Identifying and Forecasting the Turning Points of the Belgian Business Cycle with Regime-Switching and Logit Models

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Identifying and Forecasting the Turning Points of the Belgian Business Cycle with Regime-Switching and Logit Models

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Abstract

This paper seeks to elaborate econometric models that can be used to forecast the turning points of the Belgian business cycle. We begin by suggesting three reference cycles, which we hope will fill the void of an official reference chronology for Belgium. We then construct two different types of model to estimate the probabilities of recession: Markov-switching models, and Logit models. We apply each approach to a limited set of data, which are a good representation of the economy, are available early and are subject to only minor revisions. We then select the best performing model for each chronology and type of approach. The out-of-sample results show that the models provide useful indicators of business cycle turning points. They are however far from perfect forecasting tools, especially when it comes to forecasting periods of classical recession.

Keywords: Reference chronologies, Markow-switching and Logit models, forecasting business cycle turning points.

JEL Classification: C5, E32, E37

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1. Introduction

The purpose of this paper is to elaborate econometric models that are able to forecast the turning points in the business cycle of the Belgian economy. This exercise requires going through the following important steps:

Step 1. To begin with, we establish a chronology of the Belgian business cycle. This task is motivated by the fact that there is no official or universally accepted dating of the Belgian business cycle. [1] This, however, is indispensable for the analysis and prediction of cyclical fluctuations. Indeed, an important criterion in the selection of econometric models of the business cycle is their ability to replicate and forecast successfully the turning points of the business cycles that have been identified for the past. Different business cycle chronologies, called thereafter the "reference chronologies", are established in this paper. As in many similar studies, we use the real GDP to establish our chronologies.

Step 2. Next, we need to choose an econometric methodology that can replicate successfully the dates of the business cycles chronology established in the first step. Two econometric techniques have been chosen: the Markov-switching approach and the logistic approach. One important feature of these two approaches is that they can be used to calculate the probability that, at a certain date, the economy will be in expansion or in recession. The normal state of the economy is considered to be an expansion, and accordingly one concentrates on calculating probabilities of recession. The fact that the probability of recession exceeds a predetermined threshold is taken as a signal that the economy is moving from expansion into recession. Similarly, the passage to probabilities below the threshold signals the end of the recession.

Step 3. In the third step, we make a selection of the macroeconomic time series that, with the econometric techniques described above, will form the models (or indicators) of the Belgian business cycle. Finding appropriate data is not an easy task. Indeed, we require that the variables entering into the models provide a good representation of economic activity, be available at a monthly frequency and be subject to minor revisions over time. In addition, as our main goal is to obtain early forecasts of the turning points in the business cycle, the data must be available very early, notably before the release of the GDP data.

Step 4. In the final step, we evaluate how successfully the business cycle models locate the dates of the business cycle chronology established in the first step. Both in-sample and out-of-sample analyses are performed. At the end of the analysis, we only keep the models that have the best performance.

The paper is structured along the four steps above. In section 2, we establish our chronologies of the Belgian business cycle (step 1). Section 3 is devoted to a short presentation of the econometric techniques that we have chosen to elaborate the business cycle models (step 2) . In Section 4, we describe the data set to which the econometric techniques are applied (step 3). We also make the formal selection of the business cycle models that best replicate the "reference" business cycle chronologies

[1] In the case of the USA, the chronology of the National Bureau of Economic Research (NBER) serves as reference. For a number of large countries, including seven European economies, one can use the datings provided by the Economic Cycle Research Institute (ECRI, Internet site: http://www.businesscycle.com/research/).

(step 4). In-depth analysis of the business cycle properties of the selected models is performed in section 5. Section 6 concludes.

2. Establishing the reference chronologies of the Belgian business cycle

One of the most important requirements in any meaningful analysis of the usefulness of business cycle models to predict turning points is the existence of a universally acknowledged reference chronology for the past. Indeed, an important criterion in the selection of econometric models of the business cycle is their ability to replicate and forecast successfully the turning points of the business cycles that have been identified for the past.

Unlike in the case of the US economy, however, there is unfortunately no established ***reference chronology*** for Belgium. The aim of this section is therefore to define relevant reference chronologies and to construct them dividing the recent Belgian economic history into periods of recession and expansion. We have used the real GDP as the indicator that best represents the general level of activity. Thus, the cycle of the real GDP[2] will be considered as a reference cycle of the Belgian economy**.** Based on these data, three alternative reference chronologies are constructed.

Our chronologies, being based on GDP data, provide necessarily quarterly datings of the business cycle. Moreover, they start in 1980 due to the absence of relevant and consistent data series over a longer horizon.

2.1. The reference chronology 1 (Bry-Boschan)

The first reference chronology is based on the approach of Bry and Boschan (1971). This approach is well established and widely used by practitioners investigating business cycles. The procedure was created at the National Bureau of Economic Research (NBER)[3] as a tool for "automatically capturing" the phases of the business cycle. It was designed to replicate the decision-making process of the NBER that defines "a recession as a significant decline in activity, spread across the economy, lasting more than a few months, visible in industrial production, employment, real income, and trade. A recession begins just after the economy reaches a peak of output and employment and ends as the economy reaches its trough. Between trough and peak, the economy is in an expansion. The expansion is the normal state of the economy; recessions are brief and relatively rare".

The Bry-Boschan technique is a non-parametric approach because it does not use any formal statistical framework to do the dating. Instead, it translates the NBER method into a set of simple decision rules. It basically comprises two stages: (1) selecting the candidate turning points and (2) applying a censoring rule to eliminate the turns that do not satisfy certain criteria (e.g. minimum duration). When working with quarterly data,

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2 Real GDP is the Belgian GDP in billions of 2000 euros. The data in this paper are those that were available before the revision of october 2004.

3 See http://www.nber.org/cycles/recessions.html

we use the quarterly version of the Bry-Boschan (BB) algorithm provided by Harding and Pagan (2001)[4].

Harding and Pagan's code allows for two possible rules for the first stage. In our analysis, we use their first rule — coined as **BBQ rule** — which checks each point in the sample for being a local maximum or minimum. Formally:

> y_t is a peak iff y_t=max{y_{t-K},…, y_{t+L}}; it is a trough iff y_t=min{y_{t-K},…, y_{t+L}), otherwise it is neither a peak nor a trough.

Normally, when using quarterly data, one takes K=L=2, although there is no reason to consider these values as given. They stem from the original Bry-Boschan procedure where the peaks and troughs are local maxima and minima over a 13 months period (6 months before and 6 months later).

At the second stage, one usually eliminates the candidate peaks and troughs that do not satisfy two restrictions: minimum phase duration[5] should be 6 months (2 quarters) and the complete cycle must last at least 15 months (5 quarters). [6]

The most important appeal of the Bry-Boschan technique is its simplicity and its transparency. It is also very robust in the sense that changing the sample of observations will not affect the dates, although it will of course be sensitive to the choice of criteria and censoring rules applied.

The Bry-Boschan algorithm is applied to the logarithm of the quarterly real GDP.[7] The resulting chronology will be referred to as ***BRef1*.**

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4 See D.Harding's homepage : http://wff1.ecom.unimelb.edu.au/iaesrwww/people/dharding/gcode.html.

5 A phase of the recession is the period between a peak (or a trough) and the immediately following trough (or peak).

6 The second rule, which is called **Okun's rule,** states that two quarters of negative (positive) growth terminate expansion (recession). Formally: y_t is a peak iff $y_t > y_{t+1} > y_{t+2}$; it is a trough iff $y_t < y_{t+1} < y_{t+2}$, otherwise it is neither peak nor trough. Notice that here K=0 and L=2.

7 The GDP data used in this paper are those that were published before the latest revisions. Some of the chronologies change slightly when the latest data are used, without changing our overall conclusions.

Figure 1. Belgian quarterly GDP vs. reference chronology *BRef1*, 1980:I-2003:IV

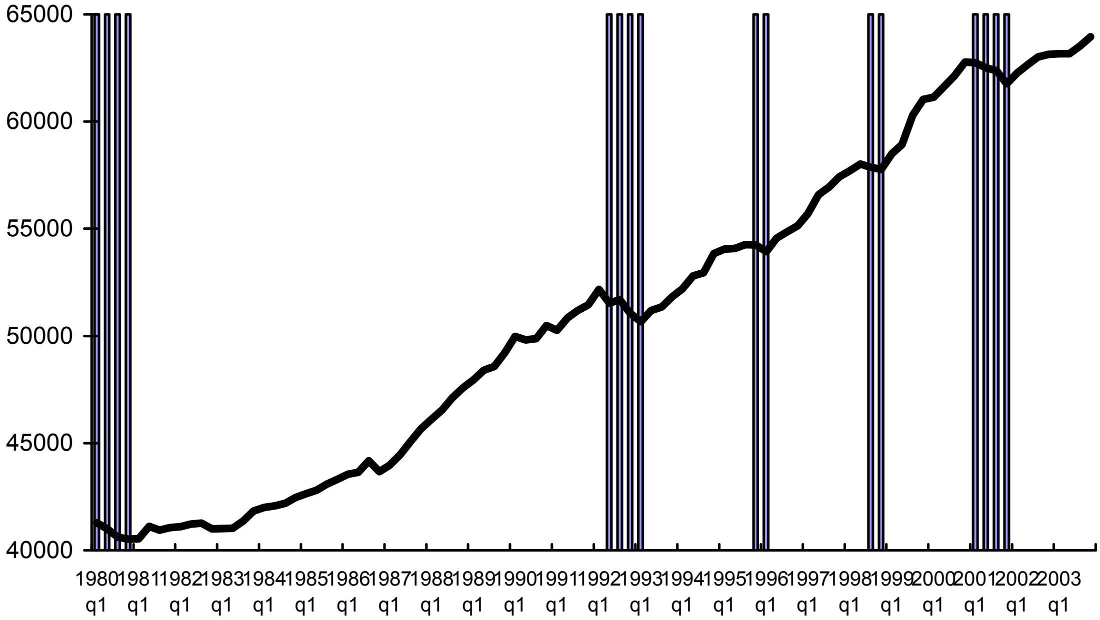


Figure 1 shows the result of this exercise. The shaded areas correspond to the recessionary periods. Five such periods with nine turning points are detected in Belgium over the period 1980-2003. The recessions occurred over the following dates: 1980:I-1980:IV, 1992:II-1993:I, 1995:IV-1996:I, 1998:III-1998:IV, and 2001:I-2001:IV. There is one exceptionally long expansion in the first half of the sample. It lasts for more than 10 years. The expansions in the 1990s are of a more or less same duration of about 2 years. The durations of recessions normally do not exceed one year.

2.2. The reference chronology 2

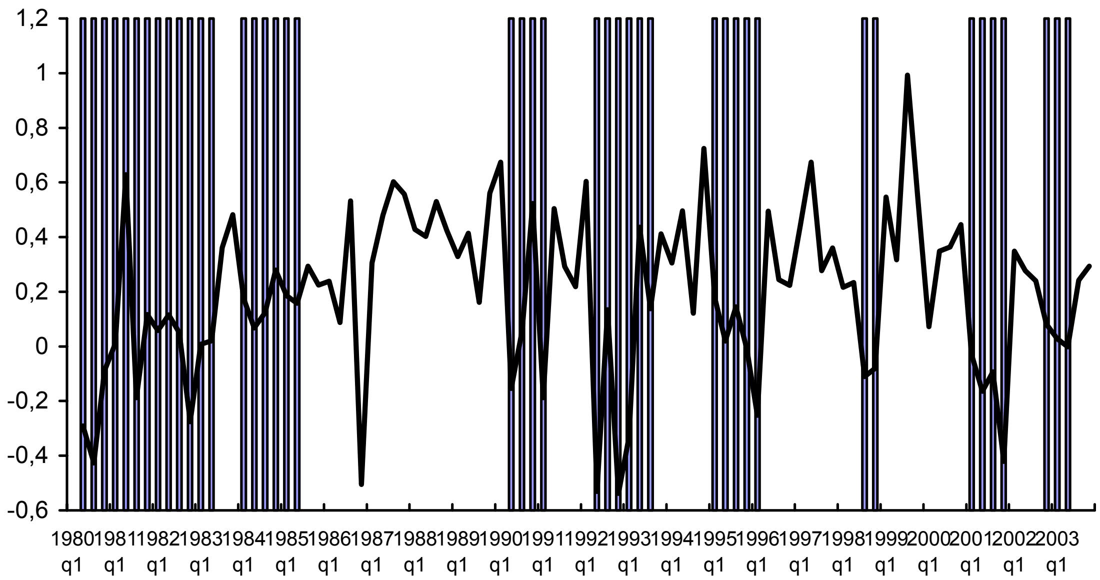
The Bry-Boschan approach is normally applied to a time series in levels and, thus, detects the so-called *classical business cycle*. However, during the last decades, periods of negative growth have been relatively rare, which implies that recessions in the classical sense occur seldom. Therefore, the Bry-Boschan chronology may not necessarily fully satisfy the needs of policymakers or business cycle analysts. For instance, they may not simply want to predict periods where there is *classical* recession, i.e. when the GDP actually declines, but even where there is a slowdown in economic growth, which is a more frequent phenomenon.[8] We therefore believe that the analysis of business cycles and the practical use that decision makers make of it, might benefit from some flexibility in the definition of the reference cycle. That is why we investigate two other possible definitions of a reference cycle.

8 Helbling and Bayoumi (2003) mention “For policymakers… knowing only the direction of output comovements is not a comforting basis for a decision-making. Any countercyclical policy measure requires some information of the magnitude of output comovements. Also, small macroeconomic shocks may not lead to recessions or strong booms, but may have international repercussions.”

The ***reference chronology BRef2*** is based on the first-differenced series, that is, on the quarterly growth rates of the real GDP, and defines a low period as one in which the annual growth rate of the real GDP is below 2% for a sustained enough period of time.[9] In terms of the quarterly growth rate, we implement it as roughly equivalent to a growth rate of below 0.5% (rather than 0) for at least 2 quarters.

As shown in Figure 2, over the period 1980-2003, there have been eight periods during which the economy grew by less than 0.5% for at least two quarters. The periods are: 1982:II-1983:II, 1984:I-1985:II, 1990:II-1991:I, 1992:II-1993:III, 1995:I-1996:I, 1998:III-1998:IV, 2001:I-2001:IV, and 2002:IV-2003:II. These results confirm that periods of slow growth occur more frequently than classical recessions. For instance, during the first half of the 80's, the growth of the Belgian economy was very slow, even if there was no *classical* recession as suggested by the Bry-Boschan results (see Figure 1).

Figure 2. The quarterly growth rate of Belgian GDP vs. reference chronology *BRef2*, 1980:II-2003:IV



2.3. The reference chronology 3

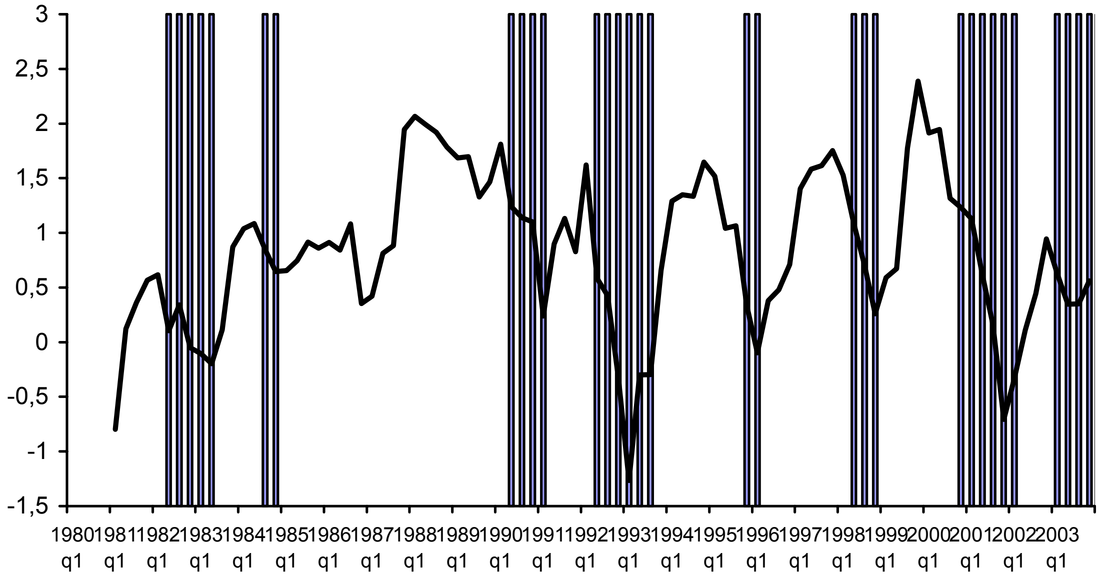
Yet another possible chronology of interest, which we refer to as the ***reference chronology BRef3*, concentrates on the year-on-year growth rate of the real GDP. Here, we define a period of slowdown in an even more subjective way than ***Ref2***. A slowdown is identified as a period when the year-on-year growth rate of the GDP follows either a downward path or is negative for at least two quarters. However, the periods where the year-on-year growth rate remains above 3% are excluded, even if it shows a downward trend for a sustained period.

Under this definition, we identify eight periods of slowdown, whose duration varies from two quarters to six quarters (see Figure 3): 1982:II-1983:II, 1984:III-1984:IV, 1990:II-1990:IV, 1992:II-1993:II, 1995:IV-1996:I, 1998:II-1998:IV, 2000:IV-2002:I, 2003:I-... There is no systematic pattern in the distribution of the slowdowns according

9 2% is approximately the potential growth rate of the real Belgian GDP.

to their duration over the time axis. As in the case of BRef1 and BRef2, we observe a relatively long recovery in 1980-1985. Only three out of the eight periods of slowdown are associated with negative year-on-year growth rates; two of them took place in 1990s suggesting deepening of the slowdowns.

Figure 3. The year-on-year growth rate of Belgian GDP vs. reference chronology *BRef3*, 1981:I-2003:IV



Before ending this section, it is worth noting here the periods of recession that are common to the three different chronologies thus derived. Clearly the periods of classical recession are automatically subsumed by the other two definitions. The periods of slow growth that also coincide with periods of sustained slowdown are: 1982:II-1983:II, 1984:III-1984:IV, 1990:II-1991:I, 1992:II-1993-III, 1995:IV-1996:I, 1998:III-1998:IV, 2001:I-2001:IV and 2003:I-2003:II. The only cases where a period of sustained slowdown does not correspond to a period of slow growth occur in conjunction with the last three recessions.

3. Descriptive models of the Belgian business cycle

Having established three alternative reference chronologies for Belgium, we next turn our attention in this section to the use of econometric models that can replicate successfully the dates of the reference chronologies. The ultimate goal of these models is to provide timely and reliable signals of the Belgian economy entering a new phase of the business cycle.

Two statistical approaches are presented in this section. The first approach makes use of regime-switching models. In this paper, we concentrate in particular on models with Markov-switching dynamics: both univariate and multivariate. The second type of approach is based on the logit model. An interesting feature of these two approaches is that they can be used to calculate the probability that, at a certain date, the economy will be in expansion or in recession. The normal state of the economy is considered to be an expansion, and accordingly one concentrates on calculating probabilities of recession.

The fact that the probability of recession exceeds a predetermined threshold is taken as a signal that the economy is moving from expansion into recession. Similarly, the passage to probabilities below the threshold signals the end of the recession.

The rest of this section is organised as follows. Subsection 3.1 describes briefly the Markov-switching approach. Subsection 3.2 does the same with the logit approach.

3.1. Markov-switching approach

3.1.a. The univariate case

The most important contribution in this area is attributed to Hamilton (1989, 1994). The main thrust of Hamilton's approach rests on the possibility that the data generating process of a random variable, e.g. the GDP, may be subject to regime change. In other words, the parameters that define this process may indeed take different values according to the regime in which the variable finds itself. For instance, the mean and variance of the growth rate of the GDP observed during recessions might be different from those observed during expansions. He argued that the usual linear model ignores possible non-linearities of the business cycle, which results in the behaviour of the economy during periods of transition between expansion and recession being fundamentally different than during prolonged periods of expansion or recession.

To model such a change across regimes, an auxiliary variable S_t is introduced to reflect the state of the random variable at time t. Clearly, if we knew *a priori* the value of S_t, the problem would be very simple. However, S_t in general is not observed. To derive appropriate estimates of the model parameters, some assumptions need to be made about the stochastic behaviour of S_t. The simplest case would be when S_t changes independently of its own past values, even if it responds to some other exogenous variable.

However, in most cases, especially cases of interest in economics, S_t will evolve depending on its own past values $S_{t-1}, S_{t-2},\ldots, S_{t-r}$. Such a process is called an *r-th* order Markov-switching process. In particular, the probability that S_t takes a particular integer value can be supposed to depend on the past only through its most recent value S_{t-1}. The simplest such case was used by Hamilton to model the quarterly real GDP in the US. This is a first-order Markov-switching process where the state variable S_t switches between two states of expansion ($S_t=1$) and recession ($S_t=0$). Hamilton applied this framework to estimate a univariate model for the growth rate of the GDP, thus allowing the latter to take on different mean values in an expansion and in a recession.

It is convenient to collect the transition probabilities in a transition matrix $\boldsymbol{P}$, with element p_{ij} representing the probability of state i being followed by state j (see Hamilton (1994)). The interesting aspect of a first-order Markov chain is that it can be given a first-order autoregressive representation in terms of a random vector ξ_t ($m\times 1$ in general when there are m regimes). The j-th element of ξ_t equals 1, if we are in state j and 0, otherwise (details are given in the appendix). The transition matrix of the probabilities is conveniently the autoregressive coefficient which allows the m-period ahead forecasts of the Markov chain and hence of the regimes.

An interesting by-product of the approach is the ability to calculate two sets of probabilities. The first set is called the *filtered probabilities* of a recession defined as

$\Pr\left[S_t = 0 \middle| \Delta y_1, \Delta y_2, \cdots \Delta y_t\right]$, conditioned on the past and present history.[10] The *filtered probabilities* are estimated by maximum likelihood, where the log-likelihood function is constructed as:

$$L(\theta) = \sum_{t=1}^{T} \log(\xi_{t|t}^{'} \eta_t)$$

The second set of probabilities are the *smoothed probabilities* of recession defined as $\Pr\left[S_t = 0 \middle| \Delta y_1, \Delta y_2, \cdots \Delta y_T\right]$ which are conditioned on the whole sample history (T is the sample size). As a rule, *smoothed probabilities* are less volatile than *filtered probabilities*, since they rely on a more extensive information set. In an exercise of analysing the past, it is always useful to compare the two sets of probabilities. When it comes to forecasting however, there is no difference between the filtered and smoothed probabilities used.

The estimated probabilities can be used as a signal of the state in which the economy finds itself. The normal practice is to choose a threshold value for these probabilities beyond which recession is considered as being signalled. In the case of two states, the value of 0.5 is often taken to be the dividing line.

3.1.b. The multivariate case

In this case, we want to examine how and whether the use of more than one variable may be helpful in estimating what state the Belgian economy is in. The basic idea is that different individual series move across the business cycle in a parallel way. These co-movements, that is, the movements which are common to all the series, can be captured by an unobserved common factor. Stock and Watson (1989, 1991, 1993) propose the use of dynamic factor analysis in a multivariate framework to capture this unobserved common factor, which can represent a coincident economic indicator or CEI. Bodart and Candelon (2000) have already built such an indicator for Belgium.

What we investigate here is the addition of the possibility of the Markov-switching of the CEI. This notion has been investigated by Chauvet (1998), Kim and Nelson (1999) and was strongly recommended by Diebold and Rudebusch (1996) as a useful method of combining the importance of capturing the co-movement of macroeconomic variables together with the asymmetric nature of their behaviour according to the state in which they are. More specifically, we have opted to follow the dynamic common factor analysis proposed by Stock and Watson, extended to its Markov-switching alternative.

The model of a single dynamic common factor with Markov switching (MS-CF) can be briefly described as follows:

$$\Delta y_t = \gamma(L)\Delta C_t + u_t$$
$$\Delta C_t = \mu(S_t) + \phi(L)\Delta C_{t-1} + \varepsilon_t$$
$$\psi(L)u_t = \eta_t$$

where Δy_t is the $n{\times}1$ vector of the growth rates of the observable time series; ΔC_t is the dynamic common factor in first differences; u_t is the $n{\times}1$ vector of the idiosyncratic

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[10] In this representation, Δy_t is the change at time t in the variable subject to regime change, and lower case letters usually refer to logarithms, in which case Δy_t is a rate of growth.

components; S_t is the regime variable taking m values, where m is the number of the regimes. Thus, for $m=2$, $S_t=\{0,1\}$. The model is basically the same as that of Stock and Watson, apart from having a very important extension — that of the regime switching. In this model, the intercept term, $\mu(S_t)$, and possibly the variance of the common factor disturbance, $\sigma_\varepsilon^2(S_t)$, are state-dependent, that is, they are different for different regimes.

The shocks to the common and specific factors are assumed to be serially and mutually uncorrelated and to be normally distributed. Moreover, the variance of the common factor disturbance may be state-dependent:

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \sim NIID\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2(S_t) & O \\ O & \Sigma_\eta \end{pmatrix} \right)$$

The application of this methodology produces not only a composite coincident economic indicator, but at the same time a set of probabilities that can help determine periods of recession and expansion. In what follows, we will examine how these probabilities match the chronologies of the business cycle determined in the previous section. Furthermore, optimal forecasts of m-period ahead probabilities of being in recession can be calculated, using the properties of the Markov chain. The Appendix gives a more extensive discussion of the dynamic common factor approach.

3.2. Logit Approach

The logit model, which belongs to a larger class of qualitative response models, assumes the existence of some unobserved variable y^*_t, underlying the cyclical movements of the economy, that switches between the cyclical phases. This variable can be thought of as a business cycle indicator.

The theoretical model describes the evolution of the unobserved indicator y^*_t, denoting the occurrence of a recession or an expansion in period t, as a function of some observed predictors in a linear model framework:

$$y^*_{t+k} = \beta' x_t + \varepsilon_t$$

Where k is some nonnegative integer defining the forecasting horizon, x_t is the vector of the independent variables, ε_t is the normally distributed error term. Note that under this specification the observed variables can be leading with respect to the latent cyclical indicator, y^*_t.

What we observe, instead of this cyclical indicator, however, is a discrete-valued (not necessarily binary) time series y_t:

$$y_t = \begin{cases} 1, & if \quad y^*_t > 0 \Rightarrow \varepsilon_t > -\beta' x_{t-k} \\ 0, & \qquad otherwise \end{cases}$$

From this, it follows that the conditional probability of the economy being in expansion is :

$$P(y_{t+k} = 1) = F(\beta' x_t)$$

where $F(\bullet)$ is some cumulative distribution function. In the Logit model $F(\bullet)$ is a logistic function :

$$F(\beta' x_t) = \frac{1}{1+\exp(-\beta' x_t)}$$

We can thus obtain the conditional recession probability which is equal to $1-F(\bullet)$. We will check whether the sequence of these probabilities replicate the turning points of the reference cycles.[11]

The Logit model can also be used to predict the conditional recession probabilities in the future, as long as observations on the explanatory variables are available in advance of the series used to establish the presence of a recession. This series is often the GDP.

In contrast to the Markov-switching approach, the application of the Logit model requires the use of some reference chronology, like those generated in section 2. Once the reference dates are determined, the parameters β of the Logit model are estimated. Finally, the parameters are used to compute the regime probabilities for the period $t+k$.

The model is estimated by maximum likelihood method. The likelihood function is constructed as:

$$L = \prod_{y_t=1} F(\beta' x_t) \prod_{y_t=0} \left[1 - F(\beta' x_t)\right]$$

3.3. Comparing the two approaches

Markov-switching and logit approaches both produce conditional recession probabilities reflecting some unobserved state of the economy. There are however some important differences between them. The regime-switching approach provides probabilities of recession or slowdown, which are independent of any prior chronologies of such periods over the sample. They thus avoid the use of any *ad hoc* definitions. Moreover, the properties of the Markov-switching model facilitate the forecasting of the probabilities over a longer horizon. On the other hand, the criticism often made of the approach is that the model thus estimated is not very transparent and that it is difficult to interpret exactly what situation these probabilities are illustrating. The logit approach has the advantage that the analyst can define exactly what he is trying to model, in other words, a period of recession or one of slowdown. One can even present different definitions of a slowdown, as we have done in section 2. Because the logit model is focused on a predetermined chronology, it is not surprising that it often provides estimated probabilities with a better relative performance than their regime-switching counterparts. The limitation of the approach, however, is that it is often applied to chronologies defined on the real GDP which is not available at the monthly frequency, obliging the analyst to somehow transform monthly observations on relevant variables in a way that makes them usable in a quarterly framework. This limitation renders the use of the available information less efficient and complicates the forecasting exercise. For these reasons, we find it imperative to consider the results by both approaches.

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[11] An alternative to the Logit model is an often-used Probit model. The only difference between the two models is that in the Probit case the function $F(\bullet)$ is simply the Gaussian (normal) cumulative distribution function of $\beta' x_t$. Normally, the estimates of the two models are not very different.

4. Data and model selection

In this section, we make a selection of the macroeconomic time series that, with the econometric techniques described above, will form the models (or indicators) of the Belgian business cycle. We then evaluate how successfully the business cycle models locate the dates of the business cycle chronology established in section 2. Both in-sample and out-of-sample analyses are performed. We aim to choose the best performing Markov-switching and logit models for each reference chronology.

4.1. Description of the data

The first important question to be solved is the choice of the macro-economic indicators that will enter into the construction of the business cycle models. We require that the data satisfy the following conditions:

- economic content — the data must adequately reflect the business cycle movements of the whole economy or of its key sectors;
- early availability — the data must be available as soon as possible in order to make timely forecasts; as we are concerned to have early signals of recession, the data must necessarily be available before the release of the GDP figures.
- high observation frequency — the data must be available at least at the monthly frequency in order to identify and predict the turning points with a sufficient precision;
- minimum of revisions — the data must be subject to no or few unimportant revisions in order to keep stable the business cycle dating.

The application of these conditions severely restricts the choice of possible data in Belgium. The time–series listed in the table below represent all that is practically available:

Table 4.1. Belgian monthly macroeconomic variables used in the analysis of the Belgian business cycle

Short-hand	Sample	Description	Source
OECD	1980:1-2004:2	OECD's composite leading indicator for Belgium	OECD
D6OECD	1980:1-2004:1	Annualised 6-months rate of change of the OECD's composite leading indicator for Belgium[12]	OECD
IMMV	1980:1-2004:1	New passenger car registrations according to INS	Institut National de Statistique
Confidence	1985:1-2004:1	Consumer confidence indicator for Belgium provided by the Eurostat	Eurostat
BBNBG	1980:1-2003:12	Global business survey indicator for Belgium	Banque Nationale de Belgique
BBNBM	1980:1-2003:12	Business survey indicator for Belgian manufacturing	Banque Nationale de Belgique
BBNBComm	1980:1-2003:12	Business survey indicator for Belgian commerce	Banque Nationale de Belgique
BBNBConst	1980:1-2003:12	Business survey indicator for Belgian construction	Banque Nationale de Belgique

In what follows, we estimate the Markov-switching and logit models. In the case of Markov-switching models, the series represent the dependent variable(s) (Δy_t) and can be used in their monthly form to produce probabilities at monthly frequency. In the logit models, the dependent variable is the reference chronology and the series are the explanatory variables (x_t). The dependent variable being only available at the quarterly frequency means that the estimated probabilities will also be only quarterly.

The time series listed in Table 4.1 give rise to a huge variety of both univariate and multivariate Markov-switching and logit models. We only keep models with sound statistical properties. We then evaluate each model according to its performance at capturing the turning points of the three alternative reference chronologies.

A widely used measure of performance is the so-called Quadratic Probability Score (QPS), proposed by Diebold and Rudebusch (1989) and further developed by Layton and Katsuura (2001). This test compares the model-derived recession probabilities to a binary variable (1 when recession and 0 when expansion) representing the business cycle chronology that has been established, that is, the reference chronology.

[12] The D6OECD is defined in the following way: "The six-month rate of change of the CLI is calculated by using the ratio between the figure for a given month m and the average of the figures from m-12 to m-1. Thus, the six-month rate of change is less volatile and provides earlier and clearer signals for future turning points than the CLI itself. In practice, peaks in GDP have been found about nine months (on average) after the signals of peaks had been detected in the six-month rate of change." (http://www.oecd.org)

The QPS is computed as :

$$QPS = \frac{\sum_{1+d}^{T} \left(P_{t-d} - D_t\right)^2}{T-d}$$

where P_t is the model-derived recession probability, [13] D_t is the binary reference cycle chronology, $d \geq 0$ is the time displacement which might be used to check whether the model-derived chronology is leading with respect to the reference cycle, T is the size of the sample.

The QPS statistic is limited within the interval [0,1]. The smaller is its value, the better is the correspondence between the model-derived dating and the reference chronology.

Two additional measures that can help to select the best performing model are: (i) the ratio of captured turns to the total number of the true turns (the turning points identified by the reference chronology); and (ii) the ratio of false alarms (the points, which are detected by the probabilistic model but are not recognized by the reference chronology) to the total number of the turns found by the probabilistic model.

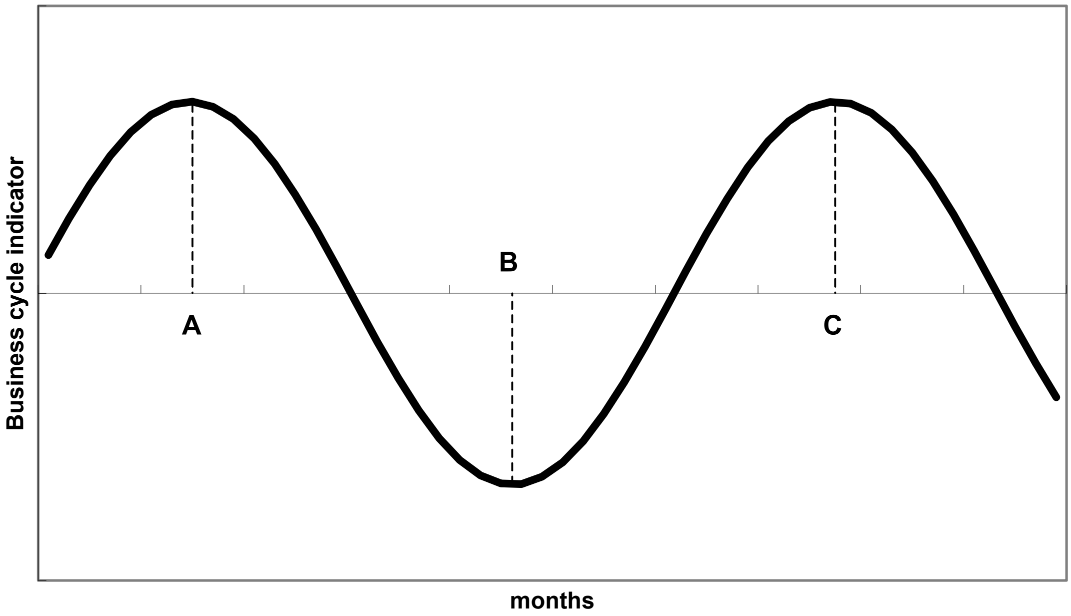
To calculate these two ratios, we set 0.5 as the probability threshold that distinguishes a recession from an expansion. We also require that the probability of recession remain higher that 0.5 for a period of at least four months (minimum phase duration condition).[14] Finally, given the previous two criteria, we consider a signal as correct if it falls within six months on either side of the true turning point (neighbourhood condition).

Let us explain some of these notions using a simple graphical example. Suppose we have a complete business cycle, which starts at a peak *A*, passes through a recession phase until it reaches a trough *B*, and then goes into a expansion phase, which lasts until the next peak *C* is attained (see Figure 4.1). So, the whole cycle duration is equal to *AC*, the recession duration is *AB*, and the expansion duration is *BC*.

[13] Here we consider only the performance of the smoothed recession probabilities, for as a rule they represent the most precise in-sample predictors of the turning points, whereas for the out-of-sample forecasting there is no distinction between the filtered and smoothed conditional regime probabilities.

[14] For the monthly data we use the minimum phase duration of four months, because the reference chronologies are based on the quarterly GDP series. Therefore we do not know exactly in which month of the quarter the recession started and in which month it terminated. Assuming that the minimum phase duration for the quarterly data is 2 quarters, we can imagine a situation in which the business cycle phase starts in the second month of quarter 1 and finishes in the second month of quarter 2, hence it may well last for 4 months only.

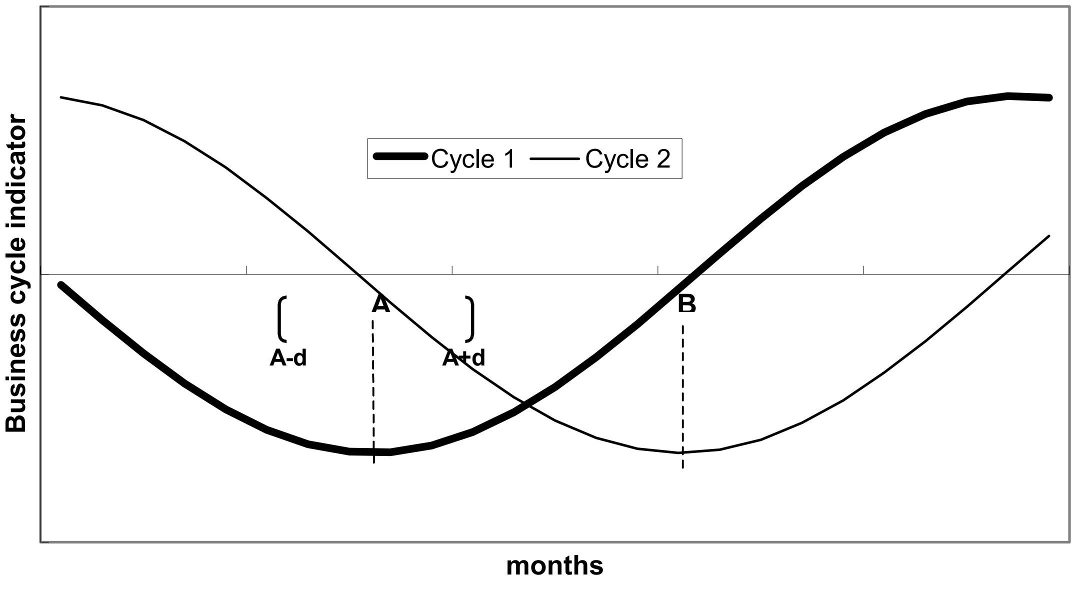
Figure 4.1. Minimum phase duration



The minimum phase duration condition requires that each phase of the cycle last more than a certain period, say 4 months: *AB>4* and *BC>4*.

Consider now two variables, each of which has its own cycle. The exact coincidence of the turning points of both cycles occurs very seldom. Normally, we will have trough *A* of cycle 1 which takes place somewhat earlier or later than the trough *B* of cycle 2 (see Figure 4.2). Hence we have to introduce some interval accounting for this imperfect coincidence.

Figure 4.2. The neighborhood of the turning point



The neighbourhood of a turning point, say, trough (peak) *A* of cycle 1 is an interval [*A-d, A+d*], such that if the trough (peak) *B* of the other cycle belongs to [*A-d, A+d*], we say that the two troughs (peaks) coincide, otherwise we say they do not. In the case illustrated on Figure 4.2, the troughs *A* and *B* do not coincide.

Ideally, the best model should have the lowest QPS, the highest "captured turning points to true turning points" ratio, and the lowest "false alarms to true turning points" ratio. Practically, we proceed as follows: To begin with, we select a small number of models with the lowest QPS. We then evaluate these according to the performance of their "capture/true" and "false/found" ratios as well as their out-of-sample forecasting abilities. [15]

4.2. Markov-switching models

Eight Markov-switching models were estimated. Three are univariate models based on BBNBG, OECD, and D6OECD. The estimation period for these three models was 1980:1-2003:12. Five are multivariate models whose composition is given in Table 4.2. These models were estimated using the time series in levels (combinations denoted by the suffix "a"). The same models were also estimated with the same series in first differences (combinations denoted by the suffix "b").[16] We found however that the latter type generally produced poor results compared to those in levels. This is why we only report and comment on the type "a" models in the main body of the paper. The appendix contains the results from both types of models.

Table 4.2. Belgian multivariate Markov-switching models

Composition	Estimation period	Model name
BBNBM, BBNBComm, BBNBConst	1980:1-2003:12	BCEI1a
BBNBM, BBNBComm, BBNBConst, IMMV	1980:1-2003:12	BCEI2a
BBNBM, BBNBComm, Confidence	1985:1-2003:12	BCEI3a
BBNBM, BBNBComm, IMMV, Confidence	1985:1-2003:12	BCEI4a
BBNBM, BBNBConst, Confidence	1985:1-2003:12	BCEI5a

The statistical properties of the various models do not indicate any major misspecification problems. We consider in particular questions of the normality and the forecastability of the residuals of the models. The residuals of almost all the models appear to be normally distributed. The only exception is the residuals of the equation corresponding to the BNB indicator for the manufacturing sector (BBNBM), for which the null of the normal distribution of residuals is rejected at 1%. In what concerns the univariate models, the null of normal distribution is accepted for BBNBG and D6OECD and rejected for OECD. The forecastability was checked by regressing the residuals of each equation on its own lagged values, and in the multivariate case, on the residuals of

[15] The classifications according to the QPS on the one hand and the two ratios on the other, can sometimes give rise to conflicting outcomes. The differences arise because small variations in the values of the estimated probabilities around the threshold probability level of 0.5 may not affect the QPS that much but can completely overturn the signal given.

[16] The reason for considering the series in first differences was to allow for the observation that some of the variables listed in table 4.1, such as new car registrations, are not convincingly stationary.

other equations appearing in the model as suggested by Stock and Watson (1991). The significance of the regression coefficients are then tested. Most of them turn out not significantly different from zero and hence the residuals can be assumed to be not forecastable.[17] In the case of univariate models, the most coefficients appear to be not significantly different from zero, except some at lags 1 or 3 with significance level of 5%.

The performance of the eight Markov-switching models is evaluated according to the conformity measures described above. We only report here, in Tables 4.3-4.5, the results for the models with the lowest QPS. (Full results can be found in Tables A4.1-A4.3 of the Appendix). It turns out that, across all the reference chronologies, the best performers in terms of QPS, are the univariate model BBNBG and the multivariate models BCEI1a, BCEI2a.

In Tables 4.3-4.5, three sets of results are presented: (a) the QPS, (b) The Diebold-Mariano statistics (DM), (c) the conformity ratios. The Diebold-Mariano statistics (see Diebold and Mariano (1995)) aims to test the null hypothesis that the QPSs for two models are equal. The bold entries correspond to the rejection of the null at the 5% significance level. In other words, the two models, for which the DM statistic is high and hence the corresponding entry in the table is in bold, replicate the turning points with a statistically different degree of accuracy.

Table 4.3. Markov-switching models : conformity measures
Reference chronology 1, 1980:3-2003:12

	QPS	DM statistic		Ratios	
		BCEI1a	BCEI2a	Captured/True	False/Found
BBNBG	0.090	**2.922**	**2.733**	0.889	0.467
BCEI1a	0.136		**1.644**	0.667	0.667
BCEI2a	0.118			0.333	0.75

Note: The bold entries are significant at 5% level

Under ***BRef1***, BBNBG outperforms all the multivariate models in terms of QPS. It has also the highest “captured/true” ratio and the lowest “false/found” ratio. Its closest rival in terms of QPS is BCEI2a. Nevertheless, first, there is statistically significant difference between the QPS of the two models, and, secondly, BCEI2a’s ratios are much worse than those of the BBNBG model.

17 The manufacturing series is once again the only series that poses a problem. It seems that the addition of extra lags might be necessary to remove this problem, although one additional lag is not sufficient. We will however review the case as additional observations become available.

Table 4.4. Markov-switching models: conformity measures
Reference chronology 2, 1980:4-2003:12

	QPS	DM statistic		Ratios	
		BCEI1a	BCEI2a	Captured/True	False/Found
BBNBG	0.180	1.317	0.199	0.733	0.267
BCEI1a	0.148		**2.847**	0.667	0.412
BCEI2a	0.184			0.467	0.364

Note: The bold entries are significant at 5% level

Under ***BRef2***, BCEI1a has the lowest QPS. However, BBNBG has the highest "captured/true" ratio and the lowest "false/found" ratio. Its QPS is the second lowest but not statistically different from BCEI1a according to the DM statistic. Therefore, we can conclude that overall, it gives the best results.

Table 4.5. Markov-switching models: conformity measures
Reference chronology 3, 1981:1-2003:12

	QPS	DM statistic		Ratios	
		BCEI1a	BCEI2a	Captured/True	False/Found
BBNBG	0.179	0.332	**3.121**	0.467	0.533
BCEI1a	0.175		**2.101**	0.667	0.412
BCEI2a	0.199			0.400	0.455

Note: The bold entries are significant at 5% level

Finally, under ***BRef3***, the smoothed probabilities of BBNBG and BCEI1a display the best performance in terms of QPS. However, it is BCEI1a, which has the highest "captured/true" ratio and the lowest "false/found" ratio.

4.3. Logit models

As for the Markov-switching models, eight logit models were estimated. Three are univariate models based on BBNBG, OECD, and D6OECD. The estimation period for these three models was 1980:I-2003:IV. Five are multivariate models whose composition is given in Table 4.6.

It is worth explaining that our logit models are based on quarterly reference chronologies, but we use monthly indicators as explanatory variables. To do this, we create three different quarterly series from each single monthly indicator. We thus have an indicator for the 1st, 2nd and third month of each quarter. Each of our regressions begins with seven indicators for each series corresponding to the first month of the current quarter plus all three months of the previous two quarters.[18] All insignificant variables are then removed through a gradual process of analysing the goodness-of-fit of the equation unless the removal of the variable seriously deteriorates the QPS.

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18 The maximum number of regressors is therefore 28.

Table 4.6. Belgian multivariate logit models

Composition	Estimation period	Model Name
BBNMB, BBNBComm, BBNBConst	1980:I-2003:IV	BLogit1a
BBNM, BBNBComm, BBNBConst, IMMV	1980:I-2003:IV	BLogit2a
BBNBM, BBNBComm, Confidence	1985:I-2003:IV	BLogit3a
BBNBM, BBNBComm, IMMV, Confidence	1985:I-2003:IV	BLogit4a
BBNBM, BBNBConst, Confidence	1985:I-2003:IV	BLogit5a

The performance of the eight logit models is evaluated again both statistically and according to the conformity measures described above.[19] We only report here, in Tables 4.7-4.9, the results for the models with the lowest QPS. (Full results can be found in Tables A4.4-A4.6 of the Appendix). It turns out that, across all the reference chronologies, the best performers are the three univariate models (BBNBG, OECD and D6OECD) and the multivariate models BLogit1a, BLogit2a.

Table 4.7. Logit models: conformity measures
Reference chronology 1, 1980:III-2003:IV

	QPS	DM statistic				Ratios	
		D6OECD	BBNBG	BLogit1a	BLogit2a	Capt/True	False/Found
OECD	0.049	0.817	**1.700**	0.025	0.410	0.556	0.286
D6OECD	0.062		0.652	0.556	1.326	0.778	0.364
BBNBG	0.079			**2.251**	**1.964**	0.556	0.375
BLogit1a	0.049				0.287	1	0
BLogit2a	0.044					0.667	0.333

Note: The bold entries are significant at 5% level

Under ***BRef1***, the logit model based on the BLogit2a component series has the lowest QPS, which is, however, statistically indistinguishable from the QPS of its neighbor-competitors, OECD[20] and BLogit1a. On the other hand, the ratios of the BLogit1a are far better than those of OECD and BLogit2a, as the last two columns of Table 4.7 show. Therefore it would be logical to select BLogit1a as the best model.

[19] In this case, the minimum phase duration and the neighbourhood of each turning point have been set equal to one quarter.

[20] In the estimation of the logit models we used the natural logarithm of the levels of the OECD leading indicator for Belgium. Therefore here OECD stands for the log of the OECD's indicator in levels.

Table 4.8. Logit models: conformity measures
Reference chronology 2, 1980:III-2003:IV

	QPS	DM statistic				Ratios	
		D6OECD	BBNBG	BLogit1a	BLogit2a	Capt/True	False/Found
OECD	0.106	1.262	1.237	0.21	0.506	0.800	0.368
D6OECD	0.093		1.557	0.17	0.123	0.800	0.368
BBNBG	0.139			**3.24**	**3.19**	0.733	0.476
BLogit1a	0.099				0.709	0.933	0.176
BLogit2a	0.088					0.867	0.381

Note: The bold entries are significant at 5% level

The best logit predictors of ***BRef2*** in terms of QPS are, according to Table 4.8, D6OECD and BLogit2a. Their forecasting accuracies are not statistically different. The logit model using D6OECD as regressor has a slightly better "False/Found" but slightly worse "Captured/True" ratios compared to model BLogit2a. On balance, BLogit2 is selected because of its lower QPS.

Table 4.9. Logit models: conformity measures
Reference chronology 3, 1981:I-2003:IV

	QPS	DM statistic				Ratios	
		D6OECD	BBNBG	BLogit1a	BLogit2a	Capt/True	False/Found
OECD	0.105	0.643	**1.886**	**2.756**	**1.955**	0.88	0.18
D6OECD	0.102		**1.989**	**3.644**	**1.868**	0.88	0.26
BBNBG	0.141			**5.279**	**4.258**	0.75	0.37
BLogit1a	0.064				0.543	0.94	0.17
BLogit2a	0.068					0.94	0.21

Note: The bold entries are significant at 5% level

Under ***BRef3***, BLogit1a and BLogit2a have the lowest QPS, which are not statistically different. Both models have exactly the same "Captured/True" ratio but BLogit1a has a lower "False/Found" ratio. Hence BLogit1a is selected as the best model.

4.4. Summary

We can now summarize the results of the selection of the best model in Table 4.10. Recall that we considered two classes of models — Markov-switching and logit — evaluating them with respect to three reference chronologies. We retain the best model for each approach because of the fundamental differences between them, as explained in section 3.3.

Table 4.10. Belgian business cycles, 1980-2003
Final selection

Reference chronology	Model	
	Markov switching	Logit
BRef1	BBNBG	BLogit1a
BRef2	BBNBG	BLogit2a
BRef3	BCEI1a	BLogit1a

5. In-depth analysis of the business cycle models

Having made the selection of the best performing model of each type for each reference chronology, we now examine in detail how precisely the models replicate and forecast the turning points of the three reference cycles for Belgium. Each subsection will begin by showing the estimated in-sample probabilities. It will then illustrate the forecasting performance of each indicator by doing an out-of-sample comparison of its forecasts with the actual periods of recession or slowdown for each reference chronology. Here, we divide the whole sample in two sub-samples: the estimation period will go to the end of 1999 and the forecast period (2000:I-2003:IV in quarters or 2000:1-2003:12 in months). The estimated parameters are then used to construct the recession probabilities for the forecast period. For the Markov-switching models, the one-step ahead forecasts are calculated by extending the estimation sub-sample by one period at each step in order to include the latest month's information and re-estimate the model parameters. We repeat this exercise until the end of the whole sample. Similarly, six-step ahead forecasts are calculated with these re-estimated parameters as outlined in the appendix. In the case of the logit models, since no dynamics are involved, we have simply used the same estimated parameters for the forecasts. We are also limited to only one-step ahead forecasts given that in all cases one or the other explanatory variable of the current time period remains significant in the model and therefore limits the forecastability of recession probabilities at longer horizons. The concluding subsection will summarise the results of this comparative analysis.

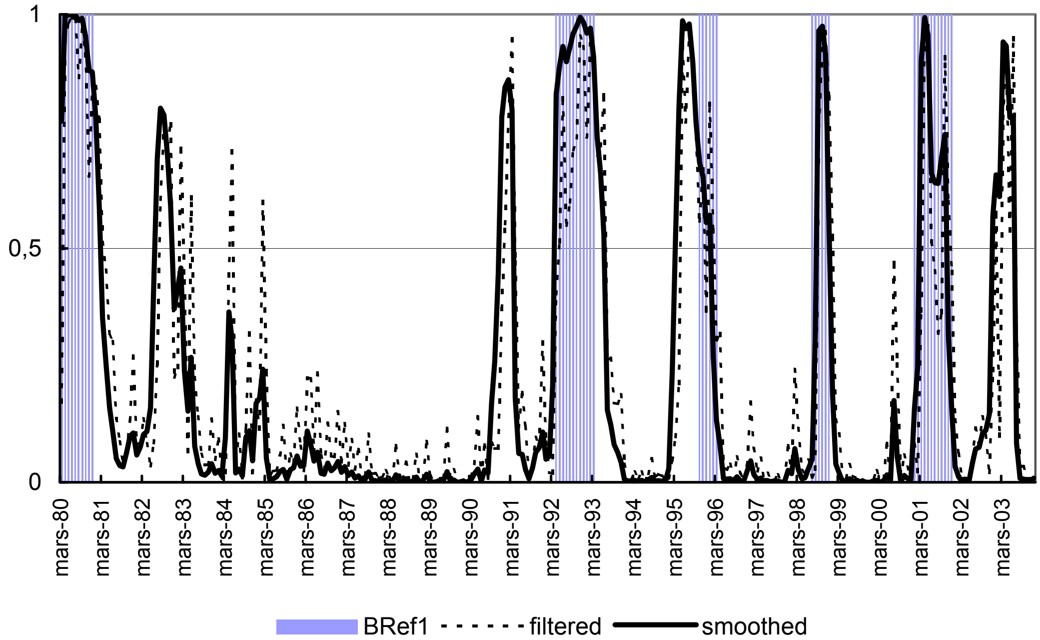
5.1. The First Reference Chronology : Periods of recession

5.1.a. Markov-switching probabilities with the BBNBG model

Our analysis in section 4.2 showed that from among the various Markov-switching models with single variables or combinations of variables, the global business climate indicator for Belgium (**BBNBG**) published by the National Bank of Belgium gave the best results when looking at the reference chronology ***BRef1***.

Figure 5.1.a1 shows the conditional (filtered and smoothed) probabilities of recession derived from the **BBNBG** univariate Markov-switching model. The probabilities (dashed and solid lines) are compared with the reference chronology ***BRef1*** (bars). The peaks in the probabilities correspond to the contraction phases of the business cycle.

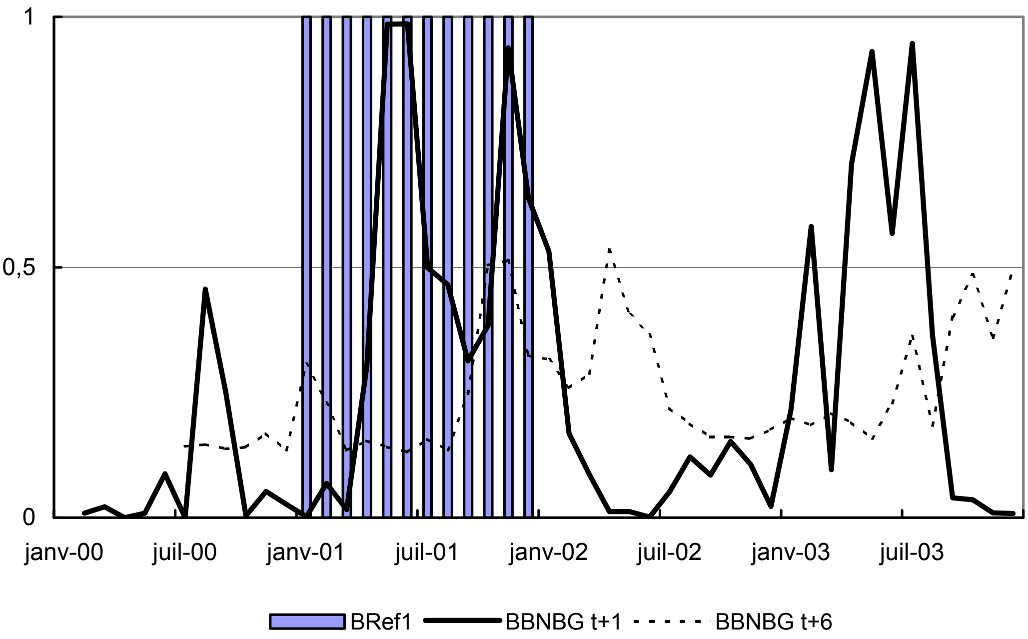
Figure 5.1.a1 Probabilities of periods of recession
MS model BBNBG, *BRef1*, 1980:4-2003:12



We can see that the recession probabilities capture five out of the five contractions depicted in this chronology. However, there are also three "false alarms" with respect to ***BRef1***: two in the first half of the sample, where ***BRef1*** claims a long uninterrupted expansion and one in the very end of the sample. Therefore, most of the discrepancies between the model-derived probabilities and the reference chronology fall in the pre-1992 period. The only recession that is signalled early is that of at the end of 1995-early 1996.

Looking next at the out-of-sample analysis of the **BBNBG** indicator**,** Figure 5.1.a2 illustrates the one- and six-step-ahead forecasts of the univariate Markov-switching model of **BBNBG** computed over the period 2000:1-2003:12. The solid continuous line represents the one-step-ahead forecast, while the dashed line represents the six-step-ahead forecast.

Figure 5.1.a2. Out-of-sample forecasting
MS model BBNBG, *BRef1*, 2000:1-2003:12

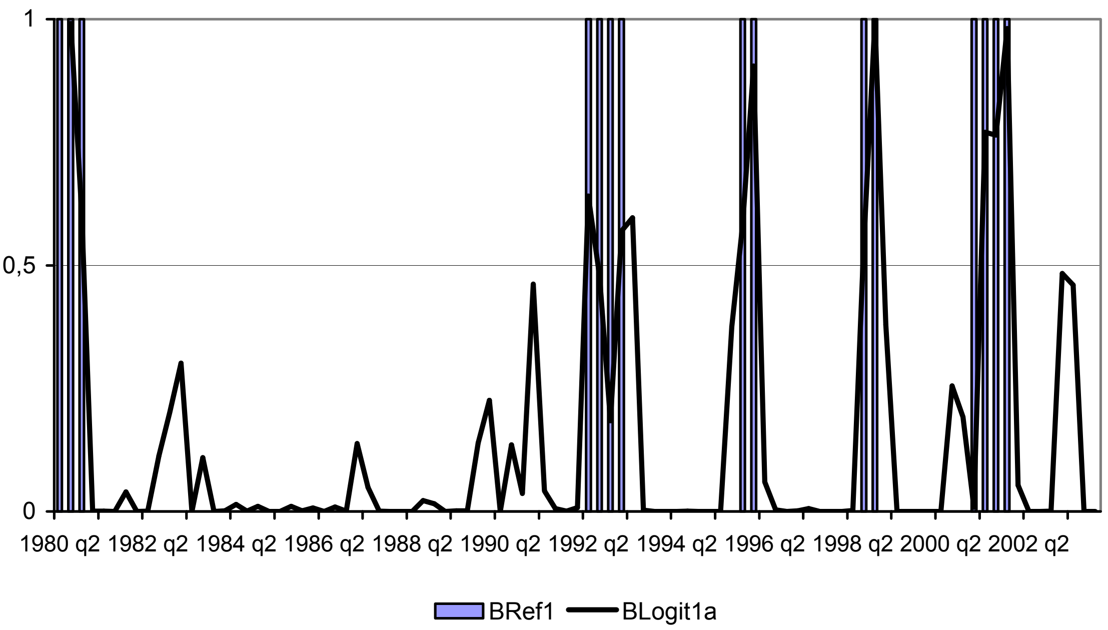


The first observation to notice is that the forecasting accuracy falls drastically when the horizon increases. The six-step-ahead forecasts are almost uninformative. The one-step-ahead forecasts give a relatively realistic picture of the recession in 2001. Note, however that the signal of the recession beginning is late whereas that relating to its end comes in advance. The one-step-ahead probability forecasts also incorrectly signal a recession in the early part of 2003, just as was the case when the whole sample estimates were calculated.

5.1.b. Logit probabilities with Blogit1a model

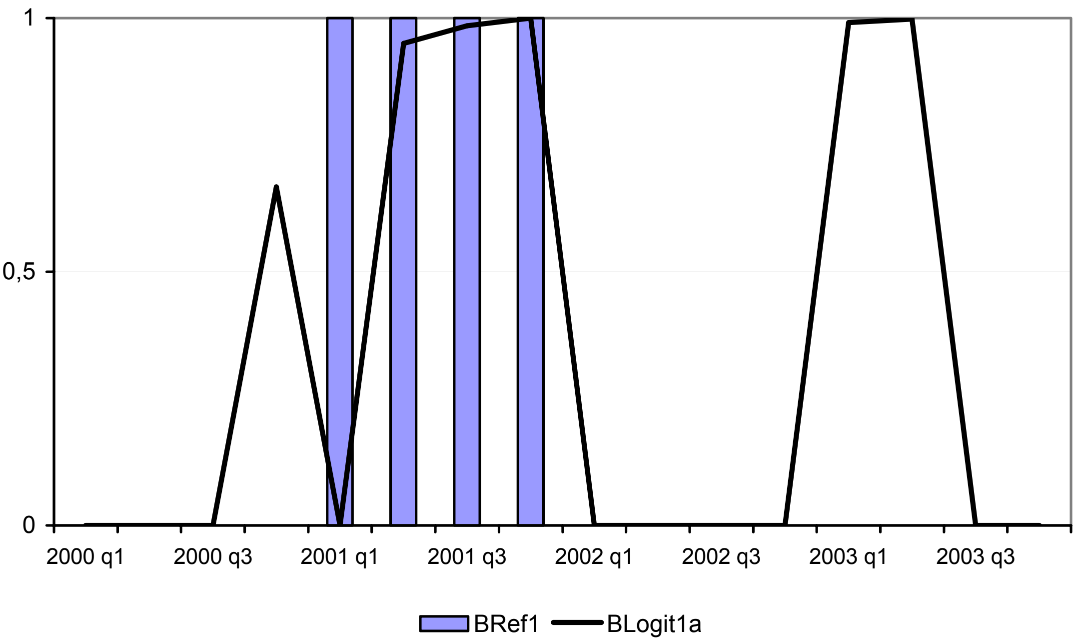
Figure 5.1.b1 shows the conditional probabilities of recession derived from ***BLogit1a***. In this case, all five periods of recession in Belgium are depicted. There is only one brief and minor peak in the first quarter of 1991, but it does not last long enough and does not exceed the 0.5 threshold to be considered as signalling a recession. At the very end of the sample, this model might also appear to suggest a recession in the first half of 2003, as was the case with the Markov-switching probabilities. However, unlike the latter case, the probabilities of recession estimated with the logit approach are lower than 0.5.

Figure 5.1.b1. Probabilities of periods of recession
Logit model BLogit1a, *BRef1*, 1980:III-2003:IV



Next, we consider the out-of-sample performance of the ***BLogit1a*** estimated probabilities. Figure 5.1.b2 illustrates the one-step-ahead forecasts for Belgium computed over the period 2000:I-2003:IV. We can see that as with the Markov-switching indicator, the recession of 2001 is well forecast, although with a one-quarter delay. There is also a false signal given in the first two quarters of 2003.

Figure 5.1.b2. Out-of-sample forecasting
Logit model BLogit1a, *BRef1*, 2000:I-2003:IV



5.2. The Second Reference Chronology: Periods of recession and slow growth

5.2.a. Markov-switching probabilities with the BBNBG model

The second reference chronology that we proposed in section 2 refers to periods in which the quarterly growth rate of the GDP is negative or below 0.5% for at least two quarters. We therefore consider periods of slow growth as well as periods of recession. For this reference chronology also, **BBNBG** was selected as showing the strongest performance.

Figure 5.2.a1 Probabilities of periods of recession and slow growth MS model BBNBG, *BRef2*, 1980:4-2003:12

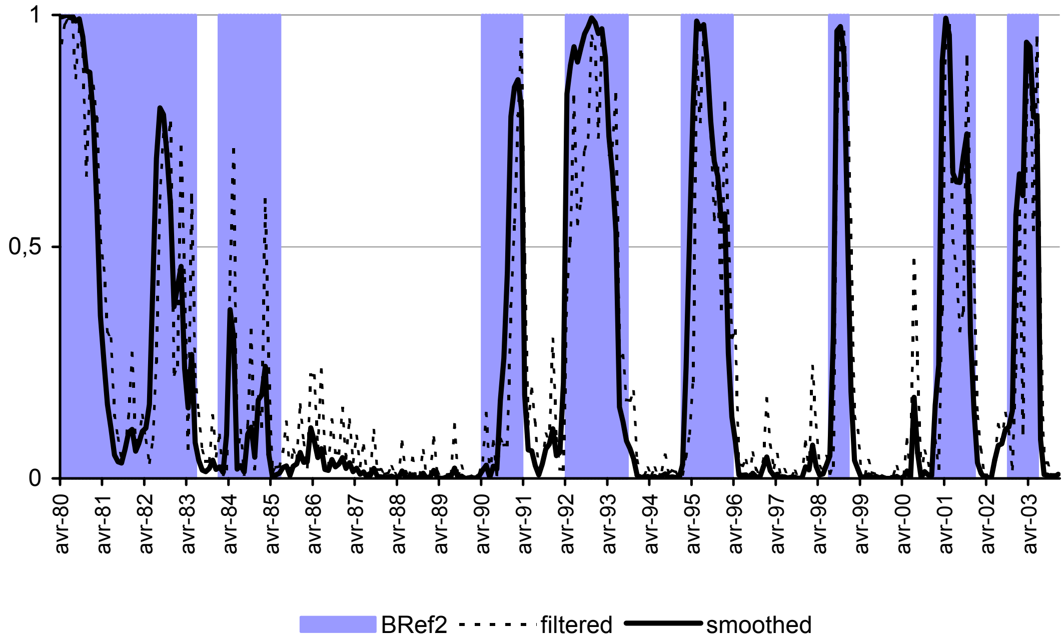
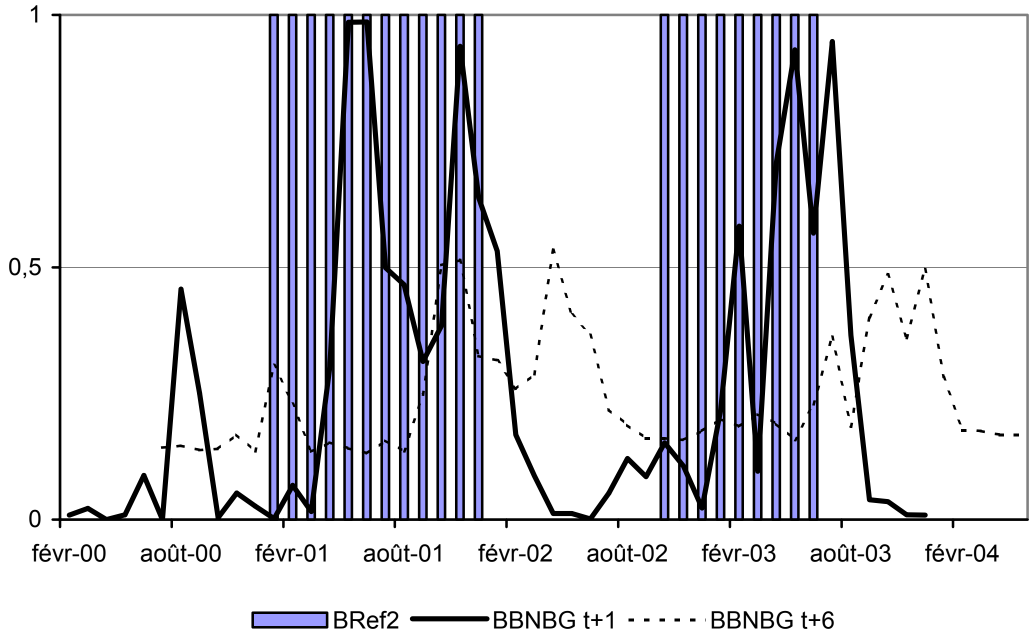


Figure 5.2.a1 shows the conditional (filtered and smoothed) probabilities of recession derived from the **BBNBG** Markov-switching model. A close look at this Figure shows that the probabilities correctly identify most periods of recession or slowdown (6 downturns out of 8 are detected), although the performance in the early 1980's is not very satisfactory: the estimated probabilities suggest an end to slow growth from mid - 81 to mid-82, contrary to reality; they also completely miss the 1984-1985 episode.

Figure 5.2.a2 shows the out-of-sample analysis of the **BBNBG** model**.** It illustrates the one- and six-step-ahead forecasts of the Markov-switching common dynamic factor model computed over the period 2000:1-2003:12.

Figure 5.2.a2. Out-of-sample forecasting
MS model BBNBG, *BRef2*, 2000:1-2003:12

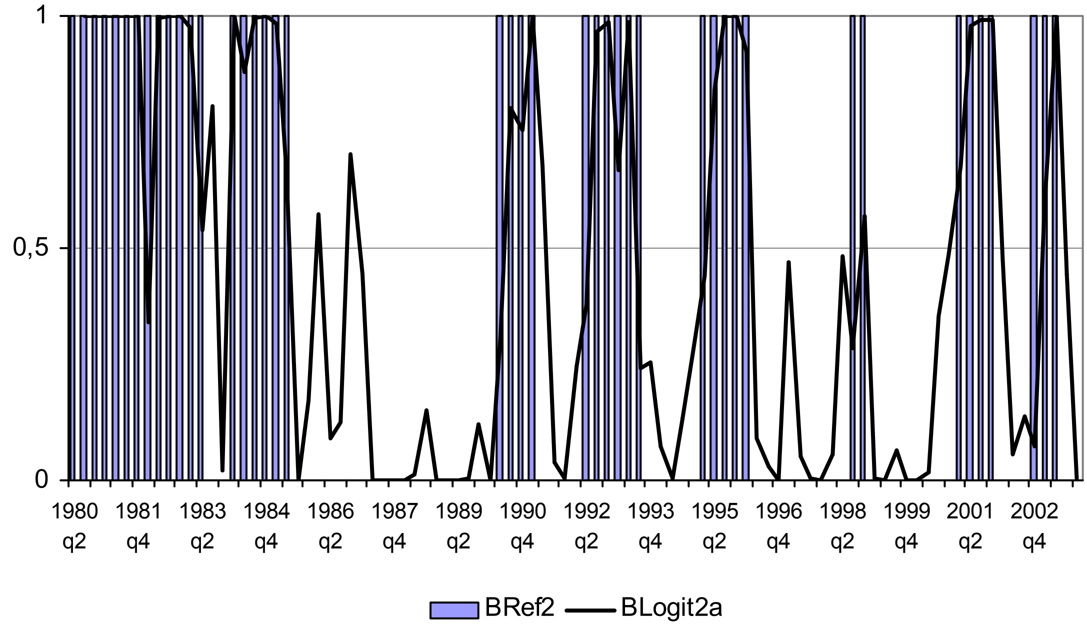


The model-derived one-step-ahead probabilities reproduce correctly but with delay, both the slowdowns of 2001 and the end of 2002 — beginning of 2003. The six-step-ahead forecasts remain continuously below the value of 0.5.

5.2.b. Logit probabilities with the BLogit2a model

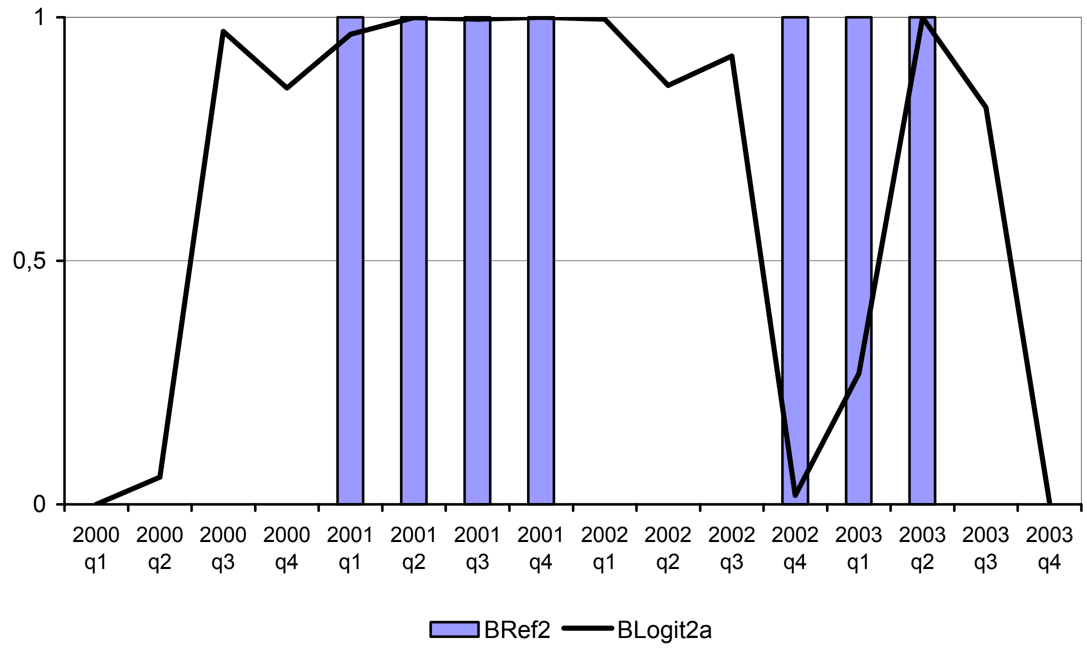
Figure 5.2.b1 shows the conditional probabilities of recession generated by the logit model of ***BLogit2a***. In this case, all periods of recession or slowdown in Belgium are depicted. There is a false signal given at the end of 1986-beginning of 1987. In addition, the recession in 1998 is signalled very weakly — the recession probabilities slightly exceed 0.5 level during only one period. This is the only case where the Markov-switching probabilities correspond better to the observed ***BRef2.***

Figure 5.2.b1. Probabilities of periods of recession and slow growth
Logit model BLogit2a, *BRef2*, 1980:III-2003:IV



Next we consider the out-of-sample performance of the ***BLogit2a*** estimated probabilities for this reference chronology**.** Figure 5.2.b2 illustrates the one-step-ahead forecasts.

Figure 5.2.b2. Out-of-sample forecasting
Logit model BLogit2a, *BRef2*, 2000:I-2003:IV



We can see that the model forecasts both slowdowns at the end of the period, although with a few quarters of anticipation in the case of the first recession and a two-quarter delay in the case of the last recession. Compared to the Markov-switching probabilities, the logit signals are once again more clearly pronounced. In the case of the recession in 2001, the MS model gives ambiguous signals both for the beginning and the end of the recession.

5.3. The Third Reference Chronology: Periods of sustained slow or negative growth tendencies

5.3.a. Markov-switching probabilities with the BBNBG model

In the case of the third reference chronology defined in section 2, periods of slow or negative growth tendencies were defined as periods in which the year-on-year growth rates of the GDP is negative or decreasing for at least two quarters. The only exception is when this growth rate remains above 3% even if it is decreasing. The analysis of section 4 showed that the **BCEI1a** model dominates the alternative models.

Figure 5.3.a1 shows that the probabilities identify most periods of sustained slow or negative growth tendencies. There are, however, a couple of signalling problems. First, the slowdown of 1990 is not signalled until it is well under way. Secondly, that of the end of 1995 is signalled too early, both as it begins and as it ends. Similar delays at either end can be observed with the final three periods.

Figure 5.3.a1. Probabilities of sustained slow or negative growth tendencies MS model BCEI1a, *BRef3*, 1981:1-2003:12

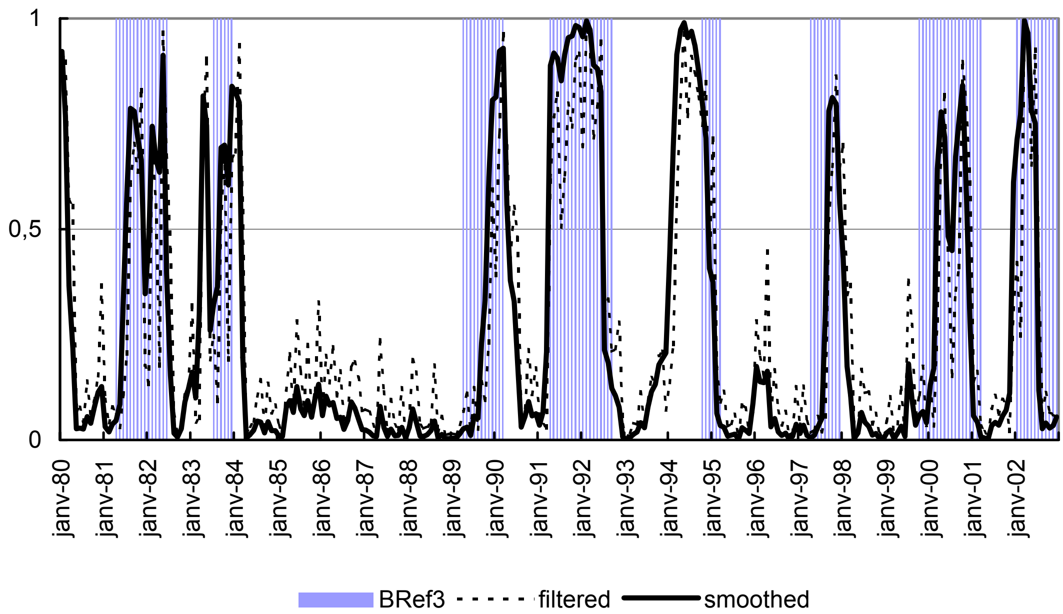
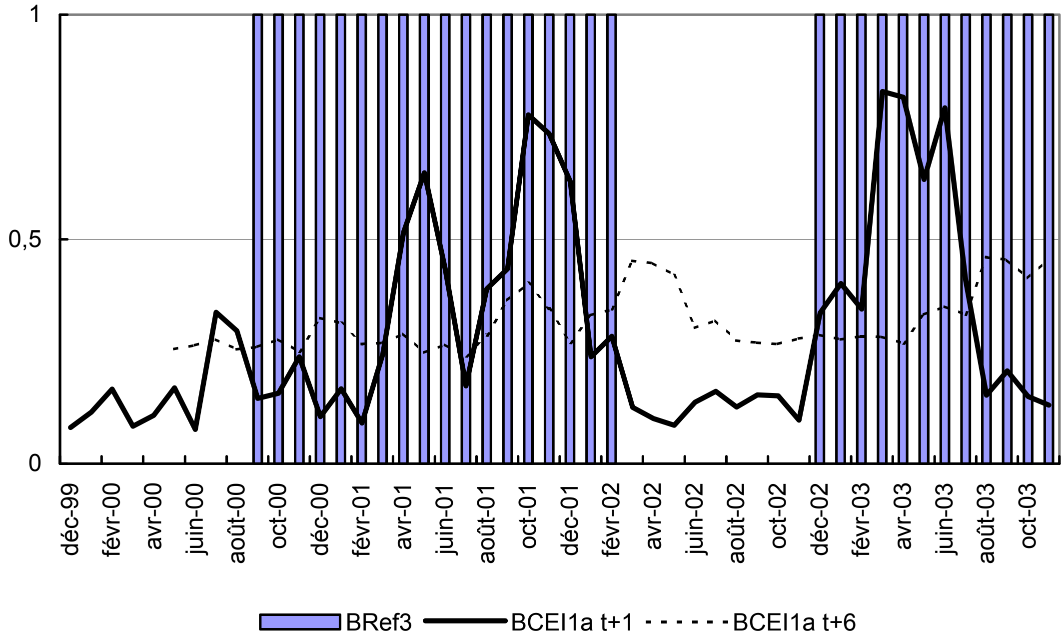


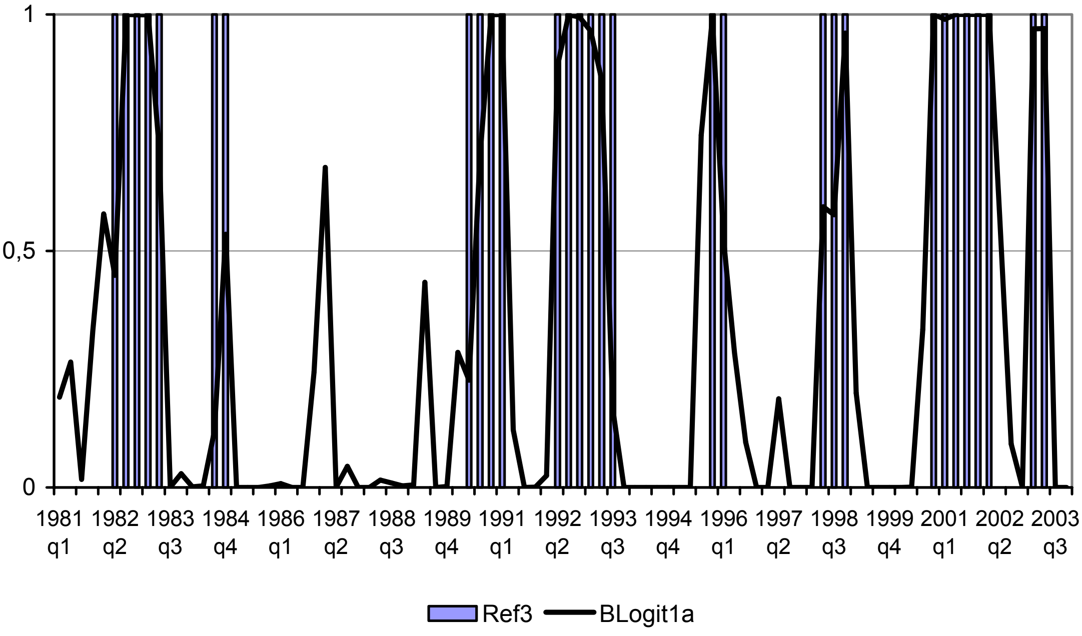
Figure 5.3.a2 shows the out-of-sample forecasts of the **BCEI1a** model**.** The forecasted probabilities display the same problems of delay, especially in the case of the slowdown at the end of 2000 — beginning of 2001. They also suggest an end to the slowdown at the end of 2003 much too early. The six-step-ahead forecasts, as before, remain constantly below the threshold of 0.5, thus unable to signal any kind of slowdown.

Figure 5.3.a2. Out-of-sample forecasting
MS model BCEI1a, *BRef3*, 2000:1-2003:12



5.3.b. Logit probabilities with the Blogit1a model

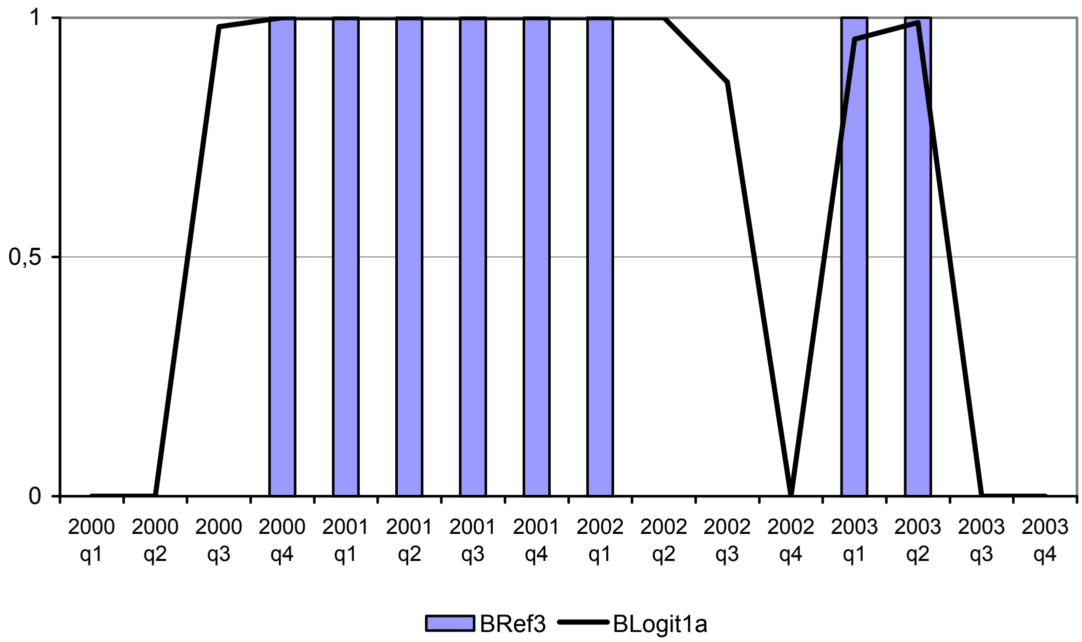
Figure 5.3.b1. Probabilities of sustained slow or negative growth
Logit model BLogit1a, *BRef3*, 1981:I-2003:IV



In the case of ***BRef3*** the model ***Blogit1a*** dominates the various alternatives considered. Figure 5.3.b1 shows the conditional probabilities generated by this model. In this case, all periods of recession or slowdown in Belgium are depicted except for the second half of 1984. The slowdown at the end of 1995 is also signalled early and not long enough. Notice that the signal given at the beginning of 1987 lasts only one period and is therefore ignored.

Next we consider the out-of-sample performance of the ***BLogit1a*** estimated probabilities for this reference chronology**.** Figure 5.3.b2 illustrates the one-step-ahead forecasts.

Figure 5.3.b2. Out-of-sample forecasting
Logit model BLogit1a, *BRef3*, 2000:I-2003:IV



We can see that the model forecasts both slowdowns at the end of the period, but the signal for the slowdown at the end of 2000 is early. Compared to the Markov-switching probabilities, the logit signals are once again more clearly pronounced. Once the signal is given in 2001, the logit probabilities remain also at a raised level, unlike the Markov-switching results, which fluctuate more widely and fall earlier than the logit ones.

5.4. Main insights

It is worthwhile summarising here the overall analysis of this section. As far as the in-sample performance of the models is concerned, it is fair to say that the models all perform relatively well. Even though the signal of a period of recession or slowdown is not always on time, all such periods are nevertheless generally detected. Where there is some weakness, is the occasional false signal. This problem is particularly important in the case of the Markov-switching model for the first reference chronology.

As for the out-of-sample analysis, the following points are worth noting. Firstly, we notice the same problem of a false signal for the first chronology, even with the logit model. The two approaches indeed announce a recession in 2003 when actually none occurred. Secondly, the correct signals do not arrive at the correct point in time. There is often a one-quarter delay. Sometimes the signal arrives too early. Finally, the six-month ahead forecasts obtained from the Markov-switching models do not detect the periods when the phase of the business cycle changes. The possibility of evaluating six-month ahead forecasts is one of the main advantages of the Markov-switching compared to the logit approach. This result is therefore particularly disappointing.

6. Conclusion

The purpose of this paper was to elaborate econometric models that can be used to forecast the turning points of the Belgian business cycle. We have suggested three reference cycles, which we hope will fill the void of an official reference chronology for Belgium. The first chronology corresponds to the usual definition of a recession in a classical sense, that is actual declines in the level of the real GDP. The second and third chronologies look instead at the growth rate of the real GDP. In the former case, we identify periods where real GDP growth is below 2% per annum for at least six months. In the latter case, we are interested in situations where the (year-on-year) growth rate of the real GDP is declining for a sustained period. Our motivation in introducing these two unconventional chronologies derives from the fact that "classical" recessions are rare phenomena and therefore the alternative chronologies provide more useful information for business cycle analysts and policy-makers.

Given the lack of consensus in the literature about which statistical model is the most appropriate approach in forecasting the turning points of the business cycle, we have opted to construct two different types of model which are the most widely used by the experts (Filardo (1999), Estrella and Mishkin (1998)). The first approach is the family of Markov-switching models, and the second is that of qualitative response models.

These two approaches were applied to a limited set of data, which are a good representation of the economy, are available early and are subject to only minor revisions. Eight models were estimated per approach and per reference chronology. A detailed analysis of the estimated models based on their statistical properties as well as a number of measures of conformity with each reference cycle led us to select one model per approach and per reference chronology. One important feature of the selected models is that they consist mainly of survey indicators. For instance, the best Markov-switching model for all the three reference chronologies is the global business cycle indicator constructed by the National Bank of Belgium. This indicator is itself built from various survey data.

The in-sample results of the two classes of models are generally satisfactory. Although no direct comparison may be made across different chronologies, it appears however that the second and third chronologies are those that are replicated more closely. We found mixed results when it comes to the out-of-sample performance of the different models. Our conclusion is that these models certainly provide useful information for the analysis and forecast of business cycle turning points. However, one cannot rely solely on them for forecasting and therefore, they are best treated in conjunction with an in-depth analysis of standard business cycle data. They must be interpreted prudently, and preferably, by a well-informed business cycle expert.

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APPENDIX A3. Markov-switching models

Basic univariate Markov-switching model

Estimation

The Markov-switching model can be motivated as follows. Suppose we observe a time series, $\boldsymbol{y_t}$, which is a sum of two unobserved components:

$$\boldsymbol{y_t = g_t + z_t},$$

where

$$\boldsymbol{g_t = g_{t-1} + \alpha_0 + \alpha_1 S_t}$$

is the Markov trend with $\boldsymbol{S_t}$ being an unobserved state (regime) of the economy, as, for instance:

$$S_t = \begin{cases} 1, & if \quad recession \quad in \quad period \quad t \\ 0, & if \quad expansion \quad in \quad period \quad t \end{cases}$$

Thus, the introduction of the auxiliary variable S_t allows us to account for different regimes. There can clearly be more than two states in which the economy might find itself. In this analysis, however, we will limit ourselves to a two-state situation.

Clearly, if we knew *a priori* the value of S_t, the problem would be very simple. However, S_t in general is not observed. To derive appropriate estimates of the model parameters, some assumptions need to be made about the stochastic behaviour of s_t. In most cases, especially cases of interest in economics, S_t will evolve depending on its own past values S_{t-1}, S_{t-2},…, S_{t-r}. Such a process is called an *r-th* order Markov-switching process. In particular, the probability that S_t takes a particular integer value can be supposed to depend on the past only through its most recent value S_{t-1}.

When the statistical model is formulated, the objective is to find the probabilities of each regime conditional on the up-to-date information set (information about the relevant variables available at the moment). These probabilities are computed recursively as:

$$\xi_{t|t} = \frac{\xi_{t|t} \otimes \eta_t}{\xi'_{t|t}}$$

and updated as follows:

$$\xi_{t+1|t} = \pi \xi_{t|t}$$

where $\xi'_{t|t} = (P(s_t = 1|Y_t), \ldots, P(s_t = m|Y_t))$ is the vector of the conditional state probabilities for each of the $\boldsymbol{m}$ regimes; $\boldsymbol{\eta'_t = (f(y_t, s_t = 1|Y_{t-1}; \theta), \ldots, f(y_t, s_t = m|Y_{t-1}; \theta))}$ is the vector of the densities of the *t-th* observation for each of $\boldsymbol{m}$ states conditioned on the previous period information set; $\otimes$ is the element-by-element multiplication operator; $\boldsymbol{\theta}$ is the vector of parameters, and

$$\pi = \begin{pmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mm} \end{pmatrix}$$

is the transition matrix, or matrix of transition probabilities.

Forecasting

After the Markov-switching model is estimated, the next important problem is to forecast both the observed variable and the predictive probabilities. A particularly interesting property of Markov chains is that they can be given autoregressive representations in terms of a random vector. ξ_t is in fact the expectation of this random vector, given the information set available at time t. In the case of a first-order Markov-switching process, we have a first-order autoregressive representation and it can be easily shown that the τ-step-ahead forecast of $\xi_{t+\tau}$ conditional on the information available at period $\boldsymbol{t}$ is calculated as[21]:

$$\xi_{t+\tau|t} = P^{\tau}\xi_{t|t}$$

If we were making a one-period-ahead forecast, then the forecast of $\boldsymbol{y_{t+1}}$ given the information available in $\boldsymbol{t}$ would be:

$$E(y_{t+1}|Y_t;\theta) = h_t^{'}\xi_{t+1|t}$$

where:

$$h_t = \begin{cases} E(y_{t+1}|s_t = 1, Y_t;\theta) = \mu_1 + \phi_1(y_{t-1} - \mu_{s_t}) + \ldots + \phi_p(y_{t-p} - \mu_{s_p}) \\ \vdots \\ E(y_{t+1}|s_t = m, Y_t;\theta) = \mu_m + \phi_1(y_{t-1} - \mu_{s_t}) + \ldots + \phi_p(y_{t-p} - \mu_{s_p}) \end{cases}$$

Multivariate models

The multivariate approach using the linear dynamic factor model

The linear dynamic factor model proposed by Stock and Watson (1989, 1991, 1993) is designed to extract the common dynamics of macroeconomic time series at the business cycle frequencies. Stock and Watson assume the existence of some common dynamic factor, or, alternatively, composite economic indicator (CEI), which is behind the co-movements of the individual economic variables. It is thought to be a measure of the state of affairs in the economy or, in other words, it is an indicator of the business cycle. This common dynamic factor is unobserved. It may depend on its own past values, and therefore is called dynamic. In principle, the CEI is a weighted average of several

21 See Hamilton (1994).

observed time series, where the weights are estimated. Along with the common factor, Stock and Watson's model also identifies a specific factor for each observed component series. It "explains" the idiosyncratic dynamics of each of these series, which can be attributed only to a particular time series.

The composite economic indicator model of Stock and Watson can be written as follows:

$$\Delta y_t = \gamma(L)\Delta C_t + u_t$$
$$\Delta C_t = \mu + \phi(L)\Delta C_{t-1} + \varepsilon_t$$
$$\psi(L)u_t = \eta_t$$

where y_t is the vector of N coincident variables in levels; $\mathbf{C}_t$ is the latent common dynamic factor (composite economic indicator); u_t is the vector of N idiosyncratic (specific) components; μ and δ are constant terms; $\gamma(L)$, D(L), and $\phi(L)$ are lag polynomials; ε_t and η_t are serially and mutually independent Gaussian noise processes:

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \sim NIID\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & O \\ O & \Sigma_\eta \end{pmatrix}\right)$$

Since, defined in this way, the model is not identified, Stock and Watson introduce two identifying assumptions: they set the variance of the common factor to 1 and make matrix Σ_η diagonal meaning independence between the idiosyncratic, or specific, components of different observed time series.

In principle, it is possible to build an unobserved components model with the variables in levels. However, with the coincident variables used by Stock and Watson, it was impossible to reject that the individual variables were integrated of order 1 and to accept that they were cointegrated. Therefore the model is estimated with the variables in first differences.

Kim (1994) and Kim and Nelson (1999) propose a promising extension of the Stock and Watson model. This approach is applied to construct the US coincident economic indicator with nonlinear dynamics in Chauvet (1998), Chauvet and Potter (2000, 2002) and in Kim and Yoo (1995).

The Markov-switching common factor (MS-CF) approach allows estimating simultaneously both the common factor, underlying the common dynamics of several macroeconomic time series, and the recession probabilities corresponding to this factor. In other words, this approach incorporates nonlinear dynamics into the common factor extraction by combining the unobserved component model of Stock and Watson with the Markov regime-switching methodology of Hamilton. This permits reflecting the two defining features of the business cycle put forward by Burns and Mitchell (1946) and stressed by Diebold and Rudebusch (1996) in their survey of modern turning points' modelling, namely: co-movement of the individual macroeconomic series within the cycle and asymmetric business cycle dynamics, when the behaviour of the economy during expansions is different from that in the recessions.

Thus, there are two outputs stemming from the MS-CF model: (1) the common factor itself and (2) the conditional regime probabilities. The latter can serve as a proxy of the turning points chronology. If an officially accepted chronology of turning points exists, such as the case of the USA, one can then compare the estimated regime probabilities to the reference chronology for validation. When such an "official chronology" is absent, it is possible to consider the recession probabilities resulting from the MS-CF model as a possible “dating”. However, the extreme complexity of the model means that the validity of this model-derived chronology must be treated with care. It would be wise to use a set of alternative chronologies at the same time in order to make their cross-validation.

The model of a single dynamic common factor with Markov switching (MS-CF) is presented in the main text of the paper. As in the Stock and Watson case, when the component series, $\boldsymbol{y_t}$, are integrated but not cointegrated, they enter the model in first differences and not in levels. Again, as in Stock and Watson (1988) the lag polynomial matrices for the specific components, $\mathbf{\Psi(L)}$ ($\boldsymbol{j=1,...,q}$, where the $\boldsymbol{q}$ is the maximum autoregressive order of the specific components), are assumed to be diagonal.

The transition probabilities, $\mathbf{p_{ij}=Prob(s_t=j|s_{t-1}=i)}$, sum up to one when added across all the possible state for the given regime in the previous period: $\sum_{j=1}^{m} p_{ij} = 1$ for all $\boldsymbol{i}$ for $\boldsymbol{m}$ states.

The MS-CF has several advantages compared both to the linear dynamic factor model and to the univariate Markov-switching models.

On the one hand, the common dynamic factor model of Stock and Watson (1989) does not capture the asymmetries between cyclical phases, which leads to loss in precision of their forecasts. "Unfortunately, Stock and Watson's model fails to account for the 1990 recession using a recession index extracted from their non-switching dynamic factor representation. The linearity imposed by their model implies a built-in symmetry which forces expansions and contractions to have the same magnitude, duration, and amplitude" (Chauvet (1998, p. 970)).

On the other hand, the univariate Markov switching model of Hamilton (1989), although it detects the business cycle asymmetries, fails to capture co-movement and hence sometimes misses the turning points, especially when the higher (monthly) frequency data are used. "… Hamilton's model, since it is univariate, cannot capture the notion of economic fluctuations corresponding to co-movements of many aggregate and sectoral variables. In addition, extensions of Hamilton's analysis to monthly growth rates fail to account for several of the historical recessions as determined by the NBER. It is possible that all underlying business cycle information cannot be extracted from only one coincident variable" (Chauvet (1998, p. 970)). Therefore the logical response to these criticisms is the MS-CF model.

APPENDIX A4 Properties of the Markov-switching and logit models

Table A4.1. QPS results of MS models, Reference chronology 1, 1985:2-2003:12

	QPS	***DM statistic***																				
		OECDs	***D6OECDf***	***D6OECDs***	***BNBGf***	***BNBGs***	***BCEI1af***	***BCEI1as***	***BCEI1bf***	***BCEI1bs***	***BCEI2af***	***BCEI2as***	***BCEI2bf***	***BCEI2bs***	***BCEI3f***	***BCEI3s***	***BCEI4f***	***BCEI4s***	***BCEI5af***	***BCEI5as***	***BCEI5bf***	***BCEI5bs***
OECDf	0.516	**2.137**	**2.25**	**1.77**	**4.214**	**4.378**	**3.969**	**4.063**	**3.44**	**3.511**	**3.934**	**4.02**	**4.046**	**4.073**	**3.549**	**3.721**	**3.533**	**3.688**	**3.005**	**3.019**	**3.998**	**3.859**
OECDs	0.550		**2.66**	**2.21**	**4.438**	**4.633**	**4.209**	**4.345**	**3.63**	**3.706**	**4.155**	**4.274**	**4.291**	**4.332**	**3.789**	**3.987**	**3.767**	**3.943**	**3.282**	**3.313**	**4.32**	**4.243**
D6OECDf	0.302			1.47	**3.888**	**4.379**	**3.267**	**3.621**	**2.41**	**2.471**	**3.291**	**3.473**	**3.764**	**4.099**	**2.332**	**2.626**	**2.314**	**2.563**	1.483	1.46	**4.088**	**4.245**
D6OECDs	0.340				**3.549**	**3.863**	**3.084**	**3.344**	**2.55**	**2.605**	**3.16**	**3.297**	**3.541**	**3.681**	**2.27**	**2.497**	**2.258**	**2.45**	1.62	1.617	**3.614**	**3.914**
BNBGf	0.096					0.374	**3.837**	1.267	0.822	0.73	**2.193**	1.233	1.05	1.621	**5.165**	**3.486**	**5.021**	**3.551**	**3.467**	**2.901**	0.917	0.913
BNBGs	0.091						**2.502**	**2.999**	0.777	0.736	1.468	**2.664**	1.144	**2.246**	**4.529**	**4.795**	**4.352**	**4.589**	**3.776**	**3.228**	1.481	1.460
BCEI1af	0.122							0.139	0.003	0.103	0.954	0.545	0.41	0.443	**3.14**	**2.262**	**2.999**	**2.288**	**2.703**	**2.262**	0.407	0.078
BCEI1as	0.120								0.05	0.035	0.347	0.537	0.257	0.584	**2.256**	**2.579**	**2.168**	**2.434**	**2.789**	**2.459**	0.318	0.198
BCEI1bf	0.122									0.511	0.301	0.182	0.29	0.271	1.241	0.975	1.246	1.008	1.637	1.509	0.204	0.046
BCEI1bs	0.118										0.183	0.095	0.174	0.369	1.391	1.135	1.395	1.17	1.809	1.667	0.124	0.125
BCEI2af	0.113											0.141	0.004	0.796	**2.921**	**2.262**	**2.905**	**2.332**	**2.625**	**2.248**	0.016	0.336
BCEI2as	0.115												0.071	0.788	**2.491**	**2.581**	**2.437**	**2.553**	**2.701**	**2.362**	0.064	0.352
BCEI2bf	0.113													1.147	**2.398**	**1.959**	**2.357**	**1.969**	**2.467**	**2.236**	0.015	0.368
BCEI2bs	0.133														1.292	1.152	1.272	1.163	**1.895**	**1.749**	0.82	0.306
BCEI3f	0.173															0.557	0.125	0.513	1.484	1.199	**2.97**	1.444
BCEI3s	0.166																0.527	0.379	**1.946**	1.684	**2.722**	1.515
BCEI4f	0.173																	0.496	1.465	1.191	**2.805**	1.404
BCEI4s	0.167																		**1.887**	1.623	**2.59**	1.463
BCEI5af	0.212																			0.092	**3.422**	**2.321**
BCEI5as	0.213																				**2.96**	**2.274**
BCEI5bf	0.113																					0.636
BCEI5bs	0.124																					

Note: The bold entries are significant at 5% level. The sample size used for calculating and comparing the QPS from all the alternative models is shorter than the results reported in the main text. This is because some of the indicators used, are only available from 1985. However the results in tables A4.1-A4.6 show that none of these shorter series are retained finally.

Table A4.2. QPS results of MS models, Reference chronology 2, 1985:2-2003:12

	QPS	DM statistic																				
		OECDs	D6OECDf	D6OECDs	BNBGf	BNBGs	BCEI1af	BCEI1as	BCEI1bf	BCEI1bs	BCEI2af	BCEI2as	BCEI2bf	BCEI2bs	BCEI3f	BCEI3s	BCEI4f	BCEI4s	BCEI5af	BCEI5as	BCEI5bf	BCEI5bs
OECDf	0.436	0.104	**2.884**	**2.418**	**3.006**	**3.387**	**3.107**	**3.5**	**1.701**	**1.838**	**2.87**	**3.21**	**2.872**	**3.1**	**3.047**	**3.422**	**3.012**	**3.359**	**2.932**	**3.146**	**3.529**	**3.739**
OECDs	0.438		**2.768**	**2.348**	**2.784**	**3.137**	**2.869**	**3.237**	1.62	**1.748**	**2.66**	**2.974**	**2.697**	**2.926**	**2.843**	**3.189**	**2.813**	**3.13**	**2.76**	**2.962**	**3.339**	**3.555**
D6OECDf	0.202			**1.914**	1.247	**1.931**	1.33	**2.14**	0.4	0.206	1.029	1.619	1.017	1.378	0.919	1.535	0.877	1.432	0.789	1.091	**2.21**	**2.399**
D6OECDs	0.246				**1.785**	**2.376**	**1.861**	**2.553**	0.155	0.339	1.585	2.11	1.651	**2.021**	1.468	1.95	1.429	**1.862**	1.302	1.547	**2.563**	**2.785**
BNBGf	0.136					**2.004**	0.146	**2.084**	**2.41**	**1.967**	0.837	1.044	0.572	0.035	0.979	0.081	1.04	0.056	0.755	0.247	1.113	1.189
BNBGs	0.108						**1.733**	0.648	**2.926**	**2.664**	**2.458**	1.113	1.853	1.119	2.38	1.087	2.51	1.259	**1.751**	1.051	0.003	0.451
BCEI1af	0.135							**2.634**	**2.252**	**1.886**	1.106	1.128	0.565	0.08	1.236	0.032	1.308	0.128	0.861	0.304	1.062	1.22
BCEI1as	0.102								**2.949**	**2.702**	**3.091**	**2.197**	**1.895**	1.257	**3.068**	1.506	**3.245**	**1.717**	**1.997**	1.245	0.27	0.243
BCEI1bf	0.233									**1.744**	**2.385**	**2.777**	**2.594**	**2.379**	1.331	1.785	1.309	**1.715**	1.178	1.336	**2.763**	**2.852**
BCEI1bs	0.218										**1.948**	**2.507**	**2.133**	**2.131**	1.067	1.548	1.046	1.478	0.952	1.139	**2.518**	**2.717**
BCEI2af	0.146											**2.453**	0.182	0.248	0.594	0.386	0.661	0.258	0.472	0.022	1.341	1.458
BCEI2as	0.119												1.17	0.652	**1.719**	0.57	**1.836**	0.732	1.287	0.69	0.441	0.789
BCEI2bf	0.150													0.707	0.372	0.486	0.426	0.365	0.333	0.086	1.893	**2.008**
BCEI2bs	0.138														0.682	0.094	0.738	0.01	0.613	0.192	1.196	1.655
BCEI3f	0.162															6.464	1.017	**5.157**	0.059	0.613	**3.037**	**2.756**
BCEI3s	0.134																**7.663**	**2.608**	1.496	0.524	1.398	1.574
BCEI4f	0.164																	**6.841**	0.023	0.683	**3.14**	**2.836**
BCEI4s	0.138																		1.311	0.36	1.555	1.69
BCEI5af	0.163																			1.581	**2.482**	**2.412**
BCEI5as	0.147																				1.366	1.577
BCEI5bf	0.108																					0.924
BCEI5bs	0.096																					

Note: The bold entries are significant at 5% level

Table A4.3. QPS results of MS models, Reference chronology 3, 1985:2-2003:12

	QPS	***DM statistic***																				
		OECDs	***D6OECDf***	***D6OECDs***	***BNBGf***	***BNBGs***	***BCEI1af***	***BCEI1as***	***BCEI1bf***	***BCEI1bs***	***BCEI2af***	***BCEI2as***	***BCEI2bf***	***BCEI2bs***	***BCEI3f***	***BCEI3s***	***BCEI4f***	***BCEI4s***	***BCEI5af***	***BCEI5as***	***BCEI5bf***	***BCEI5bs***
OECDf	0.403	0.01	**1.678**	1.223	**2.109**	**2.274**	**2.056**	**2.217**	1.193	1.263	**1.824**	**1.986**	**2.096**	**2.169**	**2.117**	**2.302**	**2.061**	**2.206**	**1.779**	**1.801**	**2.498**	**2.512**
OECDs	0.403		1.608	1.185	**1.954**	**2.113**	**1.906**	**2.065**	1.127	1.193	**1.699**	**1.854**	**1.959**	**2.045**	**1.968**	**2.146**	**1.919**	**2.057**	**1.675**	**1.699**	**2.358**	**2.392**
D6OECDf	0.252			**1.838**	1.475	**1.914**	1.252	**1.69**	0.001	0.087	0.941	1.254	1.464	**1.706**	1.142	1.607	1.065	1.419	0.647	0.631	**2.636**	**2.65**
D6OECDs	0.294				**1.96**	**2.414**	**1.767**	**2.252**	0.532	0.63	1.487	**1.829**	**2.012**	**2.31**	1.603	**2.021**	1.538	**1.869**	1.218	1.253	**2.895**	**3.17**
BNBGf	0.173					0.841	1.35	0.018	**2.021**	**1.833**	**2.922**	0.821	0.214	0.058	1.038	0.581	1.181	0.801	1.481	1.292	0.851	0.462
BNBGs	0.162						1.541	1.058	**2.158**	**2.09**	**2.668**	**2.808**	0.671	0.436	1.459	1.071	1.626	1.343	1.96	**1.698**	0.552	0.231
BCEI1af	0.184							0.776	1.547	1.397	1.158	0.129	0.21	0.242	0.708	0.244	0.853	0.48	1.232	1.064	1.321	0.789
BCEI1as	0.172								**1.677**	1.604	1.44	1.614	0.198	0.073	1.065	0.756	1.209	1.028	1.633	1.457	0.95	0.591
BCEI1bf	0.252									0.868	1.507	1.523	**2.58**	**2.049**	0.911	1.042	0.855	0.942	0.452	0.39	**2.294**	**1.901**
BCEI1bs	0.246										1.313	1.429	**2.58**	**2.135**	0.816	0.971	0.757	0.864	0.358	0.304	**2.28**	**1.928**
BCEI2af	0.198											0.879	0.731	0.636	0.124	0.196	0.239	0.011	0.716	0.643	**1.676**	1.107
BCEI2as	0.186												0.276	0.343	0.484	0.157	0.606	0.375	1.08	0.967	1.374	0.945
BCEI2bf	0.178													0.182	0.722	0.37	0.839	0.553	1.279	1.149	1.309	0.802
BCEI2bs	0.175														0.687	0.433	0.789	0.603	1.286	1.181	1.034	0.876
BCEI3f	0.202															0.826	**1.828**	0.341	1.177	0.901	**2.485**	1.408
BCEI3s	0.191																1.117	**2.89**	**1.841**	1.588	**1.899**	1.302
BCEI4f	0.205																	0.644	1.027	0.783	**2.725**	1.528
BCEI4s	0.198																		1.566	1.329	**2.242**	1.519
BCEI5af	0.225																			0.125	**3.347**	**2.285**
BCEI5as	0.226																				**2.679**	**2.218**
BCEI5bf	0.15																					0.241
BCEI5bs	0.154																					

Note: The bold entries are significant at 5% level.

Table A4.4. QPS results of logit models, Reference chronology 1, 1985:3-2003:12

	QPS	DM statistic												
		D6OECD	BNBG	BLogit1a	BLogit2a	BLogit3aComp	BLogit3a	BLogit4a	BLogit5a	BLogit1b	BLogit2b	BLogit3b	BLogit4b	BLogit5b
OECD	0.060	0.107	**1.752**	0.096	0.377	0.106	1.087	0.79	0.201	0.882	0.642	0.122	0.14	0.229
D6OECD	0.059		1.52	0.045	0.77	0.128	1.343	0.87	0.122	0.782	0.642	0.13	0.077	0.116
BNBG	0.097			**2.666**	**2.034**	**2.292**	0.033	1.004	**3.857**	**3.643**	1.444	**2.373**	**2.56**	**2.194**
BLogit1a	0.058				0.178	0.383	1.436	1.012	0.189	**1.667**	**2.102**	0.285	0.082	0.033
BLogit2a	0.054					0.298	**2.112**	1.369	0.051	0.759	1.014	0.296	0.064	0.192
BLogit3aComp	0.063						0.994	p 0.732	0.783	**1.763**	0.852	0.019	0.634	0.247
BLogit3a	0.096							0.769	1.258	**1.772**	0.656	0.864	1.003	1.257
BLogit4a	0.082								1.211	**1.937**	0.22	0.681	0.886	1.146
BLogit5a	0.055									**2.357**	**2.343**	0.948	0.109	0.098
BLogit1b	0.032										**3.864**	**1.725**	1.334	1.286
BLogit2b	0.077											0.692	0.988	1.186
BLogit3b	0.063												**2.618**	0.308
BLogit4b	0.056													0.04
BLogit5b	0.057													

Table A4.5. QPS results of logit models, Reference chronology 2, 1985:3-2003:12

	QPS	DM statistic												
		D6OECD	BNBG	BLogit1a	BLogit2a	BLogit3aComp	BLogit3a	BLogit4a	BLogit5a	BLogit1b	BLogit2b	BLogit3b	BLogit4b	BLogit5b
OECD	0.085	**1.654**	**1.825**	1.091	0.267	0.148	1.235	0.595	0.635	1.31	0.468	1.151	0.756	0.34
D6OECD	0.063		**3.696**	**4.181**	**1.696**	0.701	**2.442**	0.037	0.089	0.834	**1.924**	**2.23**	0.058	0.389
BNBG	0.139			**2.58**	**2.141**	4.272	1.104	**3.904**	**11.523**	**5.882**	**1.915**	1.013	**8.737**	**4.515**
BLogit1a	0.110				1.311	3.109	0.815	**2.935**	**5.158**	**6.739**	0.633	1.11	**6.603**	**1.724**
BLogit2a	0.093					0.796	1.335	1.183	**1.684**	**3.641**	0.377	**1.788**	**2.284**	0.906
BLogit3aComp	0.080						**2.521**	1.253	**1.808**	**1.807**	0.831	**3.168**	1.546	0.316
BLogit3a	0.124							4.76	**6.73**	**8.827**	0.875	0.366	**5.22**	**3.304**
BLogit4a	0.062								0.234	0.346	1.297	**2.844**	0.003	0.41
BLogit5a	0.065									1.589	**1.875**	**4.339**	0.34	0.42
BLogit1b	0.053										**5.512**	**4.896**	**1.73**	1.046
BLogit2b	0.100											0.953	**6.97**	0.829
BLogit3b	0.128												**3.122**	**3.688**
BLogit4b	0.062													0.482
BLogit5b	0.073													

Table A4.6. QPS results of logit models, Reference chronology 3, 1985:3-2003:12

	QPS	DM statistic												
		D6OECD	BNBG	BLogit1a	BLogit2a	BLogit3aComp	BLogit3a	BLogit4a	BLogit5a	BLogit1b	BLogit2b	BLogit3b	BLogit4b	BLogit5b
OECD	0.091	**1.793**	**1.636**	**1.803**	1.489	1.522	0.194	0.274	0.117	0.842	0.013	0.11	0.5	0.22
D6OECD	0.099		1.304	**2.188**	**1.737**	**2.129**	.NaN	.NaN	0.615	1.163	0.307	0.473	1.147	0.57
BNBG	0.125			**4.397**	**3.886**	**6.833**	**2.524**	**2.166**	.NaN	.NaN	**2.515**	**1.748**	**3.511**	**2.136**
BLogit1a	0.053				0.354	0.265	1.578	**1.887**	**2.429**	**1.933**	**3.002**	**1.751**	1.489	1.325
BLogit2a	0.057					0.017	1.327	1.497	**1.928**	**2.438**	.NaN	1.516	1.204	1.558
BLogit3aComp	0.057						1.426	**1.716**	**2.033**	.NaN	.NaN	**1.758**	1.314	1.507
BLogit3a	0.089							0.579	0.262	0.633	0.071	0.295	0.5	0.101
BLogit4a	0.095								0.201	0.964	0.162	0.076	0.669	0.277
BLogit5a	0.092										0.145	0.049	1.231	0.356
BLogit1b	0.076										**2.385**	0.795	0.391	0.513
BLogit2b	0.091											0.094	0.4	0.201
BLogit3b	0.093												0.716	0.293
BLogit4b	0.082													0.286
BLogit5b	0.086													

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