Forecasting recessions in real time*

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Abstract

This paper reviews several methods to define and forecast classical business cycle turning points in Norway, a country which does not have an official business cycle indicator. It compares the Bry and Boschan rule (BB), an autoregressive Markov Switching model (MS), and their versions augmented with surveys or financial indicators, using several vintages of Norwegian Gross Domestic Product as the business cycle indicator. Timing of the business cycles depends on the vintage and the method used. BB provides the most reliable definition of business cycles. A forecasting exercise is also presented: the BB applied to density forecasts augmented with the consumer confidence survey, the regional network survey, and the financial condition index provides the most timely predictions for Norwegian turning points in real time.

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

**Keywords:** Density combination; Forecast densities; 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 possible a larger audience, with assessments of the recent past and current business cycle. Point and density forecasts of few variables of interest are often provided. However, the analysis of current economic conditions do not rely just on this information, and there is a long tradition in business cycle analysis and related research on separating periods with contraction with periods with expansion, see Schumpeter (1954). Policy decisions vary depending on the fact the economy is in an expansion or recession period. Most of the research has focused on US data, where the NBER cycle is the official and often defined reference cycle. But many other countries do not have an official dating and, for example, a Norwegian classical business cycles does not exist.

In this paper we review several methods to define classical business cycle turning points for the Norwegian economy. The Norwegian business cycle is not fully synchronized with cycles of other Scandinavian countries, nor either with the European cycle and/or US cycle for several reasons, including Norway is a small open economy with large exports of energy (gas and oil) goods. We compare a Bry and Boschan rule (BB) as in Harding and Pagan (2002) and an autoregressive Markov Switching model (MS) as in Hamilton (1989), all two methods applied to an univariate series, the Norwegian Gross Domestic Product (GDP).

Macroeconomic data, and in particular GDP, are subject to important revisions over time. Benchmark revisions, but also revisions due to new information change series substantially and for several years. Economic decisions (see Orphanides and van Norden (2002)) are not immune to such changes. Hamilton (2011) also shows that business cycle dating can result in important differences when several vintages are considered. We compare business cycle turning points given by the three methods listed above when using 2012 ex-post revised data to real-time data.

Finally, data are released with substantial delays and therefore economic decisions rely on forecasts of the missing recent information. The literature on point forecast is
large (see Timmermann (2006) for a recent review), it is growing on density forecasting, but it is very thin on turning point prediction, see e.g. Billio et al. (2012). Markov switching models can produce point, density and turning point forecasts; on contrary, the BB rule must be extended with forecasts of the recent and future values of the economic variables to predict turning points. Furthermore, both methods can be augmented with additional leading indicators where a leading indicator is interpreted as a variable that timely summarizes the common cyclical movements of some coincident macroeconomic variables. We focus our analysis on two classes of data: financial indices and survey data.

Harvey (1989) has been one of the first study to document the relationship between financial variables and macroeconomic aggregates, focusing on the links between the term structure and consumption growth. More recently, Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) have extended such analysis. Also, there are several studies documenting that the information obtained from surveys has high forecasting power for macroeconomic variables; see, for example, Thomas (1999), Mehra (2002), Fama and Gibbons (1984), and Ang et al. (2007) when using quantitative surveys; and Hansson et al. (2005), Abberger (2007), Claveria et al. (2007) and Lui et al. (2010a,b) when applying qualitative surveys. Specifically, for Norwegian data Næs et al. (2011) and Aastveit and Trovik (2012) document the role of financial indicators, and Martinsen et al. (2013) apply survey data to forecast Norwegian economic aggregates.

We find that the BB provides a reasonable business cycle over the last four decades; whether the MS provides, on contrary, recession periods which often last too shortly. When predicting business cycle turning points, financial and survey data seems to contain substantial predictability and the BB applied to density forecasts augmented with the financial condition index, the consumer confidence survey and the regional network survey provide superior predictions to the ones from Markov Switching models.

The rest of the paper is organized as follows: the next section describes the modeling framework and discuss how business cycle turning points are defined. The third section presents data and the dating for the Norwegian economy over the last two decades. The
fourth section focuses on the prediction of the turning points in real-time, describes the recursive forecasting exercise and provide results. Finally, section 5 concludes.

2 Business cycle dating approaches

We define a business cycle as a pattern in aggregate economic activity, as first described in Burns and Mitchell (1948). This is the classical business cycle, measuring developments in the level of economic activity and characterized by peaks and troughs. An alternative concept is the growth cycle. Economic fluctuations are characterized by “high” or “low” growth, most commonly relative to trend growth. An attractive feature of the classical business cycle is that it is not necessary to calculate the unobserved trend growth. 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.

Classical business cycles in the US are defined by the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER). The committee decides when a turning point occurs, i.e. in which month 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 December 1, 2008 and the following June 2009 trough was announced September 20, 2010. The dating of the turning points are normally not revised.

A number of methods have been suggested in order to develop mechanical algorithms for calculating the start and ending of recessions, in particular for US data where recessions defined by the NBER serve as benchmarks. See Hamilton (2011) for a survey. Here we concentrate on two different methods.

2.1 Bry and Broschan

Bry and Boschan (1971) describe a method that was able to (almost) replicate 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 to develop an algorithm for
detecting turning points in quarterly data. The quarterly procedure picks potential turning points and subject 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. Formally, definitions of peaks can be written

\[ \land_t = 1 \{ (y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2}) \} \] (1)

Correspondingly for troughs:

\[ \lor_t = 1 \{ (y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2}) \} \] (2)

When forecasting peaks and troughs, the values on the right-hand side of the equations are replaced by forecasts. Formally:

\[ \land_t = 1 \{ (y_{t-2}, y_{t-1}) < y_t, \text{Prob}(y_{t+1}, y_{t+2}) < y_t) > 0.5 \} \] (3)

and

\[ \lor_t = 1 \{ (y_{t-2}, y_{t-1}) > y_t, \text{Prob}(y_{t+1}, y_{t+2}) > y_t) > 0.5 \} \] (4)

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

\[ S_t = S_{t-1}(1 - \land_{t-1}) + (1 - S_{t-1})\lor_{t-1} \] (5)

If the economy is in an expansion, \( S_{t-1} = 1 \). If no peak occurred in (t-1), then \( \land_{t-1} = 0 \) and it follows that the state \( S_t = 1 \). On the other hand, if there is a peak in (t-1) then \( \land_{t-1} = 1 \) and the state changes to \( S_t = 0 \). The state will remain at 0 until a trough is detected.
2.2 Markov Switching

There is a long tradition on using nonlinear models to capture the asymmetry and the turning points in business cycle dynamics. Among such class of models, Markov-switching (MS) models (see for example Goldfeld and Quandt (1973), Hamilton (1989), Clements and Krolzig (1998), Kim and Murray (2002), Kim and Piger (2000), and Krolzig (2000) for further extensions) are dominant. In our paper we consider an autoregressive MS model for GDP growth similar to Hamilton (1989) where only the intercept is allowed to switch between regimes:

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

\[t = 1, \ldots, T\], where \(\nu_{s_t}\) is the MS-intercept; \(\phi_l\), with \(l = 1, \ldots, p\), are the autoregressive coefficients; and \(\{s_t\}_t\) is the regime-switching process, that is a \(m\)-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). The latent process takes integer values, say \(s_t \in \{1, \ldots, m\}\), and has transition probabilities \(P(s_t = j | s_{t-1} = i) = p_{ij}\), with \(i, j \in \{1, \ldots, m\}\). The transition matrix \(P\) of the chain is

\[
P = \begin{pmatrix}
p_{11} & \ldots & p_{1m} \\
\vdots & \ddots & \vdots \\
p_{m1} & \ldots & p_{mm}
\end{pmatrix}
\]

and has, as a special case, the one-forever-shift model that is widely used in structural-break analysis (e.g., see Jochmann et al. (2010) and references therein). 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.  

\footnote{Following Krolzig (2000) and Anas et al. (2008), we also investigate a 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 on the number of regimes is often crucial and following previous literature we investigate specification from two regimes (as for example in for example Hamilton (1989)) to four regimes (such as in Billio et al. (2012)). Evidence of more than two regimes, even in forecasting applications, is rather common in finance and has suggestive economic meanings. See Guidolin (2011) for an up-to-date literature review with a deep discussion of this aspect. However, we find that two regimes are satisfactory in our empirical applications, probably due to the particular features of our (Norwegian) data set, see next section.

In this paper we apply a Bayesian inference approach. There are at least two 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, predictive densities essential for density forecasting are natural output in a Bayesian framework, overcoming difficulties of the frequentist approach in dealing with parameter uncertainty, by ignoring it or by implementing a time-consuming bootstrapping approach.

In this paper we propose 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 regressors, \( x_{0t} = (y_{t-1}, \ldots, y_{t-p}, \sigma) \), with regime invariant coefficients, \( \phi = (\phi_1, \ldots, \phi_p)' \), and the vector, \( \nu = (\nu_1, \ldots, \nu_m)' \) of regime-specific parameters. In this notation the regression model in equation (6) writes as

\[
y_t = \xi_t' \nu + x_{0t}' \phi + u_t, \quad u_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \gamma)
\]

The data-augmentation procedure (see also Frühwirth-Schnatter (2006)) yields the completed likelihood function of model (6)

\[
L(y_{1:T}, \xi_{1:T}|\theta) = \prod_{t=1}^{T} \prod_{k=1}^{m} \prod_{j=1}^{m} \frac{1}{\sqrt{2\pi \sigma_k^2}} \exp \left\{ -\frac{(y_t - \nu_k - x_{0t}' \phi)^2}{2\sigma_k^2} \right\} (7)
\]

where \( \theta = (\nu', \phi', \sigma', p)' \) is the parameter vector, with \( p = (p_1, \ldots, p_m)' \), \( p_k = (p_{k1}, \ldots, p_{km}) \) the \( k \)-th row of the transition matrix, and \( z_{s:t} = (z_{s}, \ldots, z_t)' \), \( 1 \leq s \leq t \leq T \), denotes a subsequence of a given sequence of variables, \( z_t \), \( t = 1, \ldots, T \).
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 conjugate partially improper prior. Conjugate improper 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

\[
(\phi_1, \ldots, \phi_p) \propto \mathbb{I}_{\mathbb{R}^p}(\phi_1, \ldots, \phi_p)
\]
\[
\nu_k \propto \mathbb{I}_{\mathbb{R}}(\nu_k), \quad k = 1, \ldots, m
\]
\[
\sigma_k^2 \propto \frac{1}{\sigma_k^2} \mathbb{I}_{\mathbb{R}^+}(\sigma_k^2), \quad k = 1, \ldots, m
\]
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 a 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, for example, in Frühwirth-Schnatter (2006). We identify the regimes by imposing some constraints on the parameters, as it is standard 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 as final output predictive densities for $y_{t+h}$, $p(y_{t+h}|y_t)$ and we apply iterative forecasting when $h > 1$.

**Augmented Markov Switching** The MS specification in the previous paragraph can be augmented with leading indicators. We investigate several indicators, based on financial indices or surveys. The idea is that a leading indicator is a variable that summarizes the common cyclical movements of some coincident macroeconomic variables. Hence, the approach used in this paper models the idea of business cycles as the simultaneous movement of economic activity in various sectors by using an indicator. In addition, the asymmetric nature of expansions and contractions is captured by assuming again a Markov process for GDP growth:

$$y_t = \nu_{s_t} + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \beta x_t + u_t, \quad u_t \overset{i.i.d.}{\sim} N(0, \sigma^2)$$  \hspace{1cm} (8)

$t = 1, \ldots, T$, where $\nu_{s_t}$ is the MS-intercept; $\phi_l$, with $l = 1, \ldots, p$, are the autoregressive coefficients; $\{s_t\}_t$ is the regime-switching process, and $x_t$ is a vector of exogenous indicators.

Chauvet (1998) models the process for $x_t$ also as a MS model, whether we skip it, but we allow for autoregressive terms in the observation equations for $y_t$. Model (8) is again estimated using Bayesian inference and the procedure is divided in two stages. Priors and posteriors for the these model are similar to standard MS model, where the vector of regime invariant coefficients is extended with the $\beta$ coefficient, $x_{0t} = (y_{t-1}, \ldots, y_{t-p}, \beta, \sigma)'$. We discuss the list of indicators in the section 4.

3 **Norwegian business cycle dating**

Business cycles are cycles in economic activity. We interpret “economic activity” as developments in GDP Mainland Norway. There is no official dating of business cycles in Norway. Several studies of the Norwegian business cycle exist, see for instance Bjørnland
(1995) and Eika and Lindquist (1997). These are analyzing the growth cycle. In a study by Christoffersen (2000), classical business cycles in the Nordic countries are defined by using the Bry and Boschan algorithm on monthly data on Industrial Production. Industrial Production does not seem the most appropriate variable for the Norwegian business cycle because the production sector is small compared to other sector, such as energy and the public sector; and the Norwegian business cycle is not fully synchronized with cycles of other Scandinavian countries.

National accounts data are revised. Revisions may lead to changes in the dating of business cycles, regardless of the method used to extract the cycles. Until November 2011, seasonally adjusted growth rates were substantially revised as far back as the early 1980s, even if the unadjusted data were not revised. This led to changes in the dating of peaks and troughs, and made it extremely difficult to define business cycles historically. In November 2011, Statistics Norway changed their seasonally adjustment method. They also took steps to ensure that seasonally adjusted growth in historical data (prior to the base year, which changes every year) are kept unchanged. See description of methods for seasonal adjustment on Statistic Norway’s home page.\(^2\) Seasonally adjusted growth rates will now only change when the unadjusted data are revised. The revision in unadjusted data connected to the annual change of the base year is minor, but there will be larger main revisions from time to time.

With more stable and consistent historical data, it is of increasing interest to search for a method to define classical business cycles in Norway. Since no official dating of business cycles exists, we will base the choice of method on how “reasonable” the turning points are and compare with the general idea of developments in the Norwegian economy. We use the two methods applied top GDP Mainland Norway presented in section 2 as alternatives to define turning points.\(^3\)

Quarterly national accounts data exist from 1978. We will search for turning points for the whole sample using the BB-method. The Markov Switching method (MS) entails


\(^3\)The BB provides the same result if applied to GDP level or growth, whether the MS requires stationary data.
The logarithm transformation of GDP (left axis) published in February 2012 is plotted in blue; the business cycle dates (right axis) with value 0 during recession and zero otherwise using the Bry Boschan (BB) rule in red and the Markov Switching (MS) model in green.

having a training period, hence we may only define turning points from 1985 with this method.

The two panels in Figure 1 illustrates the alternative methods for defining turning points.

Economic developments in Norway the first decades after the second world war was characterized by steady growth and small cycles. Looking at the log of the GDP level in figure 7(a), the recession in the late 1970s seems shallow. According to the BB method, there is a double dip recession starting in the second quarter of 1981 and ending in the third quarter of 1982. As far as we know, the only other study trying to date classical turning points in the Norwegian economy is Christoffersen (2000). Christoffersen (2000) finds, using the monthly seasonally adjusted industrial production index, that the peak occurred in September 1981 while the trough was pinpointed to October 1982. Hence, the recession lasted around 4 quarters. Our result is in line with the result in Christoffersen (2000), taking into account the different data and frequencies and data revisions. The main message is that the recession was mild.

The recession in the late 1980s was deep and long-lasting. The BB method defines a 9 quarter long recession, starting in the third quarter of 1987 and ending in the third
quarter of 1989. Using the MS algorithm, see 7(b) in appendix, the recession starts in the first quarter of 1988 and ends in the first quarter of 1989, i.e. lasting 5 quarters.

The characteristics of this period depend on the data vintage. In order to illustrate the challenges associated with data revisions, we have calculated turning points using national account vintages published in February 2010 and in February 2011, respectively. See Figures 5 and 6 in the appendix. The recession in the late 1980s has become a double dip recession according to the BB method and a triple dip recession when employing the MS method. The whole recessionary period lasts longer for both methods. With the 2010 and the 2011 vintages, the BB recession starts in the third quarter of 1987 and does not end until the fourth quarter of 1991, a length of 18 quarters. The recession defined by the Markov switching method starts in the fourth quarter of 1986 and ends in the third quarter of 1991 (2010 vintage) or the first quarter of 1991 (2011 vintage). To sum up, the timing of the recession in the late 1980s depends on which vintage we use and on the choice of method.

Results using data published after Statistics Norway has changed their seasonally adjustment of historical data favor the use of the BB method. The MS method produces a recession that seems to start too late and to end too early, based on a judgemental assessment of developments in the Norwegian economy in that period. It also seems more reasonable when visually inspecting the log level of GDP.

We can compare the results from this period with findings in Christoffersen (2000). He finds a peak in April 1989 and a trough in July 1990, ie around 5 quarters. Compared with analyzing quarterly GDP, using monthly industrial production points to a shorter recession, starting later and ending sooner. Again, this result seems unreasonable.

An alternative way of assessing how reasonable the turning points are, is to compare their timing with developments in the unemployment rate, which has the advantage of not being revised, see Figure 2. The unemployment rate starts to rise in the fourth quarter of 1987, supporting the timing of a peak in 1987Q3 as defined by the BB method.

The next recession in the early 2000s is defined by the BB, while the MS method does
Unemployment rate (left axis) is plotted in blue; the business cycle dates (right axis) using BB and GDP in red.

not pick any turning points in this period (but it peaks a short recession using 2010 and 2011 vintages). This mild recession is associated with the bursting of the “dot-com” bubble. The next big recession is, however, defined by all two methods. The MS method defines a very short recession, 3 quarters starting with the third quarter of 2008. The BB method defines the same peak in 2008Q2, but the trough does not occur until the second quarter of 2009 - a recession lasting 5 quarters.

Judging the business cycles produced by the alternative methods, the BB method seems to define turning points that are in line with the general assessment of developments in the Norwegian economy since the late 1970s. The MS defines peaks and troughs in unlikely quarters or not at all.

4 Forecasting Norwegian turning points in real time

The turning points defined by the quarterly version of the Bry-Boschan method can be interpreted as describing turning points in the “true” Norwegian classical business cycles. One interesting question is then: Is it possible to predict the turning points in real time?
In this exercise we will concentrate on the latest recession. The most important reason for this choice is that prior to November 2011 revisions of seasonally adjusted national affected data as far back as in the early 1980. Data vintages from the period prior to November 2011 is increasingly different from the latest published vintage as we move backwards in time. We would not expect, using real-time data, to be able to predict turning points defined by the latest available vintages. This is also to some extent true for the latest recession, since data are final only after three years of revisions. However, these are revisions based on new information and we cannot avoid taking this into account.

We will use the two methods described in section 2 on real-time data and compare their ability to forecast turning points. The Markov switching techniques already compute probabilities of being in one regime or the other (i.e., in recession or expansion). The quarterly Bry-Boschan requires predictions to be able to define a turning point in real time. We produce predictive densities from an autoregressive model AR($p$) of order $p$, where we fix $p = 4$ as in the Markov switching example. The median value of the predictive densities is then used to extend the GDP level with the forecasts. The median forecasts can be directly compared to define recession using the MS when regime 1 has 50% (or higher) probability. Since quarterly GDP is released with a lag of approximately 7 weeks, this means that if we add forecasts for 2 quarters to the latest available vintage (i.e., a nowcast and a forecast), we may at the earliest predict a turning point 7 weeks after it occurred. If we add a three-steps ahead forecast, it would in theory be possible to forecast a turning point 5 weeks before it occurs. We will, however, confine ourselves to predictive densities one- and two-steps ahead, as the uncertainty increases with the horizon.

Both the BB and the MS can be augmented with leading indicators where a leading indicator is interpreted as a variable that timely summarizes the common cyclical

\footnote{Evaluations of point forecast accuracy are only relevant for highly restricted loss functions. More generally, complete probability distributions over outcomes provide information helpful for making economic decisions; see, for example, the discussions in Granger and Pesaran (2000), Timmermann (2006) and Gneiting (2011).}
movements of some coincident macroeconomic variables. We focus our analysis on two classes of data: financial indices and survey data. Indicator models based on financial data and survey data are likely candidates for being early in detecting turning points. Publication are 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/or the respondents in the surveys, see Martinsen et al. (2013). Note that financial data is high frequency and we choose the quarterly version following Næs et al. (2011). All the surveys are just quarterly, as there are not monthly surveys in Norway that have been published long enough to be useful in model based forecasting. We have chosen two financial variables and three alternative surveys.

The financial indices are:

- Financial conditions index (FCI). The index is constructed using a dynamic factor model with financial variables, including interest rates, money and credit and spreads.

- Amihud’s illiquidity ratio (Ill). The ratio is a measure of stock market liquidity, see Amihud (2002).

The surveys are:

- The overall business confidence indicator from the business tendency survey for manufacturing, mining and quarrying (BTS). The survey is conducted by Statistics Norway in the last three weeks of the quarter and is published at the end of the first month in the next quarter.

- The overall consumer confidence (CC) index (Indicator). The survey is conducted by TNS Gallup in the fifth week of the quarter and is published in the middle of the quarter.

- Expected growth in 6 months (all industries), from Norges Bank’s regional network survey (RN). The survey is conducted in the first half of the quarter and published around three weeks before the end of the quarter.
We use growth levels of all the five indicators together with GDP itself in bivariate vector autoregressive models following Aastveit et al. (2013), and use the forecasts for GDP to apply the BB rule.\(^5\) We also use the same variables as exogenous variables in the augmented MS autoregressive models.\(^6\)

### 4.1 Results

Results are presented in tables 1 to 4. From table 1, we can see that the five alternative augmented BB models all predict in real time 2008Q3 as the peak quarter. The first model to predict the downturn is the model with the consumer confidence indicator as the second variable (in addition to GDP itself). When the survey is published 2 December, using this to predict a two-step forecast (fourth quarter 2008 and first quarter 2009) for GDP and then run the BB procedure on the resulting time series pinpoints a peak two months after the quarter ended. All three survey models predict a peak in 2008Q3 as soon as the survey for the fourth quarter of 2008 is published. The Markov switching model augmented with the Norges Bank’s regional network survey also needs the fourth quarter of 2008 to forecast the turning point, but starting in 2007Q4, which seems too early for Norway. The other models predict the turning point later and three of them starting in 2008Q2.

Table 2 summarizes the peaks identified in the previous section using ex post data, more precisely the vintage published in February 2012. In real time, the forecasted peaks occur later than the peaks defined ex post using the full database. This is no surprise, since ex post data contains information from four more years. Furthermore, data is substantially revised. For example, in Figure 3, we compare the log levels of GDP vintages published in November 2008 and February 2012, respectively. In the 2008

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\(^5\)Applying univariate autoregressive models for the GDP extended with exogenous variables produces less accurate results than bivariate VARs, confirming evidence in Aastveit et al. (2013).

\(^6\)We also investigated two definitions of unemployment; the unemployment rate from the Labor Force Survey and the registered unemployment rate; and the use of the levels; but results in all these cases are inferior with recessions starting too late and lasting too long.
Table 1. *Forecasting turning points in real time - peaks*

<table>
<thead>
<tr>
<th>Model</th>
<th>Date of detection</th>
<th>Peak quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB with AR(4)</td>
<td>2009 19 May</td>
<td>2008Q3</td>
</tr>
<tr>
<td>BB with Consumer confidence (CC)</td>
<td>2008 2 December</td>
<td>2008Q3</td>
</tr>
<tr>
<td>BB with Business Tendency Survey (BTS)</td>
<td>2009 28 January</td>
<td>2008Q3</td>
</tr>
<tr>
<td>BB with Regional Network Survey (RN)</td>
<td>2008 17 December</td>
<td>2008Q3</td>
</tr>
<tr>
<td>BB with Financial conditions index (FCI)</td>
<td>2008 2 December</td>
<td>2008Q3</td>
</tr>
<tr>
<td>BB with Amihud’s illiquidity ratio (Ill)</td>
<td>2009 19 May</td>
<td>2008Q3</td>
</tr>
<tr>
<td>Markov switching with AR(4)</td>
<td>2009 19 May</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switch with CC</td>
<td>2009 3 March</td>
<td>2008Q3</td>
</tr>
<tr>
<td>Markov Switch with BTS</td>
<td>2010 27 April</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switch with RN</td>
<td>2008 17 December</td>
<td>2007Q3</td>
</tr>
<tr>
<td>Markov Switch with FCI</td>
<td>2010 2 February</td>
<td>2008Q3</td>
</tr>
<tr>
<td>Markov Switch with Ill</td>
<td>2009 19 May</td>
<td>2008Q2</td>
</tr>
</tbody>
</table>

The table reports the real-time predicted peak quarter and the exact date of the detection using several alternative methods defined in section 2.

Table 2. *Defining peaks ex post*

<table>
<thead>
<tr>
<th>Method</th>
<th>Length of downturn</th>
<th>Peak quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>5 quarters</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switching</td>
<td>3 quarters</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switch with CC</td>
<td>ongoing in 2012</td>
<td>2007Q4</td>
</tr>
<tr>
<td>Markov Switch with BTS</td>
<td>5 quarters</td>
<td>2007Q4</td>
</tr>
<tr>
<td>Markov Switch with RN</td>
<td>ongoing in 2012</td>
<td>2007Q1</td>
</tr>
<tr>
<td>Markov Switch with FCI</td>
<td>2 quarters</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switch with Ill</td>
<td>7 quarters</td>
<td>2007q4</td>
</tr>
</tbody>
</table>

The table reports the peak quarter and the length of the downturn using the vintage published in February 2012 and several alternative methods.
vintage the growth continues through 2008, although the growth rate is slightly negative in the first quarter of 2008. In the February 2012 vintage, on the other hand, growth is on average negative the first three quarters of 2008. As for the real-time case, the BB methods all converge to 2008Q2, the MS methods indicate an early recession.

Table 3 contains an overview of the models’ ability to forecast troughs in real time. All the BB models forecast a trough in 2009Q1 and most of them do it during 2009Q2. The MS models provide more mixed evidence with troughs ranging from 2008Q2 to 2010Q1 and often with substantial delay. The first model to predict a turning point is the BB with Amihud’s illiquidity ratio in the third week of May 2019 and two weeks later the model based on the consumer confidence survey. Both models, such as all the other ones later on, predict turning points after national accounts for 2009Q1 are published.

In real-time, peaks are predicted one quarter later than what we define ex post. Troughs, on the other hand, are predicted too early (depending on the method used), see comparison with Table 4.

Figure 4 provides a graphical summary of the results. The BB with survey data, in particular the Consumer confidence and the Reginal network surveys, provides the most impinging information in predicting peaks and troughs and it seems the most robust to problems related to data revisions.
### Table 3. Forecasting turning points in real time - troughs

<table>
<thead>
<tr>
<th>Model</th>
<th>date of detection</th>
<th>Trough quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB with AR(4)</td>
<td>2009 19 May</td>
<td>2009Q1</td>
</tr>
<tr>
<td>BB with Consumer confidence (CC)</td>
<td>2009 2 June</td>
<td>2009Q1</td>
</tr>
<tr>
<td>BB with Business Tendency Survey (BTS)</td>
<td>2009 28 July</td>
<td>2009Q1</td>
</tr>
<tr>
<td>BB with Regional Network Survey (RN)</td>
<td>2009 10 June</td>
<td>2009Q1</td>
</tr>
<tr>
<td>BB with Financial conditions index (FCI)</td>
<td>2009 2 July</td>
<td>2009Q1</td>
</tr>
<tr>
<td>BB with Amihud’s illiquidity ratio (Ill)</td>
<td>2009 19 May</td>
<td>2009Q1</td>
</tr>
<tr>
<td>Markov switching with AR(4)</td>
<td>2009 19 May</td>
<td>2009Q1</td>
</tr>
<tr>
<td>Markov Switch with CC</td>
<td>2010 7 December</td>
<td>2010Q1</td>
</tr>
<tr>
<td>Markov Switch with BTS</td>
<td>2010 27 April</td>
<td>2009Q1</td>
</tr>
<tr>
<td>Markov Switch with RN</td>
<td>2008 17 December</td>
<td>2008Q2</td>
</tr>
<tr>
<td>Markov Switch with FCI</td>
<td>2010 2 February</td>
<td>2008Q4</td>
</tr>
<tr>
<td>Markov Switch with Ill</td>
<td>2009 19 August</td>
<td>2009Q1</td>
</tr>
</tbody>
</table>

The table reports the real-time predicted trough quarter and the exact date of the detection using several methods.

### Table 4. Defining troughs ex post

<table>
<thead>
<tr>
<th>Method</th>
<th>Length of downturn</th>
<th>Trough quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>5 quarters</td>
<td>2009Q3</td>
</tr>
<tr>
<td>Markov Switching</td>
<td>3 quarters</td>
<td>2009Q1</td>
</tr>
<tr>
<td>Markov Switch with CC</td>
<td>ongoing in 2012</td>
<td>..</td>
</tr>
<tr>
<td>Markov Switch with BTS</td>
<td>5 quarters</td>
<td>2009Q1</td>
</tr>
<tr>
<td>Markov Switch with RN</td>
<td>ongoing in 2012</td>
<td>..</td>
</tr>
<tr>
<td>Markov Switch with FCI</td>
<td>2 quarters</td>
<td>2008Q4</td>
</tr>
<tr>
<td>Markov Switch with Ill</td>
<td>7 quarters</td>
<td>2009Q3</td>
</tr>
</tbody>
</table>

The table reports the trough quarter and the length of the downturn using the vintage published in February 2012 and several alternative methods.
For each class of models, the figure illustrates the length of the recession in lines “Ex-post” using ex-post data. Red denotes quarters where the economy is in recession. The lines denoted “RT” in show which quarter is the first in the recession in real time, i.e. the peak quarter is the quarter before the quarter marked in red. In the lines denoted “RT out”, the red quarter is the trough quarter in real time. Black vertical lines with the real-time data indicate which date the turning point was detected.
5 Conclusion

We compare several methods to define and forecast in real time classical business cycle turning points in Norway, a country which does not have an official business cycle indicator. We apply the Bry and Boschan rule (BB), an autoregressive Markov Switching model (MS), and the two methodologies augmented with financial indicators and survey data, using several vintages of Norwegian Gross Domestic Product as the business cycle indicator. We find that the BB provides the most reliable definition of business cycles using different vintages and when augmented with density forecasts from survey models provides more timely predictions for Norwegian turning points than the Markov Switching models both using final vintage and, above all, real-time data.

Our analysis focuses on a single country and just one, large, recession. We think, however, the analysis provides useful indications on how to construct classical business cycle turning points using timely information.

References


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Appendix

In order to illustrate the challenges associated with data revisions, we have calculated turning points using national account vintages published in February 2011 (Figure 5) and in February 2010 (Figure 6), respectively.

Figure 5. Business cycle dating using vintage published February 2011

(a) BB  
(b) MS

The logarithm transformation of GDP (left axis) published in February 2011 is plotted in blue; the business cycle dates (right axis) with value 0 during recession and zero otherwise using the Bry Boschan (BB) rule in red and the Markov Switching (MS) model in green.
Figure 6. *Business cycle dating using Vintage published February 2010*

(a) BB

(b) MS

The logarithm transformation of GDP (left axis) published in February 2010 is plotted in blue; the business cycle dates (right axis) with value 0 during recession and zero otherwise using the Bry Boschan (BB) rule in red and the Markov Switching (MS) model in green.