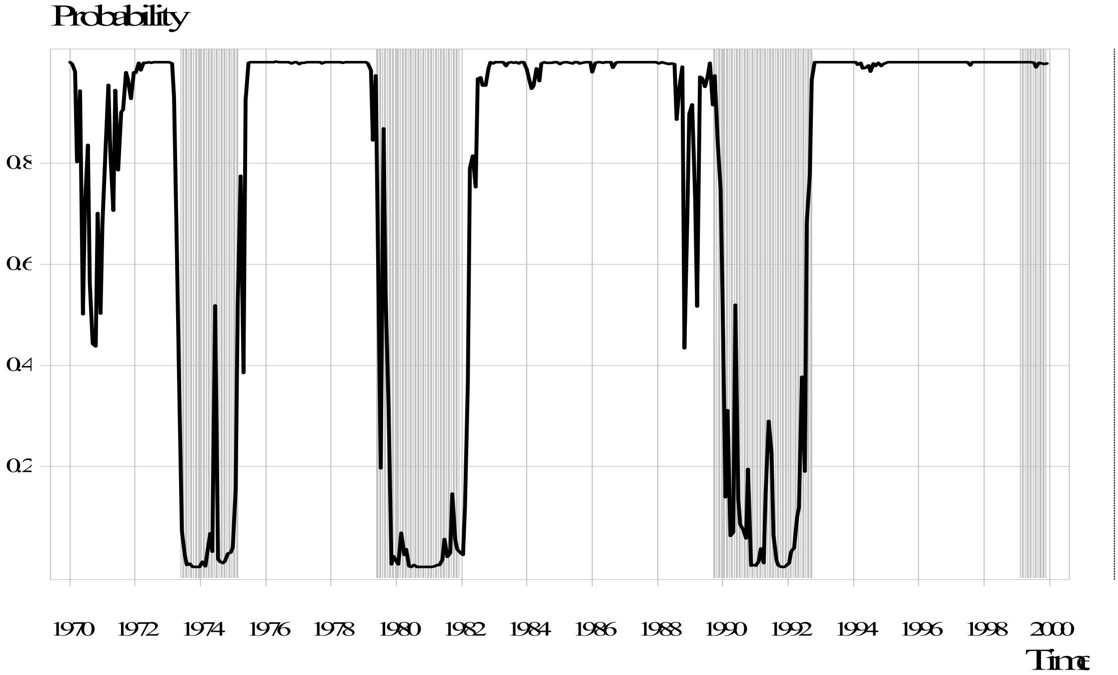


Figure 2: Expansion Probabilities from Domestic Model for France

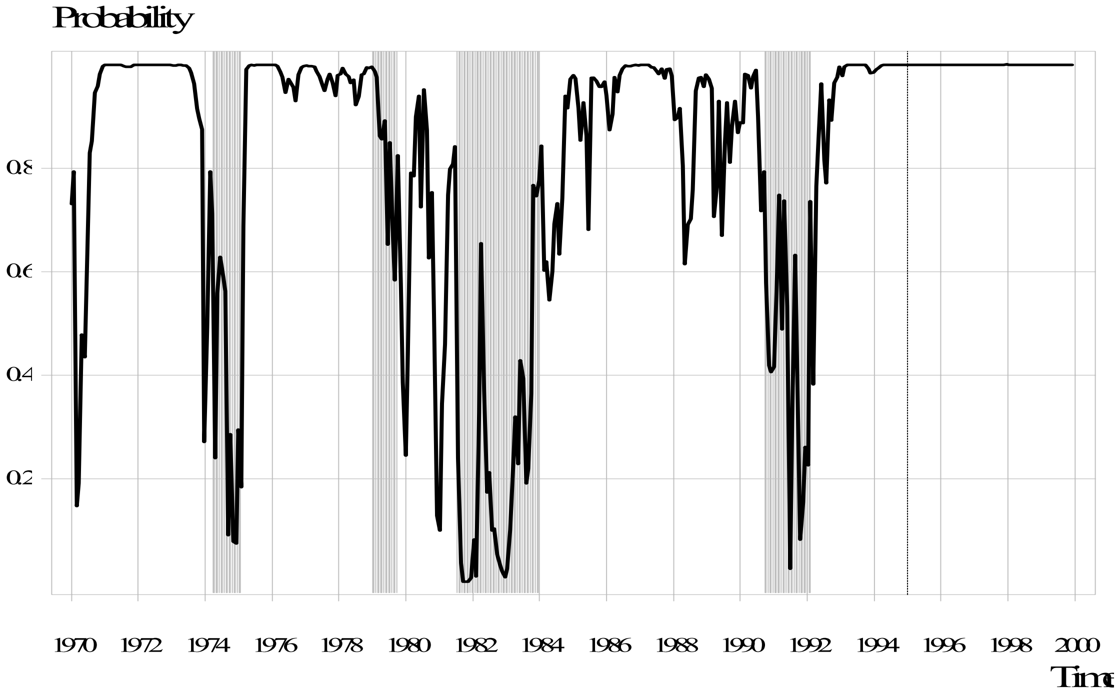


Figure 3: Expansion Probabilities from Domestic Model for Italy

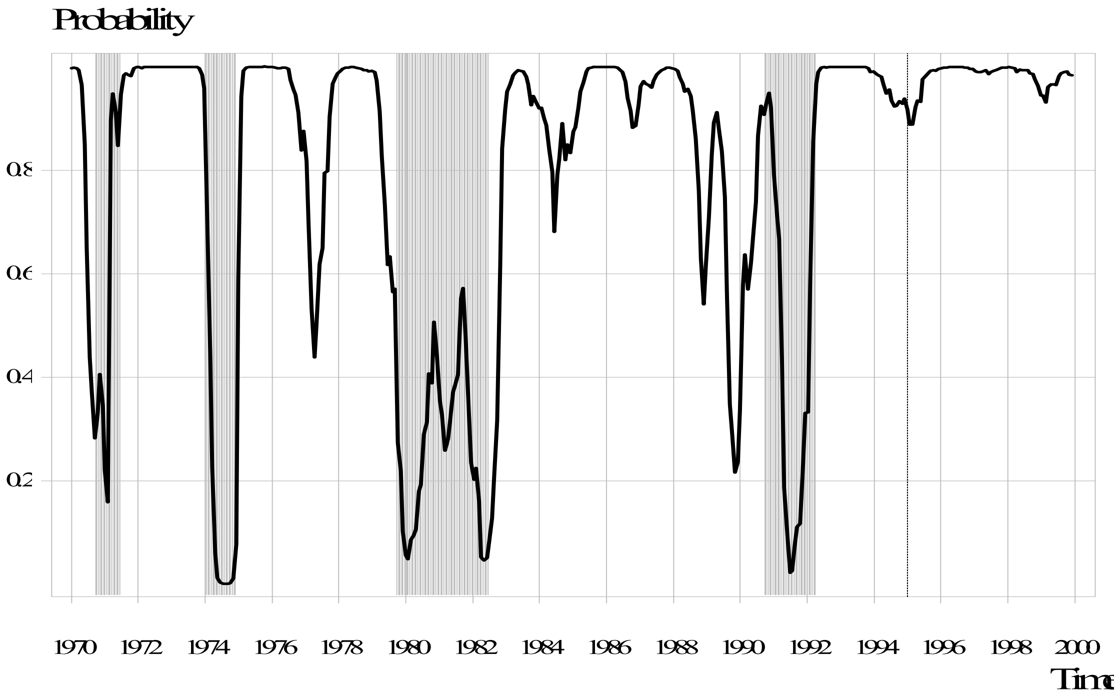


Figure 4: Expansion Probabilities from Domestic Model for the UK

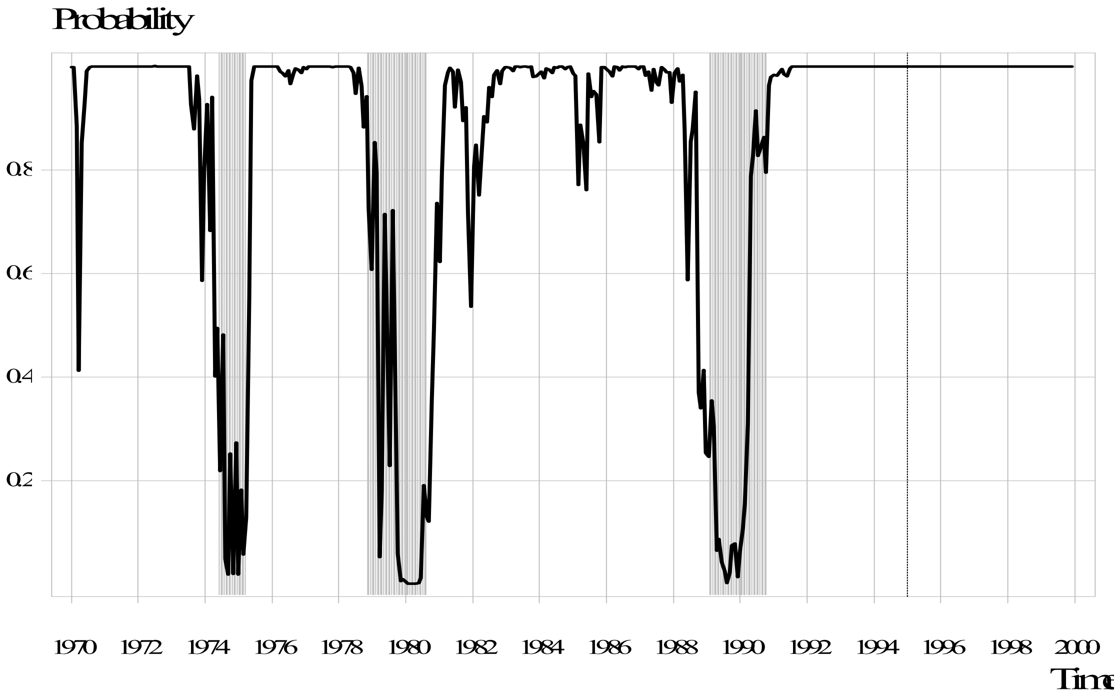


Figure 5: Expansion Probabilities from Model with International Variables for Germany

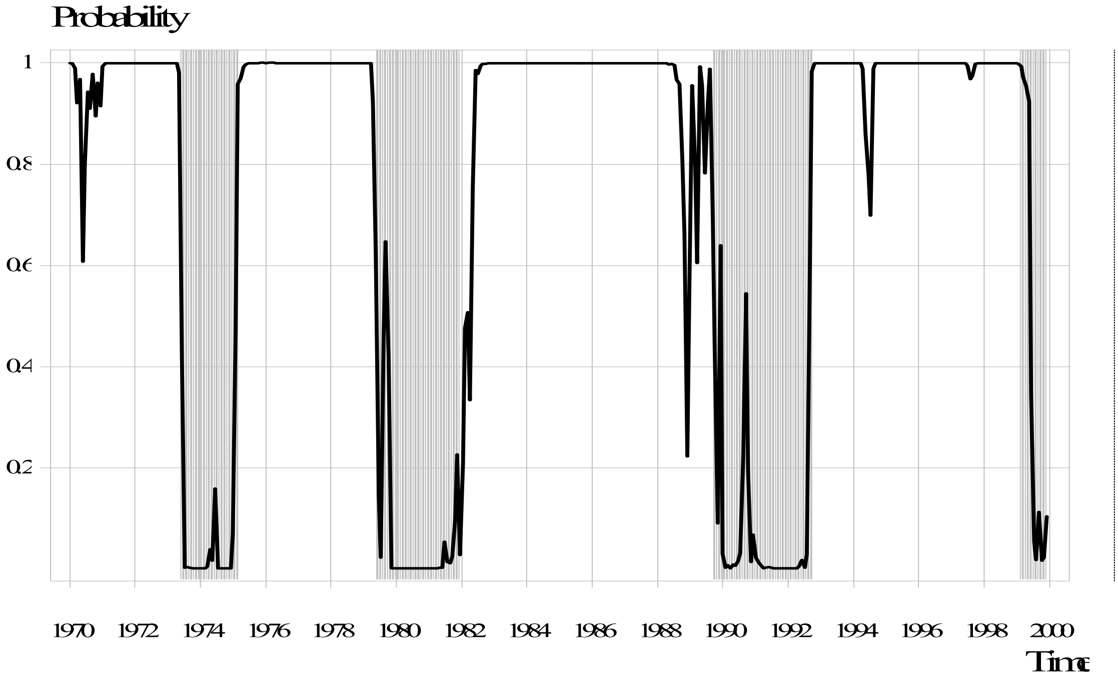


Figure 6: Expansion Probabilities from Model with International Variables for France

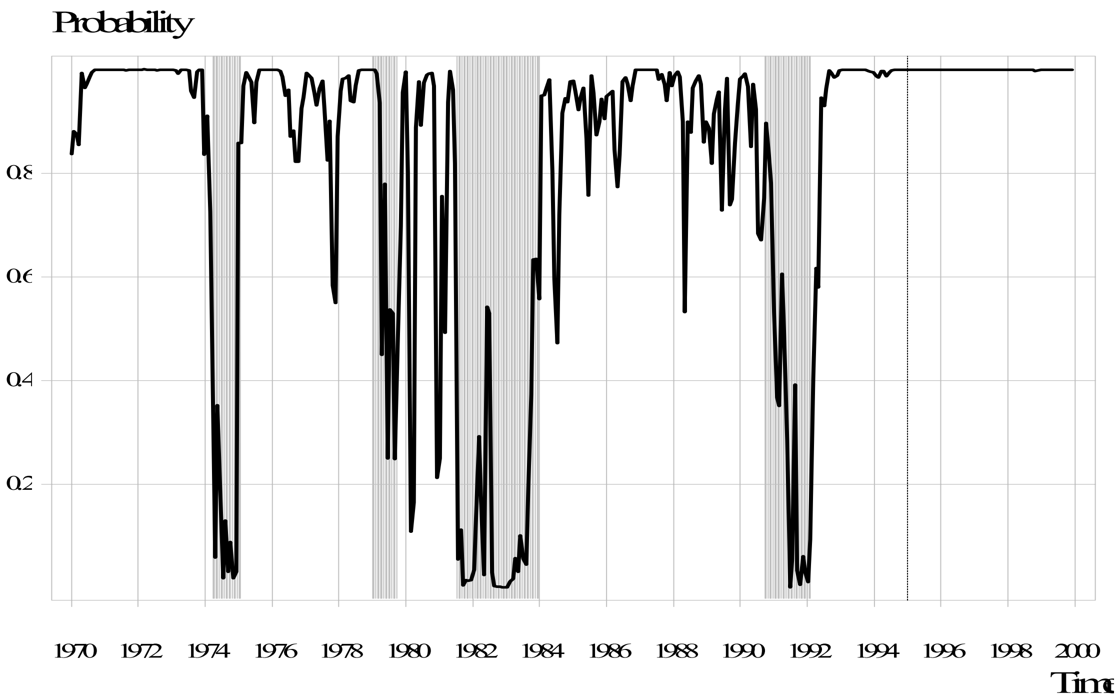


Figure 7: Expansion Probabilities from Model with International Variables for Italy

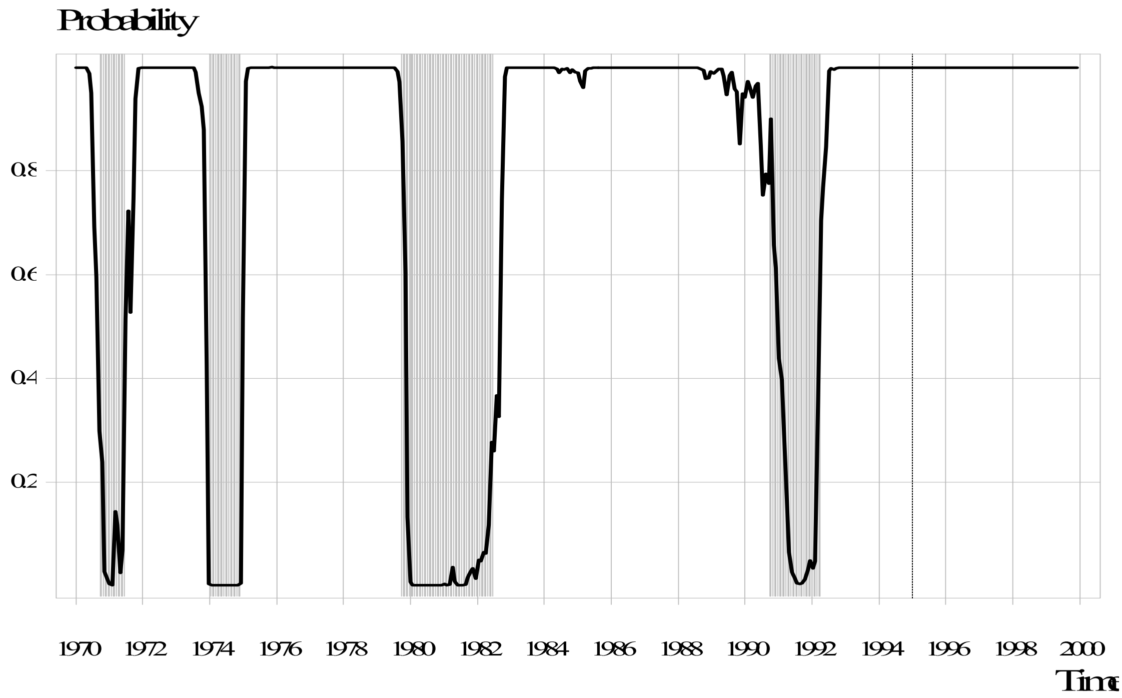
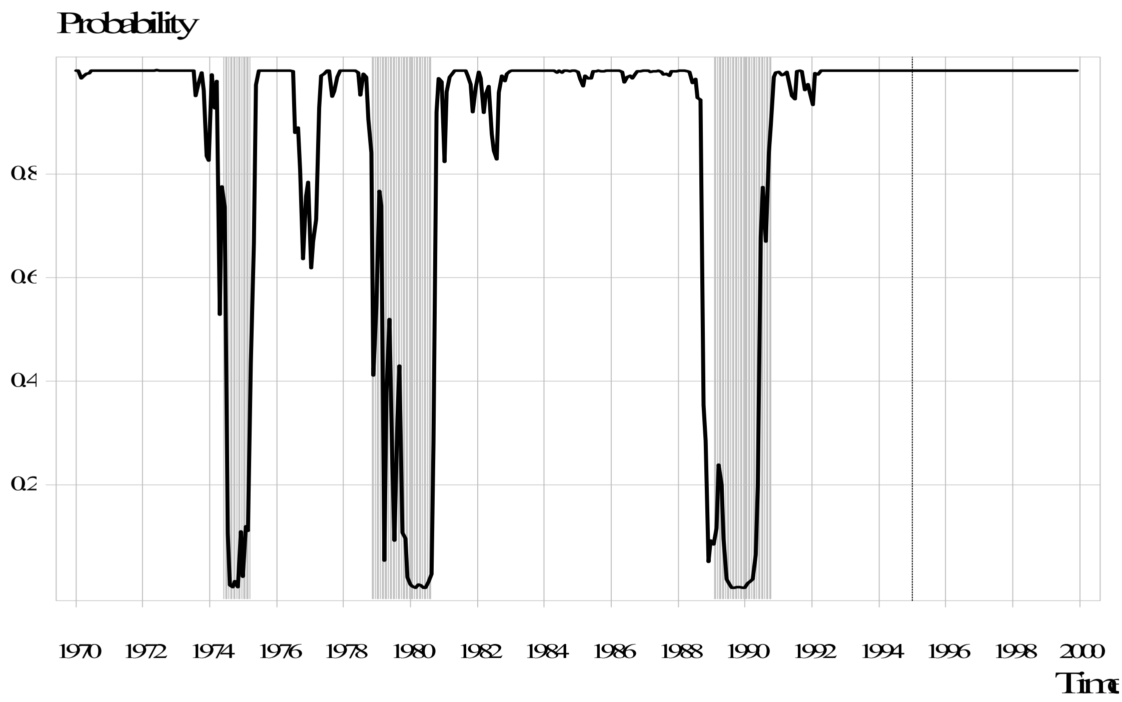


Figure 8: Expansion Probabilities from Model with International Variables for the UK



Data Appendix

Table A.1: US Data

Name	Description	Source	Code
USCLI	The Conference Board's Leading Indicators Index	Datastream	USCYLEAD
USSP	Standard & Poor's Index Of 500 Common Stocks (Monthly Ave)	Datastream	US500STK
USTB	Us Treasury Bill Secondary Market Rate On Discount Basis-3 Month	Datastream	USTRB3AV
USOIL	Spot Oil Price: West Texas Intermediate: Prior'82=Posted Price, Dollar Per Barrel (http://www.stls.frb.org/fred/data/business/)	FRED	oilprice

The exchange rate is used for all countries to convert the US oil price into the currency of the country. It is not explicitly used as a leading indicator.

Table A.2: German Data

Name	Description	Source	Code
CLI	OECD Composite Leading Indicator (Trend Restored)	Datastream	BDOCLDNG
IOP	Industrial Production – industry excluding construction, volume index, SA	Datastream	BDOCIPRDG
RS	Retail Sales, volume index, SA	Datastream	BDOCRSALG
M1*	M1 Money Supply (Continuous Series), Current prices, SA	Datastream	BDM1C...B
CPI	Consumer Price Index, all items, NA	Datastream	BDCONPRCF
SP	DAX Share Price Index, end of period, NA	Datastream	BDSHRPRCF
SR	Frankfurt inter-bank offered rate, FIBOR - 3 Month (monthly average)	Datastream	BDINTER3
LR	Long Term Government Bond Yield (9-10 Years Maturity)	Datastream	BDGBOND.
ER	German Marks To US$ (monthly average)	Datastream	BDXRUSD.

* The series for German M1 has a break at 1964m1 and then in 1990m6. A series is created for M1 that takes account of the breaks and outliers (detailed below).

Table A.3: French Data

Name	Description	Source	Code
CLI	OECD Composite Leading Indicator (Trend Restored)	Datastream	FROCLDNG
IOP	Industrial Production – industry excluding construction, volume index, SA	Datastream	FROCIPRDG
RS	Retail Sales major outlets, index, SA	Datastream	FROCRSLGE
M1	Monetary Aggregate M1, SA	OECD	discontinued
M1E*	M1 Money Supply - (French contribution to Euro Area M1), Current prices, NA	Datastream	FRM1....A
CPI	CPI - All Items Excluding Food NADJ	Datastream	FROCCPXFF
SP	Share Price Index - SBF 250, NA	Datastream	FRSHRPRCF
SR	Call Money Rate	Datastream	FRCALL%.
LR	Government Guaranteed Bond Yield (EP)	Datastream	FRGBOND.
ER	FR French Franc To US $	Datastream	FRXRUSD.

* The only available series available for French M1 after the introduction of the Euro in 1999 is a series that is not seasonally adjusted. The old M1 series is extended by adding the annual difference of the Euro M1 series to the natural log of the old series and taking the exponent.

Table A.4: UK Data

Name	Description	Source	Code
CLI	OECD Composite Leading Indicator (Trend Restored)	Datastream	UKOCLDNG
IOP	Industrial Production – industry excluding construction, volume index, SA	Datastream	UKOCIPRDG
RS	Retail Sales, volume index, SA	Datastream	UKRETTOTG
M1	M0 wide monetary base (end period), Current prices, SA	Datastream	UKAVAE..
CPI	Retail Price Index, all items, NA	Datastream	UKCONPRCF
SP	FT Actuaries all share index (10 April 1962=100), NA	Datastream	UKAJMA..
SR	Bank Bill Rare - Discount, 3 Month, SA (monthly average)	Datastream	UK3MTHINE
LR	Gross Redemption Yield on 20 Year Gilts (Period Average)	Datastream	UKAJLX..
ER	US $ TO £1	Datastream	UKXRUSD.

Table A.5: Italian Data

Name	Description	Source	Code
CLI	OECD Composite Leading Indicator (Trend Restored)	Datastream	ITOCLDNG
IOP	Industrial Production – industry excluding construction, volume index, SA	Datastream	ITOCIPRDG
RS	Retail Sales major outlets, index, SA	Datastream	ITOCRSALG
M1	Monetary Aggregate M1, SA	OECD	discontinued
M1E*	M1 Money Supply - (Italian contribution to Euro Area M1), Current prices, NA	Datastream	ITM1....A
SP	Share Prices - ISE MIB STORICO	Datastream	ITOCSPRS
CP	CPI Including Tobacco (NIC) NADJ	Datastream	ITCONPRCF
SR	Interbank Deposit Rate-average on 3-Months Deposits	Datastream	ITINTER3
LR	Treasury Bond Net Yield - Secondary Market (EP)	Datastream	ITGBOND.
ER	Italian Lire To US $	Datastream	ITXRUSD.

* See the above description for French M1E as the same procedure was used here.

Table A.6: Outliers Removed

Country	Money	Output	Retail Sales
Germany	1964m1; 1964m12; 1965m12; 1966m12; 1967m11-12; 1968m11-12; 1990m6, 12	1984m6	-
France	1968m5; 1977m12	1963m3; 1968m5-6	1968m5, 1971m1
Italy	1984m2; 1988m2; 1992m2; 1996m2;	1969m10-12; 1972m12	-
UK	1971m2-3; 1999m10-11	1972m2; 1974m1-3; 1978m4; 1979m1	1975m4, 1979m6