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Prediction of Business Cycle Turning Points in Germany

Prognose konjunktureller Wendepunkte in Deutschland

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JEL E32, C22, C25
Business cycle, leading indicators, probit model, Markov switching models, out-of-sample evaluation.
Konjunkturzyklus, Frühindikatoren, Probit-Modell, Markov-Switching-Modell.

Summary

Using a binary reference series based on the dating procedure of Artis, Kontolemis and Osborn (1997) different procedures for predicting turning points of the German business cycles were tested. Specifically, a probit model as proposed by Estrella and Mishkin (1997) as well as Markov-switching models were taken into consideration. The overall results indicate that the interest rate spread, the real effective exchange rate as well as some monetary indicators and some survey indicators can help to predict turning points of the German business cycle. The models were estimated for the in-sample period 1978 to 1997 and the reliability of the results was tested out of that sample (1998 to 2002).

Zusammenfassung

Unter Verwendung einer binären Referenzzeitreihe, deren Konstruktion auf dem Ansatz von Artis, Kontolemis und Osborn (1997) beruht, wurden verschiedene Verfahren zur Prognose konjunktureller Wendepunkte getestet. Im Besonderen wurde ein Probit-Modell, wie es von Estrella und Mishkin (1997) vorgeschlagen wurde, und Markov-Switching-Modelle verwendet. Die Resultate zeigen, dass die Zinsdifferenz, der reale effektive Wechselkurs, einige monetäre Indikatoren sowie einige Umfrageindikatoren bei der Prognose konjunktureller Wendepunkte helfen können. Die Modelle wurden für den Zeitraum von 1978 bis 1997 geschätzt und ihre Verläßlichkeit außerhalb des Stichprobenumfangs (1998 bis 2002) getestet.

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1. Motivation

Leading indicators and their properties are of great practical relevance for business cycle research and forecast. In a companion paper[1] business cycles' leading indicators for Germany were assessed according to specific requirements.[2]

The companion paper did, however, not answer an important question: How well do leading indicators perform in forecasting turning points of the business cycle? This is of great practical interest since, in most cases, forecasters fail to forecast recessions. This paper is about assessing the behaviour of leading indicators at business cycle turning points and their ability to forecast the turning points.

Traditional approaches that are used to investigate the properties of leading indicators focus on their behaviour over the whole cycle.[3] To analyse the usefulness of indicators in forecasting turning points, however, binary or qualitative approaches have to be used.[4] During the last couple of years, probit models have therefore attracted attention.[5] Furthermore, Markov switching models seem to be natural candidates for this question. First, a binary time series for recession/boom periods had to be constructed (section 2). Because there is some degree of freedom in doing this, we decided to use the well-known and established procedure proposed by Artis/Kontolemis/Osborn (1997). Second, the properties of indicator variables to forecast a turning point had to be assessed. In this paper two completely different methods were tested: a probit model and a Markov switching model. In the *probit model* (section 3.1) indicator variables were regressed on the binary time series at a varying lag structure and a measure that is comparable to the well-known R2 was calculated for each lag. In this paper a version of McFadden's R2 as proposed by Estrella (1998) was used. The local maximum of the R^2 was interpreted as the lag with the highest probability of forecasting a turning point. For instance a local maximum at lag 8 should be interpreted as the (highest probable) "lead" of the indicator with respect to the business cycle turning point.

During the last couple of years *Markov switching models* became more and more popular.[6] By construction, these models seem to be perfectly suited for the analysis of our problem (section 3.2). The Markov switching model is a "regime dependent" approach, whereby the probability of the regimes is modelled as a so-called Markov chain (see the detailed explanation in section 3.2). The regimes are unobservable and hidden in the data but their probability can be extracted using specific estimation techniques.

We assume a two-regime Markov process (which can be interpreted as a business cycle framework with boom and recession periods) for most series under investigation and estimated univariate Markov switching models for each indicator. We asked if there is

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1 Cf. *Fritsche/Stephan* (2002).

2 According to these requirements a reliable leading indicator should possess the following properties: (1) movements in the indicator series should resemble those in the business cycle reference series; (2) the relationship between the reference series and the indicator should be statistically significant and stable over time; (3) the inclusion of the indicator in out-of-sample forecasting procedures should improve the predictive power (compared to a "naïve" autoregressive prognosis).

3 Cf. *Fritsche/Stephan* (2002)

4 We exploit a two regime business cycle approach (boom-recession-approach), cf. *Artis/Kontolemis/Osborn* (1997). There are, however, good reasons to think about a multiple-regime approach, cf. *Heilemann/Muench* (1999).

5 Cf. *Estrella/Mishkin* (1997), *Döpke* (1999), *Bernard/Gerlach* (1998).

6 Cf. *Hamilton* (1989), *Hamilton* (1994), *Krolzig* (1997), *Amstad* (2000).

some information about the probability of a change in the regime of the economy (from a recession to a boom phase and vice versa), which can be detected in the leading indicator series with a "lead" compared to the binary reference series. The time series of the recession probabilities derived from each indicator series were therefore also converted into a binary series and compared to the binary reference series at varying lags. The idea behind this approach is the following: If it is possible to detect the state of the regime in the leading indicator series "before" the business cycle passes a turning point (as measured by our binary reference series), this indicator seems to be a good leading indicator for predicting the turning points.

By using these different approaches we were able to compare the results to identify "reliable" indicators. This serves as a robustness check. To guarantee the comparability with the companion paper,[7] we have used the same data set here. It is worthwhile to note that this data set consists of revised data, not real-time data. Most of the indicators under investigation (survey indicators, monetary indicators, interest rates, exchange rates) are not subject to major revisions.

The quality of indicators can be assessed by the evaluation of out-of-sample forecasts. The in-sample estimations were performed for the period from 1978 to 1997. We performed tests using 6-months ahead out-of-sample forecasts for the period from 1998 to 2002 (section 4).

2. Determination of the Reference Series

Dating recessions is not invariant with regard to the method that is applied. The often-used detrending procedures have major theoretical and practical weaknesses.[8] And there are different views of the business cycle as such.[9] We decided to use a dating procedure developed by Artis/Kontolemis/Osborn (1997) to specify the recession and boom periods. This procedure has its drawbacks as well, but several advantages: The method was used for other studies for G-7 countries and the results are therefore easily comparable,[10] the results can easily be reproduced and the results come close to definitions of the cycle which are used by practitioners.[11] The idea behind the procedure of Artis/Kontolemis/Osborn

[7] For a discussion about the choice of indicators cf. the companion *Fritsche/Stephan* (2002). In general, non-stationary time series were transformed into stationary time series using annual growth rates. The respective test statistics were presented in the above-cited paper. There are however, two deviations from the companion paper. First, we included the nominal credit supply (in annual growth rates) in spite of the fact that the augmented Dickey-Fuller test indicates non-stationarity. Second, due to the introduction of the Euro and changes in the monetary statistics, we were not able to use money supply M1 and M3 extended anymore.

[8] From a methodological point of view, detrending procedures are based on strong assumptions about the data-generating process and the kind of association between trend and fluctuations; from a practical point of view the generated trends and business cycle components often miss some "stylised facts" such as the often-cited business cycle asymmetry. Cf. *Canova* (1998a,b), *Tichy* (1994).

[9] Cf. *Tichy* (1994), who distincts the (continental) Europaean approach (cyclical movements are deviations from a potential/trend) from the Anglosaxon approach (booms and recessions are periods where a variety of predefined time series move in the same direction).

[10] Cf. *Bernard/Gerlach* (1998).

[11] For instance the widely known rule of thumb that a recession is defined by two consecutive quarters of declining output.

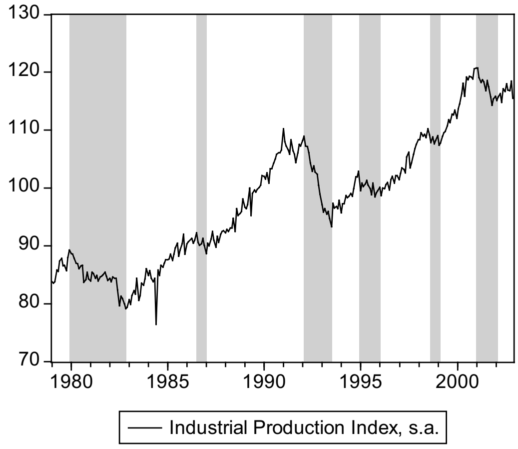

Figure 1: Recession Periods in Germany

(1997) goes back to the NBER approach of dating business cycles.[12] The reference series is Germany's industrial production as it was in our companion paper. This time series will be analysed in original values and in a seven-month moving average representation. First outliers are identified and eliminated. Possible turning points (local maxima or minima that are in a range 12 months forward or backward) have to show up in both series, the original one and the moving-average representation. To be qualified as a turning point, some further conditions regarding the strength of the decline in output with respect to the period preceding the turning point have to be met.[13] The result of this procedure applied to German industrial production is displayed in Figure 2 (shaded areas indicate recessions).

By visual inspection, the dating procedure of Artis/Kontolemis/Osborn (1997) seems to fit downswings in the reference series quite well and was therefore used as a base to construct the binary time series. For further analysis this binary time series serves as the reference series.

3. In-Sample Investigation

3.1. Probit Models

Following Estrella and Mishkin (1997), we used binary time series where the value one stands for recession and the value zero for non-recession periods. In our paper this binary series is based on the dating procedure proposed by Artis/Kontolemis/Osborn (1997). Estrella and Mishkin (1997) had been in the favourable situation that for the U.S. economy there is an official Business Cycle Dating Committee at NBER, which regularly publishes

[12] Cf. *Burns/Mitchell* (1947), *Stock/Watson* (1989).
[13] Cf. *Artis/Kontolemis/Osborn* (1997).

a schedule of booms and recession which can be used as a base for the construction of a respective binary time series.

We estimated a probit equation explaining the probability that a recession occurs ($R_t = 1$) by using lagged indicator time series [model I]:

$$\mathrm{Prob}(R_t = 1) = \Theta(\beta_0 + \beta_1 I_{t-k}) \tag{1}$$

In other words, we asked for the ability of the indicator to explain a recession period. Estrella (1998) proposed a modified McFadden's Pseudo-R^2 to test how good and at which lag an indicator series can predict recessions.[14] This measure computes a Log-Likelihood ratio of the model under investigation compared to a model, which does not take the information of the more general model into account. In our case we compare the Log-Likelihood of model I, the model including the indicator, to the Log-Likelihood of a model where the binary series is only regressed on a constant (= unconstrained model):

$$\text{Pseudo-}R^2 = 1 - \left[\frac{L_u}{L_c}\right]^{-\left(\frac{2}{n}\right)L_c} \tag{2}$$

where L_u . . . unconstrained Log-Likelihood (of the model)
L_c . . . constrained Log-Likelihood ($\beta_1 = 0$)
n . . . number of observations

The higher the Log-Likelihood of model I in comparison to the unconstrained model becomes, the lower is the Log-Likelihood ratio and the closer is the (Pseudo)-R^2 to the value of 1.[15] The local maximum of the modified McFadden's R^2 – the point where the inclusion of the indicator mostly improves the forecasting quality – is interpreted as the "lead" of the indicator.[16]

3.2. Markov Switching Models

The crucial point when modelling business cycles using Markov switching models is the decomposition of any observable economic time series into two parts: an unobservable discrete state and the remaining short-run autoregressive dynamics. The unobserved state variable is assumed to represent the fluctuations of the business cycle, which are unobservable in practice, too. The broadly accepted view of the business cycle as a series of contractions and expansions implies the discrete nature of the state variable.

A simple way to approximate the business cycle dynamics is given by a Markov chain with two possible states. The parameters of such a simple Markov chain are probabilities,

[14] The original McFaddens R^2 is defined as $1 - L_u/L_c$. The version proposed in *Estrella* (1998) furthermore adjusts for the number of regressors.

[15] The measure is called Pseudo-R^2 because it is a different concept compared with the well-known R^2 and in fact it only can come close to 1 but not equal to zero.

[16] The main shortcoming of this approach – as mentioned by *Dueker* (1997) and *Döpke* (1999) – is the fact that the traditional probit estimation can be mis-specified if there is information content in the binary time series which is not taken into consideration. Therefore we also estimated probit models were we included lagged recession probabilities. The results did however qualitatively not differ very much from the described probit models.

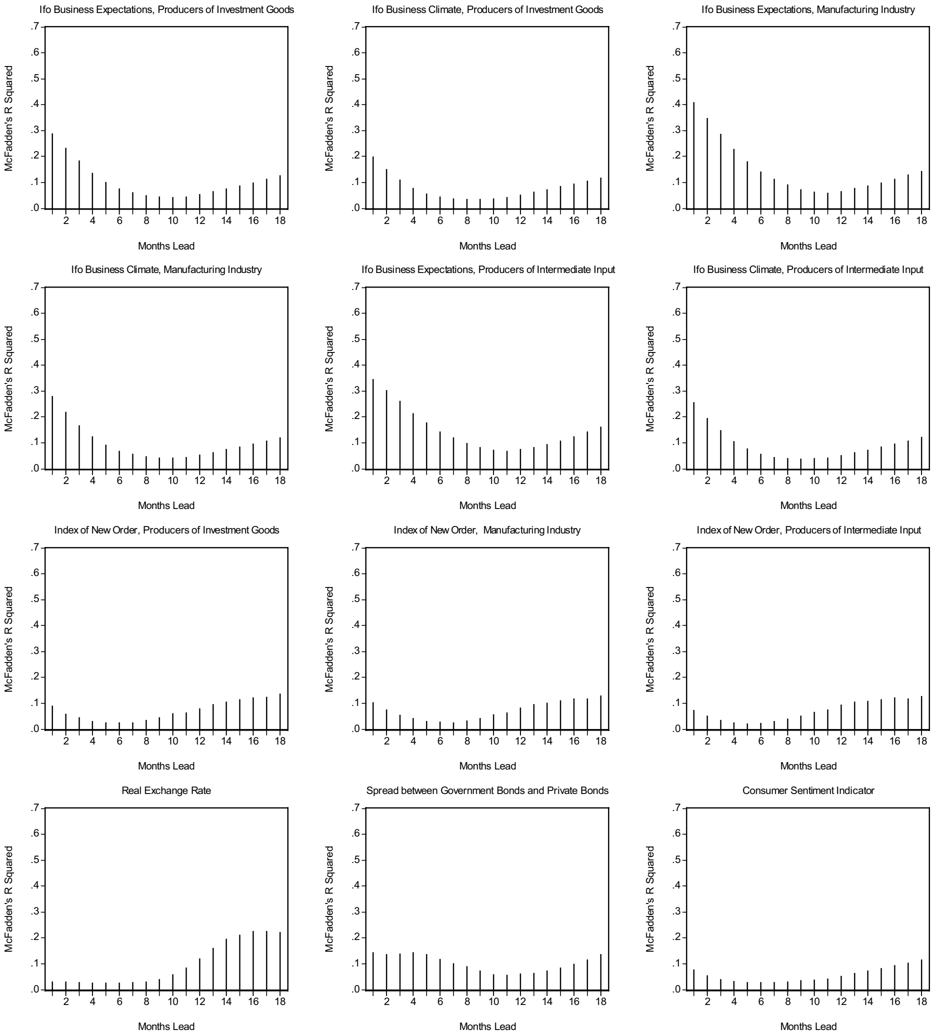

Figure 2: Mc Fadden's R squared at Different Lags in Probit Models

which govern the transitional dynamics between two regimes. Figure 3 is an attempt to describe the model in an intuitive way:

The conditional probability Pr{B|B}, for example, is the probability to stay in a boom conditional on the fact, that the economy is actually booming. Obviously, all probabilities, conditional on the same regimes, are summing up to one. All probabilities are conditional only on the last state; therefore such a Markov chain is called a first order Markov chain. If the values of the probabilities Pr{B|B} and Pr{R|R} are close to one this in turn leads to a high persistence of the regimes.

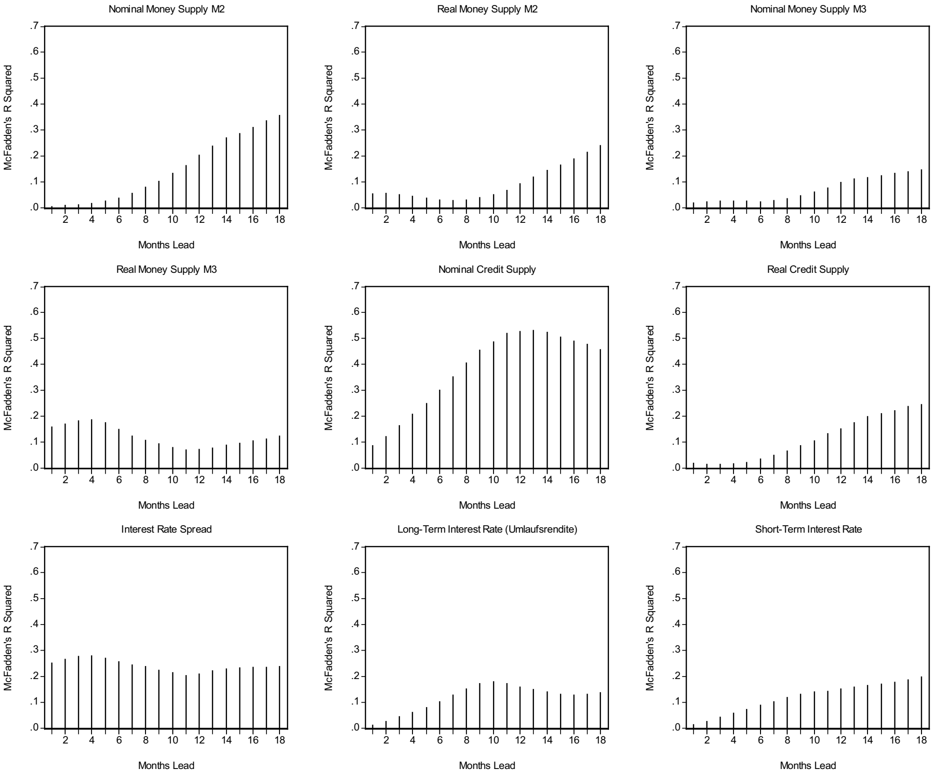

Figure 2: (Continued)

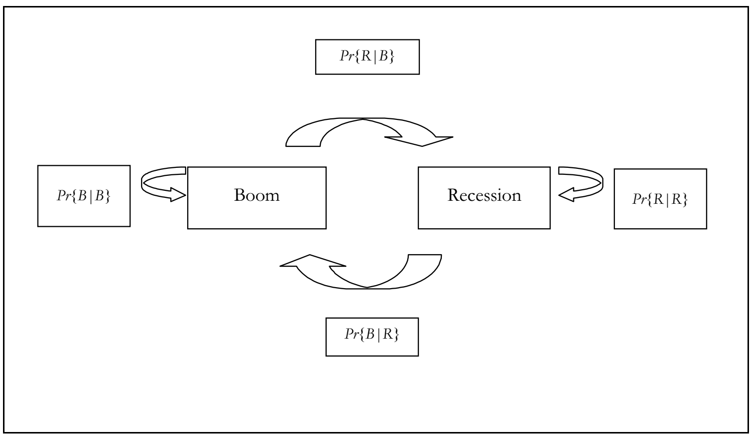

Figure 3.

The information content of Figure 3 can easily be represented in matrix form. The matrix of the transition probabilities is called the transition matrix P

$$P = \begin{bmatrix} \Pr\{B|B\} & \Pr\{R|B\} \\ \Pr\{B|R\} & \Pr\{R|R\} \end{bmatrix}, \tag{3}$$

where $\Pr\{B|B\}+\Pr\{R|B\} = \Pr\{B|R\}+\Pr\{R|R\} = 1$. The Markov chain described above is a quite abstract stochastic process. It needs not to have some real valued realizations; only a set of possible regimes has to be defined. However, the Markov switching technique allows the real valued quantification of economic variables. Therefore, the mapping of the space of regimes into a parameter space of the data-generating process is necessary. In other words, some parameters of the data-generating process are assumed to be a continuous function of the discrete Markov chain. For the purpose of business cycle modeling it is straightforward to allow the intercept of the estimated process to be dependent from some discrete Markov chain with two possible states. The following part of the subsection gives some analytical aspects of the methodology described above.

The Markov switching model is a special case of the generalized state-space model.[17] Let S_t be a discrete unobserved state variable following an ergodic first-order Markov chain with N states $s_t \in \{1, 2, \ldots, N\}$ and a transition matrix

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix}, \tag{4}$$

where $p_{ij} = \Pr\{s_{t+1} = j|s_t = i\}$, $\sum_{j=1}^{N} p_{ij} = 1 \;\; \forall i, j \in \{1, 2, \ldots, N\}$.

Let an observable leading indicator series x_t follow an autoregressive process of order p

$$x_t = \nu(s_t) + \alpha_1 x_{t-1} + \cdots + \alpha_{t-p} x_{t-p} + u_t \tag{5}$$

where $u_t \sim NID(0, \sigma)$ and the intercept $\nu(s_t)$ are functions of the unobserved state variable S_t. These specifications are denoted by MSI(N)-AR(p) or Markov switching intercept. The states of the Markov chain S_t are not directly observable, therefore the statistical inference about any state j, $j \in \{1, 2, \ldots, N\}$ is necessary. The subject of interest is the estimated probability $\Pr\{s_t = j|X_t; \Theta\}$ for the state j in t, conditional an all observations of x_t obtained through date t and the vector of all known parameters Θ. Under assumption of known parameters the rule of Bayes leads to the following non-linear recursive algorithm:[18]

$$\Pr\{s_t = j|X_t; \Theta\} = \frac{f(x_t|s_t = j, X_{t-1}; \Theta)\Pr\{s_t = j|X_{t-1}; \Theta\}}{\sum_i f(x_t|s_t = i, X_{t-1}; \Theta)\Pr\{s_t = i|X_{t-1}; \Theta\}} \tag{6}$$

[17] Cf. *Krolzig* (1997).
[18] Cf. *Hamilton* (1994).

or in vector form

$$\hat{\xi}_{t|t} = \frac{\left(\hat{\xi}_{t|t-1} \otimes \eta_t\right)}{1'\left(\hat{\xi}_{t|t-1} \otimes \eta_t\right)} \tag{7}$$

where $\hat{\xi}_{t|t}$ and η_t are the vectors of $\Pr\{s_t = j|X_t; \Theta\}$ and $f(x_t|s_t = j, X_t; \Theta)$, $j \in \{1, 2, \ldots, N\}$, $\hat{\xi}_{t|t-1} = P\hat{\xi}_{t-1|t-1}$ and $\otimes$ denotes the element wise multiplication of vectors. The likelihood function $L(\Theta)$ for the observed indicator x_t evaluated at the value of Θ that was used to perform the iterations can be calculated as a by-product of the recursive algorithm:

$$L(\Theta) = \sum_{t=1}^{T} \log f(x_t|X_{t-1}; \Theta), \tag{8}$$

where $f(x_t|X_{t-1}; \Theta) = \sum_i f(x_t|s_t = i, X_{t-1}; \Theta)\Pr\{s_t = i|X_{t-1}; \Theta\}$. To obtain the estimates $\hat{\Theta}$, the Expectation-Maximization (EM) algorithm can be used.[19] The EM algorithm is an iterative ML estimation technique designed for the general class of models, where the observed time series depends on some unobservable stochastic variables.

For the purpose of business cycle research, contractions and expansions can be modelled as realisations of the discrete Markov chain S_t with 2 states ($N = 2$). To get the inference about the states of the Markov chain, however, a Markov switching process has to be estimated.[20] The best-fitted model was selected.[21] For most of the indicator series MSI(2)-AR(1)/-AR(2) yield reasonable results. It is however worth mentioning that some monetary indicators (M2 real and nominal, M3 nominal) seem to be better modelled using a Markov switching model with 3 states. In the case of M2 real and nominal, we decided to sum up the probability of the two lower regimes, in the case of M3 nominal one regime seems to be connected with recessions whereas there are two different regimes for the boom periods.[22] The probablities connected with recessions (shaded areas) were plotted in Figure 4.

The obtained time series of the estimated recession probabilities $\Pr\{s_t = 1|X_t; \hat{\Theta}\}$ can be used to make conclusions about the current state of the business cycle. The time series of the recession probabilities are converted into binary series of 0 and 1 denoted by R_t^I according to the 50%-rule as follows:

$$R_t^I = \begin{cases} 0 \text{ if } \Pr\{s_t = 1|X_t; \hat{\Theta}\} > 0.5 \\ 1 \text{ if } \Pr\{s_t = 1|X_t; \hat{\Theta}\} < 0.5 \end{cases} . \tag{9}$$

[19] Cf. *Hamilton* (1989), *Krolzig* (1997).

[20] A wide class of Markov switching models can be estimated using MSVAR for Ox 2.10 written by Hans-Martin Krolzig.

[21] According to standard information criteria.

[22] The results and specifications are available from the authors on request.

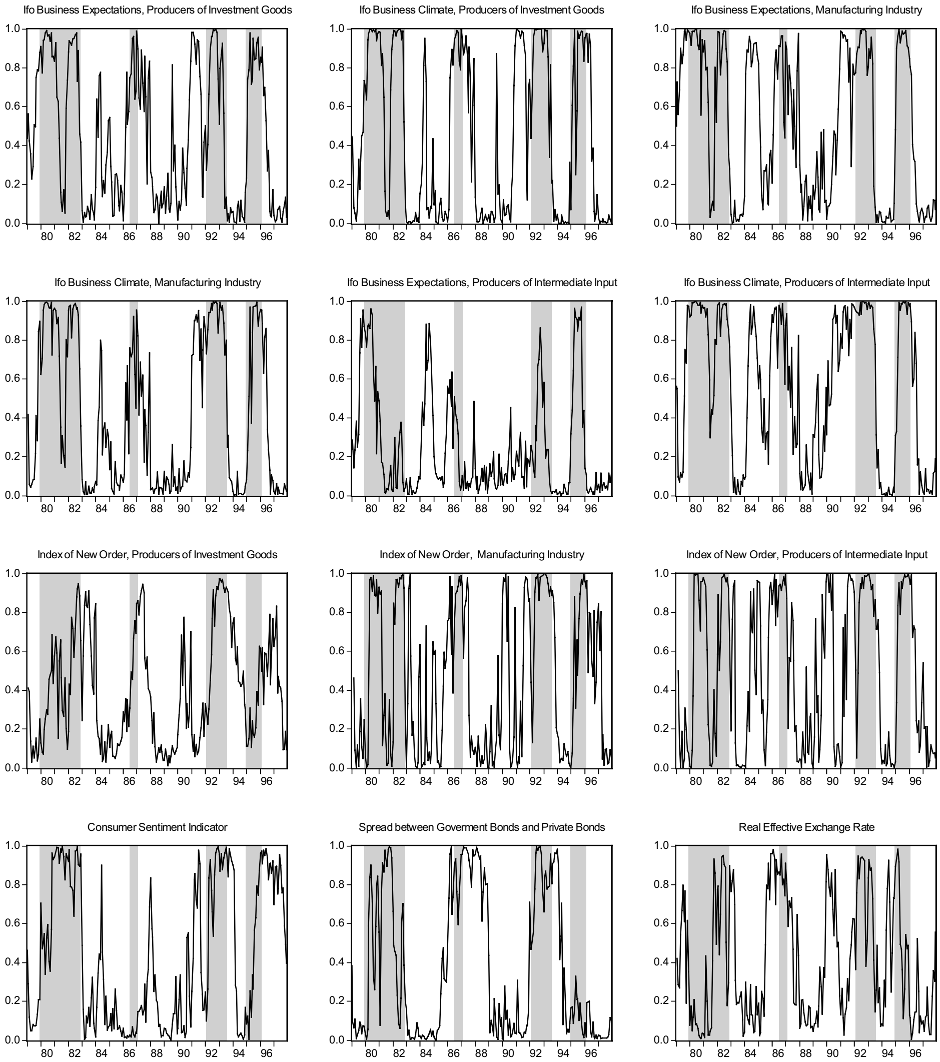

Figure 4: Filtered Probabilities

Than R_t^I series are compared with the reference binary series R_t. The share of correctly classified months can be calculated as a function of lead k from

$$\text{Share}(k) = \frac{1}{n} \sum_{t=k}^{n} \left| R_{t-k}^I + R_t - 1 \right| \tag{10}$$

where n is the number of observations in the sample. If the local maximum of the share lies in the lead area ($k > 0$), then the indicator series x_t is considered as a leading indicator.

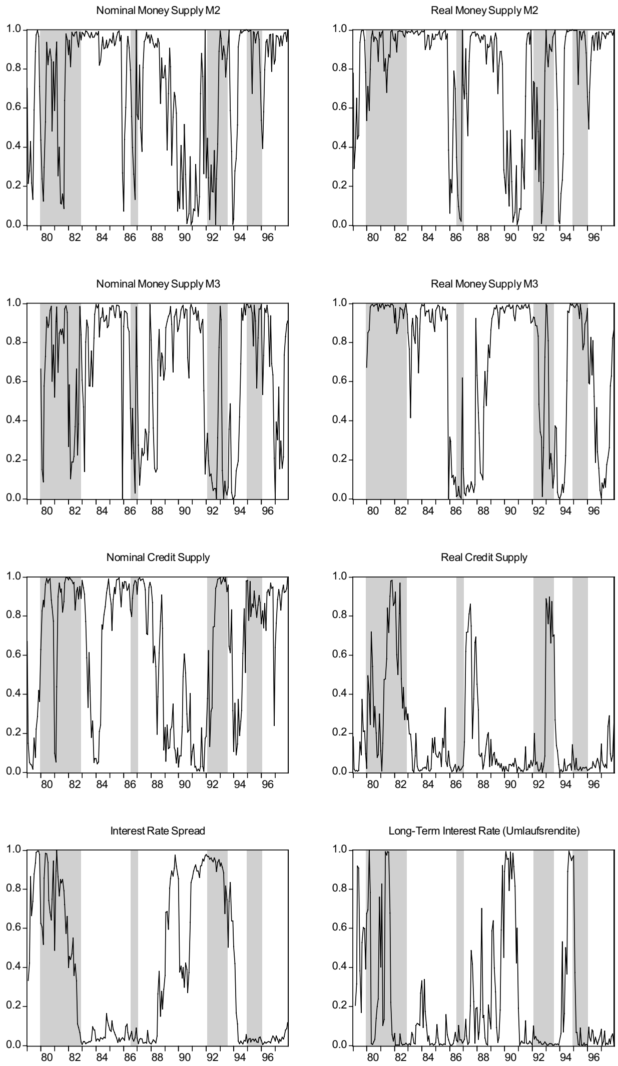

Figure 4: (Continued)

The function "Share(k)" is, of course, a quite descriptive measure of the indicator's predicting power, but at least it should be possible to distinguish the series in two subgroups: leading indicators and time series which have no indicator properties. Moreover, the graphs of "Share(k)" can be compared with the time series of the estimated recession probabilities to prove the plausibility of results.

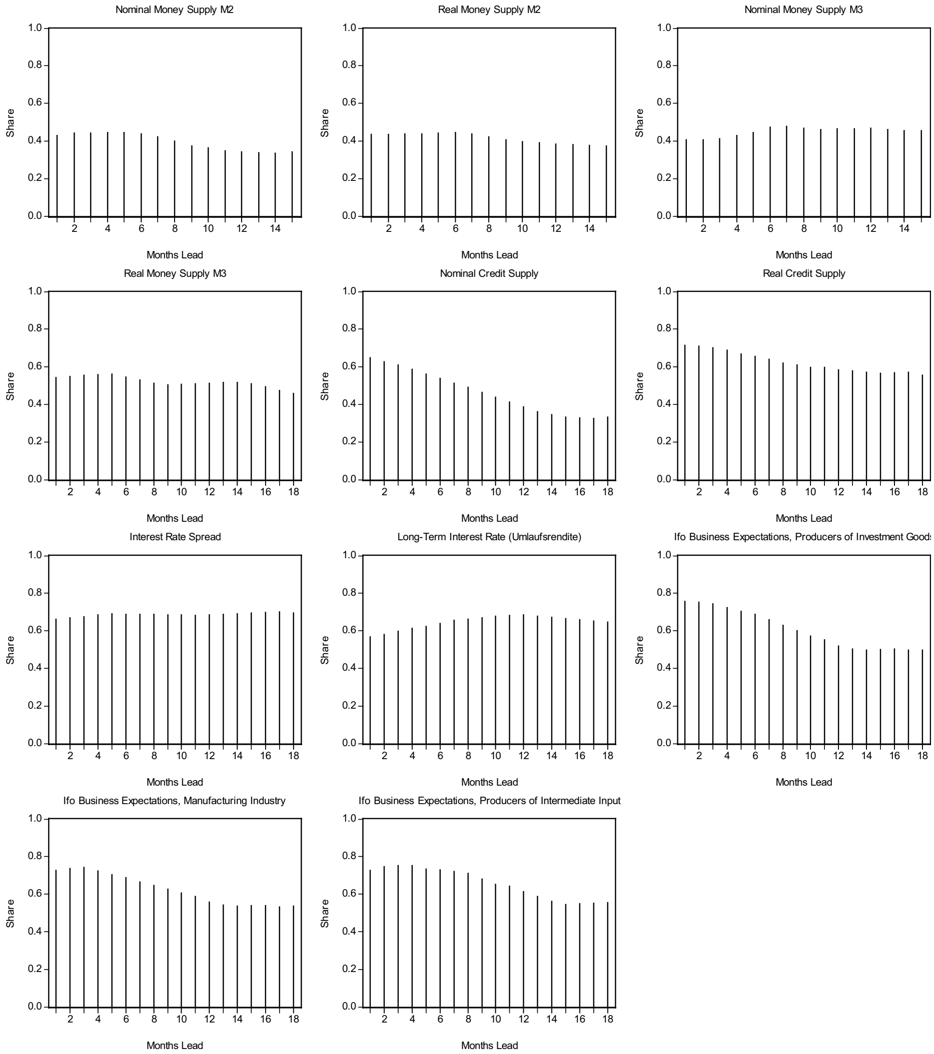

Figure 5: Share(k)

4. Out-of-Sample Results

4.1. Probit Models

The in-sample results of the probit models suggest, that there are only a few indicators, which have a significant lead with regard to the reference series. To calculate out-of-sample forecasts in a way which is comprehensible and fair with respect to all indicators, we used the following strategy: First we specified probit models in-sample according to a general-to-specific specification strategy – starting with 12 lags and allowing for a con-

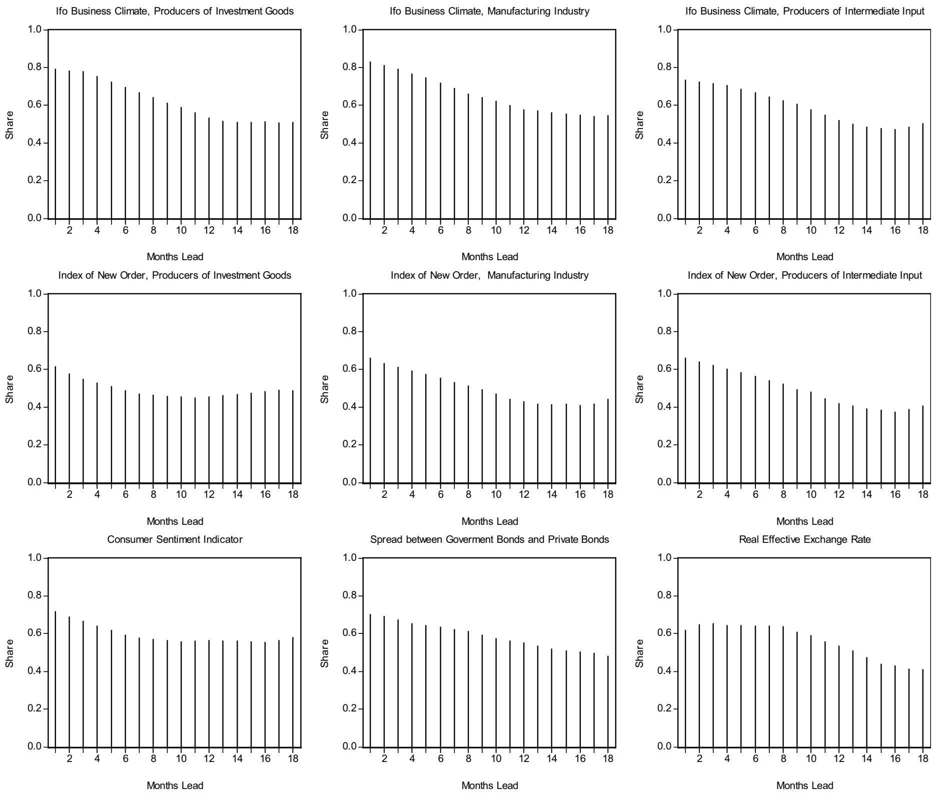

Figure 5: (Continued)

temporanous relationships between the respective indicator and the reference series. In some cases a high-order lag of the indicator was found to be significant, in other cases not. Second, we added ARMA processes specified in-sample for each indicator. We put both equations – the probit equation and the ARMA equation – together as a model and solved out of sample with an horizon of 6 months.[23] This procedure was repeated for each intervall from 1998:01/1998:06 to 2002:06/2002:12 whereby the coefficients of the model were those of the in-sample estimations. We decided to use a forecast horizon of 6 month because this seems to be a relevant horizon for evaluation from a practitioner's perspective. Furthermore, we decided to use the unconditional in-sample probability for a recession as a treshold. The forecasted probabilities together with the treshold and the realized recessions (shaded areas) are shown in Figure 6.

For the evaluation, we transformed the probability series into a binary series using the treshold.

[23] The model specifications are available from the authors on request.

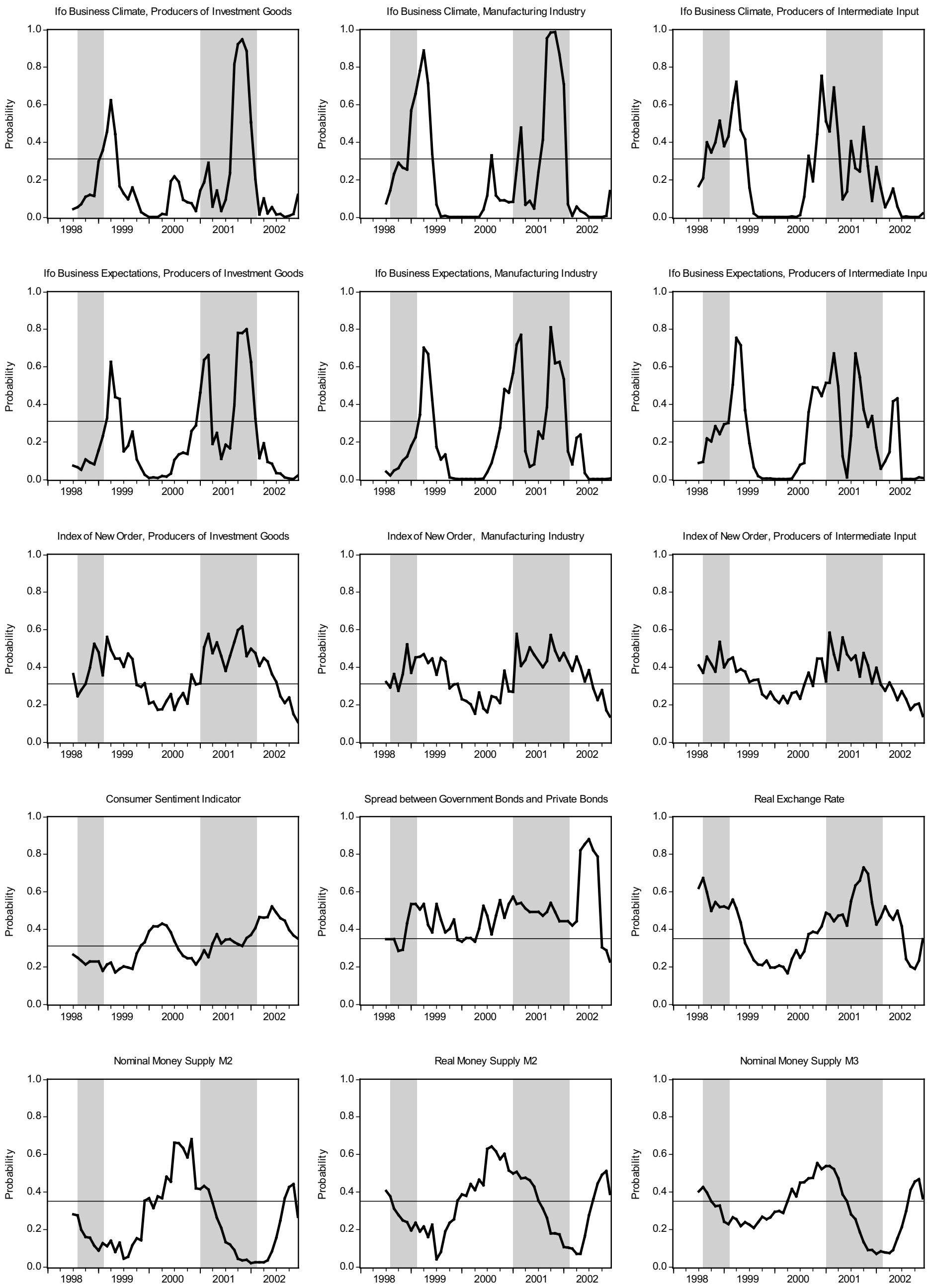

Figure 6: Out-of-Sample Forecasts: Probit Models

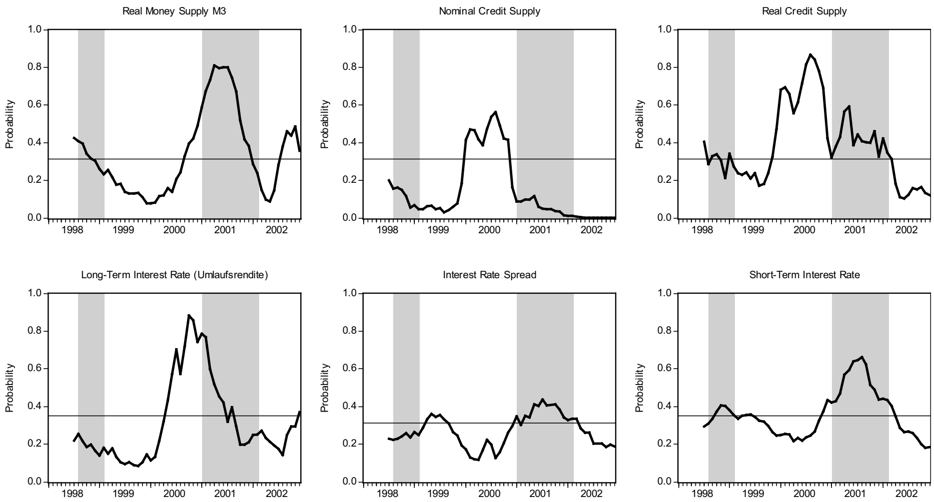

Figure 6: (Continued)

4.2. Markov Switching Models

To calculate out-of-sample forecasts of the Markov switching models we use the Markov property of the underlying state space model. In accordance with the Markov property the unobservable Markov chain is independent from the past and present values of the observable signal process. Within this state space framework we do not have to produce any forecasts of the indicator series and forecast therefore only the unobservable state. In our case the forecasts are equivalent with the forecasted probabilities of the estimated Markov chain, which can be calculated as follows:

$$\hat{\xi}_{t+h|t} = P^h \hat{\xi}_{t|t} \tag{11}$$

where P is the transition matrix and $\hat{\xi}_{t|t}$ is the vector of the filtered probabilities. As the forecasting horizon h increases, the forecasted probabilities converge to the unconditional ergodic probabilities:

$$\lim_{h \to \infty} \hat{\xi}_{t+h|t} = \pi \tag{12}$$

Therefore it makes sense to use the unconditional ergodic probabilities as thresholds for the calculation of the qualitative forecasts of the reference time series of recessions. Again, the forecasted probabilities together with the treshold and the realized recessions (shaded areas) are shown in Figure 7.

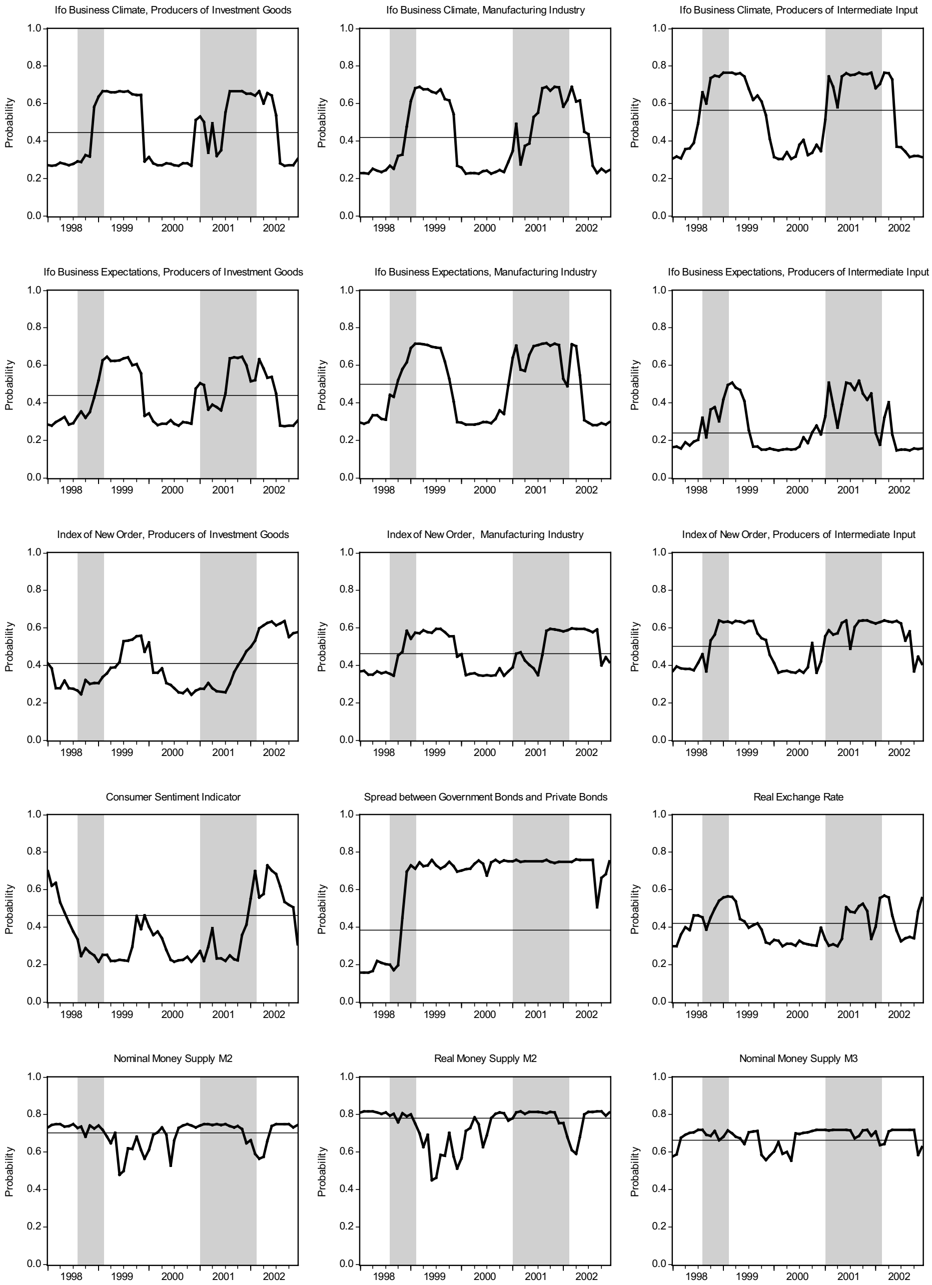

Figure 7: Out-of-Sample Forecasts: Markov Switching Models

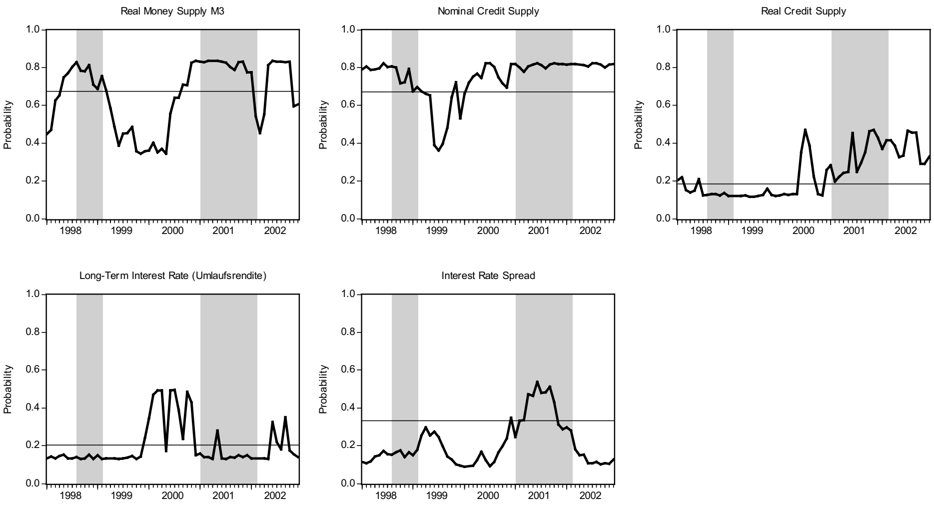

Figure 7: (Continued)

4.3. Descriptive Statistics

The quality of out-of-sample forecasts is typically assessed by measures like Theil's U or the test statistic proposed by Diebold and Mariano (1995). In the case of binary series we have to use other methods. We decided to use tests as described for instance in Diebold and Lopez (1996) or Toutenburg, Fieger and Kastner (1998). The forecast results are therefore classified in the contingency Table 1.

Table 1: Classification of directional forecast errors

		Actual outcome: Boom	Recession	Sum
Predicted:	Boom	O_{ii}	O_{ij}	$O_{i.}$
	Recession	O_{ji}	O_{jj}	$O_{j.}$
	Sum	$O_{.i}$	$O_{.j}$	O

Source: Diebold/Lopez (1996, p. 257)

E. g., symbol jj stands as an acronym for a forecasted recession, which at the end was counted as happened according to our binary reference series. The information content of the respective forecast can be summarized using the measure $I = \frac{O_{ii}}{O_{ii} + O_{ji}} + \frac{O_{jj}}{O_{jj} + O_{ij}}$.

The value of the measure I should asymptotically be bound between 1 and 2. In a "coin flip" case we have $O_{ii} \approx O_{ji}$ and $O_{jj} \approx O_{ij}$ and therefore $I \to 1$. If the forecast is "perfect" than $O_{ji} = O_{ij} = 0$ and $I = 2$. Therefore, any value of $1 < I \leq 2$ indicates a positive information content (compared to the "coin flip"). The statistical significance of the information content of the measure I can be formally tested. The consistent estimator for the cell counts is given by $\hat{E}_{ij} = O_{i.}O_{.j}/O$. We constructed the following measure $C = \sum_{i=1}^{2}\sum_{j=1}^{2}\frac{(O_{ij} - \hat{E}_{ij})^2}{\hat{E}_{ij}} \sim \chi^2(1)$. This measures the quadratic distance between realized and expected values in relation to the expected probabilities and is known as Pearson's χ^2. We report the information criterion I and the p-value of the test that both series are independent.

The strength of the relationship between the forecast and the realization can be evaluated by the (normalized) contingency coefficient as proposed by Pearson. This is a normalization of the reported χ^2 statistic which is given by $\sqrt{\frac{\min(i,j)}{\min(i,j) - 1}}\sqrt{\frac{C}{C + O}}$. The coefficient is bound between zero and 1 whereas a value close to 1 indicates a strong association. We also report the Yule coefficient which measures the association between concordant and discordant pairs of attributes. This is a measure for the direction of the association and only defined for the bivariate case. The Yule coefficient (Y) is given by $Y = \frac{O_{ii} \cdot O_{jj} - O_{ij} \cdot O_{ji}}{O_{ii} \cdot O_{jj} + O_{ij} \cdot O_{ji}}$ and bounded between 1 (positive association) and -1 (negative association).[24]

5. Results and Discussion

Frankly, the results are not at all satisfactory if someone is searching for "the one and only perfect indicator" but definitely better than to "flip a coin".

We start with the in-sample results. Only some indicators showed a strong local maximum in the probit models in sample – indicating a stable lead of this indicator with respect to turning points. This is perhaps true for the long-term nominal interest rate (lead: ten months), for the interest rate spread (lead: four months) as well as for the real money base M3 (lead: four months) and the real effective exchange rate (lead: sixteen months). The best result is given by the nominal credit supply (lead: thirteen months).[25] Most *ifo* indicator series seem to be more coincident than leading the reference series.

The results of the Markov switching model in-sample estimates are more or less in line with those of the probit models. The plots of the forecasted probablities indicate, that

[24] Remark that the Yule coefficient takes the value 1 or -1 already in case of either O_{ii} or $O_{jj} = 0$ or in case of O_{ji} or $O_{ij} = 0$. This is a special definition of an exact contiguity.

[25] The results for the nominal credit supply has to be interpreted with caution. In spite of the ADF test indicated that the nominal credit supply might be I(2), we decided to use the annual growth rate of the nominal credit supply as an I(0) variable. Therefore, the results might be a bit distorted in that specific case.

Table 2: Out-of-Sample-Evaluation. Probit Models

Indicator	I	Pearson's Chi-Squared	p-value	Contingency Coefficient	Yule Coefficient
Nominal Money Supply M2	0.74	3.92	0.05	0.37	−0.56
Real Money Supply M2	0.81	1.95	0.16	0.26	−0.38
Nominal Money Supply M3	1.00	0.00	0.97	0.01	0.01
Real Money Supply M3	1.44	10.13	0.00	0.56	0.74
Nominal Credit Supply	0.67	8.79	0.00	0.53	−1.00
Real Credit Supply	1.29	4.34	0.04	0.39	0.54
Short-term Interest Rate	1.68	23.84	0.00	0.78	0.96
Long-term Interest Rate	1.06	0.23	0.63	0.09	0.14
Interest Rate Spread	1.39	8.77	0.00	0.53	0.71
Consumer Confidence	0.79	2.32	0.13	0.29	−0.41
Real Effective Exchange Rate	1.58	18.65	0.00	0.72	1.00
Spread between Government and Private Bonds	1.00	0.00	0.96	0.01	−0.03
Index of New Orders, Investment Goods	1.42	8.98	0.00	0.53	0.73
Index of New Orders, Manufacturing Industry	1.49	12.66	0.00	0.62	0.83
Index of New Orders, Intermediate Inputs	1.55	15.78	0.00	0.67	0.86
ifo Business Expectations, Investment Goods	1.29	6.66	0.01	0.47	0.72
ifo Business Expectations, Manufacturing Industry	1.20	2.65	0.10	0.31	0.47
ifo Business Expectations, Intermediate Inputs	1.08	0.35	0.55	0.11	0.17
ifo Business Climate, Investment Goods	1.19	3.51	0.06	0.35	0.60
ifo Business Climate, Manufacturing Industry	1.28	5.13	0.02	0.42	0.62
ifo Business Climate, Intermediate Inputs	1.39	8.77	0.00	0.53	0.71

survey indicator seem to be more sensitive than monetary indicators. Most *ifo* indicators gave a clear signal in almost all historical cases of recessions. Some of them gave indeed more signals than realisations. However, with respect to recessions, these indicators seem to have more or less no leading indicator property. The "Share(k)" measure indicates that they are better classified as coincident indicators. The opposite seem to be true for some monetary indicators, e. g. the long-term interest rate. The long-term interest rate gave no signal in one of four in-sample recessions, however when a signal was given, it had a lead of about twelve months. The best leading indicators seem to be: the real effective exchange rate (lead: three months), the monetary bases M2 and M3 nominal and real (lead: about six months), the long-term interest rate (lead: twelve months) and The *ifo* business expectation for intermediate input as well as for manufacturing industry seem to have leading indicator properties as well. So, there is a group of possible leading indicators according to the methods in use here.

The out-of-sample forecast evaluation give us a better idea about the quality of the indicators under investigation.

The visual inspection of the forecasted probablities show that the models in general seem to do a good job. This is especially true for the *ifo* indicators (which however seem to

Table 3: Out-of-Sample-Evaluation. Markov Switching Models

Indicator	I	Pearson's Chi-Squared	p-value	Contingency Coefficient	Yule Coefficient
Nominal Money Supply M2	1.27	4.81	0.03	0.40	0.69
Real Money Supply M2	1.50	13.95	0.00	0.64	0.92
Nominal Money Supply M3	1.27	4.81	0.03	0.40	0.69
Real Money Supply M3	1.59	18.43	0.00	0.71	0.94
Nominal Credit Supply	1.27	6.87	0.01	0.48	1.00
Real Credit Supply	1.21	2.32	0.13	0.29	0.41
Short-term Interest Rate	0.62	9.07	0.00	0.54	−0.87
Interest Rate Spread	1.40	13.49	0.00	0.63	0.92
Consumer Confidence	0.82	2.49	0.11	0.30	−0.56
Real Effective Exchange Rate	1.29	4.24	0.04	0.38	0.53
Spread between Government and Private Bonds	0.89	2.37	0.12	0.29	−0.68
Index of New Orders, Investment Goods	0.65	6.70	0.01	0.47	−0.67
Index of New Orders, Manufacturing Industry	1.09	0.39	0.53	0.12	0.17
Index of New Orders, Intermediate Inputs	1.34	6.58	0.01	0.47	0.70
ifo Business Expectations, Investment Goods	1.12	0.70	0.40	0.16	0.23
ifo Business Expectations, Manufacturing Industry	1.52	14.16	0.00	0.64	0.85
ifo Business Expectations, Intermediate Inputs	1.63	20.53	0.00	0.74	0.92
ifo Business Climate, Investment Goods	1.21	2.32	0.13	0.29	0.41
ifo Business Climate, Manufacturing Industry	1.19	1.95	0.16	0.26	0.38
ifo Business Climate, Intermediate Inputs	1.62	20.11	0.00	0.74	0.95

have missed the beginning of the first out-of sample recession), the indizes of new orders, the real effective exchange rate, the interest rate spread, the short-term interest rate and the real money supply M3. The credit supply seems to fail completely as does the spread between government bonds and private bonds. This might be due to the fact that there is some changing in the financial sector in Germany in the end of the 1990s – which creates a structural break at the end of the sample. The evaluation criteria as calculated in Tables 2 and 3 show that the real money supply M3, the interest rate spread, the real effective exchange rate, the index of new orders of producers of intermediate inputs as well as the *ifo* business climate of producers of intermediate inputs give statistically significant signals for recessions out of sample regardless which method is used. This is a reasonable result.

There is an interesting finding when the results of this paper are compared with the investigations in the companion paper. Whereas in the first paper (Fritsche/Stephan, 2002) the question was "Can indicators help in forecasting the annual growth rate of a reference series?" the question now became "Can indicators be useful in forecasting the turning points of the cycle?" The question is "yes" for both questions, but for different indicators. The indicators, which performed quite well in the first paper, were mainly order inflows and *ifo* (expectation-based) indicators. These indicators however performed badly if the question is the signalling of turning points (with the notable exception of the *ifo* business expectations of producers of intermediate input). In contrast to that finding, the interest rate spread, the long-term interest rate, the real effective exchange rate as well as the monetary indicators performed bad in the first investigation but they are useful tools for the timely detection of turning points.

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