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Predicting Germany's recessions with leading indicators: Evidence from probit models

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Kiel Working Papers

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**Predicting Germany's Recessions
with Leading Indicators
- Evidence from Probit Models**

by
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Abstract

Probit models are employed to evaluate leading indicators for Germany's recessions. The predictive power of leading indicators is found to be lower than assumed in previous studies. Although, monetary variables provide the best predictive power for recessions, survey data and order inflows show a lag rather than a lead to the recession time series. US interest rates have also some information content with respect to the German cycle. Constructing a model with a set of variables to predict recessions does not help to improve the forecasts. The out-of-sample performance of the indicators appears to be even worse.

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1. Introduction*

In general, business cycle forecasts in Germany are unbiased and efficient (Döpke and Langfeldt 1995). This proposition, however, does not hold for the prediction of recessions, which have been very often missed in past (Heilemann 1998). Moreover, the conventional view that leading indicators contain information over the future stance of the business cycle has been challenged. Thoma and Gray (1998) provide evidence using US data that monetary variables are not useful in predicting business cycles. They argue that the standard econometric evidence is misleading because it rests mostly on in-sample properties rather than on the out-of-sample performance of the indicator series under investigation. For these reasons it is particularly important to develop models that can predict recessions (Filardo 1999, Stock and Watson 1993). One type of models which is considered to be useful in this context is the probit approach (Estrella and Mishkin (1998)). Using this methodology, the paper analyzes which time series might be useful for predicting Germany's recessions. The main result is that the predictive power of leading indicators is much more limited than the results by other methods suggests, although significant in some cases. While monetary variables turn out to be reasonable indicators, data from business surveys as well as order inflows provide no pronounced lead with respect to recession periods. The use of a set of variables rather than only an individual indicator does not improve the forecast performance. Recession prediction models built for a lead of one, three and six months, respectively, do not perform very well.

In Section 2 business cycle turning points are determined using an approach advanced by Artis et al. (1997). Section 3 describes the econometric techniques to be used in the following. The approach by Estrella and Mishkin (1998) is applied. Chapter 4 analyzes single time series. In Section 5, the single time series models are merged to construct a multifactor model to predict Germany's

* The author thanks C. Pierdzioch, J. Scheide and J. Gottschalk for helpful comments on an earlier draft of this paper. He is still responsible for all remaining errors.

recessions. Part 6 analyzes whether the indicators selected are useful in an out-of-sample prediction. The last part concludes.

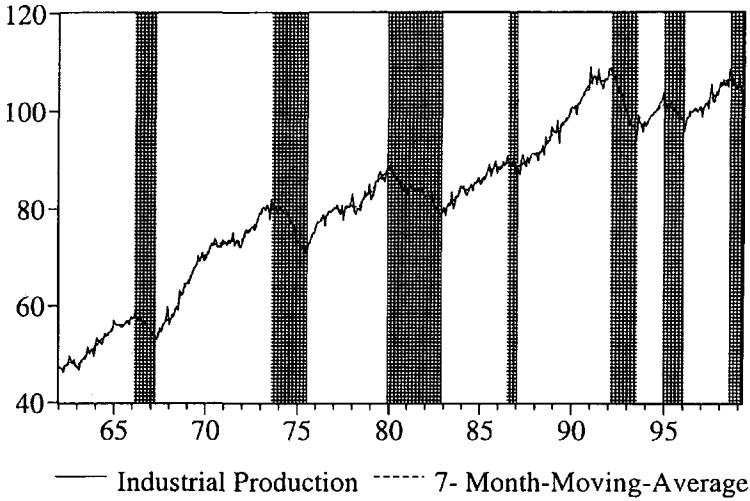
2. Dating Germany's Recessions

Recessions can be defined in many different ways (for a survey see Boldin 1994). In this paper, the concept of Artis et al. (1997) is used.¹ This definition of the cycle goes back to the NBER determination of business cycles. It refers to the industrial production. The procedure to define recessions roughly contains the following steps: Determination and elimination of extreme values, calculation of a 7-month moving average of the time series, identification of points higher (lower) than 12 months on either side using the moving average and then go back to the original time series and determine the turning point. Figure 1 shows the phases of the German business cycle as measured with this concept. Turning points which are not given by Artis et al. (1997) are own calculations.

An alternative technique to identify phases of economic activity uses trend deviations. However, since output gaps measured in this way are more or less symmetric around the trend, this concept fails to catch the pronounced recessions mentioned above. A third method often used to define recession periods is the practitioners rule that a recession is given by at least two quarters of declining real GDP (Funke 1997). However, this definition is purely ad hoc. Moreover, the dating procedure of Artis et al. (1997) looks at the absolute lowest value of the time series defining the reference cycle within 24 months. Hence, normally, the recessions according to the practitioner's rule will be recognized by the procedure used here as well.

¹ Compare Horn (1995) for an application of this concept on the German business cycle. Bernard and Gerlach (1996) use this definition, too. However, they evaluate the term structure of interest rates only.

Figure 1 — Business Cycle Turning Points Based on the Procedure of Artis et al. (1997) 1962 to 1998 (Industrial Production, West Germany, Index 1991 = 100, corrected for extreme values², Shaded areas: Recessions).



3. Econometric Methodology

The probit approach brought forward by Estrella and Mishkin (1998) is used to determine whether a variable helps to predict recessions. The dependent variable utilized in this analysis is a dummy that takes the value 1 for a recession as defined in section 1, and 0 otherwise. The following equation is estimated:

$$[1] \quad \text{Recession}_t = \beta_0 + \beta_1 \cdot I_{t-k} + u_t$$

where I_t is the indicator to be considered and

² The value of June 1984 has been replaced by the average of May and July 1984 since in June the production was depressed by a strike in the metal industry.

$$[2] \quad \text{Recession}_t = \begin{cases} 1 & \text{if the economy is in a recession} \\ 0 & \text{else} \end{cases}$$

The lead k has to be determined by statistical criteria. Following the literature, k is chosen by maximizing the so-called Pseudo- R^2 (Estrella and Mishkin 1998):

$$[3] \quad \text{Pseudo} - R^2 = 1 - (L_u / L_c)^{-(2/n)L_c}.$$

L_c is the die log-likelihood of a regression in which the series recession is explained by a constant only. L_u is the log-likelihood of the regression including the possible indicator. The number is bounded between 0 and 1 and can thus be interpreted in the same manner as the usual R^2 in standard regressions. The expected value of recession derived from the estimated model is the probability of a recession in t :

$$[4] \quad \text{Prob}(R=1) = \Phi(\beta_0 + \beta_1 I_{t-k})$$

where Φ is the cumulative standard normal density function. This kind of analysis can easily be extended to more than one regressors. For example Bernard and Gerlach (1996) add a foreign interest rate spread to the equation above.

$$[5] \quad \text{Recession}_t = \beta_0 + \beta_1(i_D^l - i_D^k)_{t-i} + \beta_2(i_{US}^l - i_{US}^k)_{t-i} + u_t$$

The significance of the variable can be analyzed by using the standard normal distributed z-statistic: $\frac{\beta_i}{s_{\beta_i}}$ where s_{β_i} devotes the standard deviation of the coefficient β_i .

Moreover it is necessary to evaluate the goodness of fit of the model. In this paper the test of Hosmer and Lemshow is used.³

³ If the data of the indicator variables are grouped into $j = 1, 2, \dots, J$ with m observations in group j . Define the number of $y = 1$ observations $y_j = \sum_{i \in j} y_i$ and the average of predicted values in group j as $\bar{p}_j = \sum_{i \in j} \hat{p}_i / m_j$. The Hosmer-Lemeshow test statistic is computed as

The basic idea of this test is that under the null of correct specification the predicted values (i.e. the probabilities of a recession) should fall into groups in a certain manner. These theoretical values can be compared to the actual estimated probabilities. If the differences turn out to be larger the null of a correct specification is rejected.

A shortcoming of probit models is their lack of dynamic specification (Duecker 1997). They do not use the information contained in the autocorrelation structure of the recession series R . However, the variables own history is often very important for forecasting. Hence, a procedure suggested by Duecker (1997) is used to test whether an indicator provides additional information as compared to the recession times series itself. Following this approach, the equation

$$[6] \quad \text{Recession} = \beta_0 + \beta_1 \cdot I_{t-k} + \beta_2 R_{t-k} + u_t$$

is estimated. Again, the Pseudo- R^2 is calculated. Note, however, that the log-likelihood of the restricted model in the case is the one for model [1]. Hence, the Pseudo- R^2 indicates whether model [6] provides additional information compared to [1]. In addition, a Langrange multiplier test is computed to test model [6] against model [1]. The test statistic

$$[7] \quad LR = -2(L_c - L_u)$$

is under the null χ^2 distributed with numbers of restriction as degrees of freedom (1 in this case).

The focus of this paper is particularly on the out-of-sample performance of the indicator series. To analyze this in the context of a probability forecast the quadratic probability score (QPS) is used (Diebold and Lopez 1996: 259):

$$[8] \quad QPS = \frac{1}{T} \sum_{t=1}^T 2(P_{t+k,t} - R_{t+k})^2$$

$$[5] \quad HL = \sum_{i=1}^J \frac{(y_i - m_j p_j)^2}{m_j \bar{p}_j (1 - \bar{p}_j)}$$

The distribution of the HL statistic is approximated by a χ^2 distribution with $J-2$ degrees of freedom (Eviews User's Guide: 466).

where P denotes the probability of an event R in t for the time $t+k$. The QPS lies between 0 and 2. Smaller numbers indicate more accurate forecasts. The QPS can therefore be seen as a rough analog of the mean square error in standard regression models.

4. Empirical Results for Individual Time Series

In this paper, the following set of possible leading indicators is investigated: monetary variables like money supply as well as nominal and real interest rates; survey data, order inflows, share prices the real external value of the domestic currency, a composite leading indicator, and variables representing monetary policy abroad.⁴ The details of the selected time series are presented in the appendix. Generally, the estimates were performed using monthly data from 1960 to 1998 unless otherwise stated in the table in the appendix.

Figure 2 shows the Pseudo- R^2 for a set of possible leading indicators for recessions in Germany. The time series are investigated in levels (survey data, interest rates) or in changes over previous year (monetary aggregates, order inflow).⁵ The Pseudo- R^2 statistic is calculated from a lead of 15 months to a lag of 5 months. The maximum of the statistic is used to determine the lead k of the indicator. The results are in contrast to findings of Döpke et.al (1994) who used leading point analysis, cross correlation's and tests on Granger-non-causality to evaluate virtually the same set of indicators. Whereas in their analysis the ifo-industrial climate index turned out to be a good indicator, the numbers here indicate that this time series is not very helpful to predict recessions.

⁴ Generally, the set of indicators investigated by Döpke et.al. (1994), Lindlbaur (1995) or Funke (1997) is used. In addition, some US variables are employed to analyze the Bernard and Gerlach (1996) results. The main difference to the related work of Funke (1997) is the use of a different definition of a recession and the inclusion of a lagged dependent variable as a control variable as suggested by Duecker (1997).

⁵ Regressions based on monthly changes lead to insufficient results and are not reported.

Figure 2a — Pseudo- R^2 in a Probit Model to Predict Germany Recessions for Selected Time Series, Leads, and Lags

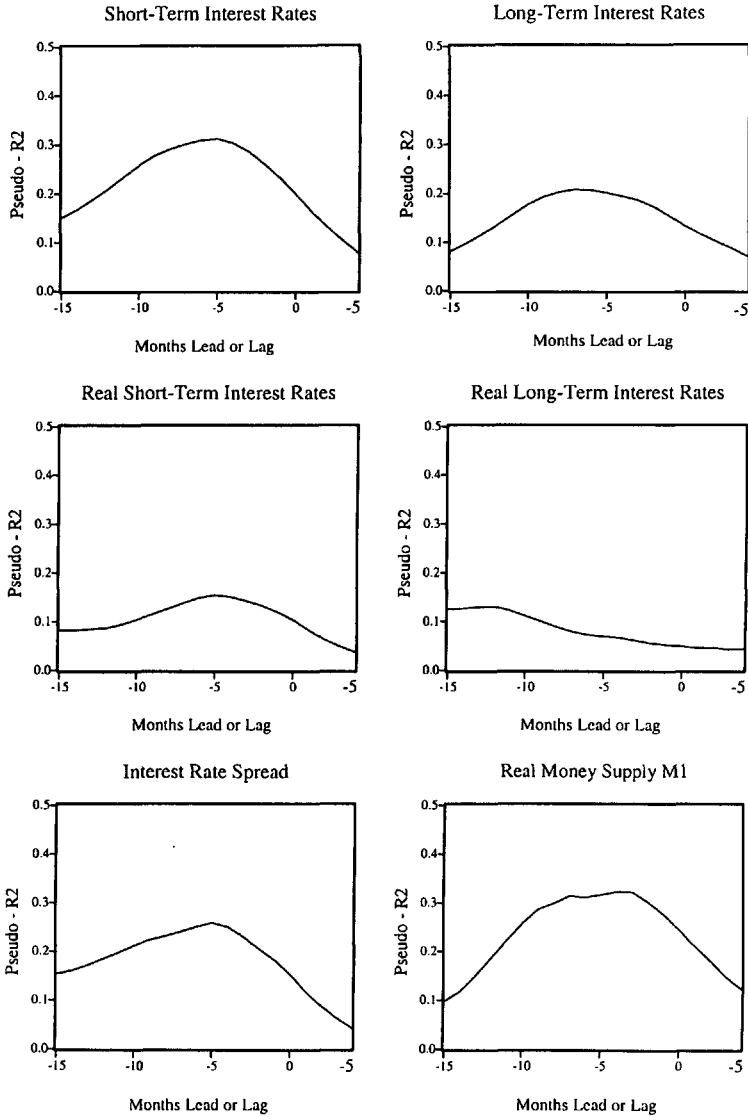


Figure 2b — Pseudo- R^2 in a Probit Model to Predict Germany Recessions for Selected Time Series, Leads, and Lags

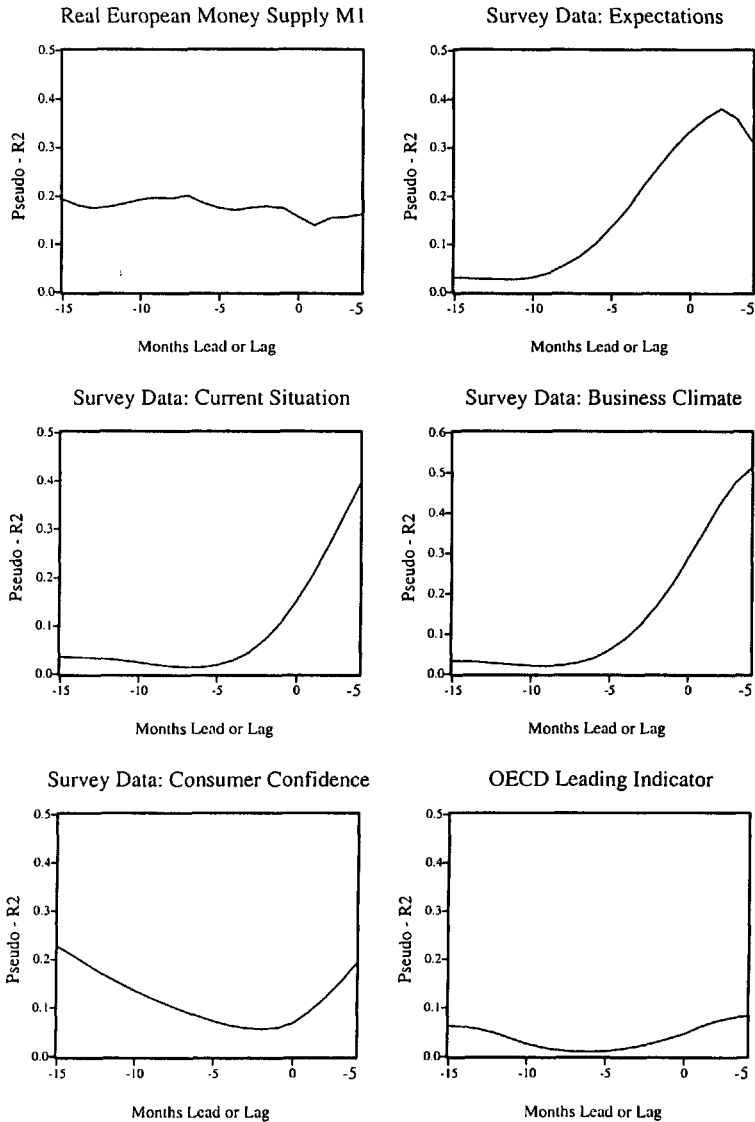
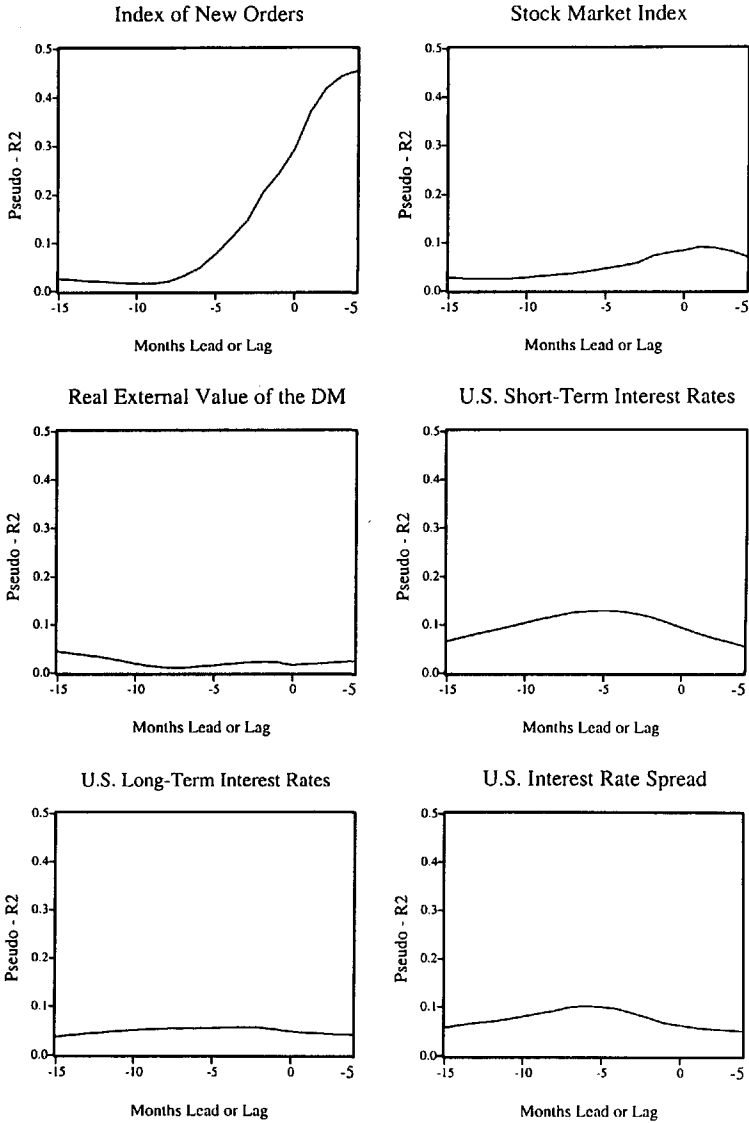


Figure 2c — Pseudo- R^2 in a Probit Model to Predict Germany Recessions for Selected Time Series, Leads, and, Lags



In fact, visual inspection of Figure 2 reveals that the series predicts recessions with a substantial lag. Moreover, if one considers the leads only, the Pseudo- R^2 is quite low as compared to other variables. However, the results can be improved if the components of the climate index — the business expectations and the current business situation — are considered separately (this confirms the results of Langmantel (1999)). The index of business expectations is a better leading indicator as both the index of the opinion on the current situation and the combined climate index. Since all the IFO time series have a lag with respect to the recession series and only a very small predictive power if considered with a lead they should be used only to predict recessions over a rather short time period. The same holds for the index of order inflows. The consumer confidence is not a good indicator for the stance of the overall business cycle. This is not surprising, since the variable is constructed to match the development of consumption, which is a relatively smooth time series as compared to the overall cycle.

Generally, monetary variables perform much better.⁶ Real money supply, long- as well as short-term interest rates and the interest rate spread have a lead of about 5 to 6 months and a much better fit than the other time series. Whereas the fit of real money supply is somewhat higher the lead of the short-term interest rates seems to be more convenient since the longer lead provides a good fit as well. Contrary to widespread belief, real interest rates have not much predictive power for recessions. Moreover, they are clear-cut outperformed by their nominal counterparts. Confirming the results of Bernard and Gerlach (1996) the estimates show some influence of the US monetary variables on the German business cycle. The real money supply M1 is not available any more after the start of the Euro. Hence, it is also tested whether the European Money Supply M1 shows some predictive power with respect to the German business cycle. Unfortunately, this is not the case. The time series shows a relatively low correlation to the recession time series and provides no clear cut lead.

⁶ The result of a good predictive power of monetary variables with respect to the business cycle is line with the vast majority of the literature. Compare e.g. Krämer and Langfeldt (1994), Langfeldt (1994), Sauer and Scheide (1995) and Bonser-Neal and Marley (1997), Dotsey (1998) and Atta-Mensah and Tkraz (1998).

Table 1 — Pseudo-R² Measures of Fit and Test on Significance for Single-Indicator-Recession Prediction Models Including the Logged Dependent Variable

Time Series	Forecasting Horizon		
	k = 3	k = 6	k = 9
Short-term interest rate	0.078 (35.2***)	0.131 (59.7***)	0.161 (74.0***)
Long-term interest rate	0.032 (14.9***)	0.063 (29.1***)	0.092 (42.0***)
Real short-term interest rate	0.035 (14.5***)	0.050 (19.4***)	0.040 (13.3***)
Real long-term interest rate	0.009 (3.3*)	0.019 (6.3**)	0.046 (16.0***)
Interest rate spread	0.078 (35.2***)	0.117 (53.5***)	0.129 (59.0***)
Real money supply M1	0.080 (4.16**)	0.126 (3.42**)	0.176 (8.02***)
Real European Money Supply M1	0.011 (22.4***)	0.043 (29.7***)	0.100 (33.9***)
Survey data: expectations	0.004 (0.9)	0.005 (0.1)	0.017 (2.0)
Survey data: current situation	0.035 (11.9***)	0.056 (17.95***)	0.061 (17.7***)
Survey data: business climate	0.016 (5.2**)	0.039 (11.9***)	0.056 (15.5***)
Survey data: consumer confidence	0.054 (2.0)	0.082 (0.1)	0.116 (1.2)
OECD leading indicator	0.006 (2.2)	0.017 (6.2*)	0.039 (13.9***)
Index of new orders	0.002 (0.3)	0.012 (3.2*)	0.030 (8.9***)
Stock Market Index	0.001 (0.08)	0.004 (0.08)	0.008 (0.31)
Real external value of the DM	0.003 (0.00)	0.004 (3.27*)	0.015 (11.9***)
US short-term interest rates	0.026 (11.9***)	0.041 (18.7***)	0.045 (20.8***)
US long-term interest rates	0.006 (2.7)	0.009 (4.3**)	0.014 (6.7***)
US yield spread	0.026 (12.1***)	0.042 (19.3***)	0.037 (17.3***)

*** (**, *) denotes that the hypothesis of a zero coefficient is rejected at the 1 (5, 10) percent level.

The OECD leading indicator⁷ as an example for composite indicators shows not much predictive power with respect to the recession periods. The stock market index does not help to predict recessions. This might be due to the fact, that the time series is extremely volatile and hence, tends to give a lot of wrong signals.

Although some variables investigated here are significant, the fit seems rather poor. In this respect one has to keep in mind that even a very low Pseudo- R^2 is consistent with significant influence of the variable. Generally, the calculations show at least some predictive power considering monetary leading indicators although their performance appears to be worse than indicated by other evaluation methods like in-sample forecasting regression (Langmantel 1999) or in-sample test on Granger non-causality (Fritsche 1999). The predictive power of the variables is tested more formally in Table 1. Generally, most of the indicators provide substantial information until they improve the fit of a model which includes the lagged depended variable only. The values of the Pseudo- R^2 against this model as well as the value of the LR-test-statistic increase with a larger forecasting horizon. This does not mean, however, that the predictive power of the leading indicators becomes greater if the forecasting horizon is increasing. Rather, the information content of the lagged recession time series is decreasing sharply.

All in all, the test confirm the results above. Survey data perform surprisingly bad and monetary variables are better leading indicators.

5. Empirical Results for a Combination of Time Series

Given the results derived in the previous section, we next try to improve the model by enlarging the set of explanatory variables used in equation [1]. Three models are considered. The first model assumes only a lead of one month, one assuming a lead of three months and a last one is estimated under the assump-

⁷ The indicator contains the index of new orders, the business survey, M1 money supply, the yield on public sector bonds, the share prices and an index of unit labour costs. Compare Peti et al.(1996) for details.

tion that the optimal lead is six months. Generally, all variables are chosen to be part of the model that show a Pseudo- R^2 of at least 0.1 at a lead of three months.

In previously — not reported — regressions it turns out, that the long- and the short-term interest rates enter the equation with coefficients of opposite signs but more or less the same size. Hence, the yield spread seems to be the natural choice. In order to measure the monetary policy of the US the yield curve is used, too. Additionally, the ifo-business expectations and the index of order inflows are included. A difficult question is, how to deal with the money supply variable. On one hand it provides additional information compared to the other variables. On the other hand, for practical purposes the variable should be omitted since it is not available any more after the start of the Euro. The Euroland Money supply M1 turns not out to be a good indicator in the single indicator analysis. Hence, no money variable is included. In contrast the lagged dependent variable is used since it improves the forecasting properties of the model significantly.

Table 2 gives the estimation results. Most of the coefficients have the expected sign. An increase in the levels of the exogenous variables reduce the probability of a recession. However, this does not hold for the ifo survey on business expectations. According to the z-statistic only the domestic spread and the lagged dependent variable are significant in all three specifications. The order inflow is always insignificant, the ifo survey enters only the six months model, though with an implausible sign. Moreover, the overall performance of the models is not sufficient. Although the Pseudo- R^2 looks better than in the single indicator models this mainly due to the lagged dependent variable. The fit decreases — not surprisingly — with the forecasting horizon. In the case of the six months model the goodness-of-fit test even rejects the hypothesis of a well-specified model.

The results of an in-sample forecasting evaluation are also presented in table 2. For example, 68.6 percent of the recession periods are forecasted by the six months model correctly if the "cut off" rate is set to 0.5, that is any probability that exceeds 0.5 is counted as a signal for a recession. In other words: If the probability is less than 50 percent an expansion is seen as more likely than a

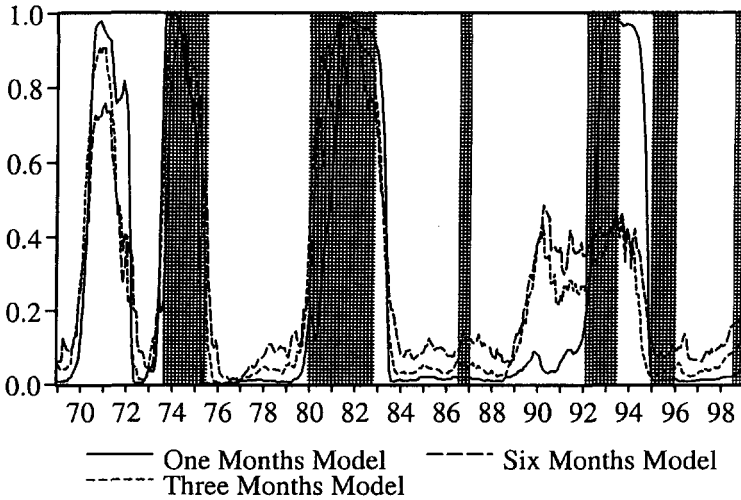
Table 2 — Prediction Models for Germany's Recession

	Model 1 (one month lead)	Model 2 (three months lead)	Model 3 (six months lead)
Constant	-1.73 (-8.0)***	-1.13 (-6.9)***	-0.69 (-4.7)
Interest Rate Spread	-0.26 (-3.1)***	-0.33 (-5.6)***	-0.38 (-7.2)***
Ifo-Index	0.01 (0.5)	0.01 (1.2)	0.02 (2.4)**
Order Inflow	-0.05 (-0.3)	-0.001 (-0.1)	-0.006 (-0.5)
US Spread	-0.09 (-1.25)	-0.12 (-2.3)**	-0.13 (-7.9)***
Recession(-k)	3.65 (11.6)***	2.56 (10.7)***	1.69 (7.9)***
Pseudo-R ²	0.86	0.65	0.44
% Correct "no recession"	98.0	94.8	90.0
% correct "recession"	94.3	84.8	68.6
Goodness of Fit test	4.64	9.45	32.96***
The t-values in brackets are corrected for heteroscedasticity using the GLS-method. ***(**,*) denotes that the null is rejected at the 1(5,10) percent level.			

recession; is the probability exceeds 50 percent the recession is more likely. Moreover, the series of the probability of a recession shows wrong signals.⁸ To As shown in figure 3 the signals of 1977 and 1990 were not followed by a recession whereas the "mini-recessions" of both 1987 and 1995 occurred without any warning. If the development in 1998 is counted as a mini-recession no signal has occurred, too. On the other hand, the models predict a recession in the early seventies which did not occur. However, on the other hand the most pronounced recession in 1974 and 1982. Only the months model signals the recession of 1993. The probabilities calculated from the three and six months model appear to be rather small.

⁸ To calculate the time series in figure 3 the insignificant variables have been omitted from the equations.

Figure 3 — Estimated Probabilities of a Recession and Recession Periods (Shaded Areas) in Germany 1968 to 1999

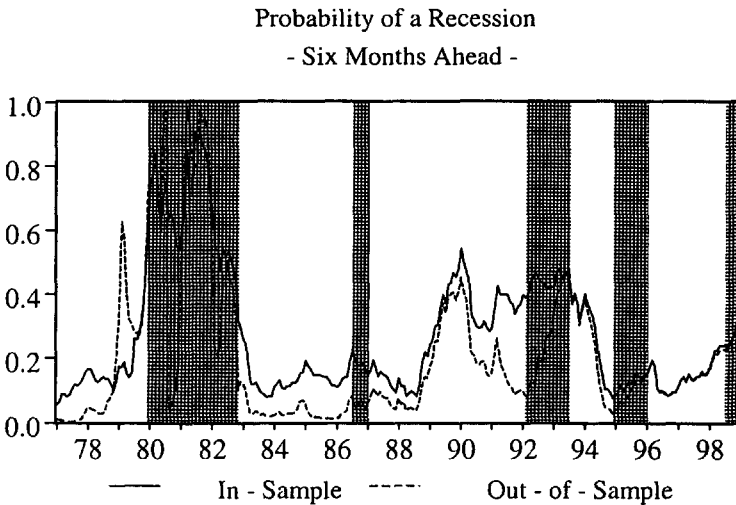
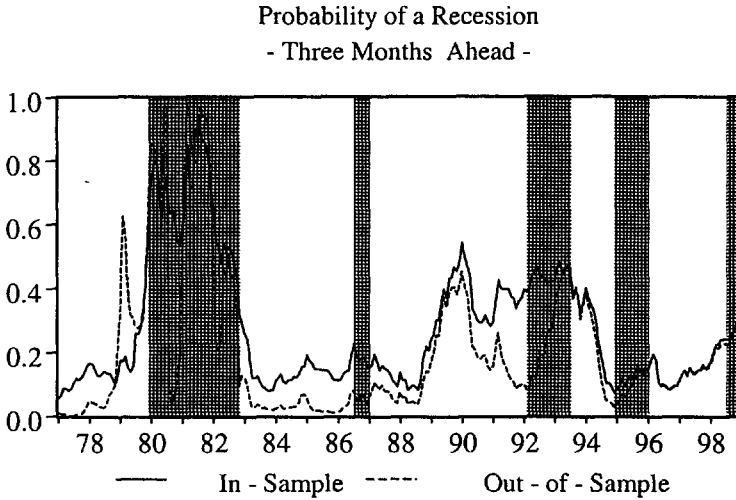


6. Out-of-sample Performance

In the recent literature dealing with the evaluation of leading indicators and recession prediction models there is a growing consensus, that the in-sample criteria are likely to be misleading in analyzing the predictive power of an indicator time series or a prediction model (Estrella and Mishkin 1998, Kirchgässner and Savioz 1998, Davis and Fagen 1997). Hence, the models developed in section 5 are used to produce out-of-sample predictions in the following way: The equation of the 3-months (6-months) model outlined in section 5 is estimated using data from 1969 to 1976. Insignificant variables are omitted from the equations as well as the lagged dependent variable. Hence the remaining variables are the domestic and the U.S. term spread. The model is used to calculate the probability of a recession for the next three (six) months. The procedure is repeated after adding additional three months of data until the

end of the sample. Figure 4 shows the probabilities of a recession given by the in-sample performance of the model and given by the procedure described above.

Figure 4 — Predicted Probabilities of a Recession (calculated from an) In-sample and an Out-of-sample Model.



The result is clear cut: the out-of-sample performance of both models is obviously different from the in-sample performance of the models. In particular, before recession of 1992/93 the probability obtained from the out-of-sample procedure is even lower than the one calculated from the in-sample models. However, as mentioned before the recession is missed in both cases. The results of the visual inspection are consistent with the statistics summarized in table 3 where the QPS statistics are given for both models and forecasting horizon's. Whereas in-sample reasoning suggest that the predictive power is more or less equal in both cases, the out-of-sample results confirm that the six months model shows larger forecast errors.

Table 3 — Average Quadratic Probability score (QPS) for In- and Out-of-sample Predictions of Germany's Recessions

Model	In-sample	Out-of-sample
Three months model	0.31	0.86
Six months model	0.30	0.94

7. Conclusions

Several time series are investigated to analyze whether they can serve as leading indicators for Germany's recessions. The so-called "classical" approach of dating turning points was used. The main results are that the predictive power of leading indicators is only low. Short-term interest rates, narrow money supply and the interest rate spread appeared to be relatively good leading indicators. Data from business surveys as well as order inflows provide lags rather than leads with respect to recession periods. The best predictive power among the survey data is provided by the business expectations. The course of American monetary policy as measured by the US yield spread helps to forecast German recessions. Predicting recessions with a set of variables rather than with only one variable does not increase the power. Recession prediction models build for a lead of one, three and six months, respectively, does not perform better than the single indicator models. For leads longer than nine months only monetary variables provide any predictive power for recessions. Out-of-sample forecasts show that the prediction of a recession is only possible for very short forecasting horizons.

Appendix table 1: Data and Sources

Time Series	Details and Source
ifo-business-expectation, ifo-business survey: current situation, ifo business climate	balance of optimistic (+) and pessimistic (-) firms in manufacturing. Monthly data. Source: ifo-Institute. Data from 1968 to 1998.
Consumer confidence	Index 1980=100. Source: GFK Marktforschung. Data from 1980 to 1998.
Order inflow	Seasonally adjusted index of new orders 1991=100 in manufacturing. Source: Deutsche Bundesbank and own calculations. Data from 1962 to 1998.
Money supply M1	Bill. DM. Seasonally adjusted. Source: Deutsche Bundesbank.
Long-term interest rate	"Umlaufrendite festverzinslicher Wertpapiere", Source: Deutsche Bundesbank
Short-term interest rate	3-Month Money Market rate
US-long-term rates	10-year government bond yield. Source: OECD, Main Economic Indicators.
US-Short-term rates	3- month money market rate, Source: OECD Economic Indicators
OECD Composite Leading Indicator Germany (trend restored)	Index 1990=100, Source: OECD Main Economic Indicators
Stock market index	Index 1987=100, Source: Deutsche Bundesbank
Inflation rate	Year on Year Change of the West German CPI (seasonally adjusted). Source: Deutsche Bundesbank
Industrial production	Index 1995=100, seasonally adjusted. Source: Deutsche Bundesbank. Data from 1962 to 1998.
European Money Supply M1	Bill. Euro. Source: European Central Bank.
European Consumer Price Index	Index 1990 = 100. Source: Datastream.

References

- Artis, M.J., Z.G. Kontolenis and D.R. Osborn (1997). Business Cycles for G7 and European Countries. *Journal of Business*: 249–279.
- Atta-Mensah, J. and G. Tkraz (1998), Predicting Canadian Recessions Using Financial Variables: A Probit Approach. *Bank of Canada Working Paper* No. 98-5. Montreal.
- Bernard, H., and S. Gerlach (1996). Does the Term Structure Predict Recessions? The International Evidence. Bank for International Settlements Working Paper No. 37.
- Boldin, M.D. (1994). Dating Turning Points in the Business Cycle. *Journal of Business*: 97–131.
- Bonser-Neal, C., and T.R. Marley (1997). Does the Yield Spread Predict Real Economic Activity? A Multicountry Analysis. *Federal Reserve Bank of Kansas City Economic Review*, Third Quarter: 37–49.
- Davis, E. P., and G. Fagan (1997). Are Financial Spreads useful Indicators of Future Inflation and Output Growth in EU Countries? *Journal of Applied Econometrics* 12: 701–714.
- Diebold, F.X., and J.A. Lopez (1996). Forecast Evaluation and Combination. In: G.S. Madalla and C.R. Rao (eds.), *Handbook of Statistics*, Vol. 14. Amsterdam: 241–268.
- Döpke, J., and E. Langfeldt (1995). Zur Qualität von Konjunkturprognosen für Westdeutschland. Kiel Discussion Paper No. 247. Institute of World Economics, Kiel.
- Döpke, J., J.W. Krämer and E. Langfeldt (1994). Konjunkturelle Frühindikatoren in Deutschland. *Konjunkturpolitik*: 135–153.
- Dotsey, M. (1998). The Predictive Content of the Interest Rate Term Spread for Future Economic Growth. *Federal Reserve Bank of Richmond Economic Quarterly* 84: 31–51.
- Dueker, M.J. (1997). Strengthening the Case for the Yield Curve as a Predictor of U.S. Recessions. *Economic Review Federal Reserve Bank of St. Louis*: 41–50.

- Estrella, A., and F.S. Mishkin (1998). Predicting U.S. Recessions: Financial Variables as Leading Indicators. *The Review of Economics and Statistics*: 45–61.
- Eviews 3.1 User's Guide (1997). Irvine.
- Filardo, A.J. (1999). How Reliable Are Recession Prediction Models? *Economic Review Federal Reserve Bank of Kansas*: 35–55.
- Fritsche, U. (1999). Vorlaufeigenschaften von Ifo-Indikatoren für Westdeutschland. DIW Discussion Paper No. 179. Berlin.
- Funke, N. (1997). Predicting Recessions: Some Evidence for Germany. *Weltwirtschaftliches Archiv*: 90–102.
- Haubrich, J.G., and A.M. Dombrosky (1996). Predicting Real Growth Using the Yield Curve. *Economic Review Federal Reserve Bank of Cleveland*: 26–35.
- Heilemann (1998). Zu den Projektionen des Jahreswirtschaftsberichts der Bundesregierung. In: U. Heilemann, D. Kath and N. Klotten (eds.), *Entgrenzung als Erkenntnis- und Gestaltungsaufgabe*. Berlin: 70–100.
- Horn, G.A. (1995). Klassische Konjunkturzyklen in den G-7 Ländern. — Eine deskriptive Analyse. DIW Diskussionspapier Nr. 122. Berlin.
- Kirchgässner, G., and M. Savioz (1998). Monetary Policy and Forecasts for Real GDP Growth: An Empirical Investigation for the Federal Republic of Germany. University of St. Gallen Discussion Paper No. 9813. St. Gallen.
- Krämer, J.W., and E. Langfeldt (1993). Die Zinsdifferenz als Frühindikator für die westdeutsche Konjunktur. *Die Weltwirtschaft* (1): 34–42.
- Langfeldt, E. (1994). Die Zinsstruktur als Frühindikator für Konjunktur und Preisentwicklung in Deutschland. Kieler Arbeitspapiere 615. Institut für Weltwirtschaft, Kiel.
- Langmantel, E. (1999). Das ifo-Geschäftsklima als Indikator für die Prognose des Bruttoinlandsprodukts. *ifo-Schnelldienst*: 16–21.
- Lindlbauer, J.D. (1995). Beurteilung ausgewählter Frühindikatoren. In: H.K. Oppenländer (ed.), *Konjunkturindikatoren*: 238–251.
- Peti, G., G. Salou, P. Beziz and C. Degain (1996). An Update of OECD Leading Indicators. Available at <http://www.oecd.org/std/limeet.htm> (in August 1999).

- Sauer, C. and Scheide, J. (1995), Money, Interest Rate Spreads, and Economic Activity. *Weltwirtschaftliches Archiv*: 708-722.
- Stock, J.H., and M.W. Watson (1993). A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience. In: J.H. Stock and M.W. Watson (eds.), *Business Cycles, Indicators, and Forecasting*. Chicago: 95-157.
- Thoma, M.A., and J.A. Gray (1998). Financial Market Variables Do not Predict Real Activity. *Economic Inquiry*: 522-539.