Markov-Switching and the Ifo Business Climate: The Ifo Business Cycle Traffic Lights

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Abstract

Business cycle indicators are used to assess the economic situation of countries or regions. They are closely watched by the public, but are not easy to interpret. Does a current movement of the indicator signal a turning point or not? With the help of Markov Switching Models movements of indicators can be transformed in probability statements. In this article, the most important leading indicator of the German business cycle, the Ifo Business Climate, is described by a Markov Switching Model. Real-time probabilities for the current business-cycle regime are derived and presented in an innovative way: as the Ifo traffic lights.

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Keywords: Ifo business climate, growth cycle, turning points, Markov-switching.

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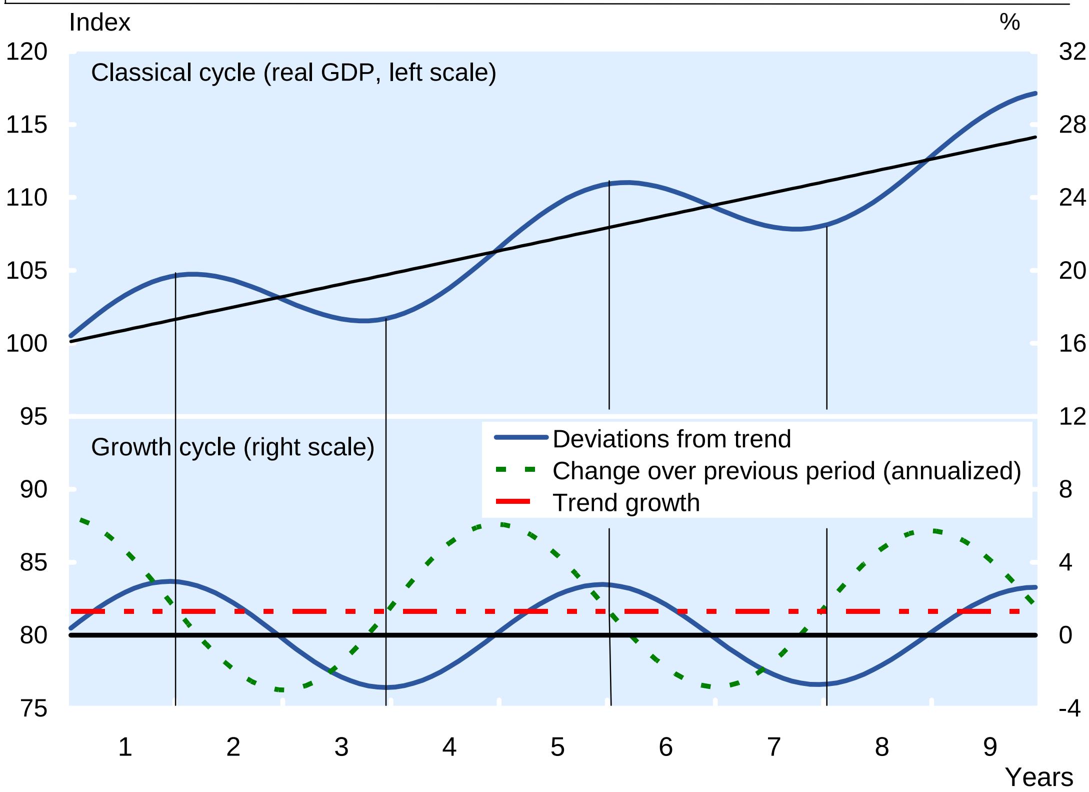
Introduction

Business cycles in market-economic systems are fluctuations of the utilisation rates of the aggregate output potential (growth cycles). Every cycle consists of one upswing and a downturn phase, with the individual phases being connected to each other by lower and/or upper turning points (see Maußner, 1994 or Zarnowitz 1992). Upswing phases are characterized by the growth rate of the aggregate output over the previous period above that of the production potential (increasing capacity utilisation); downturn phases contain phases with completely sinking production activity as well as phases with increasing production activity at a below-average rate, measured in terms of the potential rate (decreasing capacity utilisation). Thus, upper turning points are where the utilisation rate has a local maximum; lower turning points are where the utilisation rate has a local minimum. Unlike the classical cycle, which is defined as fluctuations of the level of the aggregate output, in the growth cycle a downturn phase does not begin only when the growth rate is negative but when it falls under the rate of potential growth. If one interprets the trend value of real GDP as a non-structural estimate of the production potential, business cycles can be equivalently measured by the deviations of GDP from the trend (output gap). The turning points are marked by the maximum distance of GDP from its trend value (see Fig. 1).

Business cycle indicators are meant to accurately display or forecast the cyclical economic activity especially at the turning points. They can be classified according to their chronological relationship to the respective business-cycle reference series at leading, coincident and lagging indicators. Of special importance are, of course, the leading indicators. Various organizations and institutions develop and publish indicators for the economic situation in specific countries, in regions or for the world economy. Among these institutions is for example the OECD, which publishes indicators for regions and countries, the Conference Board, which publishes indicators especially for the US economy, the Bank of Japan, conducting the Tankan survey and the European Commission, which provides indicators for the European economy. The indicators are widely used by professional forecasters (see Carnot, et al., 2005), but all these and many more indicators are also well known und closely watched by the public and by governments. The indicators are usually not easy to interpret for policy makers, though. This is especially true in real time. This is the point, at which the present article sets in. The aim of this work is to show that modern econometrics can help to transform the indicators in such a way that users of such indicators are supported by the assessment of indicator movements.

Fig. 1

Classical cycle (example: four year sine-wave fluctation of real GDP around a linear trend) and growth cycle



In the following the German business cycle is analyzed. Germany is the biggest economy within the eurozone. It is also a very open economy. So the German business cycle is important not only for the Germans but also important for Europe and beyond. An especially prominent leading indicator for the business cycle in Germany is the *Ifo Business Climate for industry and trade* (aggregated results for the sectors manufacturing, construction, wholesaling and retailing). It is computed as a geometric means according to the formula $[(GL + 200)(GE + 200)]^{1/2} – 200$, in which GL designates the percentage balances from the positive and negative responses of the *current business situation* and GE the percentage balances from the positive and negative responses to the *business outlook in the next six months*.[1] With the geometric means, the outliers, in cases of the extreme values, are slightly dampened in comparison with arithmetic means.

In many studies the forecasting qualities of the Ifo Business Climate have been examined (see Abberger and Wohlrabe 2006). Abberger and Nierhaus (2009) showed that there is strong signal

[1] To avoid negative values in the root, the variables GL and GE are increased by the constant of 200.

in the month-to-month changes of the indicator. They calculated the so-called Months for Cyclical Dominance Measure (MCD), which confirms the quality of the Ifo Business Climate as a valuable indicator. A special role in business cycle analysis is assigned to a timely and reliable recognition of cyclical turning points, which is where the Ifo Business Climate performs well. It is able to detect turning points in the growth cycle reliably and with a statistically significant lead of 1.3 quarters (see Abberger and Nierhaus 2007). In order to evaluate the quality of indicators, as a rule historical time series are employed and the turning point behaviour observed. In this way important information is gained on the qualities and reliability of indicators, which is also helpful in business cycle analysis in practice. In the actual cyclical analysis, the researcher must always assess whether a movement of a current indicator value already indicates a regime change and thus a cyclical turning point, or whether the movement is still in accord with the current regime. For this decision the estimating results from Markov Switching Models can supply important additional information. The calculations lead to probability estimates for the different regimes. Unlike a purely visual analysis or an evaluation with other models, the adaptation of the Markov Switching Models produces probability statements on whether the economy is in an upswing or in a downturn phase.

The Markov approach

In modern economic statistics, non-linear time series methods are increasingly being used for modelling structural breaks and regime-dependent dynamics, an important example of which is Markov Switching Models (MS models) based on the pioneering work of Hamilton (1989) as well as Goldfeld and Quandt (1973). Other non-linear time series methods also exist, for example Threshold Models (TAR) or Smooth Transition Autoregressive Models (STAR) (see Potter 1999, for a nice introduction). In general it is not clear whether allowing for non-linearities improves out-of-sample forecast performance, as documented by Stock and Watson (1999). However, forecasting is not the purpose of the present paper. The aim of this study is to find a transformation of the indicator movements to probabilities. That makes the interpretation of indicators much easier. This transformation can be done with the MS models, which in contrast to other models explicitly estimates conditional regime probabilities.

In the following, the Ifo Business Climate for German industry and trade will be modelled using an MS approach. Concretely, the first differences $\Delta y_t = y_t - y_{t-1}$ of the business climate index depending on a non-observable status variable s_t is modelled, which is designated as the status or regime at point-of-time t (t = 1, …, T; time variable). The modelling of the first differences implies that the change of the business climate is observed. The assessment is to be made of whether a movement of the business climate speaks for a regime change or whether it is in accord with the current regime. If the economy is in an upswing phase, for example, a falling business climate can still be in the normal fluctuation area and thus in accord with the upswing regime. It can also already signal a regime change, however. To help in making precisely this assessment we employ the MS model.

The number of cyclical regimes in this study is limited to two. For $s_t = 1$, status 1 applies (increasing business climate index, on average), which here is equated with the upswing; for $s_t = 2$, status 2 applies (falling business climate, on average; downturn). The probability with which the regime changes from one period to the other period (or remains in one) is assumed to be time-invariant and depends only on the state of the previous period s_{t-1}

$$p(s_t = i \mid s_{t-1} = j) = p_{ij}; \quad i, j = 1,2 . \tag{1}$$

With a Markov process with two states, there are a total of four transitional probabilities. For these $p_{11} + p_{12} = p_{22} + p_{21} = 1$ applies; the status variable s_t thus follows a Markov process of the first degree. The distribution of Δy_t (with a given state of i) is described by the density function

$$f(\Delta y_t \mid s_t = i, \mu_1, \sigma^2) = 1/(2\pi\,\sigma^2)^{1/2} \exp[-(1/2)(\Delta y_t - \mu_1)^2/\sigma^2] \tag{2}$$

i.e., Δy_t is normally distributed with a state-dependent mean value μ_1 and constant[2] variance σ^2. The above conditional density holds for state 1. For state 2 the same equation applies, but with μ_2 instead of μ_1 and $\mu_2 \neq \mu_1$.The vector of the total parameters to be estimated is $\theta := (p_{11}, p_{22}, \mu_1, \mu_2, \sigma^2)$.[3] The model can be estimated with the maximum-likelihood method, in which in the calculation practice numeric optimisation methods are employed due to non-linearities (see Krotzing and Luetkepohl 1995, 180f.).

At the same time, the procedure supplies, in addition to estimations of the parameter vector θ, also a quantification of regime probabilities depending on the amount of information considered in each case: The expression $p(s_t = i \mid I_T)$ designates the conditional probability of being at point t in regime i, in the case that the entire amount of information is conditioned (smoothed probability) in estimation period [1,…,T] of the MS model.[4] The expression $p(s_t = i \mid I_t)$, on the other hand, describes the conditional probability for state i, in the case that the focus is only on the amount of information available up to the calculating period t (filtered probability). The latter is especially interesting in terms of real-time aspects. For the final point-of-time T, the filtered value corresponds to the smoothed value. The smoothed probabilities are particularly suitable for examining the dynamics of the examined time series ex post. In this way, in retrospect and using the entire amount of information, regime changes can be reliably dated, since up to the edge of the time series, at all points of time both the past and the future are

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2 The modeling of the variance can also be done in dependence of the state. This generalization is not necessary however for the present application.

3 The probability p_{12}, which is also unknown and to be estimated, follows from the relationship $1 - p_{11}$; the probability p_{21} from $1 - p_{22}$.

4 For $t < T$ this thus also contains information from time window $(t < k \leq T)$.

known in the calculations. The situation in which the business-cycle forecaster finds himself, on the other hand, is stimulated in the filtered probabilities. Over the entire period under investigation, only the data from the past flow into the calculation of the status probabilities.[5] This increases the insecurity in assessing in what regime the process finds itself. Precisely in this situation the Markov Switching Models can provide additional assistance in deciding.

Apart from the basic Markov Switching Model presented above, various extensions have been suggested. Thus it is possible to introduce switching or non-switching independent variables including lagged terms of the dependent variable. Also the regime probabilities can be modelled more sophisticated (see Diebold, Lee and Weisbach, 1994). Since the aim of this study is to give additional information for the interpretation of an indicator, in our case the Ifo Business Climate, in the following only lagged terms of this indicator are considered as possible additional independent variables.

Leads and signal strength at cyclical turning points

In the following we deal in more detail with the estimation results for the *smoothed* regime probabilities of the Ifo Business Climate at cyclical turning points in the period 1970 to 2008. As a cyclical reference series, quarterly real GDP is used. For the necessary elimination of the seasonal component, the Census-X12-ARIMA procedure was selected. Since official GDP figures before 1991 are only available for West Germany, the lacking all-German values have been generated by a corresponding linking of western and all-German time series values.[6] For the extraction of the cyclical component of real GDP, the well-known Baxter-King filter was used. The Baxter-King filter is a symmetrical filter that removes not only the low-frequency trend component from a time series but also the high-frequency irregular component (see Baxter and King 1999). In order to apply the filter also at the edges, additional series values were generated at the beginning and at the end of the GDP series. The “backcasts” and “forecasts” were made with the help of auto-regressive models (ARs); the lag lengths were chosen automatically using the Akaike information criterion (AIC). For the cycle the sum of all components of the time series with oscillations between 6 and 32 quarters (=1.5 to 8 years) was applied; the length of the Baxter-King filter is twelve quarters (= three years). These settings correspond to the recommendations typically made in the literature for an optimal filter in practice. The dating of the cyclical turning points of real GDP was done using the algorithm developed by Bry and Boschan at the National Bureau of Economic Research (NBER), which

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5 This however applies only for the adaptation of the state probabilities. For the estimation of the parameter values $\mu_1$and σ^2, the entire information is used.

6 The missing all-German GDP values for the time-span 1970 to 1990 were generated by applying a recursive rule starting with all-German real GDP in the fourth quarter of 1990: $GDP_{1990|4}$ = $GDP(West)_{1990|4}/GDP(West)_{1991|1}*GDP_{1991|1}$ Historic GDP data was taken from the Federal Statistical Office (Destatis), Fachserie 18, Series 1.3 and Series S 28.

has received the greatest worldwide acceptance (see Bry and Boschan 1971). The procedure, after a sequential decision-making process, supplies a complete dating of the cyclical turning points in the period under observation. For the turning-point dating according to Bry-Boschan, the EU software tool BUSY (Release 4.1) was used, which was set with the usual standard options for the minimum phase length (three quarters) and the minimum cycle duration (five quarters) (see Fiorentini and Planas 2003).

The regime probabilities of the Ifo Business Climate for industry and trade were estimated with the help of the econometric software tools (Grocer Version 1.3.3) and Scilab (Version 5.1.1).[7] Grocer uses a Gauss routine developed by Bellone (MSVARlib) (see Bellone 2005). Since the results of the National Accounts for real GDP are only made available quarterly (and not monthly as the Ifo Business Survey), the monthly results of the Ifo Business Climate for industry and trade had to be combined into quarterly values for the sake of comparability. Furthermore, all business climate values were seasonally adjusted using the standard Ifo ASA II procedure in order to guarantee full compatibility with Ifo's regularly released business cycle data.

Real GDP filtered according to Baxter-King had a total of 17 turning points in the period 1970 to 2007, beginning with the fourth quarter of 1970 and ending with the second quarter of 2007 (see Fig. 2; upper area). Lower turning points of the business cycle are found for the years 1971, 1975, 1982, 1987, 1993, 1996, 1999 and 2005. Upper turning points can be observed for the years 1970, 1973, 1979, 1985, 1991, 1995, 1998, 2000 and 2007. In the period under examination, a total of eight growth cycles in the German economy can be observed – starting from the number of upper turning points. The average duration of a growth cycle, measured by the period of time between two consecutive upper turning points, amounts to 17.4 quarters or 4¼ years; measured by two consecutive lower turning points, 18.3 quarters or 4½ years. An upswing phase (period of time of the lower turning point to the following upper turning point) amounts, on average, to 9.5 quarters (nearly 2½ years); a downturn phase (spread of the upper turning point to the following lower turning point) to 8.8 quarters (nearly 2¼ years).

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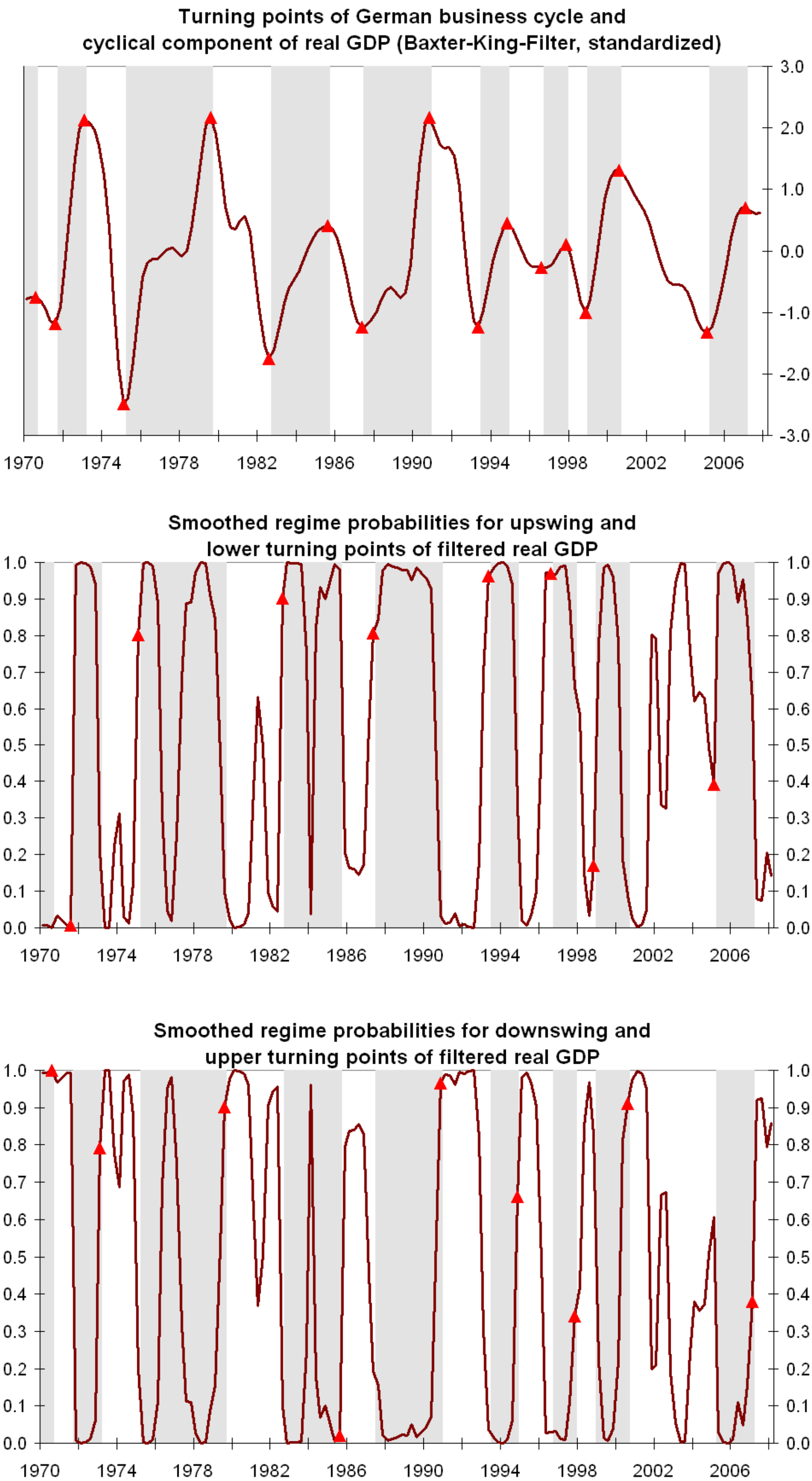
7 Grocer can be accessed under http://dubois.ensae.net/grocer.html and is a contribution to the software package Scilab (http://scilab.org).

Fig. 2


Turning points of German business cycle and
cyclical component of real GDP (Baxter-King-Filter, standardized)
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
1970
1974
1978
1982
1986
1990
1994
1998
2002
2006
Smoothed regime probabilities for upswing and
lower turning points of filtered real GDP
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Smoothed regime probabilities for downswing and
upper turning points of filtered real GDP

The regime probabilities from the Ifo Business Climate estimated using the basic MS procedure for the cyclical *upswing* phase is seen in the middle section of Figure 2. Since the focus is on the average dynamics of the time series in the entire ex-post period, the smoothed regime probabilities for the upswing phase $p(s_t = 1 \mid I_T)$ is shown. For the estimation the total available amount of information in the time period 1970 to 2008 was employed. In the middle section of Figure 2 the lower turning points of the filtered real GDP are also displayed (red triangles). One already has the optical impression that with the exception of the years 1971, 1999 and 2005, the local minimums of the regime probabilities have a considerable lead for the upswing phase in comparison to the lower turning points of the filtered real GDP. The upswing signal of the smoothed regime probabilities at the time of a lower turning point of GDP is all the stronger the higher the triangles are positioned. For the business cycle analysis it is also important that in addition to the statistical lead of the Ifo indicator there is also a technical lead due the different times of publication. The Ifo Business Climate results for a completed quarter are available 1½ months before the official quarterly results for GDP. Furthermore, they are not subsequently revised, as a rule.

The lower section of Figure 2 shows the smoothed regime probabilities for the phase upswing $p(s_t = 2 \mid I_T) = 1 - p(s_t = 1 \mid I_T)$ as well as the corresponding upper turning points of the filtered real GDP. With the exception of 1985, we also have, purely optically, a considerably large lead of the smoothed regime probabilities; also the downturn signals at the upper GDP turning points are, on average, similarly high as the upper GDP turning points. All in all, the average smoothed regime probability for the downturn phase – measured at the upper turning points of GDP – in the period 1970 to 2008 amounts to approximately two thirds; a comparably high value results for the average smoothed regime probabilities for the upswing phase at the lower turning points of the filtered real GDP.

The probability analog of the mean squared error is the quadratic probability score (QPS). The QPS statistic is defined as (see e.g. Diebold, Rudebusch, 1989):

$$QPS = \frac{1}{T}\sum_{t=1}^{T}\left(\Pr\left(S_{t-\tau} = 1 \middle| I_{t-\tau}\right) - \lambda_t\right)^2$$

where $\Pr\left(S_{t-\tau} = 1 \middle| I_{t-\tau}\right)$ is the probability of an upswing, which is estimated by the MS model, where τ is a time index accounting for the potentially leading character of the upswing probabilities and λ_t is a dummy variable, indicating the regimes of the reference cycle (1 if upswing, 0 otherwise). The quadratic probability score statistic takes values between 0 to 1, with a score of 0 corresponding to perfect accuracy. The QPS for the basic MS model is 0.146 with $\tau=1$. The introduction of switching or non-switching autoregressive variable of various lags could not improve the QPS. So the basic MS model is used in the present study.

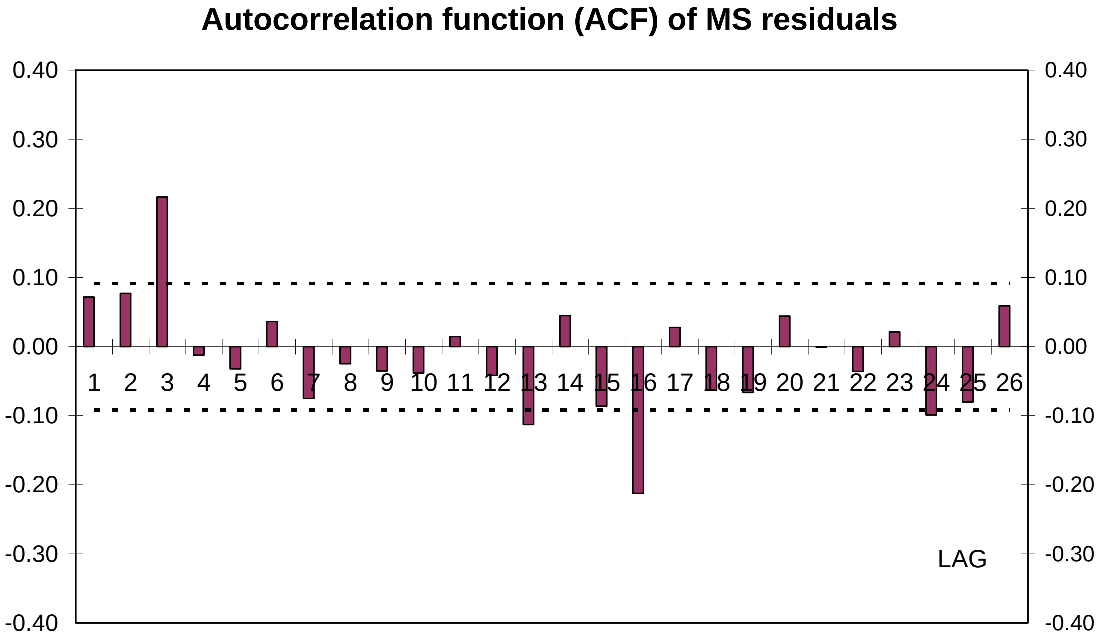
Model-endogenous dating of upturn and downturn phases

A further aspect of the MS model is the possibility of displaying, model-endogenously, i.e., only with the help of the estimated regime probabilities, the upturn and downturn phases chronologically. From the viewpoint of an up-to-date business cycle analysis, the filtered regime probabilities $p(s_t = i \mid I_t)$ are of special interest, since in their calculation only the data from the past available up to the t investigation are incorporated, which corresponds best to the information status at the current edge. In order to simulate real-time conditions as much as possible, the MS model for the Ifo Business Climate for industry and trade was re-calculated to a *monthly basis*.

Again the basic MS model is selected for the calculations. Compared with the turning points of the reference series of filtered GDP a QPS of 0.174 results for the basic model, with $\tau = 2$, thus showing that the filtered monthly regime probabilities have an average lead of two months. Introduction of autoregressive terms in the model could not lead to better QPS. Quite the reverse, the larger models lead to poorer results. A residual analysis of the basic model reveals that there are no significant autocorrelations at lower lags. Figure 3 contains the autocorrelation function of the residuals. It shows that only at lag 3 and at a few higher lags there are some remarkable correlations. The autocorrelation at lag 3 is 0.216. The findings in the autocorrelogram are confirmed by the Ljung-Box test. Up to lag 2 the p-values of the test statistic is larger than 0.05. Inclusion of lags larger than 2 leads to rejection of the Null hypothesis of no autocorrelation.

A MS model including a lag 3 autoregressive term leads to a lower QPS than the basic model, though. Moreover, calculations with different estimation periods show that the results are very unstable. That is why we handle the autocorrelations as Chatfield did (2004), who wrote on page 69 "… my own preference is to 'look' at the first few values of r, particularly at lags 1 and 2 and the first seasonal lag, and see if any are significantly different from zero using the crude limits of $\pm 2/\sqrt{T}$. …if only one (or two) values of r are just significant at lags having no obvious physical interpretation, then I would not regard this as compelling evidence to reject the model". To be on the safe side, also MS models containing lag 1 and also lag 2 autoregressive terms have been estimated. Compared to the basic MS model, they also lead higher QPS values.

Fig. 3

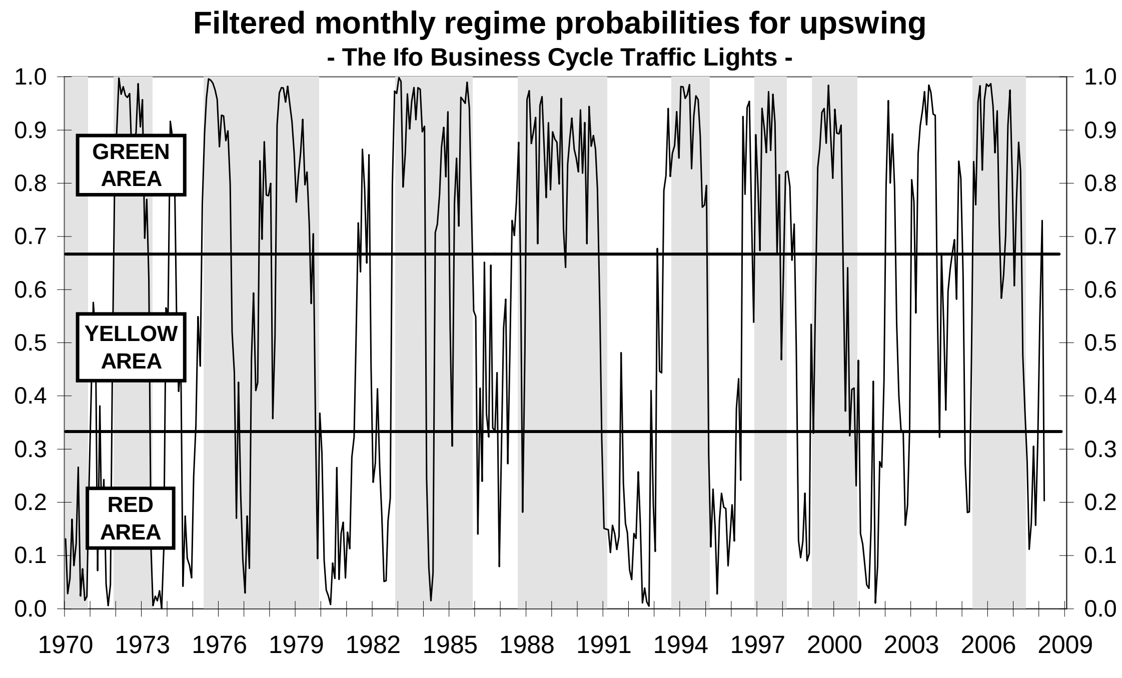


For the cyclical classification of the observed data, rules still need to be set up, however, since it is unclear as to which regime probability one should empirically speak of an upswing or downturn. The simplest symmetrical classification, based on Hamilton, consists in speaking of an upswing when the corresponding regime probability for the upswing phase $p(s_t = 1 \mid I_t)$ is larger than 50% (see Hamilton 1989, 373ff.). Conversely, a downturn is characterized such that now the regime probability for a downturn phase $p(s_t = 2 \mid I_T)$ is higher than 50% (or the regime probability for the upswing is now lower than 50%). Turning points are found where the regime probabilities for the phases upswing or downturn exceed the 50 percent mark.

The calculations submitted here for the *average* smoothed regime probabilities at the cyclical turning points of real GDP suggest, however, another, *empirically* motivated dating rule: an upswing phase exists when the filtered regime probability for the upswing phase $p(s_t = 1 \mid I_t)$ is larger than two thirds, since this value is identical with the smoothed polished regime probability for the upswing phase for the average of all lower turning points of real GDP. Conversely, there is a downturn phase when the filtered probability for the upswing phase is lower than a third. In this case, namely, the filtered regime probability for the downturn phase $p(s_t = 2 \mid I_t) = 1 - p(s_t = 1 \mid I_t)$ is higher than two thirds. This value corresponds to the median smoothed regime probability for the downturn phase at the upper turning points of real GDP. With regime probabilities between a third and two thirds, no status statement can be made with this rule; here indifference prevails. Cyclical turning points are found where the filtered regime probabilities for the upswing phase exceed the two-thirds mark or fall below the one-third mark.

Figure 4 shows the cyclical regime for Germany (Ifo business cycle traffic light) established with this rule of thumb. The filtered real-time probabilities signal an upswing (green area) insofar as they exceed the 66% mark; downturns insofar as they are under the 33% mark (red area); or indifference (yellow area) when in the range in between. This indifference area can be interpreted as a buffer zone between the regimes upswing and downturn, in which particularly great uncertainty exists about the state of the national economy. All in all, according to this dating rule, in 226 (or 49.2%) of the cases an upswing is signalled; in 143 (or 31.2%) a downturn and only in 90 (or 19.6%) is there indifference. Despite the newly added indifference interval, there is still a considerably great selectivity with regard to the assignment to the cyclical phases upswings or downturns. Due to the monthly estimation approach, the Ifo business cycle traffic light identifies not only the comparably low-frequency growth cycle of the filtered real GDP but also indicates in real time higher frequency oscillations, even including special cyclical developments.

Fig. 4



A typical example of higher frequency oscillations is seen, for example, in the clear fall (and rising again) of the filtered upswing probabilities in spring 1984. Here, because of a seven-week strike in the metal industry of Hessia and North-Württemberg/North-Baden for the introduction of a 35-hour week, great losses in production occurred that are also visible in the time series of unfiltered real GDP. On the one hand, the comparatively volatile development of regime probabilities in 2002 to 2004 is the result of the numerous shocks and uncertainties that could not always be systematically anticipated by the surveyed enterprises. On the other hand, manufacturing experienced comparably favourable and special business-cycle conditions that had a more positive effect in terms of regime probabilities, due to the higher weight of manufacturing in the Ifo Business Survey, than it had in the cyclical component of real GDP, whose decline in this period was only retarded.

The classification of indicator signals into three different states is quite intuitive for the public. And it does not demand too much from the indicator, because there is a yellow sign indicating that there is high uncertainty. With the traffic lights the communication of indicator signals can be much enhanced.

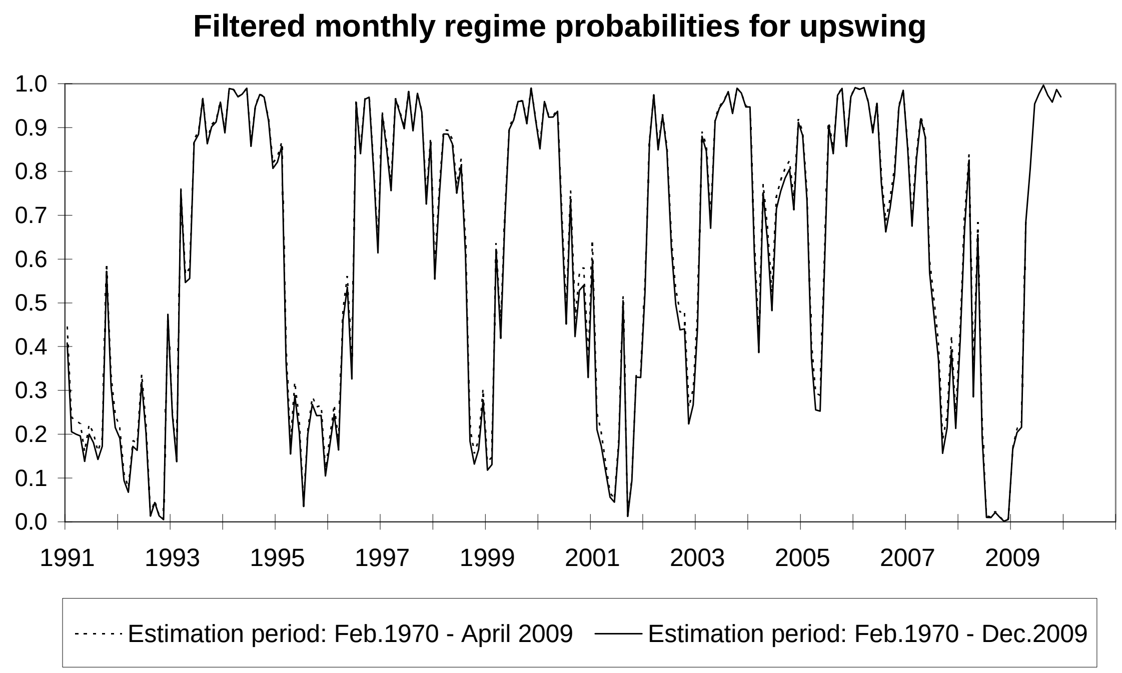
In practical business cycle analysis it is very important that current signals are reliable. Therefore indicators with strong signals are important. The indicator should also not be subject to large revisions. And when a model is used as in the present study, the estimates should be very stable over time. Only when these conditions are satisfied business cycle analysts are able to make good assessments. To gain an impression of the stability of the filtered probabilities of the estimated MS model for the Ifo Business Climate, the model is estimated at different points in time. Figure 5 shows the filtered probabilities. The model is estimated first with the data available up to April 2009. This was the first month signalling a recovery after the steep recession. Re-estimation of the model with data up to December 2009 shows only minor revisions of the estimated probabilities. Most important, the regime signals are very stable over time. Even the recovery signal in 2009 is unchanged after estimation with the full data set, including all values of that year. This shows that the basic MS model leads to quite stable probability estimates, which is very important for the business cycle analyst.

Conclusion

Business cycle indicators are important sources of information for the assessment of the business situation. They are very popular among economists, policy-makers, firms and the media. Also financial markets react to announcements of new indicator figures. Often indicators are used in times series models. For users it is also important to classify the current movement of an indicator. For these user groups in the present article a traffic light classification of indicator movements is developed. This might help publishers of indicators to enhance the communication of the results of their calculations.

The calculations presented here show that the Ifo Business Climate can be modelled with a Markov Switching (MS) approach. With this MS model the turning points of the cyclical component of real GDP can be reliably detected and with lead times. For the chronology of the turning points, the Bry-Boschan dating program developed in the USA at the NBER was used.

Fig. 5



The cyclical component of real GDP was extracted with the well-known Baxter-King filter. A further aspect of the MS model is the possibility of identifying downturn phases model-endogenously, i.e., only on the basis of the estimated real-time probabilities. The monthly regime probabilities – represented in the Ifo business cycle traffic light – can provide interesting additional information for the interpretation of the business cycle indicator, the business climate. This is the case because for the movement of the Ifo Business Climate the MS model supplies probabilities for both business-cycle regimes: the upswings and downturns. This information is of decisive importance for the analysis of the current business cycle.

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