No. 1999/15

Predicting Recessions with Interest Rate Spreads: A Multicountry Regime-Switching Analysis

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CFS Working Paper No. 1999/15

Predicting Recessions with Interest Rate Spreads: A Multicountry Regime-Switching Analysis *

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November 11, 1999

Abstract: This study uses Markov-switching models to evaluate the informational content of the term structure as a predictor of recessions in eight OECD countries. The empirical results suggest that for all countries the term spread is sensibly modelled as a two-state regime-switching process. Moreover, our simple univariate model turns out to be a filter that transforms accurately term spread changes into turning point predictions. The term structure is confirmed to be a reliable recession indicator. However, the results of probit estimations show that the markov-switching filter does not significantly improve the forecasting ability of the spread.

Keywords: Term structure, economic fluctuations, forecasting, regime-switching

JEL classification: E44, C22, C53

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* I would like to thank Martin Bohl, Martin Mandler and Pierre Siklos for their helpful comments.

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1. Introduction

In recent years, numerous empirical studies have been carried out to evaluate the usefulness of spreads between long and short-term interest rates as leading indicators of real economic activity. While in most of these studies linear regression-based techniques are applied to forecast output growth rates,[1] some authors have done probit estimations in order to calculate the likelihood of future economic recessions. In such probit models the dependent variable is a recession dummy that equals one if the economy is in recession and zero otherwise, whereas the explanatory variable is a lagged potential recession predictor. Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) provide evidence for the United States that the yield spread significantly outperforms other popular financial and macroeconomic indicators in forecasting recessions, particularly with horizons beyond one quarter. Bernard and Gerlach (1996) and Estrella and Mishkin (1997) extend this research to multicountry analyses, while Funke (1997) supplies additional evidence for Germany. In his recent study Dueker (1997) confirms the U.S. results presented by Estrella and Mishkin (1998) using a modified probit model which includes a lagged dependent variable and additionally allows for Markov-switching coefficient variation.

In this paper, the predictive power of the yield spread for eight industrialized countries is reconsidered by combining regime-switching and probit models in a different way. Following Lahiri and Wang (1996), we first fit a univariate two-state Markov-switching model to the term spread of the USA, Canada, Japan, Germany, France, the United Kingdom, Italy and the Netherlands respectively. As a next step we investigate whether one of the estimated states is systematically related to economic recessions. This is done by a graphical analysis where the estimated regime-probabilities are plotted against business cycle phases (Filardo (1999)). Finally, a formal assessment of the usefulness of the regime switching technique is offered by estimating probit models where the explanatory variable is the calculated markov-regime probability (Ang and Bekaert (1998)). The results of these estimations are then compared with the ones which are obtained by using only the spread as a leading indicator.

The main empirical findings presented in this paper are the following. For each country the yield spread can be characterized as a two-state regime-switching process. Furthermore, in nearly all cases one of the two regimes is more or less closely related to recessions while the other one corresponds to economic expansion or recovery phases. The yield curve is confirmed to be a quite reliable recession predictor across the evaluated countries, because on average it signals recessions a considerable time before they actually begin and produces only a few signals that falsely indicate business cycle turning points. As regards the chossen technique, the regime-switching model turns out to be an appropriate filter that efficiently transforms changes in the term spread variable into accurate and unambiguous turning point predictions. However, the final results of probit estimations also show that applying the markov-switching filter does not significantly improve the forecasting ability of the term spread. Though the optimal lead times of regime-probabilities are in many cases identical to the most successful forecasting horizons according to probit estimations which contain the unfiltered spread, there seems to be a tradeoff between the sharp probabilities of the Markov-model and the accuracy of fitting independent recession dates.

The paper is structured as follows. The next section briefly reviews the theoretical link between interest rate spreads and real economic activity. In section 3, the regime-switching specification and the estimation method is described. Section 4 reports the estimation results. The predictive power of the yield curve is thoroughly analyzed in section 5. Section 6 concludes the paper.

2. Theoretical background

Though it is beyond the scope of this study to discuss theoretical relations between the yield curve and future economic activity in detail, some few remarks addressing this issue are following. In general, prices of financial assets are supposed to contain expectations about the future path of the economy. The most convincing theoretical foundation of this assumption is the expectations theory of the term structure. The expectations hypothesis postulates that, for any choice of holding period, investors do not expect to realize different returns from holding bonds or bills of different maturities. Thus, a downward sloping yield curve implies an expected fall of interest rates which equalizes the ex ante returns of different investment opportunities. As a result, the current long-term rate is an average of expected future short-term rates.

Building upon the expectations hypothesis, two straightforward arguments explain why the yield curve contains information about future recessions. The first argument relates to the role of monetary policy. When a central bank raises short-term interest rates, agents may view this contraction as temporary and, consequently, raise their expectations of future short-term rates by less than the observed current change in the short rate. From the expectations theory it follows that long-term rates rise by less than the short-term rate, resulting in a flat or inverted yield curve. Since the real sector of the economy is affected by monetary policy measures with a considerable time lag, agents expect future real economic growth to decline. Hence, the monetary tightening flattens the yield curve and simultaneously increases the likelihood of a recession onset. The second argument focusses on inflationary expectations that are contained in long term interest rates. Since recessions are generally associated with low inflation rates, an anticipation of a recession probably results in a falling long-term rate. Consequently, when the short rate does not change, the yield curve flattens or invertes.

Sound theoretical foundations of the empirical regularities considered in this paper are originally given by Harvey (1988) who uses the consumption CAPM. The central assumption is that consumers prefer a stable level of income rather than very high income during expansions and very low income during slowdowns. It follows that when consumers expect a recession for the next year, they will buy one year discount bonds in order to get payoffs in the slowdown. The increased overall demand for bonds leads the one year yield to decrease. Simultaneously, to finance the purchase of the one year bonds, consumers may sell short-term financial instruments whose yields will increase. As a result, the term structure will become flat or inverted.

Which factors actually give rise to the predictive content of the term spread ist still the real question. In a newer contribution Estrella (1997) focusses on theoretical effects that different monetary policy rules have on the predictive content of the term spread. Building upon such policy-oriented work, Smets and Tsatsaronis (1997) estimate structural VARs to analyse and quantify the importance of economic factors determining the term structure slope in the USA and Germany. For applied business cycle research, like the one documented in this paper, it is important to keep in mind that there are some well-founded arguments which suggest a positive relationship between the yield curve spread and future real output. In our empirical study, however, the essential question concerns the optimal filtering of term spread signals and the methodically adequate assessment of their forecasting ability.

3. Model specification and estimation method

To describe the regime-switching behaviour of the yield spread we apply the popular Markov-switching approach developed by Hamilton (1989). The estimation procedure we use was introduced by Hamilton (1994) and Gray (1996). Depending on the value of an unobserved regime indicator S_t, the mean and the variance of a stationary series are allowed to take two different values. That is, the observed realization of the term spread is presumed to be drawn from a $N(\mu_1, \sigma_1^2)$ distribution when $S_t = 1$, whereas y_t is distributed $N(\mu_2, \sigma_2^2)$ when $S_t = 2$. Because of the theoretically founded indicator properties of the term spread, we expect that one of the two regimes corresponds to recession or low growth phases, while the other regime is presumed to be associated with phases of economic expansion or recovery. Note that the spread is distributed as an iid normal variate around the mean of the corresponding state (Engel and Hamilton (1990)). At first glance, this simplicity of the statistical specification seems to be surprising. In markov-models, however, serial correlation could be captured well by the persistence of the two states. Thus, a priori there is no need to incorporate autoregressive terms in the mean as part of the regime switching model. In addition, earlier research has shown that the forecasts generated by more complicated models are often worse, despite the fact that they fit the data better (Lahiri and Wang (1994)).

The regime indicator S_t is parameterized as a first-order Markov process. Thus, the switching or transition probabilities P and Q have the typical Markov structure:

$$\begin{aligned} &\Pr[S_t = 1 | S_{t-1} = 1] = P \\ &\Pr[S_t = 2 | S_{t-1} = 1] = (1 - P) \\ &\Pr[S_t = 2 | S_{t-1} = 2] = Q \\ &\Pr[S_t = 1 | S_{t-1} = 2] = (1 - Q) \quad . \end{aligned} \tag{1}$$

Under the assumption of conditional normality for each regime, the conditional distribution of the spread y_t is a mixture of normal distributions,

$$y_t | \Phi_{t-1} \sim \begin{cases} N(\mu_1, \sigma_1^2) & \text{w. p. } p_{1t} \\ N(\mu_2, \sigma_2^2) & \text{w. p. } p_{2t} = (1 - p_{1t}) \end{cases}, \tag{2}$$

where $p_{1t} = \Pr(S_t = 1 | \Phi_{t-1})$ is the probability that the analyzed process is in regime 1 at time t conditional on information available at time $t-1$. The probability p_{1t} is called 'ex ante regime probability', because it is based solely on information already available and because it forecasts the prevailing regime in the next period. Hence, this probability can be directly used to forecast turning points in the business cycle.[2] If regime 1 is associated with recessions and p_{1t} is higher than 0.5 we will conclude that a recession is near or already prevailing, provided the evaluated yield curve indicator performs well.[3]

Following Hamilton (1994) and Gray (1996) the unobserved regime probability is formulated as a recursive process,

$$p_{1t} = P\left[\frac{f_{1t-1}p_{1t-1}}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}\right] + (1-Q)\left[\frac{f_{2t-1}(1-p_{1t-1})}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}\right],$$

with the regime-dependent conditional distributions $f_{1t} = f(y_t | S_t = 1)$ and $f_{2t} = f(y_t | S_t = 2)$. This specification is very similar to a GARCH model where unobserved conditional variances follow a recursive structure with unknown parameters. The recursive representation of the regime-switching model allows us to construct the log-likelihood function conveniently as

$$\begin{aligned} L = \sum_{t=1}^{T} \log\Bigg[& p_{1t}\frac{1}{\sqrt{2\pi}\,\sigma_1}\exp\left\{\frac{-(y_t-\mu_1)^2}{2\sigma_1^2}\right\} \\ & + (1-p_{1t})\frac{1}{\sqrt{2\pi}\,\sigma_2}\exp\left\{\frac{-(y_t-\mu_2)^2}{2\sigma_2^2}\right\}\Bigg] \quad . \end{aligned} \tag{3}$$

All models were estimated by (quasi) maximum likelihood using RATS 4.2. Parameter estimates were obtained using the BFGS algorithm. The reported t-statistics are based on heteroskedastic-consistent standard errors (White (1980)).

Compared to the probit model, whose probability does predict a recession at a particular forecasting horizon, the regime-switching technique is characterized by determining lead or lag times of recession predictors endogenously. Because the ex-ante regime probability gives a likelihood of recession sometime in the future, a precise assessment of the forecast is difficult. Of course, this lack of precision could also be an advantage in practical forecasting exercises, since probit models may miss recessions that exhibit unusual lead times.[4] As a further advantage, the estimation procedure described above does not rely on the ex-post knowledge of recession dates. Hence, actual turning points are only used for reference purposes. As it is typical for Markov-switching models, we let the data decide when to switch into a regime that may be generally associated with recessions. A last benefit of the regime-switching approach is the possibility to take into account the number of false turning point signals. This statistic should be a further important criterion of accuracy in business cycle predictions.[5]

4. Estimation results

The estimates presented in this study are derived from a monthly data set of interest rates which are taken from the IMF Financial Statistics Database. A short description of the series is provided in the appendix. The sample extends from January 1970 (Italy: January 1971) to December 1996. To calculate the term spread, we have selected the yield on government bonds as the long-term rate for all countries.[6] As regards the short-term rate we use day-to-day money market rates for the USA, Japan, Germany and the Netherlands. For the remaining countries day-to-day rates are not continuously available since 1970. Therefore, we take the three-month money market rate in the case of Italy and the three-month Treasury bill rate in the case of Canada, France, and the United Kingdom. Using different short-term rates for the countries under investigation can be justified for two reasons. First, Lahiri and Wang (1996) demonstrate for the USA that the Federal Funds rate and the one-year Treasury bill rate are almost equally useful in constructing the term spread indicator. Second, day-to-day rates and three-month Treasury bill rates generally move together strongly in those countries for which both series are available.

TABLE 1

Parameter estimates of univariate regime-switching models for the term spread

	USA	*Canada*	*Japan*	*Germany*
μ_1	- 1.062** (4.53)	- 1.024** (4.62)	- 1.056** (2.29)	- 0.436** (4.21)
μ_2	1.890** (20.90)	1.930** (20.64)	1.139** (7.31)	2.288** (30.57)
σ_1^2	2.558** (7.78)	1.396** (7.47)	1.395** (8.25)	1.101** (4.20)
σ_2^2	0.598** (7.32)	0.863** (10.19)	0.349** (3.76)	0.985** (6.65)
P	0.954** (63.78)	0.944** (46.49)	0.943** (37.02)	0.967** (73.24)
Q	0.980** (153.33)	0.978** (150.38)	0.979** (106.50)	0.984** (150.30)
$\overline{P}$	0.305	0.284	0.271	0.325
$\overline{Q}$	0.696	0.712	0.730	0.675
$(1-P)^{-1}$	21.787	17.762	17.575	30.675
$(1-Q)^{-1}$	49.751	44.843	47.393	63.694
Log-Likelihood	- 482.32	- 484.99	- 381.11	- 488.25
Wald Tests				
H_0: $\mu_1 = \mu_2$	239.37**	249.61**	47.67**	532.70**
H_0: $\sigma_1^2 = \sigma_2^2$	36.19**	5.87*	22.65**	0.16

TABLE 1
(continued)

	France	*UK*	*Italy*	*Netherlands*
μ_1	- 0.871** (8.84)	- 1.0500** (4.03)	- 1.6891** (12.92)	0.0799 (0.48)
μ_2	1.192** (18.88)	2.4518** (16.90)	1.4810** (17.74)	3.2314** (15.70)
s_1^2	0.857** (9.64)	1.6943** (5.87)	1.7427** (6.21)	1.7930** (4.07)
s_2^2	0.472** (8.71)	1.5844** (9.25)	0.6941** (9.93)	1.9896** (7.62)
P	0.942** (67.00)	0.9803** (63.72)	0.9676** (94.85)	0.9650** (95.71)
Q	0.967** (72.84)	0.9891** (159.96)	0.9669** (77.03)	0.9629** (71.79)
$\overline{P}$	0.361	0.356	0.505	0.515
$\overline{Q}$	0.639	0.644	0.495	0.485
$(1-P)^{-1}$	17.241	50.761	30.864	28.571
$(1-Q)^{-1}$	30.488	91.743	30.212	26.954
Log-Likelihood	- 411.88	- 551.24	- 489.93	- 591.11
Wald Tests				
H_0: $\mu_1 = \mu_2$	522.58**	334.17**	561.98**	448.51**
H_0: $s_1^2 = s_2^2$	13.65**	0.09	13.08**	0.14

Notes: The sample contains monthly observations from January 1970 (Italy: January 1971) to December 1996. The term spread variables are calculated as the percentage difference between the interest rate on a government bond and the Federal Funds Rate (USA), the Treasury bill rate (Canada, France, UK), the call money rate (Japan, Germany, Netherlands) and the money market rate (Italy) respectively. t-statistics in parentheses are based on heteroskedastic-consistent standard errors. * (**) denotes significance at the 5% (1%) level. The Wald test statistics are asymptotically χ^2 (1)-distributed. The critical value at 5% is 3,84.

Maximum likelihood estimates of univariate regime-switching models for term spreads of all eight analyzed countries are reported in Table 1. According to Table 1, all term spreads are successfully modelled as two-state regime-switching processes. The estimated switching probabilities P and Q are highly significant and range from 0.94 to 0.98 indicating persistence in both regimes for all variables. In all cases the second regime is obviously characterized as a period of an upward-sloping yield curve with an average percentage spread ranging from 1.14 to 3.23. Alternatively, the average term spread in regime one is negative. Here, the only exception is the Netherlands with a small average term spread which does not differ significantly from zero. Hence, we can conclude that regime one represents periods in which an inverted or at least flat yield curve prevails. As the estimated variances in Table 1 suggest, regime one is in many cases a 'high-volatility' regime compared to regime two. However, the reported Wald test statistics imply that the two regimes describing the spreads in Germany, the UK, and the Netherlands are separated by differential means only. The contribution of the markov chain in explaining the behaviour of the term spread is also reflected in Figure 1 whose panels show the estimated conditional mean together with the original series. The panels reveal how the regime-switching model transfers movements of a financial variable into „on/off“ inferences regarding recessions: though the spread is allowed to fluctuate around its estimated regime-dependent mean, it has to exceed a „threshold value“ before regime changes do occur.

FIGURE 1

The term spread and its regime-dependent mean

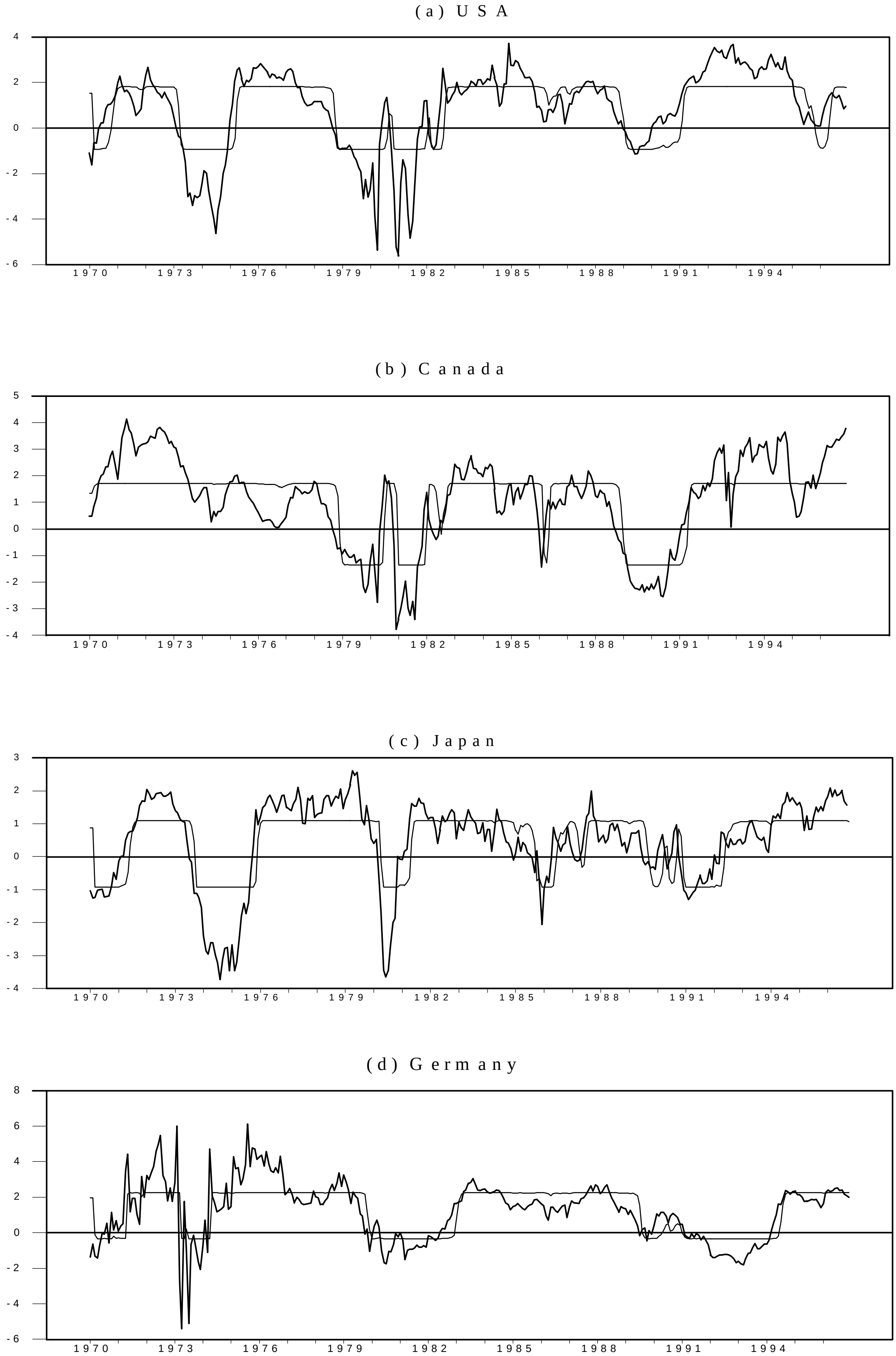
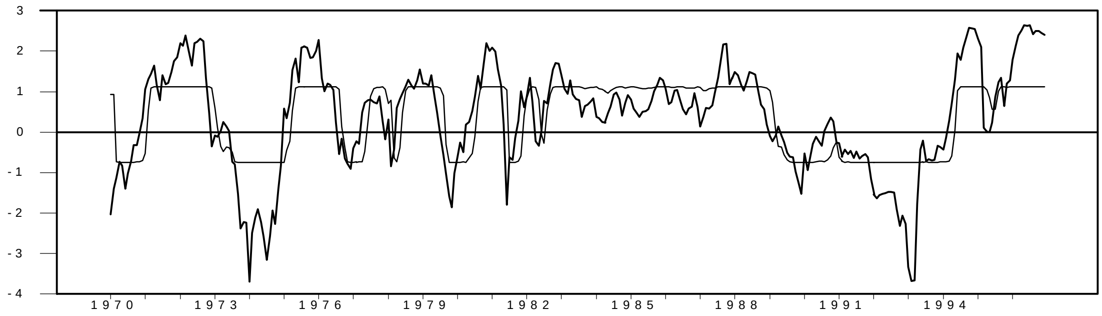


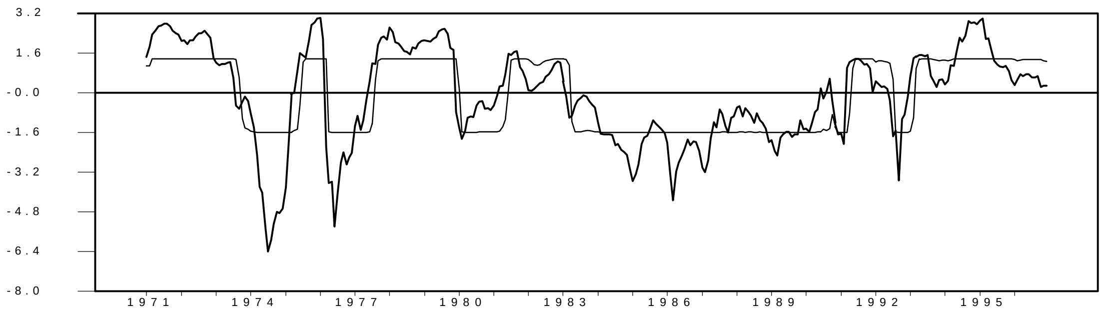
FIGURE 1
(continued)

(e) France



(f) United Kingdom

(g) Italy



(h) Netherlands

Fig. 1. The panels (a) to (h) contain time series plots of the term spread (bold lines) and its regime-dependent (conditional) mean according to the estimated regime-switching models (see table 1). Parameter estimates are based on the percentage difference of monthly observed interest rates. The sample period is January 1970 (Italy: January 1971) to December 1996.

For an assessment of further features characterizing the two states, one has to look at unconditional regime probabilities in Table 1. The unconditional probabilitiy of being in the inverted yield curve regime $\overline{P} = \frac{1-Q}{2-P-Q}$ is about 30 percent in most of the countries. If the term spread is in fact a useful recession predictor, this finding seems to be reasonable, because economies generally stay longer in expansion phases than in recessions. In constrast, the unconditional regime probability $\overline{P}$ calculated for Italy and the Netherlands calls into question the predictive content of the term spread. It amounts to 50 percent respectively which seems to be extremely high for an unconditional recession probability. However, Artis, Kontolemis and Osborn (1995, p.14) demonstrate for the Netherlands that the average duration of recessions is relatively long with 20 months, whereas the average expansion duration is the shortest one of all countries with 30 months. A high unconditional recession probability thus can be explained. Since for Italy durations are reported to be much more asymmetrical, our doubts about the predictive content of the term spread in this country remain. Here, the average recession lasts 15 months while the average expansion duration is 63 months.

Table 1 also provides the expected duration of both regimes. Except for the UK where it is computed to be 50 months, the duration of state one $(1-P)^{-1}$ varies between 17 and 30 months among all countries. It may be noted that this finding corresponds roughly with the country-specific average durations of recessions as estimated by Artis et al. (1995) which vary between 11 and 24 months. Again with the exception of the UK the expected duration of state two $(1-Q)^{-1}$ varies between 27 months in the Netherlands and 64 months in Germany. This result also corresponds impressingly well with the estimated average duration of expansion phases calculated by Artis et al. (1995). The authors find for Germany with 77 months the longest and for the Netherlands with 30 months the shortest average expansion duration among all the countries which are analyzed in this paper. Thus, in many cases the substantial differences between the two regimes seem to reflect not only the term spread behaviour, but also the asymmetry of business cycles. On balance, the estimation results presented in Table 1 let us hope that the relationship between interest rate spreads and the business cycle is captured well by the simple Markov-switching model we have applied.

5. The predictive power of the term spread

5.1 Analysis of markov-regime probabilities

The results presented so far show that all considered spreads are sensibly modelled within a regime-switching framework. Next, we want to investigate directly whether the identified regimes are associated with business cycle phases. When looking at the reported zero or negative mean estimates, we roughly anticipate, keeping the above mentioned theoretical considerations in mind, regime one to correspond with recession phases in all eight countries. To address this question more precisely and to examine the country-specific forecasting ability of the term spread with respect to future recessions, one has to take a look at the panels (a) to (h) of Figure 2. These panels contain series of ex ante probabilities of the respective spread being in the inverted yield curve regime at date t conditional on information available at date $t-1$. Shaded areas indicate recessions. Following conventional practice, a recession is defined to start with a business cycle peak and to end with a trough. While recognizing that the identification of business cycle turning points is a problem of its own, our analysis relies on recession dates as determined by Artis, Kontolemis and Osborn (1995) who apply a four-step procedure to the indexes of industrial production.[7]

FIGURE 2

Forecasting probability of recession using the term spread

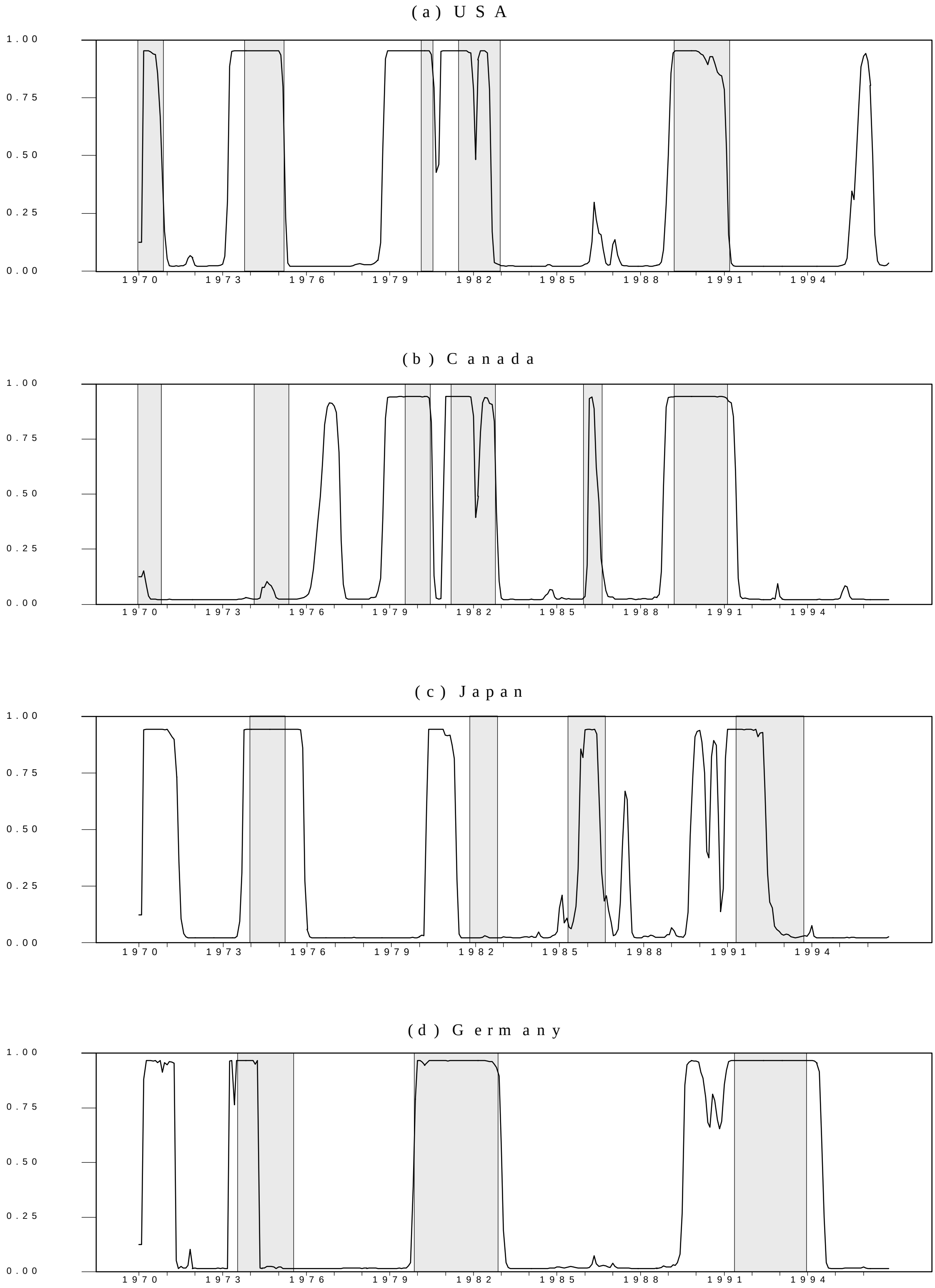


FIGURE 2
(continued)

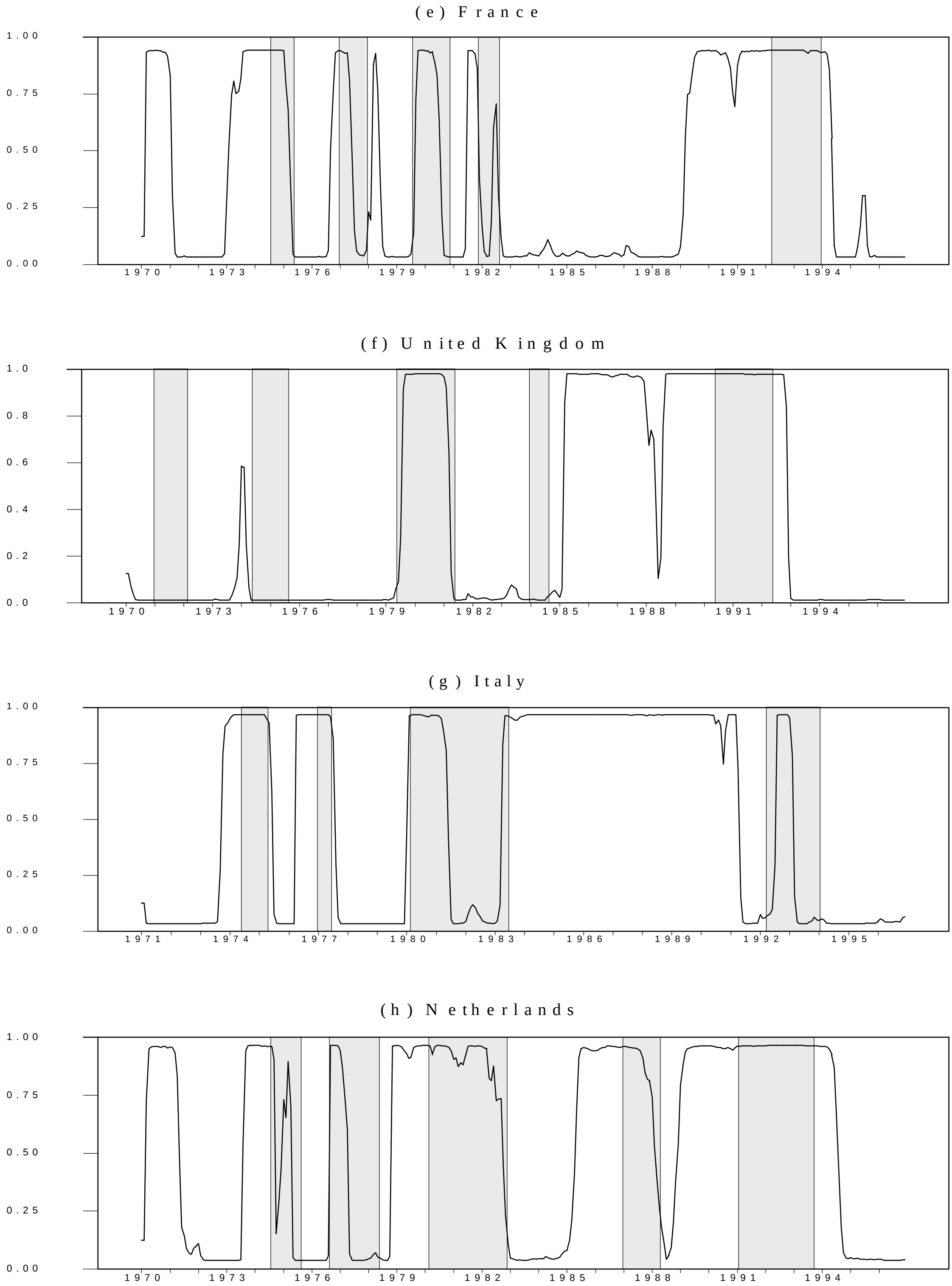


Fig. 2. The panels (a) to (h) contain time series plots of ex ante probabilities that the process of the respective term spread is in regime 1 at time t according to the estimated regime-switching models (see table 1). The ex ante probabilities are based on information available at time t-1 ($Pr[S_t = 1|\Phi_{t-1}]$). Parameter estimates are based on the percentage difference of monthly observed interest rates. The sample period is January 1970 (Italy: January 1971) to December 1996. Shaded areas indicate recessions starting with business cycle peaks and ending with troughs. Business cycle turning points are determined by Artis, Kontolemis and Osborn (1995).

Visual inspection of the plotted probabilities reveals that the yield curve performs impressingly well in signalling and forecasting business cycle peaks. As supposed, for all countries under consideration regime one is related to recession phases, though this relation is of variable strength. Among all recessions across the evaluated countries there are only two in the UK and one in Canada which were not identified by the term spread. The other cases show that the probability of staying in regime one is extremely high immediately before or at least during recessions. Moreover, for the USA, Germany, and the Netherlands all recession beginnings were indicated in advance or signalled coincidently.[8] In Japan, France and Italy each business cycle peak was preceded by a shift into the recession regime with the only exception of one peak in each country that was indicated with a lag. Panel (f) and (g) reveal that the performance of the yield curve in the UK and Italy was on the whole worse in the eighties. Here, the Markov-switching models calculate regime probabilities that are obviously not related to prevailing business cycle phases. Hence, the doubts mentioned in section III about the predictive quality of the term spreads in the UK and Italy turn out to be reasonable.

Notwithstanding these disappointing experiences, one major result of our analysis is that regime one is exclusively associated with recessions throughout nearly the whole multicountry sample. In addition, the lead time of the yield curve indicator seems to be reasonably long on average, even though the results presented in Figure 2 suggest that it varies considerably across the sample period as well as across countries.

As far as the recession endings are concerned, the predictive power of the yield curve is significantly lower. On that score, turning point signals generally came late and troughs were indicated often after the recession already passed by. Nevertheless, almost each business cycle trough is associated with a shift into regime two which reflects an upward sloping yield curve. To summarise these results, the term spread indicator matches the business cycle well. Moreover, the regime-switching model turns out to be an appropriate filter that efficiently transforms changes in the term spread variable into accurate and unambiguous turning point predictions. Compared to the recession probabilities documented in Bernard and Gerlach (1996, pp. 16-19) and Estrella and Mishkin (1997, p. 1389) the ones reported in Figure 2 are clearer to interprete and much less volatile. This is surprising because probit models use actual recession dates in the estimation process which are important additional information.

In order to complement the graphical analysis and to present empirical results more comprehensively, Table 2 contains the dates of predicted regime changes that signalled the beginnings and the endings of historical recessions together with actual turning point dates.

TABLE 2

Business cycle turning point predictions

Peak	Signal	Lead Time	Trough	Signal	Lead Time
			USA		
69:10	--	--	70:11	70:10	1
73:11	73:04	7	75:03	75:03	0
80:03	78:10	17	80:07	80:08	- 1
81:07	80:11	8	82:12	82:08	4
89:04	89:01	3	91:03	91:02	1
			Canada		
69:07	--	--	70:10	NO	--
74:03	NO	--	75:05	NO	--
79:08	78:11	9	80:06	80:07	- 1
81:04	81:01	3	82:10	82:10	0
86:01	86:03	- 2	86:08	86:06	2
89:04	88:11	5	91:02	91:06	- 4
			Japan		
74:01	73:10	3	75:03	75:11	- 8
81:11	80:04	19	82:10	NO	--
85:05	85:10	- 5	86:08	86:06	2
91:05	90:12	5	93:09	92:05	16
			Germany		
73:08	73:04	4	75:07	74:04	15
79:12	79:12	0	82:11	83:01	- 2
91:06	89:08	22	93:12	94:07	- 7
			France		
74:08	73:02	18	75:05	75:03	2
77:01	76:09	4	77:12	77:05	7
79:08	79:09	- 1	80:11	80:07	4
81:12	81:07	5	82:08	82:07	1
92:04	89:03	37	93:12	94:04	- 4

TABLE 2
(continued)

		United Kingdom			
71:01	NO	--	72:02	NO	--
74:06	74:01	5	75:08	NO	--
79:06	79:08	- 2	81:05	81:03	2
84:01	NO	--	84:08	NO	--
90:06	88:08	22	92:05	92:11	- 6
		Italy			
74:06	73:10	8	75:04	75:06	- 2
77:01	76:04	9	77:06	77:07	- 1
80:03	80:02	1	83:06	81:05	25
92:04	92:08	- 4	94:01	93:02	11
		Netherlands			
74:08	73:08	12	75:08	75:04	4
76:09	76:09	0	78:05	77:04	13
80:03	78:11	16	82:11	82:09	2
87:01	85:05	20	88:04	88:02	2
91:02	88:12	26	93:09	94:07	- 10

Notes: Actual turning points are determined by Artis et al. (1995). At the dates which are documented in the columns labelled "Signal" regime changes of the term spread series are predicted, indicating business cycle turning points. A change between regimes generally occurs at dates where the estimated ex ante regime probability to stay in a certain regime increases from less than 0.5 to more than 0.5 or decreases from more than 0.5 to less than 0.5. Reported 'Lead times' with a negative sign indicate a lagged identification of turning points. 'NO' means that turning points were not identified at all.

The results in Table 2 emphasize that business cycle troughs were generally harder to predict than peaks. Obviously, the best performing predictors of recession onsets are the term spreads in the USA, Germany, and the Netherlands, followed by the ones constructed for France, Japan and Italy. Although the forecasting power of the spread compares favourably for Canada too, it missed completely to signal the 1974-75 recession. In the UK only two recessions were predicted in advance, one was indicated with a lag and two were not signalled at all. In accordance with Bernard and Gerlach (1996), who show that the term structure has a high informational content up to eight quarters ahead, in our study the longest lead time is 37 months, estimated for the latest recession in France. In three further countries, the maximum lead time was above 20 months.

Regarding business cycle troughs, the predictive performance varies across countries too. As the last column of Table 2 and previous research for the USA (Lahiri and Wang (1996)) shows, interests rate spreads are useful to forecast recession endings only a few months ahead. Nevertheless, in the case of the USA, Germany, France and the Netherlands all troughs except one for each country were successfully predicted. For Canada, Japan, the UK, and Italy one half of the signals came too late, thereby indicating troughs with a lag or they were missed completely.

The non-formal analysis of regime probabilities is completed with Table 3 containing the number of missed as well as the number of misleading turning point signals. For each country except of Japan there are at most three regime changes which falsely indicate turning points. This finding additionally strengthens the case for using the term spread as a reliable predictor of recessions in industrialized countries.

TABLE 3

Number of missed and false signals

	USA	*Canada*	*Japan*	*Germany*	*France*	*UK*	*Italy*	*NL*
Missed Signals	0	1	1	0	0	2	0	0
Falsely indicated peaks	1	1	4	1	2	1	1	1
Falsely indicated troughs	1	1	1	0	1	1	0	1

Notes: Missed signals, as documented in the first row, are recessions that were not identified by the term spread indicator. False signals, as documented in the second and the third row, are inferred regime changes of the term spread series that were not followed by an actual business cycle turning point.

5.2 Probit estimations

In order to assess the value of the regime switching filter, one has to compare the empirical findings documented in section 5.1 statistically with the results obtained by conventional probit estimations using the unfiltered spread. We start this exercise by estimating probit regressions of the following type which has been proposed by Ang and Bekaert (1998):

$$\Pr(rec = 1) = F(a + b\,(p_{t-j+1})). \tag{4}$$

The dependent variable in model (4) is the recession dummy rec which takes either the value one (recession) or zero (expansion). F(.) is the normal cumulative distribution function and p_{t-j+1} is the (lagged) ex ante probability of being in the inverted yield curve regime as shown in the panels of Figure 2.[9] Given a prespecified lead time j, the pseudo R^2 measure,

$$1 - \left(\frac{\log L_u}{\log L_c} \right)^{-(2/n)\,\log L_c},$$

together with calculated t-statistics summarizes the forecasting performance of the filtered spread throughout the sample.[10] Empirical findings are documented in Table 4.

Table 4

Pseudo R2 and t-statistics for probit models using ex-ante regime probabilities

$$\Pr(rec = 1) = F(a + b(p_{t-j+1}))$$

j = Months Ahead

	1	3	6	9	12	15	18	21	24
US									
Pseudo R^2	0.421	0.523	0.527	0.433	0.349	0.270	0.200	0.141	0.129
t-statistic	10.24a	10.04a	9.65a	9.43a	8.28a	6.89a	5.05a	2.36b	- 0.03
Canada									
Pseudo R^2	0.283	0.342	0.307	0.273	0.225	0.164	0.125	0.112	0.115
t-statistic	9.10a	9.60a	8.84a	7.89a	6.53a	4.68a	2.76a	1.13	0.35
Japan									
Pseudo R^2	0.080	0.096	0.090	0.068a	0.070	0.081	0.098	0.078	0.051
t-statistic	4.95a	5.43a	5.09a	4.17a	4.05a	4.23a	4.60a	3.66a	1.84c
Germany									
Pseudo R^2	0.362	0.370	0.353	0.292	0.241	0.198	0.147	0.101	0.070
t-statistic	10.18a	10.19a	9.90a	8.99a	8.06a	7.12a	5.77a	4.14a	2.29b
France									
Pseudo R^2	0.112	0.172	0.221	0.157	0.073	0.029	0.034	0.042	0.054
t-statistic	5.88a	7.03a	7.72a	6.53a	4.15a	1.47	1.46	1.71c	2.22b
UK									
Pseudo R^2	0.048	0.050	0.048	0.040	0.034	0.046	0.068	0.094	0.127
t-statistic	3.93a	3.87a	3.51a	2.79a	1.99b	1.32	0.66	- 0.35	- 1.17
Italy									
Pseudo R^2	0.002	0.038	0.010	0.016	0.028	0.062	0.102	0.105	0.077
t-statistic	0.78	0.57	0.21	0.02	- 1.38	- 3.17a	- 4.42a	- 4.29a	- 2.85a
Netherlands									
Pseudo R^2	0.100	0.151	0.201	0.221	0.255	0.215	0.151	0.102	0.075
t-statistic	5.56a	6.62a	7.39a	7.57a	7.93a	7.11a	5.52a	3.60a	1.24

Notes: The sample contains monthly observations from January 1970 (Italy: January 1971) to December 1996. The recession dummy rec equals one if the economy is in recession and zero otherwise. Recessions are determined by Artis, Kontolemis and Osborn (1995). The probability p_t is calculated by Markov-switching estimation (Table 1) and is shown in Figure 2. a (b, c) denotes significance at the 1% (5, 10%) level.

For all countries, except Italy, the regime probability is confirmed to predict recessions with horizons ranging from one to four quarters or even more. Apparently in contrast to the results documented above, t-statistics indicate predictive ability of the spread for the UK. This result should teach us to proceed with caution when interpreting empirical findings that are aggregated over the sample. Indeed, Figure 2 shows that only two out of five UK recessions were actually indicated in advance and most of the stated forecasting power can be explained by the relatively early signal of the latest recession.

As the second step, we estimate standard probit models with the unfiltered term spread y_t as the explaining variable:

$$\Pr(\mathrm{rec} = 1) = \Phi\left(\alpha + \beta\left(y_{t-j}\right)\right). \tag{5}$$

Pseudo R^2 and t-statistics of these estimations are shown in Table 5. They correspond well with previous findings that are already documented in the literature (Bernard and Gerlach (1996), Estrella and Mishkin (1997), Funke (1997)).

Unfortunately, a comparison of the 72 pseudo R^2 documented in Tables 4 and 5 does not lead to a definite answer regarding the usefulness of markov-switching. In 32 cases, the estimations of the probit models give evidence in favour of increased predictive ability by using the markov-switching filter. In 40 cases, however, the pseudo R^2 and thus the predictive content of the yield curve is higher when using the spread alone. Because the competition ends in a draw, one can conclude that if the probit likelihood is adopted as a metric, on average there is no way to improve on the probit predictions of the recession dates, conditioning only on the spread. Thus, the usefulness of regime-switching models for predicting recessions reduces to the question, if one prefers sharp signals, which may cause larger errors.

TABLE 5

Pseudo R2 and t-statistics for probit models using the term spread

$$\Pr(rec = 1) = F(\alpha + \beta(y_{t-j}))$$

j = Months Ahead

	1	3	6	9	12	15	18	21	24
US									
Pseudo R^2	0.235	0.364	0.468	0.439	0.337	0.309	0.241	0.175	0.147
t-statistic	- 8.02a	- 9,20a	- 9.66a	-9.24a	- 7.93a	- 7.35a	- 5.97a	- 3.89a	- 2.23b
Canada									
Pseudo R^2	0.341	0.416	0.454	0.336	0.283	0.204	0.148	0.115	0.119
t-statistic	- 9.15a	- 9.43a	- 9.24a	- 8.21a	- 7.28a	- 5.64a	- 3.72a	- 1.31	0.83
Japan									
Pseudo R^2	0.124	0.121	0.111	0.064	0.044	0.042	0.057	0.053	0.046
t-statistic	- 5.99a	- 5.96a	- 5.60a	- 3.96a	- 2.76a	- 2.29b	- 2.86a	- 2.28b	- 1.13
Germany									
Pseudo R^2	0.316	0.344	0.387	0.306	0.214	0.124	0.087	0.060	0.056
t-statistic	- 9.27a	- 9.51a	- 9.59a	- 8.57a	- 7.17a	- 5.19a	- 3.74a	- 1.95c	0.70
France									
Pseudo R^2	0.130	0.200	0.274	0.248	0.106	0.031	0.030	0.037	0.043
t-statistic	- 6.10a	- 7.25a	- 8.11a	- 7.68a	- 5.14a	- 1.52	0.70	0.99	1.10
UK									
Pseudo R^2	0.012	0.027	0.059	0.096	0.123	0.134	0.133	0.130	0.134
t-statistic	- 1.83c	- 2.58a	- 3.85a	- 4.85a	- 5.36a	- 4.97a	- 4.12a	- 2.83a	- 0.89
Italy									
Pseudo R^2	0.023	0.038	0.028	0.023	0.027	0.071	0.110	0.139	0.132
t-statistic	- 2.55b	- 3.13a	- 2.26b	1.33	0.94	3.38a	4.44a	5.00a	4.64a
Netherlands									
Pseudo R^2	0.038	0.078	0.107	0.141	0.168	0.146	0.102	0.070	0.075
t-statistic	- 3.36a	- 4.61a	- 5.23a	- 5.79a	- 6.13a	- 5.44a	- 3.82a	- 1.48	0.74

Notes: The sample contains monthly observations from January 1970 (Italy: January 1971) to December 1996. The recession dummy rec equals one if the economy is in recession and zero otherwise. Recessions are determined by Artis, Kontolemis and Osborn (1995). The term spread variable y_t is calculated as described in Table 1. a (b, c) denotes significance at the 1% (5, 10%) level.

6. Conclusions

This paper has studied the ability of the term spread variable to predict the likelihood of future recessions in eight OECD countries within a regime-switching framework. The main advantage of this approach is that lead times for forecasting discrete events like onsets and endings of recessions are determined endogenously. Thus, compared to the popular probit regression technique, the optimal forecasting horizon is free. Another important benefit of the applied strategy is that, again in contrast to previous probit estimations, ex post dated business cycle turning points have not been used in the estimation process. Three aspects of our results are of special interest.

First, the term spread is confirmed to be a reliable recession predictor. For each country analyzed the two estimated regimes are found to be associated with recessions or expansion phases respectively. Moreover, it turned out that business cycle troughs are generally less predictable than peaks. Second, the simple Markov-switching model we have applied seems to be quite successful in filtering term spread signals. The estimated recession probabilities are more accurate and less volatile than those probabilities which are calculated in previous studies using conventional probit estimations. Third, results of probit estimations using the markov-regime probability as the explaining variable show that the markov-switching filter does not significantly improve the forecasting ability of the spread. This implies that there is a tradeoff between the sharp probabilities calculated by the Markov-model and the accuracy of fitting independent recession dates. Probabilities close to zero or one improve the fit, when they match the recession dates. But when they do not, the errors tend to be much larger. Hence, regime-switching models should be applied by forecasters who prefer unambiguous signals, which, of course, could imply larger errors, too.

Appendix: the data description

All interest rates are taken from the IMF Financial Statistics Database. Since the availability of the data from 1970 onwards was the most important criterion for selecting the series, different short-term rates for the eight analyzed countries are used.

Short-term interest rates:

USA:	Federal Funds Rate	(line 60b)
Canada:	Treasury Bill Rate	(line 60c)
Japan:	Call Money Rate	(line 60b)
Germany:	Call Money Rate	(line 60b)
France:	Treasury Bill Rate	(line 60cs)
UK:	Treasury Bill Rate	(line 60c)
Italy:	Money Market Rate	(line 60b)
Netherlands:	Call Money Rate	(line 60b)

Long-term interest rates (line 61):

USA:	10-Year Government Bond Yield
Canada:	Goverment Bond Yield > 10 Years
Japan:	Goverment Bond Yield
Germany:	Goverment Bond Yield
France:	Goverment Bond Yield
UK:	Goverment Bond Yield: Long-Term
Italy:	Goverment Bond Yield: Long-Term
Netherlands:	Goverment Bond Yield

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Notes

[1] See, among many others, Harvey (1991), Plosser and Rouwenhorst (1994), Bonser-Neal and Morley (1997), Davis and Fagan (1997) and Kozicki (1997).

[2] Lahiri and Wang (1994) use the more popular filter probability $Pr(S_t = 1| \Phi_t)$ to infer the *current* regime. For determining if and when regime switches occurred in the sample, rather than forecasting them, one has to look at the smoothed probability $Pr(S_t = 1| \Phi_T)$ which is calculated ex post using the entire information of the whole sample and is typically used in business cycle studies to determine turning points (Hamilton (1989), Krolzig (1997)).

[3] The boundary of $Pr(S_t = 1) > 0.5$ was suggested by Hamilton (1989, p. 374) as a decision rule. In contrast, Lahiri and Wang (1994) imposed a much higher 'critical value' of 0.9.

[4] See Filardo (1999, pp. 37-39) for a discussion.

[5] We define 'false turning point signals' as changes of an indicator series into a regime which is generally associated with recessions but without an actual recession following, or as changes into a regime associated with expansions which are not followed by an actual recession ending.

[6] Note that the series are not exactly comparable across all countries. For example, Italy did not have a long-term government bond until relatively recently. Thus, the Italian interest rate refers to the yield on a floating rate long bond, which has a duration substantially shorter than the corresponding series for the US and Germany.

[7] It is necessary to define recessions for different countries by the same criteria. For the latest recession in Japan, Germany, France and the Netherlands respectively Artis et al. (1995) only determined the starting dates. As the corresponding ending dates we thus use the ones supplied by Bernard and Gerlach (1996, p. 23). For Italy, which is not considered by Bernard and Gerlach (1996), the same problem arises. Therefore, we follow exceptionally the Center of International Business Cycle Research (CIBCR) in defining the latest recession in Italy (see Zarnowitz (1995, pp. 263-264)).

[8] The U.S. results documented in this study correspond well with the empirical findings of Lahiri and Wang (1996) who use a sample period from January 1955 to March 1993.

[9] Note that p_t is already the forecast of the regime prevailing at t.

[10] L_u denotes the likelihood of the estimated model, L_c the likelihood of a model incorporating solely a constant regressor, and n the number of observations.