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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 the business cycle turning points of 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. However, the models are less accurate and timely in calling the trough in real time.

1. Introduction

Short-term analyses in central banks and other policy institutions are intended to provide policy makers, and possibly larger audiences, 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 to date 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 whether Norwegian business cycles are synchronized fully with the cycles of other Scandinavian countries, or with the European or US cycles.

The contributions of this paper are twofold. First, we define classical business cycle turning points for the Norwegian economy for the period 1978Q1–2011Q4, exploring a widely used set of 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 & Boschan, 1971; Harding & Pagan, 2002) and a univariate Markov-switching (MS) model (see Hamilton, 1989). We

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apply these methods to the GDP for mainland Norway, and label the results BB-GDP and MS-GDP, respectively. For multivariate methods, we consider a quarterly Markov-switching dynamic factor model (MS-FMQ; see Chauvet, 1998; Chauvet & Piger, 2008), and also apply the BB rule to a coincident index constructed by an inverse standard deviation weighting (BB-ISD; see Stock & Watson, 2014).

We begin by comparing 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 related more closely 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 the best of our knowledge, only two earlier studies have aimed to date classical turning points in the Norwegian economy. Christoffersen (2000) defined classical business cycles in the Nordic countries by using the BB algorithm on the monthly index of manufacturing production from 1960 to 1998. A more recent study by Fushing, Chen, Berge, and Jordà (2010) utilized 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 of Christoffersen (2000) and Fushing et al. (2010), there are also clear differences.

Berge and Jordà (2011) introduced the receiver operating characteristic (ROC) curve methodology for classifying economic activity in the US as 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, and the ROC curve analysis, we select the cycle identified by the MS-FMQ approach as our reference cycle.

We then turn to the prediction of business cycle peaks and troughs in real time. As was emphasized by Hamilton (2011), this is a challenging task due to factors such as data revisions, time-lagging data availability and changes in economic relationships over time. While Harding and Pagan (2003) found that the BB approach was preferable to MS models when 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, Jansson, & Löf, 2005, Abberger, 2007, and Claveria, Pons, & Ramos, 2007, for applications using survey data; and Estrella & Mishkin, 1998, and Stock & Watson, 2003, for applications to financial data[1]). As was highlighted by Evans (2005), Giannone, Reichlin, and Small (2008), and Aastveit, Gerdrup, Jore, and Thorsrud (2014), for example, one advantage of surveys and financial market data is that they are available in a timely manner and not revised much.

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 in order to forecast turning points in real time. We suggest the use of bivariate VAR models with the GDP for mainland Norway, together with either one of the surveys or the FCI, and call a recession whenever the forecasted values of GDP imply a peak.

Focusing on the last recession, we show that the univariate MS models that use survey data and the FCI accurately call 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 the start of December 2008, respectively, i.e., about one and five 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 later in terms of calling the peak quarter. Importantly, these models also call the peak in 2008Q3, i.e., one quarter after the peak provided by the ex-post reference cycle. Finally, all of the models find it more challenging to predict the trough in 2009Q3. The majority of the models detect the trough quarter to be 2009Q1, 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 for example Anas, Billio, Ferrara, and Mazzi (2008), Darné and Ferrara (2011) and Billio, Casarin, Ravazzolo, and van Dijk (2012) for applications to the Euro area; and 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 the definition of business cycle turning points. Section 3 presents data and the dating of business cycles in Norway over the past four decades. Section 4 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 and describing developments in the level of economic activity across many sectors. An alternative concept is the growth cycle, where economic fluctuations are characterized as being above or below an unobservable trend. One 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

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

of the 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 turning points occur, i.e., the months in which recessions start and end. Decisions are made by deliberation based on available data, and 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 different methods have been suggested for the development of mechanical algorithms for calculating the beginnings and ends of recessions, particularly 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) built on the work of Bry and Boschan and developed 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 five quarters seems to produce reasonable results. After potential turning points have been identified, the final turning points are selected based on several rules that ensure alternating peaks and troughs and minimum durations of phases and cycles. Following Harding and Pagan (2003), peaks can be defined 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 the 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 peak occurred at $(t-1)$, then $\wedge_{t-1} = 0$, and it follows that the state $S_t = 1$. On the other hand, if there is a peak at $(t-1)$, 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] An alternative parametric model that allows for different regimes in business cycles is the threshold autoregressive model (see for example Potter, 1995, Tommaso, 1998, Ferrara & Guégan, 2005, Billio, Ferrara, Guégan, & Mazzi, 2013 for a comparison of MS models to threshold models).

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 for example Goldfeld & Quandt, 1973, Hamilton, 1989, Clements & Krolzig, 1998, Kim & Piger, 2002) are dominant. Hamilton (1989) proposes an autoregressive MS model for GDP growth where only the intercept is allowed to switch between regimes:

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

for $t = 1, \ldots, T$, and 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 any 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, unlike the original model of Hamilton (1989), 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 the 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 included naturally in a Bayesian framework. Second, parameter uncertainty plays a crucial role in such models and Bayesian inference offers an efficient and fast approach to its estimation. Third, the choice of the number of regimes is often crucial. Following previous studies in the literature, we investigate specification from two regimes (as per Hamilton, 1989, for example) to four regimes (as per Billio et al., 2012) and choose between them using a Bayes factor comparison based on the predictive likelihood, as per Billio, Casarin, Ravazzolo, and van Dijk (2013) (see Eq. C.2 in the online Appendix C for details). This selection strategy accounts for parameter uncertainty and prefers the models that provide the most 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, the results for specifications that include autoregressive terms are very similar, 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 it as the dependent variable in Eq. (3), resulting in the following specification:

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

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

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, the results from selecting $p = 1$ or $p = 2$ are very similar, 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 those of Bjørnland (2000) and Bjørnland, Brubakk, and Jore (2008), analyze the growth cycle based on quarterly national accounts. To the best of our knowledge, only two earlier studies have aimed to date classical turning points in the Norwegian economy. Christoffersen (2000) defined classical business cycles in the Nordic countries by using the BB algorithm on the monthly index of manufacturing production. A more recent study by Fushing et al. (2010) utilized 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 by exploring the four different methods explained in Section 2, BB-GDP, MS-GDP, BB-ISD and MS-FMQ.

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

[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.

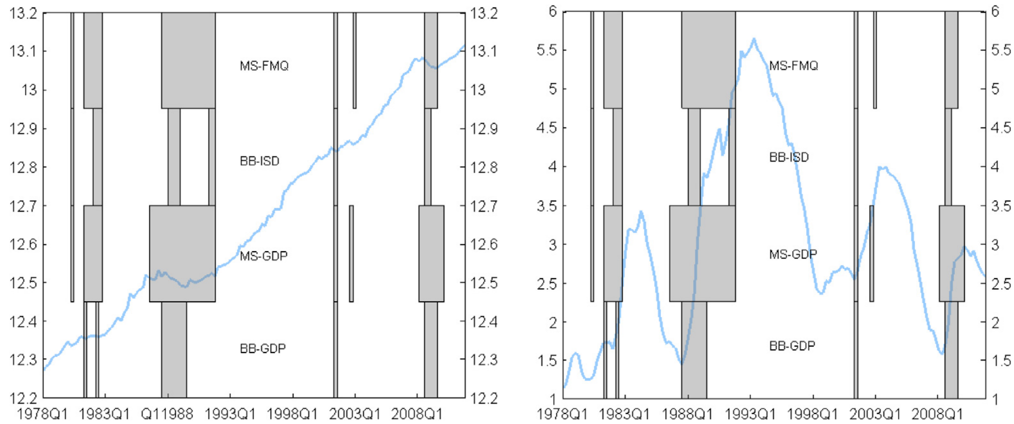
When investigating economic conditions in Norway, it is common to use the gross domestic product for mainland Norway as the measure of economic activity. This measure excludes offshore activity, namely oil and gas extraction and international shipping. One reason for the exclusion of these sectors is the fact that their production may show large fluctuations that have 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 the discussion by Bowitz & Hove, 1996). All revenues are transferred to a sovereign wealth fund, and a fiscal policy rule determines the size of withdrawals from the fund each year.

3.1. Dating

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

According to BB-GDP, there is a double dip recession with a peak in 1981Q1 and a final trough in 1982Q3. This is in contrast to the other three methods, which agree that the double dip recession started with a peak in 1980Q1 and ended with a final trough in 1982Q4. Using the monthly seasonally adjusted manufacturing production index, Christoffersen (2000) found that the peak occurred in September 1981, while the trough was pinpointed to October 1982. Fushing et al. (2010) found a peak in February 1980, and signaled a single recession lasting only two quarters. The main message seems to be that this recession was mild, when measured as the loss in GDP, even if it was fairly long-lasting. However, the unemployment rate reached levels unprecedented in the post-war period. The development between 1980 and 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 Fig. 1). Taken together, there is quite strong evidence of a double dip recession starting in 1980Q2 and 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 1979 after the revolution in Iran. Comparing this with turning point dates abroad, the dates defined by the MS, BB-ISD and MS-FM are particularly close to the turning point dates for the US, but are also similar to those of Sweden and the euro area.

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



(a) log(GDP). (b) Unemployment rate.

Fig. 1. Business cycle dating for Norway, 1978 to 2011. Four alternative dating methods. Notes: The shaded areas indicate recessions. The bottom tier turning points are calculated by using BB-GDP. The second-bottom tier turning points are calculated by MS-GDP, while the two upper tiers show turning points constructed by BB-ISD and MS-FMQ, respectively.

In 1984, a strong expansion started, fueled by the deregulation of the credit and housing markets and supported by a continuing high oil price level (and hence, investment in the petroleum sector). The abrupt fall in oil prices in the winter of 1985/86 represented a considerable shock to the Norwegian economy. The downturn eventually turned into a banking crisis in the late 1980s, meaning that the recession that started in the late 1980s was 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 nine 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. The GDP was already starting growing by the end of 1989 (see panel (a) in Fig. 1), and hence, the trough defined by the BB method seems plausible. However, taking into account a broader set of indicators (MS-FMQ) and referring to panel (b) in Fig. 1, it seems more reasonable that the trough occurred later. Christoffersen (2000) found the peak in April 1989 and a trough in July 1990, giving a recession of around five quarters. The findings of Fushing et al. (2010) indicate two recessions in this period: a recession with a peak in August 1987 and a trough as soon as December of the same year, and a second recession with a peak in May 1991 and a trough in October of the same year.

This recession was triggered mainly by domestic factors. Downturns started around three years later in the US, the UK and Sweden, while the peak quarter in the euro area was as late as 1992Q1 according to CEPR: 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 that lasted two quarters. This corresponds quite closely to the recession in the US. Next, two of the models (MS-GDP and MS-FMQ) find another recession in 2002. This is a specific Norwegian downturn, and was probably triggered by the tightening of monetary policy in response to signs of wage inflation and expectations of increasing consumer price inflation. This downturn was also picked up by Fushing et al. (2010), with a peak pinpointed in 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 that lasted several quarters longer. A peak quarter in 2008Q2 and a trough in 2009Q3 are consistent with the findings of 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) of Fig. 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 recession would have started earlier in the US than in Norway.

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

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

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

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

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 the specific dates of peaks and troughs detected by the four models described in Section 2, as well as authoritative dates of peaks and troughs for the US, the UK, Sweden and the euro area.

Table 2
Business cycle characteristics 1978–2012. Ex post; four 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 triangle 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 a triangle with the duration as the length and the amplitude as the height. The size and sign of the excess loss form a measure of the cycles' deviations from the triangle approximation. A positive loss entails a larger loss than the triangle approximation.

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, the amplitudes are smaller in Norway. Taking durations and amplitude into account together using the triangular approach (see Harding & 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 only exception is the MS-GDP method, for which the cumulative loss is very small. The main reason for this is 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, the numbers are much larger, and

Table 3
AUROC statistics, Norway.

	BB-GDP	MS-GDP	MS-FMQ	BB-ISD
BB-GDP	–	0.895	0.926	0.770
MS-GDP	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 calculate the AUROC when the chronology of turning points is matched to the BB-GDP, MS-GDP, MS-FMQ and BB-ISD, respectively.

again, the statistics for the four methods are closer to the US statistics than to those for the other countries.

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

The receiver operating characteristic (ROC) curve methodology was introduced by Berge and Jordà (2011) in order 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, which is fairly close to a near-perfect classification ability. Turning this viewpoint on its head, the BB-GDP and BB-ISD have considerably lower classification abilities for the MS-GDP and MS-FMQ dates, obtaining AUROC values of between 0.72 and 0.77. Finally, the classification abilities 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 those defined by BB-GDP and BB-ISD. One advantage of the MS-FMQ approach, relative to the MS-GDP approach, is that it captures cycles that reflect movements in a broader set of variables, more in line with Burns and Mitchell's (1946) idea of a "reference cycle". Based on international comparisons, the results from other studies of Norwegian cycles, how "reasonable" the cycles are in relation to historical developments in the Norwegian economy, and 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 now address the problem of forecasting turning points in real time. Using US data, Chauvet and Piger (2008) found that the real-time performances of Markov-switching models outperformed those of 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 relationships 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 abilities to forecast the peak and trough of the latest recession. The Markov-switching techniques 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, in order 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 also investigate the role of information from surveys and financial data in predicting business cycle turning points. Models using financial and survey data are likely candidates for the early detection of turning points, as they are published in a more timely manner than GDP, and the nature of the statistics ensures that a wide range of information and considerations are taken into account by both financial market participants (see Næs et al., 2011) and the respondents to 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 broad-based financial indicator covering foreign exchange rates, total returns, house prices, the oil price, interest rates, money and credit.[8]

All of the surveys are quarterly, as Norway has no monthly surveys that have been being published for long enough to be useful for model-based forecasting. However, since the quarterly surveys are released earlier than the GDP data, the indicators are generally available for quarter t, while the 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; and 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.

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. For the BB approach, we produce forecasts from bivariate vector autoregressive models:

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

8 The index is constructed using a dynamic factor model with data available since 1995, see Table A.1 in the online appendix.

where $Y_t = (y_{1,t}, y_{2,t})$ and $y_{1,t}$ and $y_{2,t}$ denote 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 the quarterly GDP is released with a lag of approximately seven weeks, if we add forecasts for two quarters (i.e., a nowcast and a forecast) to the latest available vintage, we cannot predict a turning point until at least 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 the data used for real-time forecasting.

4.2. Results

The 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, which detected 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 one of the first sectors to be affected by downturns that originate among our trading partners.[9] 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, which utilizes more timely monthly information, but is not constructed to reflect financial conditions, predicted a peak in June 2008, but not until early November. Hence, indicators based on qualitative surveys, incorporating expectations, predict the 2008 turning point earlier than more frequent quantitative 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 release of the national accounts for 2008Q4 in mid-February 2009. This is substantially later than MS models applied to survey information, the FCI, or monthly factor models.

Turning to the BB-based methods, BB-GDP and the bivariate VARs that include 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. The BB-based methods are less timely than the MS models, and our results support the findings of 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 either GDP itself or factor models that use quarterly "hard" data.

Table 5 shows real-time predictions of the trough. In contrast to the results for predicting the peak, all of the BB models predict the trough in a more timely fashion than the MS models. 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 in either 2009Q4 or 2010Q1, one or two quarters respectively 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 the detection of business cycle peaks in real time. Markow-switching models are more accurate and more timely than approaches based on the BB rule. However, the results for detecting troughs are less clear. Both the predicted trough quarter and the timing of the detection show a substantial degree of 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 with the business cycles of some of Norway's main trading partners, supported by the results from two earlier studies applied to the Norwegian economy and evidence from the ROC curve methodology, we found that the 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 gains by detecting peaks in real time at an earlier date than through the application of MS to more traditional factor models or GDP itself.

Predicting the trough quarter in real time is more challenging than predicting the peak. Both the predicted trough quarter and the timing of the detection show a substantial degree of variation across the different approaches, and none of the approaches can pinpoint the reference cycle trough in real time.

[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, although the manufacturing sector is small compared to the mainland economy.

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

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

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 by the date of detection.

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 trough quarter and date of detection using alternative methods and variables. Ordered by the date of detection.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.ijforecast.2015.06.006.

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