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Domestic and International Influences on Business Cycle Regimes in Europe

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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. Regimes are examined as binary variables representing expansions versus recessions. A range of domestic real and financial variables are initially used as leading indicators, with these variables predicting regimes in Germany reasonably well at during the in-sample period to 1996, followed (in order) by the UK, Italy and France. Consideration of foreign variables leads to important roles for the composite leading indicators and interest rates of the US and Germany. The relative importance of these variables differs over countries, but overall they underline the role of international influences in the business cycles of these European countries. Post-sample forecasts are examined, with the international model for Germany correctly indicating recession during 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 played an important role in leading interest rates in other European countries in the pre-ERM period; 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 the levels of 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 value of exploiting the links between Germany, France, Italy and the UK in the prediction 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 recent recession in the US, dated by the National Bureau of Economic Research (NBER) as beginning 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. Due to the importance of the US in the world economy, and also in the light of the on-going debate about whether any US recession will 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 a development of the methodology of 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, including post-sample forecasts from 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 logistic regression 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

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[1] The usefulness of this approach was confirmed by a real time update of the BJOS study that predicted the 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.

classical business cycle is available over the last century, but no such history is available for other countries. Nevertheless, the Economic Cycle Research Institute (ECRI) uses NBER-style procedures (the Bry and Boschan, 1971 algorithm) to date classical cycle turning points for various countries based on their coincident indexes (defined by production, sales, employment and income data). Their chronology for the US is identical with that of the NBER. We adopt the ECRI turning points dates for our economies[3], with these shown in Table 1 for our sample period of January 1970 to December 2001.

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 (months) within overall expansions taking the value unity[4]. We allocate the month of a turning point to the previous regime, with the new regime defined to commence in the month after a turning point. This convention is the usual one adopted in the analysis of business cycle regimes. 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

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.php

[3] We do not know of any other classical business cycle chronology for these European countries. The Centre for Economic Policy Research (CEPR, www.cepr.org) has recently provided a dating of the growth cycle for the Euro Area since 1988, and this may be useful for future research.

[4] 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.

is estimated we need no further regime information for prediction purposes, since the regime probability then depends only on the observed values of the leading indicators.

We now turn to a description of the methodology we use[5]. Using a data vector $\boldsymbol{x}_{t-h}$ of observed variables up to and including period *t-h*, we construct a *h*-period ahead business cycle regime predictor of the form

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

where p_t is the probability that the business cycle regime for at quarter t will be an expansion, based on information up to and 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 $\boldsymbol{x}_{t-h}$ consists of leading indicators. Using sample information for $t = 1, \ldots, T$, the log-likelihood function for this binary model is given by

$$\log(L) = \Sigma_1 \log(p_t) + \Sigma_0 \log(1-p_t) \qquad (2)$$

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 $\boldsymbol{x}_{t-h}$ and finding the maximum likelihood estimate of β.

The choice of the components in $\boldsymbol{x}_{t-h}$ 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 Schwarz Information Criterion (SIC) in the form

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

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

[5] A lengthier account of the principles can be found in BJOS.

variables are retained only if they make a sufficiently strong contribution to the 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 the detailed results presented in this paper, n was set to 9. This choice was based on our experience with sequential elimination 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 or reduces 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 should be emphasised that hypothesis testing plays 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. In any case, we prefer SIC for the same reasons as Swanson and White (1995), namely this focuses more directly on the issue of out-of-sample forecasting performance and does not require an assumption of a correctly specified model for its validity. Indeed, Sin and White (1996) show that 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 Kullback–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 this autocorrelation can be important for regime prediction; see also Harding and Pagan (2001). However, our approach that considers many potential explanatory variables makes such modelling impractical. Also, as argued in BJOS, we allow dynamics to enter through the lags (or here differencing intervals) considered for each explanatory variable. Furthermore, the use of a lagged regime variable would complicate real time forecasting as regimes can only be identified with a lag.

An important purpose of this paper is to empirically investigate the role of international variables in the prediction of business cycle regimes. If there are significant causal mechanisms linking cycle regimes between countries then we would expect the use of international variables would improve our ability to predict those regimes. The evidence below suggests this improvement is confirmed and thus consistent with the hypothesis that significant linkages are at work across these countries.

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 in the US context, Green and Beckman, 1993). 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 econometric model that allows for structural changes over different business 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 leading indicator 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 numerous 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 interest rate spread leads to an improvement in the forecasting performance of output for around half of the European countries examined, 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 European country, namely the OECD series (http://www.oecd.org/). 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. Activity is represented by the index of industrial production and retail sales (both real variables)[6]. 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[7]. We also consider a possible role also for the oil price (converted from US dollars to the appropriate European currency using the exchange rate for each month)[8].

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 we also 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 all series except interest rates 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 estimate three-months-ahead models, 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 by linear interpolation and these are generally associated with events that do not relate

[6] Initially we also considered unemployment for each country, apart from Italy (for which the unemployment series is not available for our sample period), but this did not improve fit. Employment was not used, as a consistent monthly series is not available for each country.

[7] A classical business cycle leading indicator is available for the US, namely the composite leading indicator, and we use this in preference to the OECD growth cycle leading indicator in this case.

[8] For the full list of variables used in this study see the Data Appendix of the original draft of this paper which is available from the web at http://www.ses.man.ac.uk/cgbcr/DPCGBCR/dpcgbcr11.pdf.

to the business cycle, e.g. strikes. Where official series are not adjusted for the structural break of German reunification, we adjust the series for this event. A table of the adjustments performed on the data is given in the Data Appendix. After all other transformations, each series is standardised to zero mean and unit variance over the in-sample period. Thus the magnitudes of the coefficients in the estimated models can be compared as an indication of the relative strength of the effects of the respective leading indicators on the binary dependent variable for the regime.

4. Results

Two tables of results are presented. The first contains the selected model for each country using 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.

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, whilst the second included the term structure but not the separate rates. Otherwise, all domestic variables were included in the initial set. In the case of the international models, sequential elimination was conducted with each of these two initial sets of domestic variables except the retail sales variable (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. From these, the four models with lowest SIC values were taken as indicating four potentially relevant international variables. The *n*-search algorithm was then applied to initial sets consisting of all domestic variables (excluding retail sales) and different combinations of two potentially relevant international variables. Finally, the *n*-search model with minimum SIC was selected. 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. It may be noted that the quadratic probability score (QPS), sometimes used in the context of regime prediction, is a scaling of the mean-square error, and hence is not quoted here. Prediction errors are shown as percentages of the number of observations classified as within expansions and recessions[9], 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 in 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 selected 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 relevant 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.

[9] No forecast comparison is made with a "naïve" model. A simple model that always forecast expansion would necessarily produce errors for every period in recession, while a "no change" model is not applicable in practice here because the current regime (recession or expansion) is typically not known with certainty as turning points are not dated until some months after the event.

Table 2: Three-Months-Ahead Domestic Models

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: 1997m1-2001m12.

In considering the extent to which business cycle recessions and expansions are domestic or international phenomena, the summary and error 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 clarity of the 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. In fact, 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 quite well in Germany and reasonably well in the UK, but not so well for Italy and, still less, France. 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 1997-2001 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 period as it does not predict the 2001 recession.

Table 3 presents the results for the three-months-ahead models for each country when international variables are also considered[10]. 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 the annual change in the domestic CLI is no longer important for Italy. Domestic real money growth now enters positively as a three-month difference for Germany but the

[10] The international model reported for Germany in Table 3 is the second best model obtained from the *n*-search procedure applied with different combinations of international variables. The first best model (according to SIC) included a role for the French leading indicator. This may partly proxy a US influence on Germany, since the OECD French CLI includes the US leading indicator as a component. We regard the reported model that directly uses the US CLI as being more plausible.

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

Variables:	Germany	France	Italy	UK
Intercept	4.503	3.723	5.693	7.019
$\Delta_3\log(CLI)_{-3}$	3.544			
$\Delta_6\log(CLI)_{-3}$		2.683		
$\Delta_{12}\log(IOP)_{-3}$	3.692			
$\Delta_3\log(RM1)_{-3}$	2.745			
$\Delta_{12}\log(RM1)_{-3}$			-2.917	-3.249
$\Delta_3\log(SP)_{-3}$	-2.514			
$\Delta_6\log(SP)_{-3}$		-1.446		
$\Delta_{12}\log(SP)_{-3}$		-1.455		
$(TS)_{-9}$	5.562			
$(SR)_{-3}$		-3.731	-3.649	-4.149
$(SR)_{-6}$		-1.622		
$(SR)_{-12}$				-5.548
$(LR)_{-3}$				2.576
$(LR)_{-9}$				-3.989
$(FIBOR)_{-9}$		4.295		
$(FIBOR)_{-12}$		-3.845	-3.450	
$\Delta_{12}\log(BDCLI)_{-3}$			4.056	
$(USTB)_{-3}$	-5.301			
$(USTB)_{-6}$	6.302	2.704		
$(USTB)_{-9}$				3.555
$\Delta_6\log(USCLI)_{-3}$	2.901			
$\Delta_{12}\log(USCLI)_{-3}$				2.807
Summary Statistics:				
RMSE Sample	0.1646	0.2363	0.1743	0.1908
Log Likelihood	-29.68	-64.28	-31.18	-35.45
SIC	111.4	180.6	91.3	117.1
Errors In-Sample:				
Expansion	1% (4/229)	1% (5/253)	2% (7/246)	2% (8/268)
Contractions	6% (6/95)	22% (16/71)	8% (7/78)	17% (10/56)
Uncertain	7/324	31/324	8/324	18/324
Errors Out-of-Sample:				
Expansion	0% (0/49)	(0/60)	(0/60)	(0/60)
Contractions	72% (8/11)	(0/0)	(0/0)	(0/0)
Uncertain	2/60	0/60	0/60	0/60
Prediction:				
Forecast 2002m1	0.8551	1	0.9991	1
Forecast 2002m2	0.0264*	1	0.9977	1
Forecast 2002m3	0.0000*	1	0.9990	1

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

annual change is negative for the UK and Italy. Where domestic stock market prices are included for Germany and France, these price changes have a negative effect on the expansion probability.

The term structure (TS) 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, and for Italy the short-term rate now becomes more important than the long rate.

The composite leading indicator for the US (USCLI) is important for Germany and the UK. The effect is positive in both cases, with a six-month difference used for Germany and the annual difference for the UK. The annual difference of the German OECD leading indicator (BDCLI) is strongly positive for Italy. These results imply that the US economy is leading the UK economy as found in Artis and Zhang (1997, 1999), with an influence also on Germany. The importance of US growth in leading that of the UK and Germany is also found by Canova and De Nicoló (2000).

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[11], while short interest rates in the US (USTB) influence regimes in Germany, France and the UK. These interest rates have mixed effects. The German short-term rate affects the Italian economy negatively at 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. There are strong effects from the USTB to Germany where a negative short lag and positive lag of six months are found. Table 3 implies positive effects for the US interest rate at 6 and 9 months later for France and the UK respectively.

The role of German interest rates in the three other European countries substantiates the literature on the German leadership hypothesis, 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 German leadership hypothesis than the former and do not exclude that US interest rates are also important for European economies. The role of the USTB, but not FIBOR, for the UK backs up the evidence of Artis and Zhang (1997, 1999) that the UK cycle is more closely related to the US economy than to Europe. Our results may also help to clarify the ambiguous previous results on the international effect on growth of US interest rates, with Kim (2001) finding that US monetary policy shocks (through instruments like the short-term interest rate) affect growth in the remaining G7 countries, but Canova and De Nicoló (2000) detect little impact on industrial production growth.

In contrast with the roles found for interest rates, no international stock market variables appear in Table 3, confirming findings of Canova and De Nicoló (2000). 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 Tables 2 and 3, 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 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 both expansions and recessions, and also 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 during the in-sample period is that for Italy, where both SIC and RMSE drop very substantially, with regime prediction errors during contractions being less than half the corresponding values in Table 2. Even for Germany, where the domestic model of Table 2 provides a relatively good fit, the introduction of international variables improves in-sample regime prediction and SIC.

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 August 2001, slightly later than the February 2001 recession start dated by ECRI. The predictions for February and March of 2002 are for continuation of this recession. Despite noting

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[11] Note that the FIBOR has been the domestic interest rate for France and Italy since monetary union in January 1999.

above that international variables had relatively little impact on the in-sample 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.

Finally, it is to be noted that the above exercise was repeated for all four countries using a sample period running from the first month of 1970 to the last month of 1989, with the aim of testing the robustness of the above results to the choice of sample period. In particular, it may be anticipated that inter-relationships among European countries will have altered over the entire period from 1970. Although our modelling of a binary regime indicator may make this a less severe problem than for, say, modelling growth rates, we provide this check. While the full results of this round of models are not reported in detail here[12], the following comments are in order. Problems of perfect fit became more severe even with the *n*-search method, so that lower values of *n* had to be used; here we report results with the *n*-search restricted to five variables. We compared the domestic models with those allowing international variables. In the case of Germany, the SIC criterion chose to replace the domestic composite leading indicator and stock prices with US short term rates and the US composite leading indicator. Both the domestic model and the international model did not perform well in predicting out of sample, although the domestic model did a little better here. In the case of France, the SIC criterion chose to replace the domestic industrial production index with Germany's short term interest rate. Again both models did not do well in predicting out-of-sample regimes, although in this case the international model did slightly better. In the case of Italy, the SIC criterion chose to replace the domestic composite index and retail sales index with the German short rate of interest and German composite index. The international model was somewhat better at prediction out-of-sample. In the case of the UK, the SIC criterion chose to replace the domestic composite index and retail sales index with domestic real money and the US composite index. Both models did not predict well out-of-sample and there was little to choose between them on this count.

Overall, it is not surprising that these models estimated to 1990 have poorer forecasting performance than those reported in Tables 2 and 3, since their estimation has less information about recession events. In general, while a comparison with the variables selected in Tables 2 and 3 indicates some evidence of structural change in

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[12] These are available on the web as an addendum to the original version of this paper, see http://www.ses.man.ac.uk/cgbcr/DPCGBCR/dpcgbcr11.pdf.

the 1990s, our key conclusion that the use of international variables improves regime prediction for these countries is not undermined. Indeed, the general pattern remains unchanged, with the US playing a role for Germany and the UK, with German variables entering for France and Italy.

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 composite leading indicators and short-term interest rates for Germany and the US. The introduction of the composite leading indicator and interest rates for Germany have a particularly marked effect on the performance of the regime prediction model for Italy, underlying the leading role of Germany for other European countries.

In general, our results are consistent with the hypothesis 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 US composite leading indicator and short-term interest rates) is important in the context of predicting the recession of 2001. The models reported here make no claim to be causal models and it is to anticipate that the construction of models to predict business cycle regimes will be assisted by a better understanding of the international mechanisms linking cycles in different countries and how this may have changed in the late decade of the twentieth century.

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Figure 1: Expansion Probabilities from Domestic Model for Germany

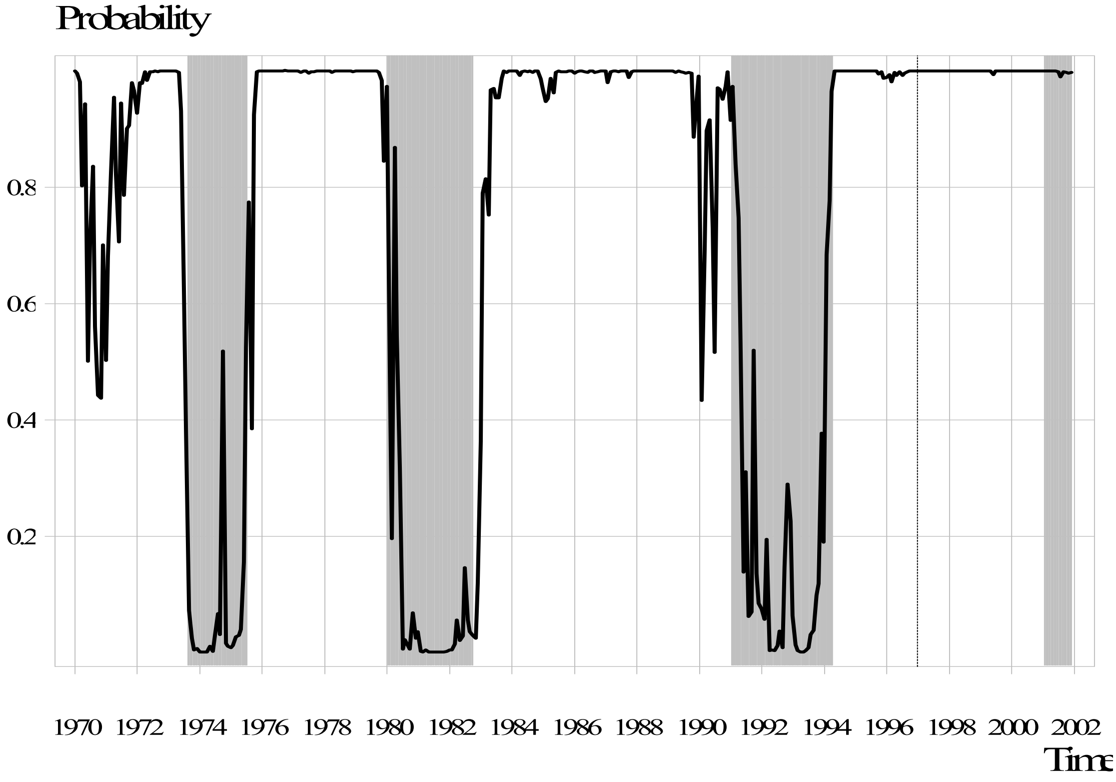

Figure 2: Expansion Probabilities from Domestic Model for France

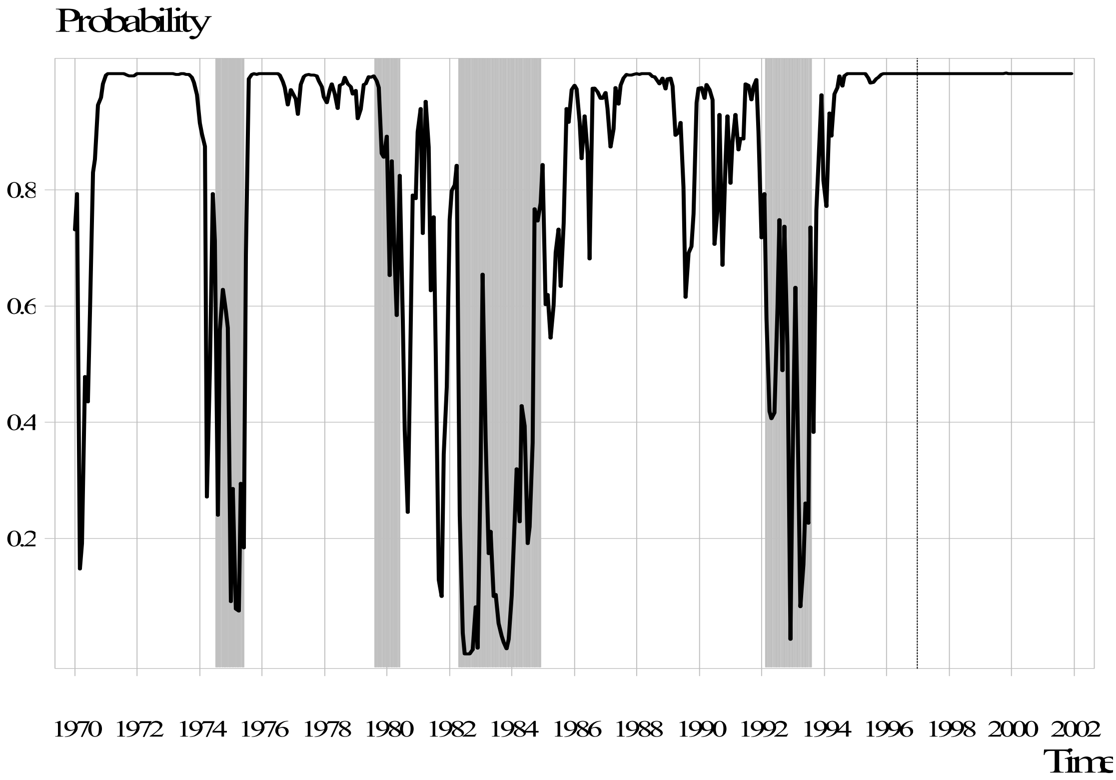

Figure 3: Expansion Probabilities from Domestic Model for Italy

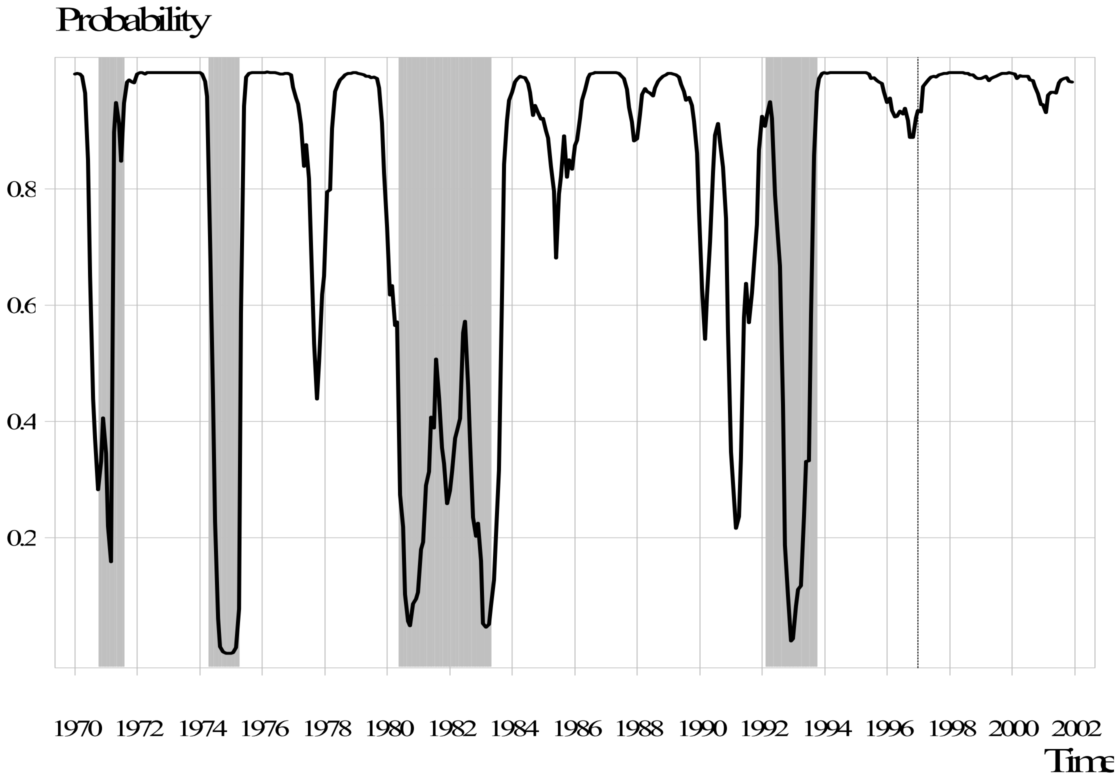

Figure 4: Expansion Probabilities from Domestic Model for the UK

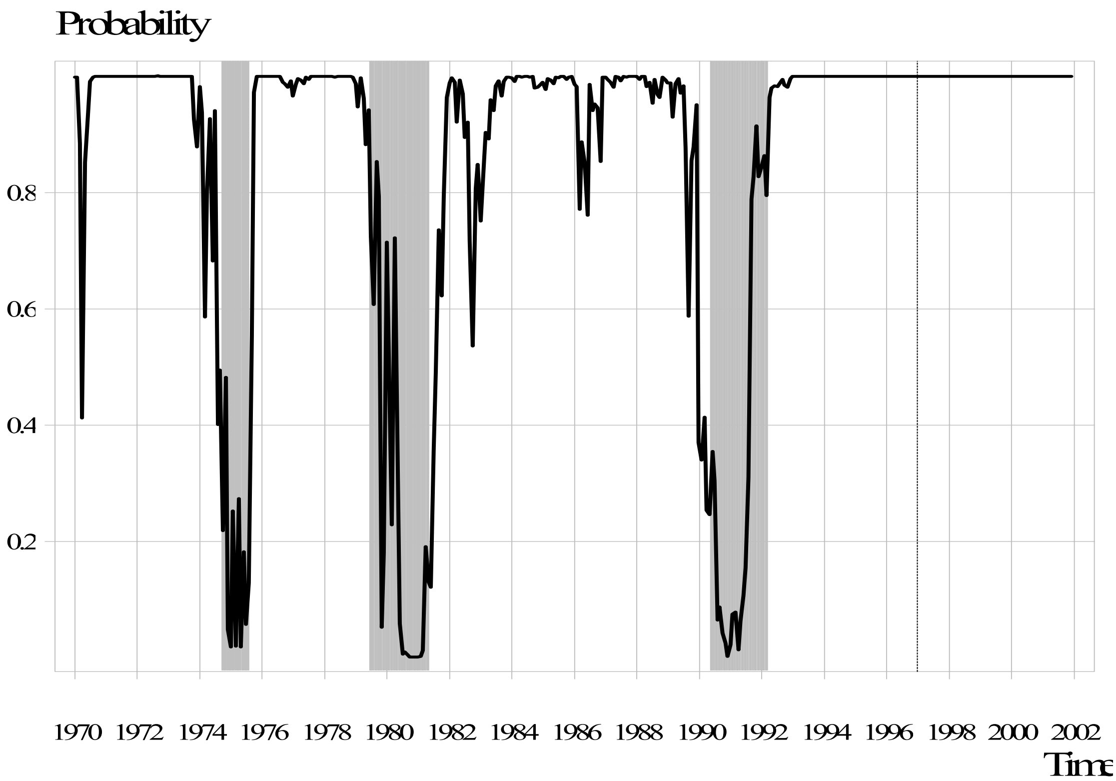

Figure 5: Expansion Probabilities from Model with International Variables for Germany

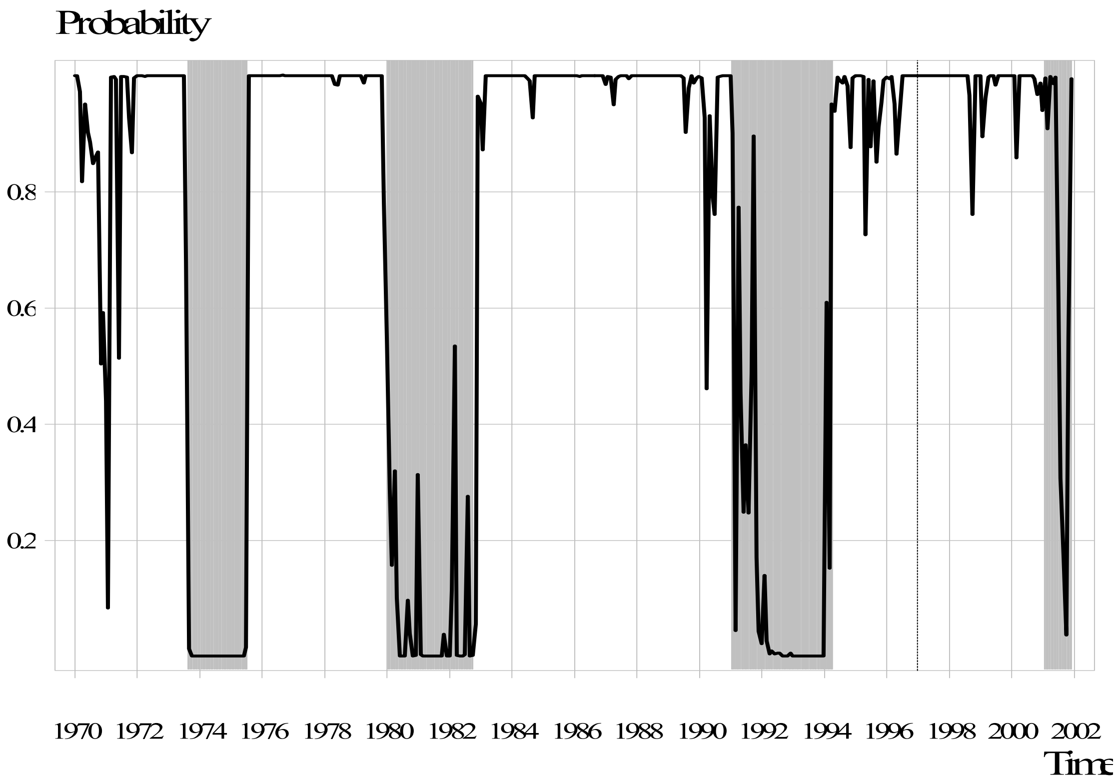

Figure 6: Expansion Probabilities from Model with International Variables for France

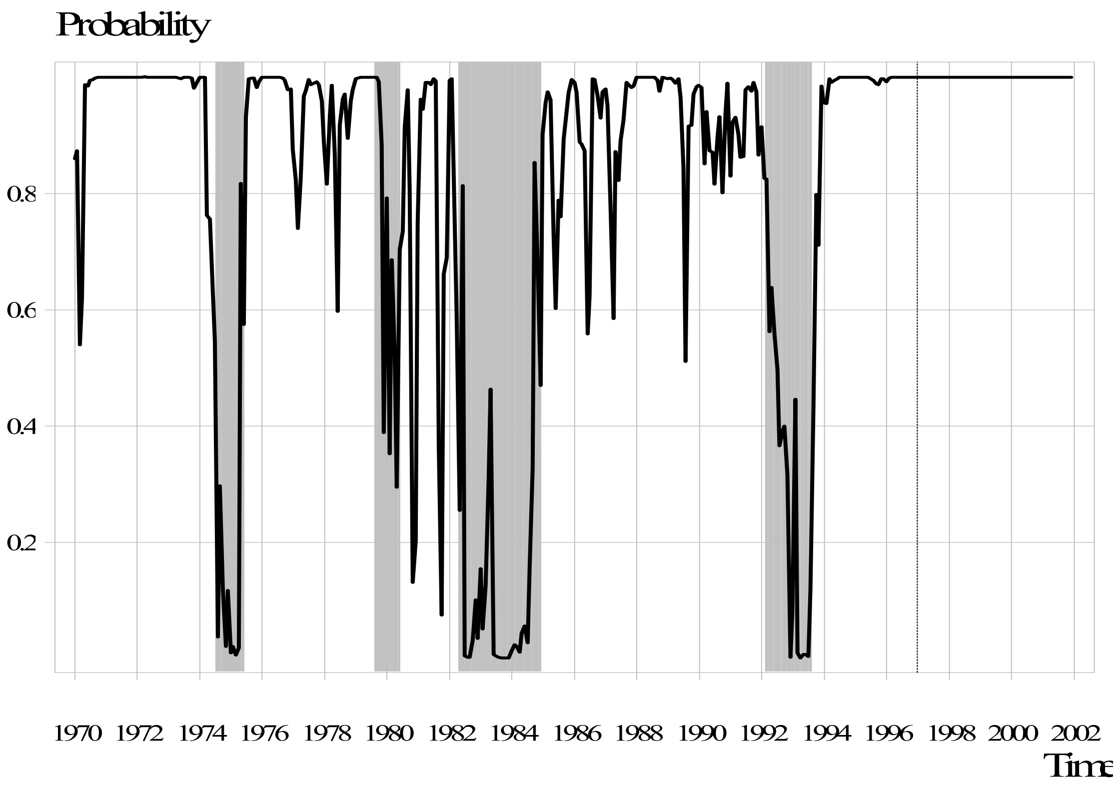

Figure 7: Expansion Probabilities from Model with International Variables for Italy

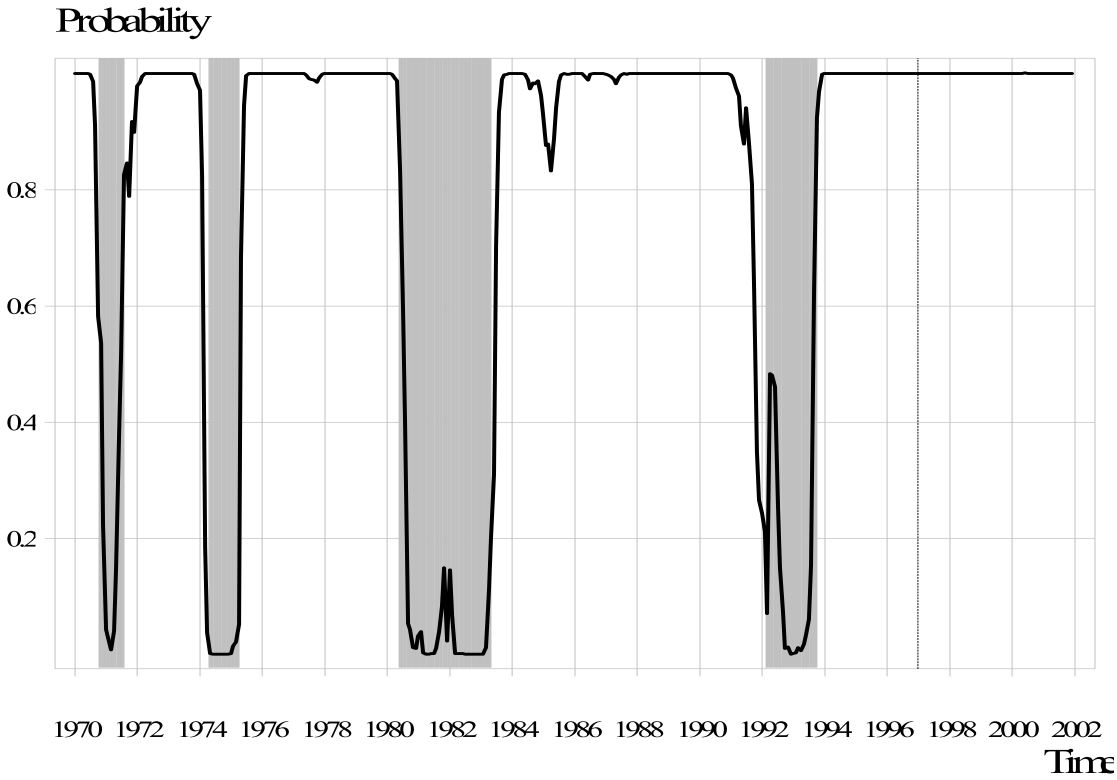

Figure 8: Expansion Probabilities from Model with International Variables for the UK