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Abstract

In this paper we present two new composite leading indicators of economic activity in Germany estimated using a dynamic factor model with and without regime switching. The obtained optimal inferences of business cycle turning points indicate that the two-state regime switching procedure leads to a successful representation of the sample data and provides an appropriate tool for forecasting business conditions.

JEL Classification: C32, C53.

Keywords: business cycles, leading indicators, turning points, Markov switching, Germany

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"... the first law of forecasting: give them a prediction or give them a date, but never give them both."

B. Eichengreen (2000) "The Euro One Year On", *Journal of Policy Modelling* 22, p. 366.

1. Introduction

Economic policy requires a high degree of foresight because policy actions typically take effect only after a long lag. In the light of these policy needs, it is now routine for policy makers, central banks and economic research institutes to report and analyse an array of so-called leading indicators that are supposed to give a clear indication of the status of the real economy. Since economies move in cycles, the obvious question is where are we on the clock.[1] An extensive literature exists which attempts to find reliable forecasting tools for the business cycle turning points, from the early landmark study by Burns and Mitchell (1946) to the more sophisticated of Stock and Watson (1989, 1991, 1993). Both approaches assume that the business cycle is characterised by simultaneous comovement in may economic activities. We interpret similarities and comovements among macroeconomic variables as a challenge to applied economic research, suggesting the development of composite leading indicators of economic activity. The composite leading indicator is a key element in an analytic system designed to anticipate the direction in which the economy is heading. Composite indicators tend to smooth out a good part of the volatility of the individual series and thereby serve as handy summary measures of the business cycle.

An important features of our paper is that we focus on the model´s ability to forecast turning points. Generally speaking, the major task in economic forecasting is to anticipate turning points in economic activity – points when an expansion will reach its zenith, or peak, or when a contraction will reach its nadir, or trough. A reliable method for forecasting turning points has continued to elude forecasters, despite advances in mathematical and statistical techniques. Forecasting turning points is a crucial issue since policymakers are often very much interested in answers to simple questions like "Is GDP going to take off next quarter?" Another important motivation for this exercise comes from the recognition that GDP forecasts are playing an increasing role in the development of stock markets. To address this question, we use dynamic factor analysis, Kalman filtering and regime switching

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[1] To be fair, economic forecasting is even harder than weather forecasting. At least weathermen know what the temperature is right now. Economists, in contrast, have to forecast the immediate past, which is constantly being revised. Orphanides (1998) has highlighted the uncertainty due to the revisions that are made to the real-time estimates of real GDP.

techniques. Our goal is to consider a general-enough framework which permits the data to determine the stance of the business cycle and recession probabilites at some future unspecified date.

The remainder of this paper is organised as follows. In section 2 the basic dynamic common factor model is described, while in Section 3 a dynamic Markov switching factor model is suggested. In Section 4, the alternative measures are evaluated in terms of their ability to predict future business cycle developments by means of non-nested tests. Section 5 concludes and suggests areas for future research.

2. The Dynamic Common Factor Model

There are two main purposes for this Section. First, we want to develop a composite leading indicator model for the German economy. Second, an additional goal is to evaluate the measure in terms of its ability to forecast business cycle developments.[2] This section briefly describes the empirical methodology. It consists in constructing a common unobserved factor from a group of indicators, following the tradition of dynamic factor analysis. This common factor is assumed to represent the shared influence of the state of the economy on the leading indicator.[3] To the best of our knowledge, this is the first attempt to construct such a composite leading indicator for Germany using the dynamic common factor model.

An important issue in the construction of a leading indicator includes the selection of variables. Using "economic theory screening", we have initially tried a number of alternative specifications, not reported in the paper. In particular, we have considered new orders manufacturing, industrial production, the stock of finished goods, oil prices, the interest rate spread, new orders for residential buildings, the nominal effective exchange rate as well as a broad share price index to the empirical model as candidate variables. Because of the large number of possible specifications, we have applied various testing procedures to help with model selection. The specifications were evaluated based on their within-sample performance. It generally turned out that the turning point predictions were considerably less satisfactory for larger models than those reported in the text.[4] Moreover, dropping additional variables simplified the estimated Kalman filter and led to more robust and plausible

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[2] A composite indicator is said to be leading by x time periods, when information up to time t-x is required to calculate a point estimate of real GDP at time t. The leading indicator is then said to have a lead time of x.

[3] The modelling philosophy, certainly not new in the econometric literature, has recently been rigorously laid out and applied using data for the U.S., by Chauvet (1998), Kaufmann (2000), Kim (1998) and Kim and Nelson (1999). The concept of co-movements is related to the idea of "common features" in the language of Engle and Kozicki (1993).

[4] For example, using oil prices, share prices, interest rates or exchange rates as candidate series led to various "false alarms", i.e. turning points which did not occur subsequently. We have also avoided the selection of closely related series.

estimates. Our final list therefore includes only two variables.[5] Let Y_{1t} be the fourth difference of the index of new orders total manufacturing (1995 = 100) and Y_{2t} the finished goods stock level (% balance).[6] Unit root tests for both series suggest that one cannot reject the hypothesis of both variables being I(0). Additionally, both series are not cointegrated. Borrowing from Stock and Watson (1989), we therefore consider the following bivariate dynamic factor model:

(1) $\qquad Y_{1t} = D_1 + \gamma_1 I_t + e_{1t}$

(2) $\qquad Y_{2t} = D_2 + \gamma_2 I_{t-1} + e_{2t}$

(3) $\qquad I_t = \delta + \phi\, I_{t-1} + \omega_t \qquad\qquad \omega_t \sim i.i.d.\ N\left(0,1\right)$

(4) $\qquad e_{it} = \psi_{i,1} e_{i,t-1} + \psi_{i,4} e_{i,t-4} + \varepsilon_{it} \qquad\qquad \varepsilon_{it} \sim i.i.d.\ N\left(0,\sigma_i^2\right) \qquad i = 1,2$

where I_t is the common component (leading indicator) which enters equation (1) and (2) with different weights.[7] These weights γ_i indicate the extent to which each series is affected by the common component, I_t, which arises from a single source. In (3) it is assumed that the unobserved component follows a stationary first-order autoregressive process. The autoregressive structure of the idiosyncratic component is given in (4). The main identifying assumption in the model is that (e_{1t}, e_{2t}, I_t) are mutually uncorrelated at all leads and lags. Stock and Watson (1991) have shown that the parameters D_i and δ are not separately identified. Therefore they have suggested to write the model in deviations from means, thus concentrating the likelihood function.

(5) $\qquad y_{1t} = \gamma_1 i_t + e_{1t}$

(6) $\qquad y_{2t} = \gamma_2 i_{t-1} + e_{2t}$

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[5] The insignificance of monetary and financial variables is in harmony with the results in Fritsche and Stephan (2000). The exact data definitions and data sources are given in the appendix.
[6] We have constructed a quarterly index because monthly GDP data for Germany are not available. Another reason is that month-to-month movements in leading indicators tend to be characterised by a high noise-to-signal ratio. Stock and Watson (1989) have therefore elected to smooth the resulting monthly series to improve the indicator´s forecasting performance.
[7] We have lagged I_t in equation (2) in order to take into account the phase shift between Y_{1t} and Y_{2t}.

(7) $i_t = \phi\, i_{t-1} + \omega_t$ $\omega_t \sim i.i.d.\ N\left(0,1\right)$

(8) $e_{it} = \psi_{i,1} e_{i,t-1} + \psi_{i,4} e_{i,t-4} + \varepsilon_{it}$ $\varepsilon_{it} \sim i.i.d.\ N\left(0,\sigma_i^2\right)$ $i = 1,2$

where $y_{it} = Y_{it} - \overline{Y}_i$ and $i_t = I_t - \delta$. In general, the Kalman filter estimation, a model is expressed in its state-space form. The latter is composed of two parts: the measurement and the transition system. The following two equations describe our model in deviations from mean in a particular state-space representation.

(9)

$$
\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} =
\begin{pmatrix}
\gamma_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \gamma_2 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3}
\end{pmatrix}
$$

$i_t = H\beta_t$ [Measurement Equation]

(10)

$$
\begin{pmatrix}
i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3}
\end{pmatrix}
=
\begin{pmatrix}
\phi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \psi_{11} & 0 & 0 & \psi_{14} & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & 0 & 0 & \psi_{24} \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}
\begin{pmatrix}
i_{t-1} \\ i_{t-2} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{1,t-4} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \\ e_{2,t-4}
\end{pmatrix}
+
\begin{pmatrix}
\omega_t \\ 0 \\ \varepsilon_{1t} \\ 0 \\ 0 \\ 0 \\ \varepsilon_{2t} \\ 0 \\ 0 \\ 0
\end{pmatrix}
$$

$\beta_t = F\beta_{t-1} + v_t$ [Transition Equation]

In the above state-space representation, the ten rows of the transition equation describe identities. Estimation of the model will allow the unobserved components ("states") to be uncovered. The parameters and the variances of the state-space model given in (9) and (10) can be estimated using the MLE method. Given the parameters the Kalman filter recursions can be employed to obtain the time-varying parameters $\beta_{t/t}$. The Kalman filter estimation is composed of two stages, a filtering procedure and a smoothing procedure. The first is a recursive process that computes the optimal estimate for the state variables at a moment t using information available up to t-1, minimising the forecast error by maximum likelihood. The second procedure smoothes the obtained estimate on the basis of the information available over the whole sample period. Parameter estimates of the state-space model are reported in Table 1.[8]

Table 1: Parameter Estimates of the Dynamic Factor Model, 1971:1 – 2001:1

Parameters	Estimates	Asymptotic t-values
γ_1	0.253	5.4
γ_2	-0.399	15.1
ϕ	0.9092	25.6
ψ_{11}	0.490	5.7
ψ_{14}	-0.355	4.5
ψ_{21}	0.778	7.7
ψ_{24}	0.083	3.1
σ_1^2	0.314	7.6
σ_2^2	0.001	0.00
Log-Likelihood	-58.75	
Diagnostics:	Test Statistics	Prob-Values
LB(ε_1)	7.74	0.10
LB(ε_2)	7.75	0.10
DH	30.16	0.0001
BDS(2)-(ε_1)	0.02	0.01
BDS(4)-(ε_1)	0.03	0.01
BDS(2)-(ε_2)	0.03	0.001
BDS(4)-(ε_2)	0.05	0.001

Note: LB(ε_i): Ljung-Box Q test measuring general AR(4) residual autocorrelation (*p*-values in parentheses); DH: Doornik and Hansen´s (1994) multivariate omnibus normality test; BDS(*m*)-(ε_i): portmanteau test for time based independence in a series where *m* is the so-called embedding dimension [see Brock et al. (1996) for details].

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[8] The GAUSS code developed to perform the Kalman filtering and the maximum likelihood estimation largely draws on programs which were kindly made available by Chang-Jin Kim. Kim (1994) and Kim and Nelson (1998, 1999) provide details on additional identifying restrictions and estimation of the system using the Kalman

At this point it is useful to consider the estimates in somewhat closer details. All parameters are consistent with that predicted by theory and are statistically significant at the 5 percent level. In other words, according to the results, the model seems to fit the data quite well. With regard to the estimated autoregressive coefficient ϕ, the coefficient is positive and significant. This suggests a great deal of persistence in business cycle fluctuations. In order to check the adequacy of the model specification, we analyse the disturbances ε_i. If the model is correctly specified, then the residuals are serially uncorrelated and normally distributed. The Ljung-Box tests for residual autocorrelation are satisfactory, their results providing evidence that does not allow to reject the null hypothesis of uncorrelated distributed residuals. On the other hand, the Doornik and Hansen (1994) normality test indicates departure from normality. The Table also displays various BDS tests which suggest some neglected nonlinearity remaining in the disturbances. Despite these minor failures, the overall impression is that the model works very well. Given these parameter estimates, we get $i_{t/t}$ and $I_{t/t}$, $t = 1$, 2, ..., T, by running the Kalman filter.[9]

The first step in our evaluation of the resulting index is to look at how well the measure does at tracking GDP over the sample period for which we have data. Following a common practice, we consider real GDP as the relevant measure of economic activity. Economist have, however, quibbled about what "recession" means. The popular definition in the U.S. – two consecutive quarters of GDP decline – is too crude. It might make more sense to define a recession as a period when GDP falls significantly below its potential trend. We therefore check whether our new leading indicator has any predictive for the German output gap series (the difference between actual and trend output in percent). In order to calculate the output gap, real GDP must be detrended. Unfortunately, estimating output gaps is more an art than a science. A wide variety of both conceptual and empirical methods have been proposed to estimate potential output and make the notion of an output gap operational. The selection of a detrending procedure is a complex task because there are several possible ways of doing so, each of which is pertinent in certain circumstances and has its own implications. On the empirical side, the two most habitual methods are the Hodrick and Prescott (1997) filter, HP, and the band-pass filter. The first method has been widely used, specially in those contributions interested in the coherence of business cycles, but several authors have warned of the consequences of applying

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filter. Maybeck (1979) provides a wondeful, very simple and yet revealing introduction to some of the concepts of Kalman filtering.

[9] Please note that the resulting leading indicator is identified only up to an arbitrary choice of the initial value. We are not providing confidence bands around I_t because it is well-known that deriving bands around state variables in a Kalman filter estimation is far from being trivial. This fact stems from the many sources of uncertainty, which inlude uncertainty on the initial conditions, the sample dependence of the estimated hyper-parameters and the relative flatness of the likelihood function.

this filter.[10] In particular, when studying comovements in HP-filtered series, there exists one potential problem, which may be important. A common tool in the analysis of comovements of time series is the estimation of cross-correlations, but the standard errors of these estimates may be large. For HP-filtered independent random walks, Harvey and Jaeger (1993) report asymptotic standard deviations of the sample cross-correlations much higher than those obtained when at least one of the filtered series is white noise. Hence the danger of finding spurious comovements if correct standard errors are not used.[11] Given all these warnings and the potential problems, the GDP data will be detrended using the band-pass filter suggested by Baxter and King (1999) which has been designed to mitigate these problems. The band pass filter isolates the component of GDP that lies between 2 and 32 periods, a typical business cycle frequency range with quarterly data.[12] The estimated output gaps are typically in the range of $\pm$ 3 percent. Figure 1 plots the resulting new leading indicator I_t in levels against the output gap, expressed in percentages.[13] A rise (fall) in the leading indicator points to an improvement (deterioration) in the business climate.

**Figure 1: The Leading Indicator I_t and the Output Gap GAP_t, 1971:1 – 2000:4**
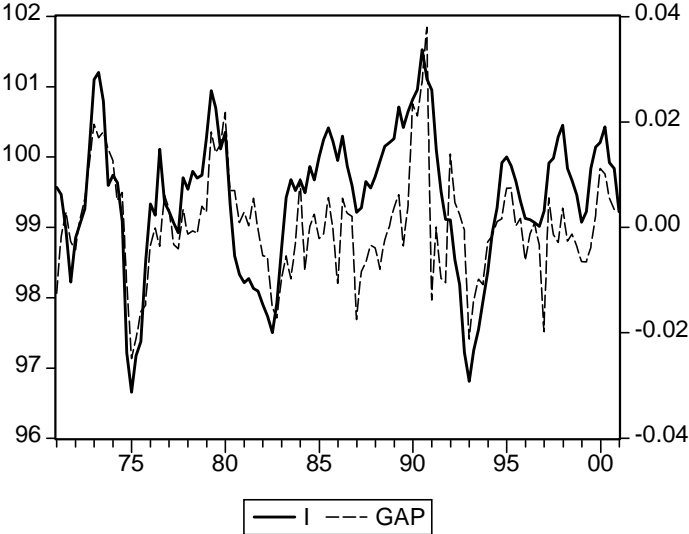
Notes: The output gap is measured in percent (right scale) and the leading indicator has been normalised to 100 in 1995:1 (left scale).

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[10] See Cogley and Nason (1995), Jaeger (1994) and King and Rebelo (1993). Pedersen (2001) has recently presented a procedure to determine the optimal value of the smoothing parameter in the HP-filter.
[11] Cogley and Nason (1995) argue that the resulting "stylized facts" are often rather "stylized artefacts" since they are merely the result of the filter and not the time series itself.
[12] See Christiano and Fitzgerald (1999) and Stock and Watson (1998). The HP-filter is an approximation to an ideal band-pass filter, though it has some leakage and compression, i.e. it passes (leaks) some frequencies which it was supposed to suppress, and it removes part of fluctuations which was supposed to pass the filter.
[13] Growth rates in this paper indicate changes compared to the corresponding quarter of the previous year.

German business cycles have not been regular, no two cycles are identical. The main movements were a trough in 1974/75 (following the first oil price shock), a peak in 1979/80, a trough in 1981/82 (after the second sharp rise in oil prices), a peak in 1990/91 (following the exceptional event German unification) and finally a trough in 1992/93. In recent years there is a tendency to observe lower amplitudes. Since the beginning of the 1970s, expansions (measured from trough-to-peak) have varied in length from 12 quarters to the about 32 quarters. Recessions (measured from peak-to-trough) have ranged from 6 quarters to 12 quarters. The deepest recessions were in 1974/75 and 1992/1993, when the output gaps were about 3 percent. Our main results with respect to the I_t variable can be summarised as follows. Most expansions and recessions have been correctly preceded by a rise or fall of our leading indicator. In other words, the index has done resonably well in forecasting the business cycle. This finding offers support for the reasonabless, reliability, and accuracy of the leading index forecasts.[14]

In Figure 2 our new leading index is depicted against the well-known business climate measures of the *Ifo-Institute for Economic Research* in Munich and the *Centre for European Economic Research (ZEW)* in Mannheim. Both indicators are based upon surveys, i.e. the approach is judgemental and the indexes do not have well-defined statistical properties. In addition, movements in the indicators do not lend themselves to a straightforward interpretation. Although the indicators may be easy to understand at a conceptual level, it is not entirely clear what they are actually measuring.

Figure 2: Alternative Leading Indicators of Economic Activity in Germany

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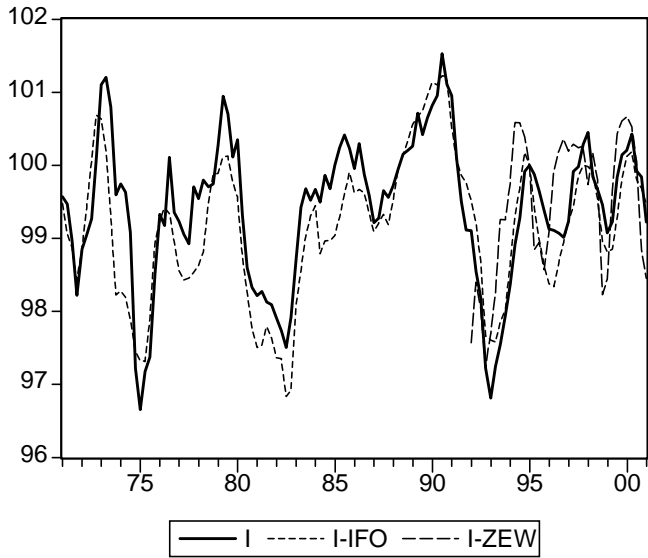
[14] A change in the direction of the composite leading index does not signal a cyclical turning point unless the movement is of significant size, duration and scope. The main value of the leading index is in signalling that either the risk of a recession has increased or that a recession may be coming to an end.

A visual inspection suggests that all three indices move together synchronously, i.e. they are characterised by a very similar fluctuating pattern. In particular, the similarity between the I_t and the *I-Ifo$_t$* indices is striking. In terms of explaining and forecasting, the "headline" *Ifo* survey measure therefore does not make a significant addition to the information already contained in the published new order and finished stock series.

Another index which has been pretty good at spotting turning points for the UK and the American economy is the so-called "*R*-word" index published by the *Economist* since 1992.[15] Using a computer database, the quarterly *R*-word index counts how many stories in British newspapers and in the *New York Times* and the *Washington Post* include the word "recession". An obvious advantage is that the index is instantly available. On the other hand when counting the word "recession" it is impossible to pin down to which country it refers. There is also no way to distinguish between different uses of the word "recession". This means that the *R*-word index is probably just a fun way of picking up the mood in an economy. But how does the index perform in Germany? Using the idea of the *Economist*, the *HypoVereinsbank* has recently constructed an *R*-word index for Germany counting the number of times stories appearing in the newspaper *Handelsblatt* mentioning the word "Rezession".[16]

The *R*-counts seems to be a coincident indicator which has spotted two of the three phases of slowdown since 1986, including the recession of 1992/93. On the other hand, the *R*-word index gave a clearly wrong signal after German unification and provided only a late signal of the recession 1992/93. In other words, the *R*-word index does not capture future economic activity in a timely manner. The poor performance of the "recession index" *I-R$_t$* is not puzzling: a priori we would have expected that this measure, which discards no new information, ought not outperform the other measures.

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[15] See *Economist*, 5 April 2001 and http://www.economist.com/displaystory.cfm?Story_ID=566293.
[16] See *HypoVereinsbank*, "Policy Watch Economics", 27 April 2001.

Figure 3: The Dynamic Factor Model Leading Index (I_t) and the R-Word Index (I-R_t)
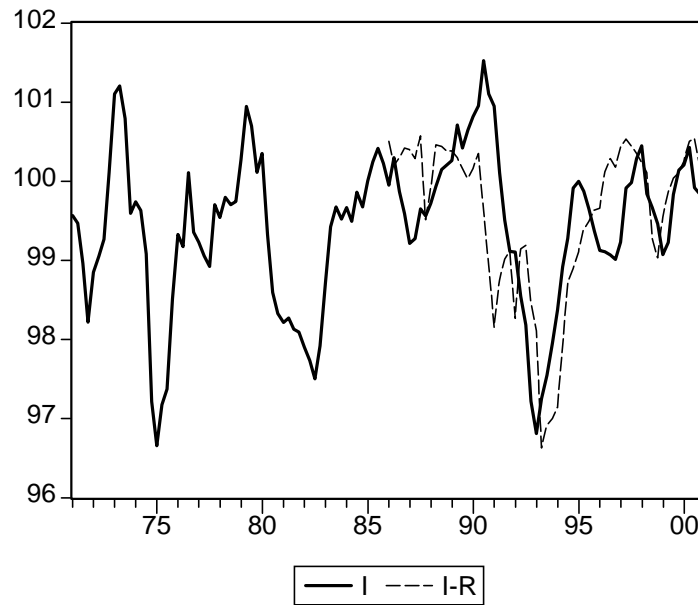
Ideally we should expect an acceptable leading indicator model to be a model which passes specification tests for structural stability. We have therefore reestimated I_t recursively starting in 1991:1.

Figure 4: Recursive Estimates of the Parameters, 1991:1 – 2001:1
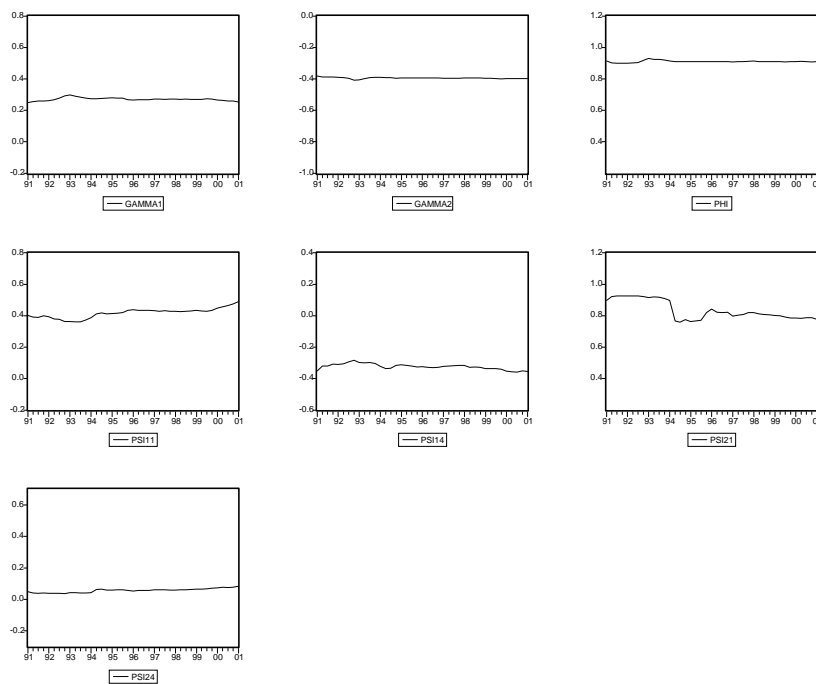
3. A Dynamic Markov Switching Factor Model

As far as the time pattern of the recursively estimated parameters is concerned, our estimation provides evidence of a consistent and hence quite robust behaviour over the period 1991:1 – 2001:1, as the "eye ball econometrics" evidence from Figure 4 shows. The above mentioned results suggest that the leading indicator already possesses two interesting properties, namely its seemingly acceptable forecasting properties and robustness to structural change in the sample. It seems therefore to pursue the analysis further, extending it to turning point predictions since it is well-known that leading indicators rarely succeed in predicting recessions. In order to calculate turning point predictions for our leading indicator we have augmented the dynamic factor model suggested above with a bivariate Markov switching model in the tradition of Diebold and Rudebusch (1996), Kaufmann (2000) and Kim and Nelson (1999).[17] In other words, for the purpose of forecasting expansions and recessions, we establish a procedure which translates movements in the leading indicator into a signal about future turning points in economic activity. We again consider the model in deviation from mean form. The mean growth rate of the leading index now depends upon an unobserved dichotomous latent state variable S_t taking values according to a first-order Markov chain. Formally, the above model is altered as follows:

(9) $\qquad y_{1t} = \gamma_1 i_t + e_{1t}$

(10) $\qquad y_{2t} = \gamma_2 i_{t-1} + e_{2t}$

(11) $\qquad \left(1 - \phi L\right)\left(i_t - \mu_{S_t}\right) = \omega_t \qquad\qquad \omega_t \sim i.i.d.\ N\left(0,1\right)$

(12) $\qquad e_{it} = \psi_{i,1} e_{i,t-1} + \psi_{i,4} e_{i,t-4} + \varepsilon_{it} \qquad\qquad \varepsilon_{it} \sim i.i.d.\ N\left(0,\sigma_i^2\right) \qquad i=1,2$

(13) $\qquad \mu_{S_t} = \mu_0 + \mu_1 S_t \qquad\qquad\qquad S_t = \{0,1\},\ \ \mu_1 > 0$

(14) $\qquad \Pr[S_t = 1 \mid S_{t-1} = 1] = p\ , \qquad \Pr[S_t = 0 \mid S_{t-1} = 0] = q$

where *L* is the lag operator. A state-space representation is given by:

$$(15) \quad \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \gamma_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_2 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \end{pmatrix}$$

$$i_t = H^* \beta_t^* \qquad\qquad\qquad\qquad \text{[Measurement Equation]}$$

$$(16) \quad \begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \end{pmatrix} = \begin{pmatrix} \mu_{S_t} - \phi \mu_{S_{t-1}} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} \phi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_{11} & 0 & 0 & \psi_{14} & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & 0 & 0 & \psi_{24} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} i_{t-1} \\ i_{t-2} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{1,t-4} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \\ e_{2,t-4} \end{pmatrix} + \begin{pmatrix} \omega_t \\ 0 \\ \varepsilon_{1t} \\ 0 \\ 0 \\ 0 \\ \varepsilon_{2t} \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\beta_t = R_{S_t}^* + F^* \beta_{t-1}^* + v_t \qquad\qquad\qquad \text{[Transition Equation]}$$

To make the turning point model tractable, the econometrician must specify a stochastic process for the state variable S_t. The above model assumes that two different regimes exist in the data-generating process characterised by either expansions ($S_t = 1$) or recessions ($S_t = 0$), and that the process is subject to discrete (sporadic) regime shifts governed by a two-state Markov process. This feature of regime-dependence implies that the model is able to mimic the asymmetric behaviour of

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[17] Neftci (1982) was the first to develop a statistical methodology to transfer movement in the composite leading indicator into a measure of the probability of a cyclical turning point. The BDS tests in Table 1 provide some empirical evidence in favour of such a nonlinear specification.

macroeconomic variables over the business cycle we often observe. The mean parameter $\mu_{S,t}$ refers to the Markov switching deviation of the leading indicator from its long run growth rate δ. The probability of being in each state is determined by the transition equation (14). The calculated probability can therefore be viewed as a direct prediction of the underlying state of the economy in the near future. To estimate the model, it is necessary to make inferences about both the unobserved common factor and the latent Markov state. Hamilton´s (1989) paper popularised the use of bivariate Markov regime switches, but the methodology precludes the estimation of multivariate unobservable dynamic models. On the other hand, the dynamic factor models proposed by Stock and Watson (1989, 1991) is governed by a linear stochastic process and can therefore be estimated using the Kalman filter. The nonlinearity in the transition equation of the model given by (9) to (16), however, implies that the usual Kalman filter cannot be applied directly. The following estimation procedure therefore consists of a combination of Hamilton´s (1989) algorithm and a nonlinear version of the Kalman filter, as proposed by Kim (1994). This permits estimation of the unobserved factor as well as the probabilites associated with the latent Markov state. Kim (1994) also provides a fast approximation algorithm for the full sample smoother which substantially reduces computational time.[18] Table 2 contains information on how well the augmented model fits the historical data.

The empirical results provide support for the two-state Markov switching model. Note first that many of the same patterns observed in Table 1 are also present in Table 2. There is a significantly positive growth rate in state 1 and a significantly negative growth rate in state 0. The estimated transition probabilities are highly significant and the probability of staying in expansion, p, is higher than the probability of staying in a recession, q. This confirms previous findings that the average duration of expansions is larger than the duration of recessions. The reason is that the occurence of recessions is irregular, which means that expansions usually last longer than contractions. The expected duration for expansion [$1/(1-p)$] and recession [$1/(1-q)$] implied by the model is 20.75 and 6.01 quarters, respectively.

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[18] An inuituve explanation of the computational burden is the following. Each iteration of the Kalman filter produces a twofold increase in the number of cases to be considered. Since S_t takes on two possible values in each time period, there would be 2^T possible paths to consider in evaluating the conditional log likelihood [see Kim (1994)].

Parameters	Estimates	Asymptotic t-values
γ_1	0.180	5.8
γ_2	-0.296	12.7
μ_0	-1.743	4.9
μ_1	0.475	3.8
ϕ	0.828	19.0
ψ_{11}	0.532	6.5
ψ_{14}	-0.366	4.9
ψ_{21}	0.828	13.8
ψ_{24}	0.099	4.1
p	0.952	33.5
q	0.834	10.1
σ_1^2	0.323	7.5
σ_2^2	0.0001	0.00
Log-Likelihood	-72.978	

Figure 5 plots the composite leading indicators implied by the dynamic factor model without (I_t) and with ($I\text{-}MS_t$) Markov switching, respectively. Both indices show a very similar pattern regarding amplitude, timing, and duration of fluctuations. Another graphical way of evaluating the two series is the scatter diagram in Figure 6. If I_t and $I\text{-}MS_t$ were exactly the same, they would lie on the 45-degree line shown. As Figure 6 shows, the leading indicators were quite close. However, there seems to be a tendency that more points lie above the 45-degree line. This indicates that $I\text{-}MS_t$ forcasted on average slightly higher gaps than did I_t. Contemporaneous correlation between the two series is 0.9813.

Figure 5: The Leading Indicators with ($I\text{-}MS_t$) and without Markov Switching (I_t)
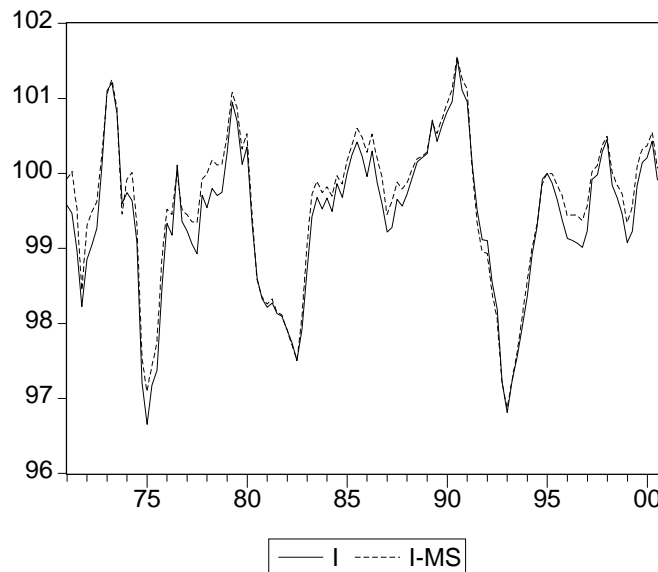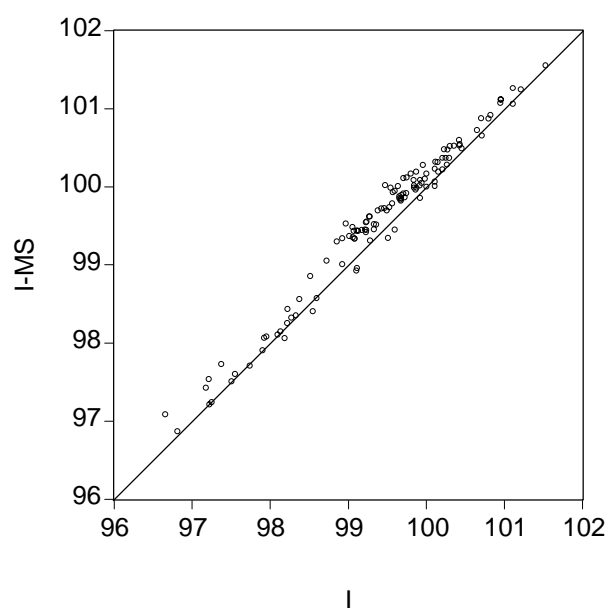

15

**Figure 6: Leading Indicators I_t and $I_{t,MS}$**

Next we have calculated the posterior recession probabilities from the Markov switching model. Figure 7 depicts the probability that the German economy was in the recession regime. The general impression is that the posterior recession probabilities (right scale) are in close agreement with the German business cycle when the cut-off rate is set to 0.50, i.e. any probability that exceeds 0.50 is counted as a signal for a recession. How can the empirical results be interpreted? As shown in Figure 7, our leading indicator correctly pointed to storm after the first and the second oil price shock and anticipated the recession in 1992/93. Another interesting feature is that the "mini-recessions" of 1995/96 and 1998/99 are not classified as "regular" recessions. Thus, overall the *I-MS$_t$* leading indicator appears to score relatively well in forecasting German business cycles and therefore the *I-MS$_t$* decision rule approach is a promising development.[19] Finally, at the end of the sample period the recession probability started to turn up. This "downside" risk suggests a (mild?) slowdown in 2001/2002. In other words, Germany may face a recession – or a mere pause.[20]

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[19] This result confirms the results in Kim (1994) and Hamilton and Pérez-Quiros (1996) who have presented evidence for the predictive power of the composite indicator model.

[20] The interpretation of this signal is, however, difficult because the "New Economy" may have created a new kind of business cycle. Greater vigilance from central banks, globalisation and deregulation has helped to hold down inflation. The traditional trigger of recession, therefore has not been pulled. As a result, the expansion has endured for longer than usual. The obvious snag is that longer periods of expansion allow various sorts of imbalances – notabably, personal and corporate debt, soaring asset prices, and overinvestment – to build up instead.

Figure 7: Recession Probabilities (Right Scale) and the Output Gap (Left Scale)
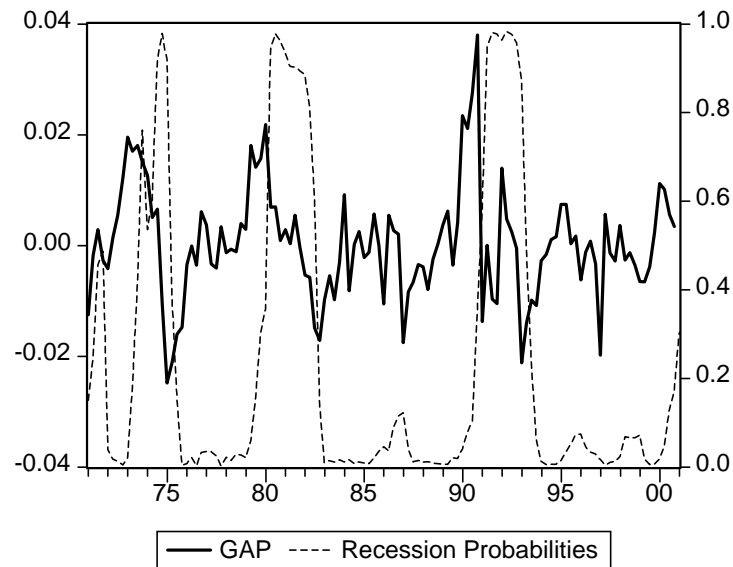
The evidence presented so far, only proves one thing: from an ex-post point of view the dynamic factor Markov switching model correctly anticipates recessions. Although this result is encouraging, we should not forget that there is a growing consensus in the recent forecasting literature that the in-sample evaluation of leading indicators is likely to be misleading in analysing the predictive power of an indicator time series. In other words, forecasters agree that forecasting methods should also be assessed for accuracy using out-of-sample tests rather than in-sample tests since the performance of models on data outside that used for estimation remains the touchstone for its utility in applications. Hence, we have re-estimated the model recursively starting in 1990:4. This procedure is designed to reproduce the reality that forecasters have data only up to the starting point of their forecast. Moreover, tracking the performance of the Markov switching indicator in different years allows us to assess the robustness ot its forecasting power. The graphs in Appendix A show the probabilities of a recession given by the recursive estimates as well as the full sample results. For example, consider the recession probability in 1992:2. To compute this probability, the model is estimated using data through 1992:2, at which point the leading indicator is calculated. Moving forward two quarters, the coefficients are recalibrated using data through 1992:4 and the next leading indicator is computed. This procedure generates a series of "real-time" leading indicators. One feature is particularly noteworthy. The recursively estimated real-time recession indices nearly match the full-sample results, i.e. it makes very little difference to the prediction of turning points when real-time data are used.

4. Non-Nested Tests

Indeed, when two or more leading indicators are under consideration, it is a common approach to attempt to reject one model in favour of another. In other words, in this section we would like to evaluate, in a systematic manner, the forecasting performance of different leading indicators. To test whether I_t, $I\text{-}MS_t$ and/or other leading indicators have leading indicator properties for the business cycle we first test for Granger causality, i.e. we test whether past values of the output gap along with the leading indicators better "explain" the cyclical movement of GDP than past values of the output gap (GAP_t) alone. This of course does not imply that the leading indicators cause GAP_t. instead it is possibly reflecting expectations as to where GDP might be headed. In assessing the leading indicator properties, the Granger causality test can be supplemented by non-nested tests. Such tests can be used to evaluate whether a candidate variable gives a useful contribution in forecasting, relative to a variable chosen as a benchmark. We first specify dynamic equations linking the output gap to the respective leading indicator variable. A conventional general to specific testing-down procedure was followed until parsimonious equations for the rate of inflation were achieved. The resulting OLS results are reported in Table 3 below. As many other researchers, we have found that the lagged output gaps helps to explain variations in economic activity. This result confirms the presence of inertia and/or duration effects in the growth pattern of economic activity. After the testing down procedure, we are therefore left with four rival statistically significant leading indicators. The next step is to investigate whether any of these measures is superior in predicting the quarterly output gap. A straightforward procedure is to adopt non-nested tests to discriminate among the alternative gap measures.[21] Alternative pairwise non-nested tests are reported in Table 4 and 5 below. The non-nested tests are referred to as Cox´s (1961) and Pesaran´s (1974) *N*-test, Davidson and MacKinnon´s *J*-test and Godfrey and Pesaran´s (1983) *W*-test.[22] All tests are null hypothesis specific. The null and alternative hypothesis must be reversed and the test repeated for the results to be conclusive. Thus it is perfectly possible, that both H_0 and H_1 are accepted, or that they are both rejected. If neither model is accepted (rejected), the test is inconclusive, meaning that the data do not allow discrimination between the two competing hypothesis.

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[21] In appraising the comparative performance of the various leading indicators, it must be borne in mind that they are not made at precisely the same times, and therefore the information set available to the forecasters is not identical. This also opens up the possibility of "herding behaviour", i.e. the first published leading indicator can exert a direct influence on later survey measures. See Trueman (1994), for example.

[22] Godfrey and Pesaran (1983) have shown that the traditional Cox-test overrejects in small samples. This led them to derive a modified version of the Cox-statistic which is used in this paper. Both statistics have the same asymptotic properties, so no ambiguities should arise.

Table 3: Baseline Models for the German Output Gap

Regressor	(a)	(b)	(c)	(d)
Constant	-0.418	-0.372	-0.359	-0.252
	(4.6)	(4.2)	(4.2)	(2.3)
GAP_{t-1}	0.369	0.411	0.437	0.383
	(4.0)	(4.6)	(5.0)	(3.0)
GAP_{t-4}	-0.151	-0.152	-0.121	-0.222
	(2.1)	(2.1)	(1.7)	(1.6)
I_{t-1}	0.004	-	-	-
	(4.7)			
$I\text{-}MS_{t-1}$	-	0.004	-	-
		(4.2)		
$I\text{-}Ifo_{t-1}$	-	-	0.004	-
			(4.2)	
$I\text{-}ZEW_{t-1}$	-	-	-	0.003
				(2.3)
Diagnostics:				
Sample Period	1971:2-2000:4	1971:2-2000:4	1971:2-2000:4	1992:2-2000:4
R^2	0.49	0.47	0.47	0.44
LM(1)	0.26	0.02	0.62	1.99
	(0.61)	(0.88)	(0.43)	(0.16)
LM(8)	14.3	12.88	12.18	7.39
	(0.07)	(0.12)	(0.14)	(0.50)
RESET	0.48	0.283	0.18	0.02
	(0.49)	(0.59)	(0.67)	(0.89)
JB	45.15	52.79	88.51	39.93
	(0.00)	(0.00)	(0.00)	(0.00)

Notes: All equations have been estimated by OLS. The dependent variable is GAP_t. t-values in parentheses; R^2 denotes the coefficient of determination; LM(n) denotes the Lagrange Multiplier test for nth-order serial correlation; JB is the Jarque-Bera test for residual normality. RESET is the RESET test (using the squared predictions) for omitted variables and incorrect functional form. The p-values are given in parentheses. The $I\text{-}R_t$ indicator has not been considered because it turned out to be a coincident or even lagging indicator of economic activity.

Table 4: Non-Nested Tests of I_t versus $I\text{-}Ifo_t$ (1972:1-2000:4) and $I\text{-}ZEW_t$ (1992:2-2000:4)

Test Statistic	I_t versus $I\text{-}Ifo_t$	$I\text{-}Ifo_t$ versus I_t
N	-0.88	-2.56
	(0.38)	(0.01)
W	-0.75	-2.25
	(0.45)	(0.02)
J	0.80	2.08
	(0.42)	(0.04)
Schwarz´s *BC* criteria I_t vs. $I\text{-}Ifo_t$ = 1.88 favours I_t		
Test Statistic	I_t versus $I\text{-}ZEW_t$	$I\text{-}ZEW_t$ versus I_t
N	-0.005	-4.26
	(0.99)	(0.00)
W	0.13	-2.91
	(0.89)	(0.004)
J	0.04	2.52
	(0.99)	(0.01)
Schwarz´s *BC* criteria I_t vs. $I\text{-}ZEW_t$ = 3.37 favours I_t		

Table 5: Non-Nested Tests of $I\text{-}MS_t$ versus $I\text{-}Ifo_t$ (1972:1-2000:4) and $I\text{-}ZEW_t$ (1992:2-2000:4)

Test Statistic	$I\text{-}MS_t$ versus $I\text{-}Ifo_t$	$I\text{-}Ifo_t$ versus $I\text{-}MS_t$
N	-1.67	-1.93
	(0.10)	(0.05)
W	-1.44	-1.68
	(0.15)	(0.09)
J	1.41	1.60
	(0.16)	(0.10)
Schwarz´s *BC* criteria $I\text{-}MS_t$ vs. $I\text{-}Ifo_t$ = 0.30 favours $I\text{-}MS_t$		
Test Statistic	$I\text{-}MS_t$ versus $I\text{-}ZEW_t$	$I\text{-}ZEW_t$ versus $I\text{-}MS_t$
N	-0.19	-3.30
	(0.85)	(0.001)
W	-0.03	-2.30
	(0.97)	(0.02)
J	0.17	2.09
	(0.86)	(0.04)
Schwarz´s *BC* criteria $I\text{-}MS_t$ vs. $I\text{-}ZEW_t$ = 2.36 favours $I\text{-}MS_t$		

Notes: *p*-values are given in parentheses. The decision rule always is to reject H_0 in favour of H_1 for large values of the test statistics. The different sample periods are given in the headline.

What does our analysis reveal about the predictive power of the various indicators? Overall, the pairwise non-nested test statistics do establish the dominance of I_t and $I\text{-}MS_t$, i.e. our measures appear to have greater predictive value than do the alternative leading indicators $I\text{-}IFO_t$ and $I\text{-}ZEW_t$. [23] Our (necessarily tentative) conclusion therefore is that our leading indicators do better at tracking the German business cycle than either of the alternatives. There is therefore good reason to be wary of placing too much confidence in forecasts of economic activity that rest on survey climate indicatos like *I-Ifo* or *I-ZEW*.

5. Conclusions

Both policymakers and the private sector maintain a keen interest in understanding the state of business affairs and the most likely path the economy will take over the near future. In this paper we have therefore constructed a composite leading economic indicator of economic activity in Germany using the dynamic factor modelling approach over the 1971-2001 period. In order to refine our forecast of future recessions and expansions, we then outlined a methodology for the construction of a recession and expansion index. The historical performance of our indices suggests that the information they convey about the timing and the likelihood of a recession or expansion shows great promise and represents an improvement over the information offered by other "headline" survey measures which are closely monitored by the financial and popular press. Another advantage of our methodology is that forecasts can be made quickly and are based on a small set of series only. Such assessment should of course trigger further research, part of it being quite straightforward, namely a comparison exercise for Euroland. We leave this topic for future research.

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[23] It is worth mentioning that in evaluating the *ZEW* survey indicator caution is in order because the sample period used for the non-nested tests is relatively short, due to the short history of the *ZEW* indicator on which inference can be drawn.

Appendix A: Full-Sample and Real-Time Recession Probabilities for the Dynamic Markov Switching Factor Model
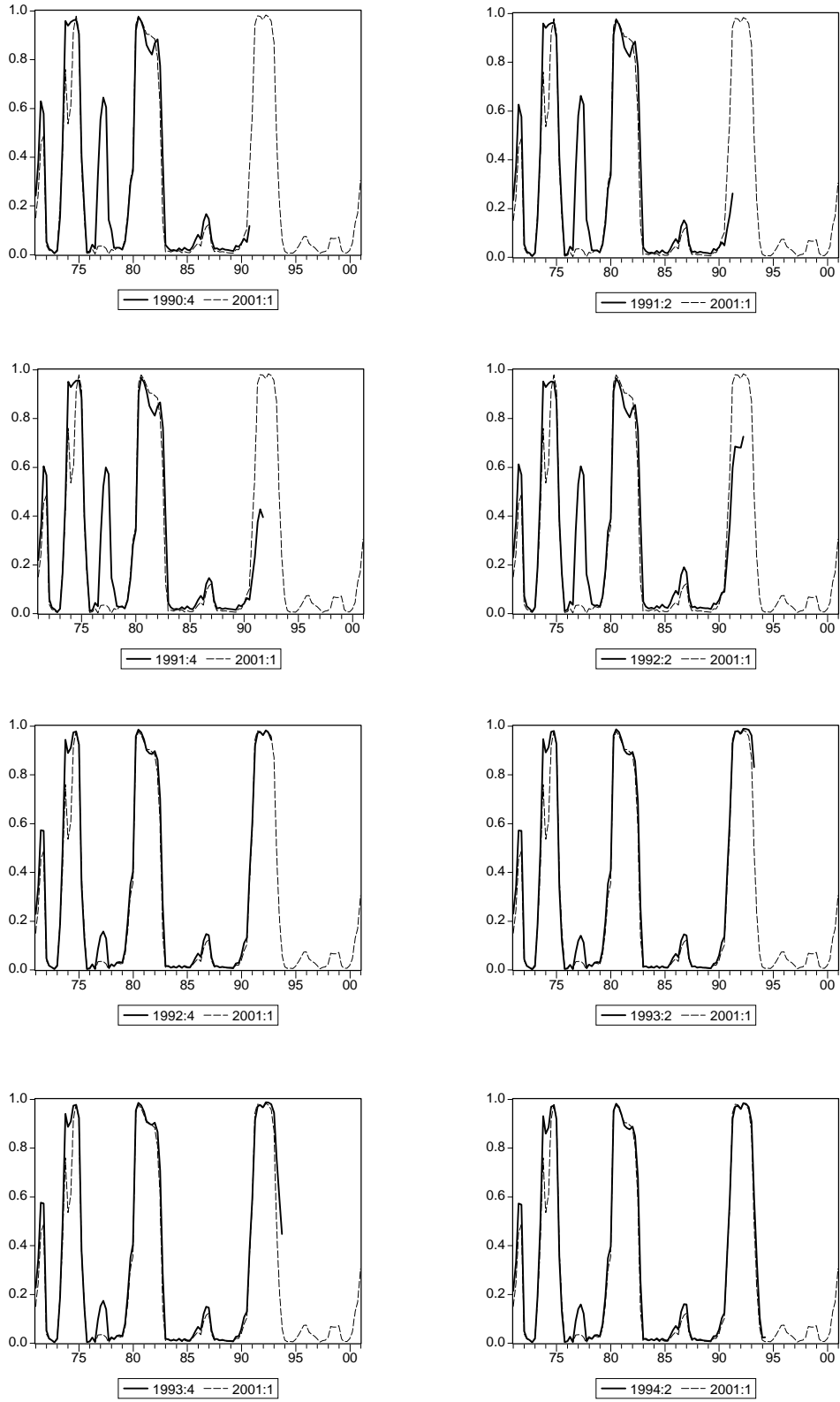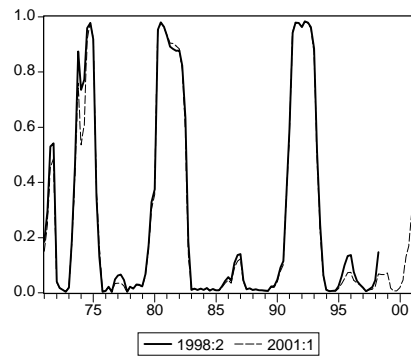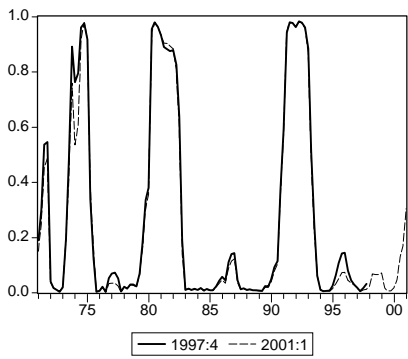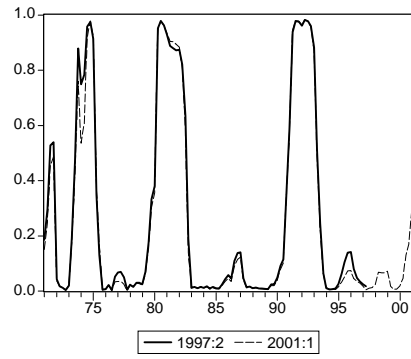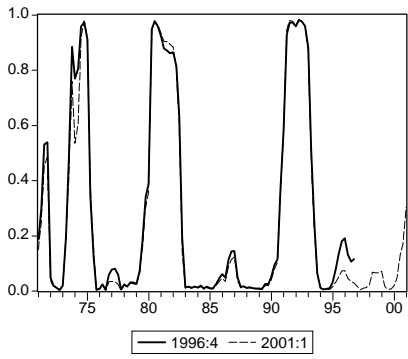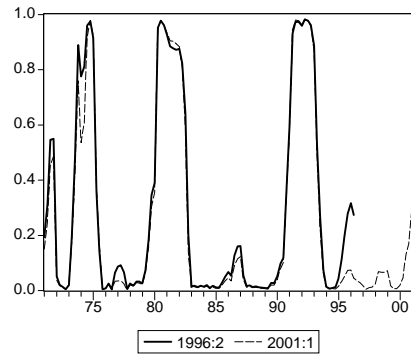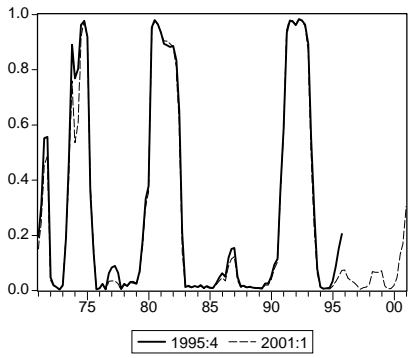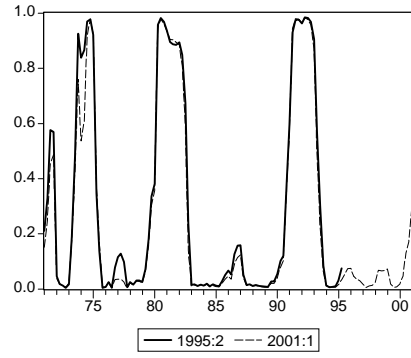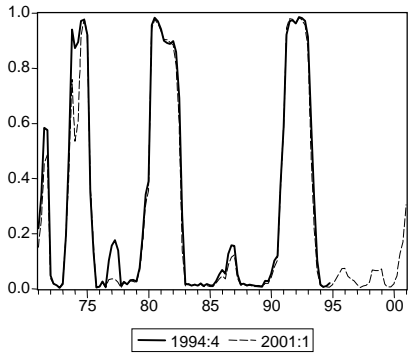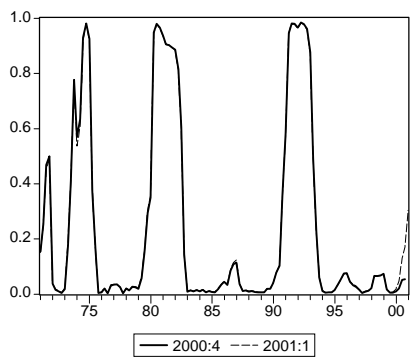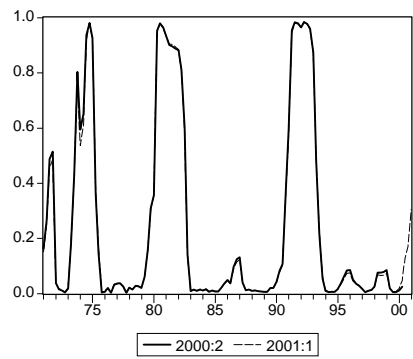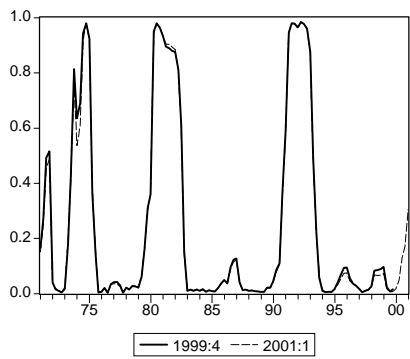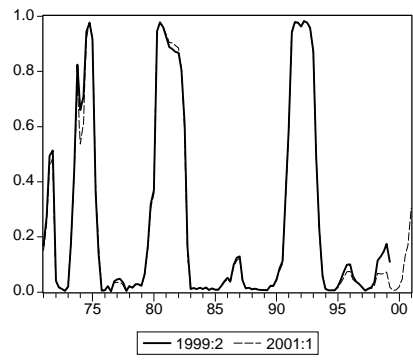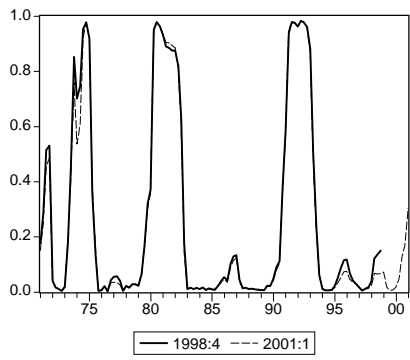
Appendix B: Data Used

Time series for unified Germany exist only as of 1991. We have therefore joined the two series (pan-German, West German) after having re-scaled the "old historical" data to the "new" German series. In addition, due to the recent changeover to ESA95, it was necessary to backdate the National Account series. The "old" series were re-based and joined to the "new" series, applying the same method used to overcome the German unification problem. All series were seasonally adjusted (if necessary) using X12. Quarterly data are simple averages of monthly data.

Time Series	Details and Source
New Orders Manufacturing (Index 1995 = 100)	Source: Statistisches Bundesamt, Fachserie 4
Finished Goods Stock Level (% Balance)	Source: Ifo-Institute (Munich); the survey measure (published monthly) is presented in the form of the difference (hence the term balance) between the percentage of firms which have noted an increase an those which have reported a decrease of finished goods stock levels.

Only finally revised data have been used for the estimates. Therefore, the exercise is a "pseudo" forecasting exercise because, strictly speaking, due to subsequent revisions the data used here were not available to a "real time" forecaster.[24]

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[24] The GDP and therefore the output gap measure is normally more affected by frequent revisions, while the two variables used to construct the leading indicator are the subject of infrequent, but perhaps larger, changes in definitions and classifications. GDP growth is often overstated at first when an economy slows sharply. This is because initial GDP numbers includes estimates for some components of GDP that are derived by extrapolating recent trends.

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