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Identification and real-time forecasting of Norwegian business cycles*

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Abstract

We define and forecast classical business cycle turning points for the Norwegian economy. When defining reference business cycles, we compare a univariate and a multivariate Bry-Boschan approach with univariate Markov-switching models and Markov-switching factor models. On the basis of a receiver operating characteristic curve methodology and a comparison of business cycle turning points with Norway's main trading partners, we find that a Markov-switching factor model provides the most reasonable definition of Norwegian business cycles for the sample 1978Q1-2011Q4. In a real-time out-of-sample forecasting exercise, focusing on the last recession, we show that univariate Markov-switching models applied to surveys and a financial conditions index are timely and accurate in calling the last peak in real time. The models are less accurate and timely in calling the trough in real time.

JEL-codes: C32, C52, C53, E37, E52

Keywords: Business cycle; Dating rules; Turning Points; Real-time data

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1 Introduction

Short-term analysis in central banks and other policy institutions is intended to provide policy makers, and possibly a larger audience, with assessments of the recent past and current business cycle. There is a long tradition in business cycle analysis of separating periods of contraction from periods of expansion (see Schumpeter (1954)). Policy decisions vary depending on whether the economy is in an expansionary or a recessionary period. Most of the research has focused on US data, where the cycle defined by the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) cycle is regarded as the official reference cycle.

There is no authoritative dating of classical business cycles for the Norwegian economy. Norway is characterized by being a small open economy with large exports of energy (gas and oil) goods, and it is not obvious that Norwegian business cycles are fully synchronized with the cycles of other Scandinavian countries, or with the European or the US cycles.

The contribution of this paper is twofold. First, we define classical business cycle turning points for the Norwegian economy for the period 1978Q1-2011Q4 exploring a set of widely used methods. Second, in a real-time out-of-sample forecasting exercise, we study the timeliness and accuracy of the different methods in order to predict the peak and trough of the last recession.

To define reference business cycles for the Norwegian economy, we estimate and compare cycles from various univariate and multivariate approaches. In particular, we consider a univariate Bry-Boschan (BB) approach (see Bry and Boschan (1971) and Harding and Pagan (2002)) and a univariate Markov-switching (MS) model (see Hamilton (1989)). We apply these methods to GDP for mainland Norway, labeling the result BB-GDP and MS-GDP, respectively. For multivariate methods, we consider a quarterly Markov-switching dynamic factor model (MS-FMQ) (see Chauvet (1998) and Chauvet and Piger (2008)) as well as applying the BB rule to a coincident index constructed by an inverse standard deviation weighting (BB-ISD) (see Stock and Watson (2014)).

We first compare dating, duration and amplitude measures of the Norwegian business cycles provided by the various methods to business cycles for the US (obtained from NBER), for the euro area (obtained from the Center for European Policy Research's (CEPR) Euro Area Business Cycle Dating Committee (EABCDN) and for the UK and Sweden (obtained from Economic Cycle Research Institute (ECRI)). Most of the peaks and troughs in the Norwegian economy are related to peaks and troughs in other countries. In particular, business cycles in Norway seem to be more closely related to US business cycles than to business cycles in the euro area, Sweden and the UK, in terms of dating as well as duration and amplitude.

To our knowledge, there are only two earlier studies aiming to date classical turning points in the Norwegian economy. In Christoffersen (2000), classical business cycles in the Nordic countries are defined by using the BB algorithm on the monthly index of manufacturing production from 1960 to 1998. A more recent study by Fushing et al. (2010) utilizes non-parametric coding on the basis of three variables: quarterly GDP, quarterly employment and monthly industrial production. While we find that the four methods that we use share some similarities with the peak and trough dates in Christoffersen (2000) and Fushing et al. (2010), we also find clear differences.

Berge and Jordà (2011) introduced the receiver operating characteristic (ROC) curve methodology to classify economic activity for the US into recessions and expansions. We perform a similar analysis applied to the four methods described above. On the basis of the international comparison, results from other studies of Norwegian cycles, as well as the ROC curve analysis, we select the cycle identified by the MS-FMQ approach as our reference cycle.

We then turn to predicting business cycle peaks and troughs in real time. As emphasized by Hamilton (2011), this is a challenging task due to factors such as data revisions, time-lagging data availability and changes in economic relations over time. While Harding and Pagan (2003) found that the BB approach was preferable to MS models for defining business cycles ex post for the US economy, Chauvet and Piger (2008) showed that a Markov switching dynamic factor model was superior for detecting business cycles in real time.

Several papers have documented that surveys and financial data are useful for predicting macro variables (see e.g. Hansson et al. (2005), Abberger (2007), Claveria et al. (2007) for applications using survey data, and Estrella and Mishkin (1998) and Stock and Watson (2003) for applications to financial data[1]). As highlighted by, e.g., Evans (2005), Giannone et al. (2008), and Aastveit et al. (2014), an advantage of surveys and financial market data is that they are timely available and not much revised.

Motivated by these studies, we also consider univariate MS models applied to three different quarterly surveys and a monthly financial condition index (FCI). When using the BB approach, predictions are required to be able to forecast turning points in real time. We suggest using bivariate VAR models with GDP for mainland Norway together with either one of the surveys or the FCI and call a recession whenever forecasted values of GDP entail a peak.

Focusing on the last recession, we show that the univariate MS models that use survey data and the FCI are accurate in calling the peak in 2008Q2. The univariate MS models that use the FCI and the consumer confidence survey detect this turning point at the start of August 2008 and start of September 2008, respectively, i.e. about one and two months after the peak quarter. In comparison, the quarterly MS-FMQ calls the same peak in mid-February 2009. It should be noted that the BB rule applied to the bivariate VAR models that include GDP and a survey or FCI, is about one quarter slower in terms of calling the peak quarter. Importantly, these models are also calling the peak in 2008Q3, i.e. one quarter after the peak provided by the ex-post reference cycle. Finally, all the models find it more challenging to predict the trough in 2009Q3. The majority of the models detect 2009Q1 as the trough quarter, two quarters earlier than in the reference cycle.

Our paper is related to a vast number of papers that estimate and predict business cycle turning points. See e.g., Anas et al. (2008), Darné and Ferrara (2011) and Billio

[1] Næs et al. (2011) and Aastveit and Trovik (2012) document the role of financial indicators, and Martinsen et al. (2014) the role of survey data for forecasting Norwegian economic aggregates.

et al. (2012) for applications to the Euro area, Chauvet (1998), Chauvet and Piger (2008), Harding and Pagan (2002, 2006), Hamilton (2011) and Stock and Watson (2014) for applications to the US.

The rest of the paper is organized as follows: the next section describes the modeling framework and discusses how business cycle turning points are defined. The third section presents data and the dating of business cycles in Norway over the past four decades. The fourth section focuses on the prediction of turning points in real time, describes the recursive forecasting exercise and presents the results. Section 5 concludes.

2 Business cycle dating approaches

Following Burns and Mitchell (1946), we define business cycles as fluctuations in aggregate economic activity. This is the classical business cycle characterized by peaks and troughs, describing developments in the level of economic activity across many sectors. An alternative concept is the growth cycle. Economic fluctuations are then characterized by being above or below an unobservable trend. An attractive feature of the classical business cycle is that it is not necessary to estimate an unobserved trend. This is particularly important when it comes to forecasting turning points, since the uncertainty in the measurement of trend growth is at its highest at the end of the time series for commonly used two-sided filters.

Classical business cycles in the US are defined by NBER. The dating committee decides when a turning point occurs, i.e. in which months a recession respectively starts and ends. Decisions are made by deliberation based on available data, hence announcements of turning points are not very timely. The December 2007 peak was announced on December 1, 2008, and the following June 2009 trough was announced on September 20, 2010. The dating of the turning points is normally not revised.

A number of methods have been suggested for developing mechanical algorithms for calculating the start and end of recessions, in particular for US data where recessions defined by the NBER serve as benchmarks. Here we concentrate on univariate and multivariate versions of the Bry-Boschan approach and Markov-switching models.[2]

2.1 Bry-Broschan

Bry and Boschan (1971) described a method that was able to replicate most of the business cycles in the US as measured by the dating committee of the NBER. Harding and Pagan (2002) build on the work by Bry and Boschan and develop an algorithm for detecting turning points. The procedure picks potential turning points and subjects them to conditions that ensure that relevant criteria for business cycles are met. In the first step, the BB procedure identifies a *potential peak* in a quarter if the value is a local maximum. Correspondingly, a *potential trough* is identified if the value is a local minimum. Searching for maxima and minima over a window of 5 quarters seems to produce reasonable results. After potential turning points are identified, the choice of final turning points depends on several rules to ensure alternating peaks and troughs and minimum duration of phases and cycles. Following Harding and Pagan (2003), definitions of peaks can be written as:

$$\wedge_t = \{(y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2})\} \tag{1}$$

and correspondingly for troughs:

$$\vee_t = \{(y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2})\} \tag{2}$$

When forecasting peaks and troughs, the values on the right-hand side of the equations are replaced by the forecasts $\hat{y}_{t+1}$ and $\hat{y}_{t+2}$.

The business cycle can be interpreted as a state S_t, which takes value 1 in expansions and 0 in recessions. Turning points occur when the state changes. The relationship between the business cycle and the local peaks and troughs can be written as $S_t = S_{t-1}(1 - \wedge_{t-1}) + (1 - S_{t-1})\vee_{t-1})$. If the economy is in an expansion, $S_{t-1} = 1$. If no

[2] An alternative parametric model that allows for different regimes in business cycles is the threshold autoregressive model (see e.g. Potter (1995), Tommaso (1998) and Ferrara and Guégan (2005), and Billio et al. (2013) for a comparison of MS models to threshold models).

peak occurred in (t-1), then $\wedge_{t-1} = 0$ and it follows that the state $S_t = 1$. On the other hand, if there is a peak in (t-1) then $\wedge_{t-1} = 1$ and the state changes to $S_t = 0$. The state will remain at 0 until a trough is detected.

2.2 Markov-switching models

There is a long tradition of using nonlinear models to capture the asymmetry and the turning points in business cycle dynamics. Among such classes of models, Markov-switching (MS) models (see e.g. Goldfeld and Quandt (1973), Hamilton (1989), Clements and Krolzig (1998) and Kim and Piger (2002)) are dominant. Hamilton (1989) proposes an autoregressive MS model for GDP growth where only the intercept is allowed to switch between regimes:

$$y_t = \nu_{s_t} + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + u_t, \quad u_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2) \tag{3}$$

$t = 1, \ldots, T$, where ν_{s_t} is the MS intercept, ϕ_l, with $l = 1, \ldots, p$, are the autoregressive coefficients; and $\{s_t\}_t$ is the regime-switching process that can visit m states. This process is unobservable (latent) and s_t represents the current phase, at time t, of the business cycle (e.g. contraction or expansion). Therefore, the MS model does not require knowledge of y_{t+1} and y_{t+2}, as the BB rule does, to define the cycle at time t. The latent process takes integer values, say $s_t \in \{1, \ldots, m\}$, and has transition probabilities $\mathbb{P}(s_t = j | s_{t-1} = i, s_{t-2}) = p_{ij}$, with $i, j \in \{1, \ldots, m\}$. In the transition chain, different from the original Hamilton (1989) model, we impose a minimum phase duration of two quarters such that both the BB rule and the MS models call recession or expansion periods of at least two quarters. The value of s_{t-2} is therefore important for the minimum phase duration; see the online Appendix C for more details on the model and estimation algorithm.

We apply a Bayesian inference approach. There are at least three reasons for this choice. First, inference for latent variable models calls for simulation based methods, which can be naturally included in a Bayesian framework. Second, parameter uncertainty plays a crucial role in such models and Bayesian inference offers an efficient and fast approach to estimate it. Third, the choice of the number of regimes is often crucial. Following previous literature we investigate specification from two regimes (as for example in Hamilton (1989)) to four regimes (such as in Billio et al. (2012)) and choose between them using a Bayes factor comparison based on the predictive likelihood as in Billio et al. (2013) (see equation (C.2) in the online Appendix C for details). This selection strategy accounts for parameter uncertainty and prefers the models that provide more accurate out-of-sample forecasts. Our selection strategy favors only two regimes in our empirical application.

In what follows, we will report results for a univariate MS model in mean for GDP, denoted MS-GDP, i.e. the model contains no autoregressive terms ($p = 0$). However, results are very similar for specifications including autoregressive terms, see Table B.1 in the online Appendix B.

2.3 Multivariate approaches

Burns and Mitchell (1946) introduced the idea of a "reference cycle", capturing cycles that reflect movements in a broad set of variables.[3] Various multivariate approaches have been proposed in the literature, and we include two alternatives.

First, following Stock and Watson (2014), we construct a coincident economic indicator based on inverse standard deviation weighting (ISD). Let $\mathbf{x}_t$ represent a vector of N macroeconomic variables and let $C_{it}^{ISD} = \exp[\sum_{i=1}^{N} \alpha_i ln(x_{it})]$, where $\alpha_i = \frac{s_i^{-1}}{\sum_{i=1}^{N} s_i^{-1}}$ and s_i is the full sample standard deviation of $\Delta ln(x_{it})$. We then apply the BB rule to C_{it}^{ISD} and label this BB-ISD.

Second, we consider the Markov switching factor model proposed by Chauvet (1998) and Chauvet and Piger (2008). We extract a factor f_t from a set of variables and use the factor as the dependent variable in (3), resulting in the following specification:

$$\mathbf{x}_t = \lambda f_t + \epsilon_t, \quad \epsilon_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma_y^2) \tag{4}$$

$$f_t = \alpha_{s_t} + \alpha_1 f_{t-1} + \ldots + \alpha_p f_{t-p} + u_t, \quad u_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma_z^2) \tag{5}$$

[3] Burns and Mitchell (1946) also pointed out that aggregate activity could be given a definite meaning and made conceptually measurable by GDP.

where $\mathbf{x}_t$ is a vector of variables at time t. Chauvet and Piger (2008) use this model to detect US business cycles in real time. We label this model MS-FMQ.

For both BB-ISD and MS-FMQ we include six quarterly variables in $\mathbf{x}_t$: the Brent Blend oil price, employment in mainland Norway, household consumption, private real investment in mainland Norway, exports of traditional goods and GDP for mainland Norway.[4] For the MS-FMQ, we select a model with $p = 0$. However, results are very similar when selecting $p = 1$ or $p = 2$, see Table B.2 in the online Appendix B.

3 Norwegian business cycle dating

There is no authoritative dating of classical business cycles in Norway. Most studies, see for instance Bjørnland (2000), and Bjørnland et al. (2008), analyze the growth cycle based on quarterly national accounts. To our knowledge, there are only two earlier studies aiming to date classical turning points in the Norwegian economy. In Christoffersen (2000), classical business cycles in the Nordic countries are defined by using the BB algorithm on the monthly index of manufacturing production. A more recent study by Fushing et al. (2010) utilizes non-parametric coding on the basis of three variables: quarterly GDP, quarterly employment and monthly industrial production.

In this section, we will define classical business cycle turning points for the Norwegian economy exploring the four different methods, BB-GDP, MS-GDP, BB-ISD and MS-FMQ, explained in section 2.

When investigating economic conditions in Norway, it is common to use gross domestic product for mainland Norway as the measure of economic activity. This measure excludes offshore activity, i.e. oil and gas extraction and international shipping. One reason these sectors are excluded, is that their production may show large fluctuations with very small short term effects on the Norwegian labor market (and domestic production). Furthermore, the mainland economy is insulated from (short term) fluctuating revenue from the petroleum sector (see discussion in Bowitz and Hove (1996)). All rev-

[4] Chauvet (1998) and Chauvet and Piger (2008) use monthly frequency data. For Norway, there are few relevant monthly data series available for the full sample period.

enues are transferred to a sovereign wealth fund, and a fiscal policy rule determines the size of withdrawal from the fund every year.

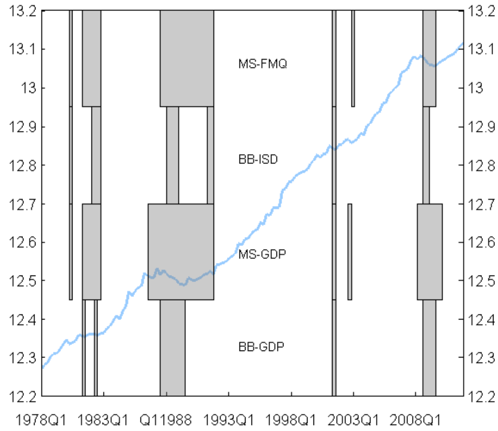
3.1 Dating

The estimated cycles from the four alternative methods, for the sample period 1978Q1-2011Q4, are shown in Figure 1.[5] In both panels, the shaded areas represent downturns. The cycles are generated by the following models, from bottom to top tier: BB-GDP, MS-GDP, BB-ISD and MS-FMQ. Panel (a) shows the cycles together with GDP for mainland Norway, while panel (b) shows the cycles with the unemployment rate. In Table 1, turning points from the four methods are listed in the first four columns, and reference turning points for the US, the UK, Sweden and the euro area are listed in the four last columns. For the US we use NBER dates, while we report turning point dates for the euro area given by the EABCDN and for Sweden and the UK dates defined by ECRI.

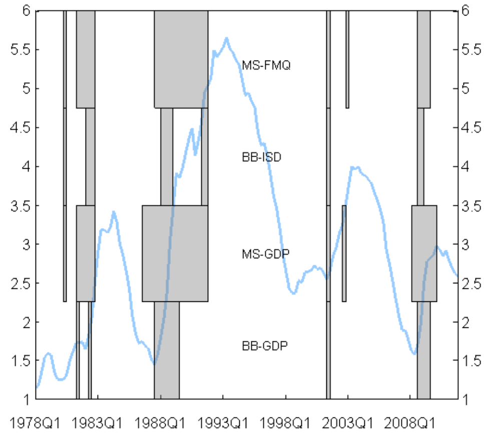
According to BB-GDP, there is a double dip recession with a peak in 1981Q1 and a final trough in 1982Q3. This contrasts with the three other methods, which agree that the double dip recession started with a peak in 1980Q1 and ended with a final trough in 1982Q4. Christoffersen (2000) finds, using the monthly seasonally adjusted manufacturing production index, that the peak occurred in September 1981 while the trough was pinpointed to October 1982. Fushing et al. (2010) find a peak in February 1980, signalling a single recession lasting 2 quarters only. The main message seems to be that this recession was mild measured as loss of GDP, even if it was fairly long-lasting. The unemployment rate, however, reached unprecedented levels for the post-war period. The development from 1980 to 1982, with the unemployment rate reaching a plateau after a small increase through 1980, is consistent with a double dip recession (see panel (b) in Figure 1). Taken together, there is quite strong evidence of a double dip recession starting in 1980Q2, ending with a trough in 1982Q4. The main reason for the recession was the cyclical downturn among our trading partners caused by the oil price hike in

[5] Quarterly national accounts are available from 1978Q1.

Figure 1. *Business cycle dating for Norway. 1978 to 2011. Four alternative dating methods*



(a) log(GDP)



(b) Unemployment rate

Notes: The shaded areas indicate recessions. The bottom tier turning points are calculated by using BB-GDP. The second tier (from the bottom) turning points are calculated by MS-GDP, while the two upper tiers show turning points constructed by BB-ISD and MS-FMQ, respectively.

1979 after the revolution in Iran. Comparing with turning point dates abroad, the dates defined by the MS, BB-ISD and MS-FM are very close to turning point dates for the US in particular, but also to Sweden and the euro area.

In 1984 a strong expansion started, fueled by deregulations of the credit and housing market and supported by a continuing high oil price level (and hence investment in the petroleum sector). When oil prices fell abruptly in winter 1985/86, this represented a considerable shock to the Norwegian economy. The downturn eventually turned into a banking crisis in the late 1980s, making the recession starting in the late 1980s deep and long-lasting.

The MS-FMQ and MS find long recessions lasting between 16 and 22 quarters. The downturn defined by the BB method is considerably shorter, only 9 quarters, while the BB-ISD method identifies two separate recessions in this period. The peak quarter varies between 1986Q2 and 1987Q4. The trough quarter varies between 1989Q3 and 1991Q4. GDP started growing already at the end of 1989 (see panel (a) in Figure 1), hence the trough defined by the BB method seems plausible. However, taking account of a broader set of indicators (MS-FMQ) and referring to panel (b) in Figure 1, it seems more reasonable that the trough occurs later. In Christoffersen (2000) the peak is found in April 1989 and a trough in July 1990, a recession of around five quarters. Findings in Fushing et al. (2010) indicate two recessions in this period: A recession with a peak in August 1987 and a trough already in December the same year and a second recession with a peak in May 1991 and a trough in October the same year.

This recession was triggered mainly by domestic factors. Downturns in US, UK and Sweden started around three years later, and in the euro area the peak quarter according to CEPR was as late as 1992Q1, five years later.[6]

The next recession in the early 2000s is associated with the bursting of the "dot-com" bubble. All methods agree that there was a recession in 2001 lasting two quarters. This corresponds quite closely to the recession in the US. Then two of the models, (MS-GDP and MS-FMQ) find another recession in 2002. This is a specific Norwegian downturn, most likely triggered by tighter monetary policy after signs of wage inflation and expectations of increasing consumer price inflation. This downturn is also picked up in Fushing et al. (2010), with a peak pinpointed to August 2002 and a trough in April 2003.

Finally, we arrive at the great recession. In Norway it was not so "great", as it was characterized by a relatively moderate increase in the unemployment rate. BB-GDP and MS-FMQ both find a peak in 2008Q2 and a trough in 2009Q3, while the MS-GDP finds a recession lasting several quarters more. A peak quarter in 2008Q2 and a trough in 2009Q3 is consistent with findings in Fushing et al. (2010). They find a double dip downturn with a peak in May 2008 and a trough in July 2009. According to panel (b) in Figure 1, the unemployment rate starts to rise in 2008Q3, the same quarter as the start of the downturn. Turning to other countries, the peak quarter is 2008Q2 in the UK and Sweden, 2007Q4 in the US and 2008Q1 in the Euro area. It seems reasonable that this

[6] Interestingly, the downturn in the early 1990s in Sweden also turned into a domestic banking crisis, and the recession lasted three years.

Table 1. *Reference cycles. 1978 to 2012*

	Norway				US	UK	Sweden	Euro
	BB-GDP	MS-GDP	BB-ISD	MS-FMQ	NBER	ECRI	ECRI	CEPR
1978-1980								
–Peak		1980Q1	1980Q1	1980Q1	1980Q1	1979Q2	1980Q1	1980Q1
–Trough		1980Q3	1980Q3	1980Q3	1980Q3			
1981								
–Peak	1981Q1	1981Q1	1981Q4	1981Q1	1981Q3			
–Trough	1981Q3					1981Q2		
1982-1983								
–Peak	1982Q1							
–Trough	1982Q3	1982Q4	1982Q4	1982Q4	1982Q4		1983Q2	1982Q3
1986-1989								
–Peak	1987Q2	1986Q2	1987Q4	1987Q2				
–Trough	1989Q3		1989Q1					
1990-1994								
–Peak			1991Q1		1990Q3	1990Q2	1990Q2	1992Q1
–Trough		1991Q4	1991Q4	1991Q4	1991Q1	1992Q1	1993Q3	1993Q3
1995-2001								
–Peak	2001Q1	2001Q1	2001Q1	2001Q1	2001Q1			
–Trough	2001Q3	2001Q3	2001Q3	2001Q3	2001Q4			
2002-2003								
–Peak		2002Q2		2002Q3				
–Trough		2002Q4		2003Q1				
2004-2010								
–Peak	2008Q2	2007Q4	2007Q4	2008Q2	2007Q4	2008Q2	2008Q2	2008Q1
–Trough	2009Q3	2010Q1	2009Q1	2009Q3	2009Q2	2010Q1	2009Q1	2009Q2
2010-2012								
–Peak						2010Q3		2011Q3
–Trough						2012Q1		

Notes: The table reports specific dates of peaks and troughs detected by the four models described in section 2, as well as authoritative peaks and troughs dates the US, the UK, Sweden and the euro area.

Table 2. *Business cycle characteristics 1978 - 2012. Norway. Ex post. 4 methods*

	Norway				US	UK	Sweden
	BB-GDP	MS -GDP	BB-ISD	MS-FMQ	NBER	ECRI	ECRI
Mean duration (quarters)	27.3	22.2	22.6	22.6	27.75	41.7	56.5
Peak to trough	4.0	7.3	3.2	6.0	3.6	6.5	9.7
Trough to peak	23.5	15.2	19.4	16.4	24.75	35	43.5
Mean amplitude (%)							
Peak to trough	-1.8	-0.6	-1.2	-1.0	-2.0	-2.9	-3.4
Trough to peak	19.6	15.2	15.7	15.4	22.2	26.3	33.0
Cumulative change (% of GDP in first quarter of phase)							
Peak to trough	-5.6	-1.7	-2.3	-3.5	-4.5	-9.7	-11.7
Trough to peak	330.8	191	224.5	200.9	355.1	687.7	819.6
Excess loss (Difference between triangel calculation and actual losses, %)							
Peak to trough	0.11	0.11	0.01	0.49	0.18	0.63	0.49
Trough to peak	0.8	0.49	0.02	-0.06	-0.97	-0.02	-1.18

Notes: The cumulative change is an approximation, calculated as the area of the triangle with duration as length and amplitude as height. The size and the sign of the excess loss is a measure of how cycles deviate from the triangle approximation. A positive loss entails a larger loss than the triangle approximation.

recession started earlier in the US than in Norway.

In Table 2 we have collected some business cycle characteristics (see Harding and Pagan (2002) for more details). The four columns to the left show statistics for the four alternative methods, and the three columns to the right show statistics for the US, UK and Sweden. All statistics are calculated on the basis of GDP (mainland GDP for Norway).[7]

The first three lines show mean duration for the whole cycle, peak to trough and trough to peak, respectively. The mean duration for the whole cycle is comparable to the duration of US cycles across all four methods. Duration in the UK and Sweden is considerably longer. Dividing the cycle into contractions and expansions, the similarities

[7]We have not been able to find aggregated quarterly GDP for the euro area going back to 1978.

across the methods largely disappear, as we would expect from the discussion above. The two alternative MS models tend to have longer peak-to-trough and shorter trough-to-peak periods than the two BB alternatives.

The mean amplitude from peak to trough ranges between -0.6% and -1.8%. Compared to the other countries, amplitudes are smaller in Norway. Taking account of durations and amplitude together using the triangular approach (see Harding and Pagan (2002) for details), the size of the cumulative change in Norway is quite similar to that in the US, but smaller than in the other countries. The exception is the MS method, where cumulative loss is very small. The reason for this is mainly the long duration of the downturn in the late 1980s, resulting in an extremely low amplitude. Turning to the cumulative change from trough to peak, numbers are much larger, and again statistics for the four methods are closer to the US statistics than statistics for the other countries.

The statistics in the two bottom lines indicate how the shape of contractions and expansions deviate from the triangular approach. A positive number means that cumulative losses are larger, i.e. the downturn is U shaped. A negative number indicates smaller losses, i.e. a "narrow" V. Hence, recovery from trough to peak in the US and Sweden is more rapid than is the case for Norway and the UK.

The receiver operating characteristic (ROC) curve methodology was introduced by Berge and Jordà (2011) to classify economic activity for the US into recessions and expansions. Here we use the ROC curve methodology to compare the four different methods. The results can be summarized by calculating the area under the ROC curve (AUROC) and are shown in Table 3. The table illustrates that the MS-GDP and MS-FMQ match the BB-GDP and BB-ISD turning points well, obtaining AUROC values close to or exceeding 0.9, fairly close to near-perfect classification ability. Turning the viewpoint on its head, the BB-GDP and BB-ISD has a considerably lower classification ability for the MS-GDP and MS-FMQ dates, obtaining AUROC values between 0.72 and 0.77. Finally, the classification ability of MS-GDP for MS-FMQ dates and MS-FMQ for MS-GDP dates are high, with AUROC values exceeding 0.9 in both cases.

In conclusion, the cycles defined by MS-GDP and MS-FMQ are preferable to the

Table 3. *Auroc statistics. Norway*

	BB-GDP	MS-GDP	MS-FMQ	BB-ISD
BB	..	0.895	0.926	0.770
MS	0.727	..	0.904	0.716
MS-FMQ	0.770	0.945	..	0.757
BB-ISD	0.781	0.891	0.922	..

The table reports AUROC values. The columns calculates the AUROC when the chronology of turning points is matched to the BB-GDP, MS-GDP, MS-FMQ and BB-ISD, respectively.

cycles defined by BB-GDP and BB-ISD. An advantage of the MS-FMQ approach, compared with the MS-GDP approach, is that it captures cycles that reflect movements in a broader set of variables, more in line with the idea of a "reference cycle" by Burns and Mitchell (1946). Based on international comparisons, results from other studies of Norwegian cycles, how " reasonable" the cycles are in relation to historical developments in the Norwegian economy as well a ROC curve analysis, we select the cycles identified by the MS-FMQ approach as our reference cycle.

4 Forecasting Norwegian turning points in real time

Having defined a reference business cycle for Norway, we will address the problem of forecasting turning points in real time. Using US data, Chauvet and Piger (2008) found that the real-time performance of Markov-switching models outperformed the non-parametric Bry-Borschan methodology, picking up NBER turning points in a more timely and accurate manner. We will perform a similar analysis using Norwegian data, concentrating on picking up the latest recession.

4.1 Forecasting exercise

Detecting peaks and troughs in real time is a challenging task due to factors such as data revisions, publication lags and changes to economic relations over time (see e.g. Hamilton (2011)). We apply the four methods (BB-GDP, BB-ISD, MS-GDP and MS-

FMQ) described in Section 2, using real-time data, and compare their ability to forecast the peak and the trough of the latest recession. The Markov-switching techniques (MS and MS-FMQ) already compute predicted probabilities of being in one regime or the other (i.e. in recession or expansion). The Bry-Boschan approach requires predictions of GDP or C_{it}^{ISD}, respectively, to be able to forecast a turning point in real time. We produce forecast densities for GDP and the ISD index from an AR(1) model.

In addition to these four models, we investigate the role of using information from surveys and financial data in order to predict business cycle turning points. Models using financial data and survey data are likely candidates for detecting turning points early. Publication is timely compared to GDP, and the nature of the statistics ensures that a wide range of information and considerations are taken into account by financial market participants (see Næs et al. (2011)) and by the respondents in the surveys (see Martinsen et al. (2014)). For high-frequency financial data, we use monthly averages of daily observations. We have constructed a financial conditions index as a broadly based financial indicator covering foreign exchange rates, total returns, house prices, the oil price, interest rates, money and credit.[8]

All the surveys are quarterly, as there are no monthly surveys in Norway that have been published long enough to be useful for model-based forecasting. However, since the quarterly surveys are released earlier than GDP data, indicators are generally available for quarter t, while GDP is only available for quarter $t-1$. We consider three different surveys: the overall business confidence indicator from the business tendency survey for manufacturing, mining and quarrying (BTS), conducted by Statistics Norway in the last three weeks of the quarter and published at the end of the first month in the following quarter, the overall consumer confidence index (CC), conducted by TNS Gallup in the fifth week of the quarter and published around four weeks before the end of the quarter, the expected growth over the next six months (all industries) from Norges Bank's regional network survey (RN), conducted in the first half of the quarter and published around three weeks before the end of the quarter.

[8]The index is constructed by a dynamic factor model with data available from 1995, see table A.1.

We apply both the BB and MS approaches to models that incorporate surveys and financial data. We specify univariate MS models for the three surveys and the financial conditions index directly and label these models MS-BTS, MS-CC, MS-RN and MS-FCI. With the BB approach, we produce forecasts from bivariate vector autoregressive models:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \epsilon_t, \qquad \epsilon_t \sim N(0, \Sigma_\epsilon), \tag{6}$$

where $Y_t = (y_{1,t}, y_{2,t})$ and $y_{1,t}$ and $y_{2,t}$ denotes GDP growth and FCI, C_{it}^{ISD} or one of the surveys, respectively.

By exploring Kalman filtering techniques, we can take into account the unbalancedness of the data and, thus, exploit the timely release of surveys and financial market data. Since quarterly GDP is released with a lag of approximately seven weeks, this means that if we add forecasts for two quarters (i.e. a nowcast and a forecast) to the latest available vintage, we may at the earliest predict a turning point seven weeks after it occurred.

Finally, we also include a monthly version of the MS-FMQ, extracting a common factor from the Brent Blend oil price, unemployed persons, industrial production and retail sales. We label this model MS-FMM. See the online Appendix A for information about data used for real-time forecasting.

4.2 Results

Results from the real-time out-of-sample forecasting exercise are reported in Tables 4 (peaks) and 5 (troughs). The first model to predict a peak is MS-BTS, detecting a peak quarter in 2008Q1, one quarter earlier than the reference cycle peak, at the end of July 2008. This is not surprising, since the manufacturing sector is likely to be among the first sectors to be affected by downturns originating among our trading partners.[9]

[9]Even if the predicted peak is earlier than the reference peak, it is natural to view this result as a forewarning of a downturn to come, even if the manufacturing sector is small compared to the mainland economy.

Table 4. *Forecasting turning points in real time - peaks*

Model	Date of detection	Peak quarter/month
MS-BTS: Business Tendency Survey	2008 27 July	2008Q1
MS-FCI: Financial Conditions Index	2008 1 August	2008M6
MS-RN: Regional Network Survey	2008 20 September	2008Q2
MS-FMM: Monthly Factor Model	2008 7 November	2008M6
BB-FCI: GDP with Financial Conditions Index	2008 1 December	2008Q3
MS-CC: Consumer Confidence	2008 2 December	2008Q2
BB-CC: GDP with Consumer Confidence	2008 2 December	2008Q3
BB-RN: GDP with Regional Network Survey	2008 17 December	2008Q3
BB-BTS: GDP with Business Tendency Survey	2009 28 January	2008Q3
MS-FMQ: Quarterly Factor Model	2009 19 February	2008Q2
BB-ISD: Inverse standard deviation weighting	2009 19 February	2008Q2
BB-GDP: GDP AR(4)	2009 19 May	2008Q3
MS-GDP: GDP	2009 19 May	2007Q4
Reference cycle:		**2008Q2**

Notes: Real-time predicted peak quarter and date of detection using alternative methods and variables. Ordered after date of detection.

MS-FCI is the first model to detect the correct peak 2008M6 at the beginning of August. MS applied to the regional network survey (MS-RN) predicts a peak in 2008Q2 when the survey is published in September.[10] The MS-FMM, utilizing more timely monthly information, but not constructed to reflect financial conditions, predicts a peak in June 2008, but not until early November. Hence, indicators based on qualitative surveys, incorporating expectations, predict the turning point in 2008 earlier than quantitative and more frequent indicators, unless these indicators reflect financial conditions.

In Section 3.1 we defined the reference cycle as the cycle defined by the MS-FMQ. In real time, MS-FMQ does not detect the peak quarter of 2008Q2 until the national accounts for 2008Q4 are released in mid-February 2009. This is substantially later than MS models applied to survey information, the FCI and to monthly factor models.

[10]Interestingly, the key policy rate in Norway was kept unchanged at the monetary policy meeting 13 August and again at the monetary policy meeting 24 September.

Table 5. *Forecasting turning points in real time - troughs*

Model	Date of detection	Trough quarter/month
BB-ISD: Inverse standard deviation weighting	2009 19 February	2008Q4
BB-GDP: GDP AR(4)	2009 19 May	2009Q1
BB-CC: GDP with Consumer Confidence	2009 1 June	2009Q2
BB-FCI: GDP with Financial Conditions Index	2009 1 June	2009Q1
BB-RN: GDP with Regional Network Survey	2009 10 June	2009Q1
BB-BTS: GDP with Business Tendency Survey	2009 28 July	2009Q1
MS-FMM: Monthly Factor Model	2009 7 August	2009M4
MS-CC: Consumer Confidence	2009 7 September	2009Q1
MS-RN: Regional Network Survey	2010 20 June	2009Q1
MS-GDP: GDP	2010 19 August	2009Q4
MS-BTS: Business Tendency Survey	2010 28 October	2009Q2
MS-FMQ: Quarterly Factor Model	2010 23 November	2010Q1
MS-FCI: Financial Conditions Index	:	:
Reference cycle:		**2009Q3**

Notes: Real-time predicted peak quarter and date of detection using alternative methods and variables. Ordered after date of detection.

Turning to the BB-based methods, BB-GDP and the bivariate VARs including surveys or the FCI, predict 2008Q3 as the peak quarter in real time, one quarter later than in the reference cycle. BB-ISD is the exception, detecting a peak in 2008Q2. Compared with the MS models, the BB-based methods are less timely. Our results supports the findings in Chauvet and Piger (2008) that MS models are both more timely and more accurate in detecting peaks and troughs than the BB method. We show that applying the MS approach to surveys or a monthly FCI can provide additional gains in terms of detecting the peak in real time at an earlier date than applying MS to GDP itself or factor models that use quarterly "hard" data.

Table 5 shows real-time predictions of the trough. In contrast to results for predicting the peak, all the BB models are more timely in predicting a trough than the MS models are. However, none of the alternative models or methods predict the reference cycle trough. As early as mid-February, BB-ISD predicts a trough in 2008Q4. BB-CC predicts the trough in 2009Q2, while the remaining BB-models find 2009Q1 to be the trough quarter. Among the MS models, MS-FMM is the first model to predict a trough, detecting 2009M4 as the trough month in August 2009. At the other end of the scale, MS-FCI does not find a trough at all in our time frame.[11] The remaining MS models detect a trough quarter either in 2009Q4 or 2010Q1, respectively one or two quarters after the reference cycle trough, with a substantial time delay.

To sum up, surveys and the monthly FCI seem to contain important information with respect to detecting business cycle peaks in real time. Markow-switching models are more accurate and more timely than approaches based on the BB rule. Results are less clear when detecting the trough. The predicted trough quarter as well as the timing of the detection show substantial variation across alternative approaches. None of the approaches are able to pinpoint the reference cycle trough in real time.

5 Conclusion

We have compared alternative business cycle turning points for the Norwegian economy from 1978Q1 to 2011Q4, defined by Markov-switching models and the nonparametric Bry-Boschan method. Based on business cycle statistics and comparisons to business cycles for some of Norway's main trading partners, supported by results from two earlier studies applied to the Norwegian economy and evidence from the ROC curve methodology, we found that peak and trough dates provided by a quarterly Markow-switching factor model provided the most reasonable definition of reference Norwegian business cycles.

In a real-time out-of-sample forecasting exercise, we then studied the timeliness and accuracy of the various methods in order to predict the peak and trough of the recession in 2008-2009. It is clear that MS models are both more timely and more accurate than the BB method when predicting the peak quarter. We show that applying the MS approach to surveys and a monthly financial conditions index can provide additional

[11] This is probably due to interest rates still hovering around levels associated with recessions.

gains in terms of detecting peak in real time at an earlier date than applying MS to more traditional factor models or GDP itself.

Predicting the trough quarter in real time is more challenging than predicting the peak. The predicted trough quarter as well as the timing of the detection shows substantial variation across alternative approaches, and none of the approaches are able to pinpoint the reference cycle trough in real time.

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Online Appendix

Material available upon request

In the first section we document the data sources. The next section explores turning points produces by alternative specifications of the Markov switching model. In the final section we discuss the Markov-switching model in more detail.

A Data sources

A.1 Dating

For BB-GDP and MS-GDP we have used seasonally adjusted mainland GDP published 16 February 2012 by Statistics Norway. For the multivariate models BB-ISD and MS-FMQ we added, from national accounts published 16 February 2012, final household and NPISH consumption expenditure, mainland gross fixed capital formation excluding general government and export of traditional goods. The Brent Blend oil price was collected from Datastream, and for seasonally adjusted employed persons we used the final vintage published by OECD[12].

A.2 Real-time forecasting

Information about data used for real-time forecasting is summarized in table A.1.

[12] The labor force survey is conducted and published by Statistics Norway. Long time series are, however, not easily available. Changes in the questionnaire and some other minor adjustments led to a break in the series in 2006, and Statistics Norway has chosen to discontinue historical series and publish new series starting in 2006. In Main Economic Indicators, OECD publishes a continuing series, starting as early as 1972.

Table A.1. *Overview of models and data for forecasting turning points in real time*

Model	Variables	Published by	Vintage
BB-GDP	GDP Mainland Norway	Statistics Norway	Real time
MS-GDP	GDP Mainland Norway	Statistics Norway	Real time
BB-ISD, MS-FMQ	GDP Mainland Norway	Statistics Norway	Real time
	Household consumption	Statistics Norway	Real time
	Mainland gross fixed capital formation excluding general government	Statistics Norway	Real time
	Export of traditional goods	Statistics Norway	Real time
	Brent Blend oil price	Datastream	Real time
	Employed persons	OECD	Final vintage
BB-BTS	GDP Mainland Norway	Statistics Norway	Real time
	Industrial confidence indicator (manufactoring)	Statistics Norway	Real time
MS-BTS	Industrial confidence indicator (manufactoring)	Statistics Norway	Real time
BB-CC	GDP Mainland Norway	Statistics Norway	Real time
	Consumer confidence	TNS Gallup	Real time
MS-CC	Consumer confidence	TNS Gallup	Real time
BB-RN	GDP Mainland Norway	Statistics Norway	Real time
	Output growth next 6 months	Norges Bank	Real time
MS-RN	Output growth next 6 months	Norges Bank	Real time
BB-FCI, MS-FCI	GDP Mainland Norway	Statistics Norway	Real time
	Interest rates	Norges Bank	Real time
	Foreign exchange rates	Norges Bank	Real time
	Total returns	Datastream	Real time
	House prices	Eiendom Norway	Real time
	Brent Blend oil price	Datastream	Real time
	Credit and money	Statistics Norway	Final vintage
MS-FMM	Brent Blend oil price	Datastream	Real time
	Manufactoring production	Statistics Norway	Final vintage
	Retail sales	Statistics Norway	Final vintage
	Number of unemployed persons	Statistics Norway	Real time

Notes: The data in MS-FMM are truncated to mimic real-time data, and the factors are constructed using the truncated data.

B Dating: Alternative specifications

In the main text we compared turning points resulting from four alternative models. While the Bry-Boschan method is non-parametric, the Markov-switching models allow for different specifications. In Table B.1 we explore some alternative specifications for the univariate Markov-switching model.

The first column repeats the MS-GDP peaks and troughs from Table 1 in the main text. The next three columns show turning points for MS models with autoregressive autoregressive orders of 1, 2 and 4, respectively. The four alternative specifications produce quite similar turning points, with notable exceptions. For example, the model with an AR(1) term picks one long recession in the early 1980s instead of a double-dip recession. The AR(4) model does not pick up the recession in 2002-2003.

In table B.2 we compare the reference cycle turning points (MS-FMQ) with alternatives containing autoregressive terms. The alternative turning points are comparable for most of the downturn, but we also find some differences.

Table B.1. *Markov switching. Alternative specifications. 1978 to 2012*

	MS-GDP Mean	MS-GDP AR(1)	MS-GDP AR(2)	MS-GDP AR(4)
1978-1980				
–Peak	1980Q1	1980Q1	1980Q1	1980Q1
–Trough	1980Q3		1980Q3	1980Q3
1981-1982				
–Peak	1981Q1		1981Q1	1981Q1
–Trough	1982Q4	1982Q4	1982Q4	1982Q3
1983-1994				
–Peak	1986Q2	1986Q3	1986Q3	1986Q3
–Trough	1991Q4	1991Q4	1991Q2	1990Q3
1995-2001				
–Peak	2001Q1	2001Q1	2001Q1	2001Q1
–Trough	2001Q3	2001Q3	2001Q3	2001Q3
2002-2003				
–Peak	2002Q2	2002Q2	2002Q2	
–Trough	2002Q4	2003Q1	2003Q1	
2004-2010				
–Peak	2007Q4	2007Q4	2007Q4	2007Q4
–Trough	2010Q1	2010Q1	2009Q4	2009Q3

Notes: The first column repeats the MS-GDP peaks and troughs from table 1 in the main text. The next three columns show turning points for MS models with autoregressive terms.

Table B.2. *Markov switching factor model (FMQ). Alternative specifications. 1978 to 2012*

	MS-FMQ mean	MS-FMQ AR(1)	MS-FMQ AR(2)
1978-1980			
–Peak	1980Q1	1980Q1	1979Q4
–Trough	1980Q3	1980Q3	1980Q3
1981-1983			
–Peak	1981Q1	1981Q1	1981Q1
–Trough	1982Q4	1982Q4	1982Q4
1986			
–Peak			1986Q2
–Trough			1986Q4
1987-1994			
–Peak	1987Q2	1987Q2	1987Q2
–Trough	1991Q4	1991Q4	1991Q4
1995-2001			
–Peak	2001Q1	2001Q1	2000Q2
–Trough	2001Q3	2001Q3	2001Q3
2002-2003			
–Peak	2002Q3	2002Q1	2002Q1
–Trough	2003Q1	2003Q1	2003Q1
2004-2010			
–Peak	2008Q2	2008Q2	2008Q1
–Trough	2009Q3	2009Q4	2009Q2

Notes: The first column repeats the FMQ peaks and troughs from table 1 in the main text. The next two columns show turning points for FMQ models with autoregressive terms.

C Markov Switching Models

An autoregressive Markov Switching model for GDP growth is specified as:

$$y_t = \nu_{s_t} + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + u_t, \quad u_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2) \tag{C.1}$$

$t = 1, \ldots, T$, where ν_{s_t} is the MS intercept, ϕ_l, with $l = 1, \ldots, p$, are the autoregressive coefficients; and $\{s_t\}_t$ is the regime-switching process, that is an m-states ergodic and aperiodic Markov-chain process. This process is unobservable (latent) and s_t represents the current phase, at time t, of the business cycle (e.g. contraction or expansion). Therefore, the MS model does not require knowledge of y_{t+1} and y_{t+2}, as the BB rule does, to define the cycle at time t. The latent process takes integer values, say $s_t \in \{1, \ldots, m\}$, and has transition probabilities $\mathbb{P}(s_t = j | s_{t-1} = i, s_{t-2}) = p_{ij}$, with $i, j \in \{1, \ldots, m\}$ and s_{t-2} is important for the minimum phase duration. The transition matrix P of the chain is

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

and the minimum phase duration imposes the following restrictions:

$$\mathbb{P}(s_t = j | s_{t-1} = i, s_{t-2}) = \left\{ \begin{array}{ll} p_{ij} & \text{if } s_{i\,t-2} = 1, \forall j,\ i = 1 \\ 0 & \text{if } s_{i\,t-2} = 1, \forall j,\ i = 0 \\ 1 & \text{if } s_{i\,t-2} = 0, \forall j,\ i = 1 \\ p_{ij} & \text{if } s_{i\,t-2} = 0, \forall j,\ i = 0 \end{array} \right\}$$

In our applications we assume that the initial values, $(y_{-p+1}, \ldots, y_0)$, and s_0, of the processes $\{y_t\}_t$ and $\{s_t\}_t$ respectively, are known. A suitable modification of the procedure in Vermaak et al. (2004) can be applied for estimating the initial values of both the observable and the latent variables.[13]

[13] Following Krolzig (2000) and Anas et al. (2008), we also investigate an MS model which assumes that both the intercept and the volatility are driven by a regime-switching variable. The results are qualitatively similar and available upon request.

The choice of the number of regimes is often crucial. Following previous literature we investigate specification from two regimes (as for example in Hamilton (1989)) to four regimes (such as in Billio et al. (2012)) and choose the model that maximizes the predictive likelihood:

$$pl_p = \prod_{t=1}^{T-1} \prod_{i=1}^{N} p(y_{t+1}|y_t, p) \tag{C.2}$$

where $p(y_{t+1}|y_t, m)$ is the 1-step ahead predictive likelihood, defined as the predictive density $p(\tilde{y}_{t+1}|y_t, p)$ for y_{t+1} conditional on information up to time t and p lags in the model evaluated at y_{t+1}. The model with maximum predictive likelihood is associated to the highest Bayes factor in bivariate comparison between models.

We estimate model in equation (C.1) using a Bayesian inference framework that relies on data augmentation (see Tanner and Wong (1987)) and on a Monte Carlo approximation of the posterior distributions as in Billio et al. (2012). We follow Frühwirth-Schnatter (2006) and define the vector of regime invariant regressors, $\mathbf{x}_{0t} = (y_{t-1}, \dots, y_{t-p})'$; the vector of regime invariant coefficients, $\boldsymbol{\phi} = (\phi_1, \dots, \phi_p)'$; the vector of regime variant regressors, $\boldsymbol{\xi}_t = (\xi_{1t}, \dots, \xi_{mt})$, where $\xi_{kt} = \mathbb{I}_{\{k\}}(s_t)$ indicates the regime to which the current observation y_t belongs to, and $\mathbb{I}_A(x)$ is the indicator function that takes value 1 if $x \in A$ and 0 otherwise; and the vector of regime-specific parameters, $\boldsymbol{\nu} = (\nu_1, \dots, \nu_m)'$. In this notation the regression model in equation (3) can be written as

$$y_t = \boldsymbol{\xi}_t'\boldsymbol{\nu} + \mathbf{x}_{0t}'\boldsymbol{\phi} + u_t, \quad u_t \overset{i.i.d.}{\sim} \mathcal{N}\left(0, \sigma^2\right) \tag{C.3}$$

The data-augmentation procedure (see also Frühwirth-Schnatter (2006)) yields the complete likelihood function of model (3)

$$L(\mathbf{y}_{1:T}, \boldsymbol{\xi}_{1:T}|\boldsymbol{\theta}) = \prod_{t=1}^{T} \prod_{k=1}^{m} \prod_{j=1}^{m} p_{jk}^{\xi_{jt-1}\xi_{kt}} \left(2\pi\sigma^2\right)^{\frac{-\xi_{kt}}{2}} \exp\left\{-\frac{\xi_{kt}}{2\sigma^2}(y_t - \nu_k - \mathbf{x}_{0t}'\boldsymbol{\phi})^2\right\} \tag{C.4}$$

where $\boldsymbol{\theta} = (\boldsymbol{\nu}', \boldsymbol{\phi}', \boldsymbol{\sigma}', \mathbf{p})'$ is the parameter vector, with $\mathbf{p} = (\mathbf{p}_{1\cdot}, \dots, \mathbf{p}_{m\cdot})'$, $\mathbf{p}_{k\cdot} = (p_{k1}, \dots, p_{km})$ the k-th row of the transition matrix, and $\mathbf{z}_{s:t} = (\mathbf{z}_s, \dots, \mathbf{z}_t)'$, $1 \leq s \leq t \leq T$, denotes a subsequence of a given sequence of variables, $\mathbf{z}_t$, $t = 1, \dots, T$.

In a Bayesian framework we need to complete the description of the model by specifying the prior distributions of the parameters. Again following Billio et al. (2012) we apply the data-dependent prior approach suggested by Diebolt and Robert (1994) and consider a partially improper conjugate prior. Improper conjugate priors are numerically close to the Jeffreys prior, provide similar inferences and yield easier posterior simulations. We assume uniform prior distributions for all the autoregressive coefficients, the intercept and the precision parameters

$$
\begin{aligned}
(\phi_1, \ldots, \phi_p) &\propto \mathbb{I}_{\mathbb{R}^p}(\phi_1, \ldots, \phi_p) \\
\nu_k &\propto \mathbb{I}_{\mathbb{R}}(\nu_k), \quad k = 1, \ldots, m \\
\sigma^2 &\propto \frac{1}{\sigma^2} \mathbb{I}_{\mathbb{R}_+}(\sigma^2)
\end{aligned}
$$

and do not impose stationarity constraints for the autoregressive coefficients. We assume standard conjugate prior distributions for the transition probabilities. These distributions are independent and identical Dirichlet distributions, one for each row of the transition matrix

$$
(p_{k1}, \ldots, p_{km})' \sim \mathcal{D}(\delta_1, \ldots, \delta_m)
$$

with $k = 1, \ldots, m$.

When estimating an MS model, which is a dynamic mixture model, one needs to deal with the identification issue arising from the invariance of the likelihood function and of the posterior distribution (which follows from the assumption of symmetric prior distributions) to permutations of the allocation variables. Many different ways to solve this problem are discussed, see for example Frühwirth-Schnatter (2006). We identify the regimes by imposing some constraints on the parameters, a standard procedure in business cycle analysis. We consider the following identification constraints on the intercept: $\nu_1 < 0$ and $\nu_1 < \nu_2 < \ldots < \nu_m$, which allow us to interpret the first regime as the one associated with the recession phase.

Samples from the joint posterior distribution of the parameters and the allocation variables are obtained by iterating a Gibbs sampling algorithm. We refer to Billio et al.

(2012), section 3.3, for specific details of the sampling procedure for the posterior of the allocation variables (see also Krolzig (1997)). The methodology produces predictive densities for y_{t+1}, $p(\tilde{y}_{t+1}|y_t)$, see equation (12) in Billio et al. (2012), which accounts for the uncertainty on the regime the variable y_{t+1} could be at time $t+1$.

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