# Nowcasting Norway*

Matteo Luciani[a,b] and Lorenzo Ricci[a]
[a]ECARES, SBS-EM, Université libre de Bruxelles
[b]F.R.S.-FNRS

We produce predictions of Norwegian GDP. To this end, we estimate a Bayesian dynamic factor model on a panel of fourteen variables (all followed closely by market operators) ranging from 1990 to 2011. By means of a *pseudo* real-time exercise, we show that the Bayesian dynamic factor model performs well both in terms of point forecast and in terms of density forecasts. Results indicate that our model outperforms standard univariate benchmark models, that it performs as well as the Bloomberg survey, and that it outperforms the predictions published by the Norges Bank in its Monetary Policy Report.

JEL Codes: C32, C53, E37.

## 1. Introduction

Due to publication delays of economic data, policy institutions, such as central banks and ministries, are always forced to set their policies without knowing the current state of the economy and, sometimes, even without knowing the recent past. Institutions have practically solved this problem by producing predictions of the current/previous quarter either by judgmental processes or by simple

*We are indebted to Daniela Bragoli, Alberto Caruso, Domenico Giannone, Silvia Miranda Agrippina, Michele Modugno, and David Veredas for useful suggestions and comments. We also would like to thank Now-Casting Economics for advice, feedback, and access to data. This paper has benefited also from discussions with seminar participants at the Norges Bank and at the $7^{th}$ CSDA International Conference on Computational and Financial Econometrics (University of London). Matteo Luciani is *Chargé de Recherches* F.R.S.-FNRS and gratefully acknowledges their financial support. Of course, any errors are our responsibility. Corresponding author: Matteo Luciani, ECARES, Solvay Brussels School of Economics and Management, Université libre de Bruxelles, 50 Av F.D. Roosevelt CP114/04, B1050 Brussels, Belgium. Tel.: +3226503366; E-mail: matteo.luciani@ulb.ac.be.

univariate models. Surprisingly, despite being of great interest for policy analysis, this problem received almost no attention by the academic literature until recently, when Evans (2005) and Giannone, Reichlin, and Small (2008) formalized it in statistical models.

In this paper, we produce predictions of the previous, the current, and the next-quarter Norwegian Mainland GDP.[1] To this end, we estimate a Bayesian dynamic factor model (D'Agostino et al. 2014) on a panel of fourteen variables (all followed closely by market operators) ranging from 1990 to 2011.

There exists a large literature on *nowcasting* with dynamic factor models (DFMs). This literature, pioneered by Giannone, Reichlin, and Small (2008), has shown that DFMs produce *nowcasts* that outperform standard univariate benchmark models such as random-walk models, autoregressive models, and bridge models, and that perform as well as institutional forecasts. Moreover, this literature has shown that as more data pertaining the current quarter become available, the *nowcasting* error decreases monotonically—that is, the DFM is able to revise efficiently its prediction as new data are released. A non-exhaustive list of papers that have used DFM for *nowcasting* is Rünstler et al. (2009), Barhoumi, Darné, and Ferrara (2010), Marcellino and Schumacher (2010), Matheson (2010), Angelini et al. (2011), Bańbura and Rünstler (2011), Aastveit and Trovik (2012), and D'Agostino, McQuinn, and O'Brien (2012) (see Bańbura, Giannone, and Reichlin 2011 for a review).

There exists also a large literature on *forecasting/nowcasting* Norway. Most of this literature studies the properties of the system of averaging models (SAM) introduced in 2006 by the Norges Bank. SAM provides short-term forecasts of GDP and inflation by combining forecasts from vector autoregressive models, leading indicator models, and factor models. Bjørnland et al. (2008) show that SAM outperforms standard univariate models when forecasting both

[1] Henceforth, we will refer to the prediction of the next quarter as *forecast*, to the prediction of the current quarter as *nowcast*, and to the prediction of the previous quarter as *backcast*.

Statistisk Sentralbyra defines Mainland Norway as consisting "of all domestic production activity except from exploration of crude oil and natural gas, services activities incidental to oil and gas, transport via pipelines and ocean transport" (see Statistisk Sentralbyra website).

GDP and inflation, Bjørnland et al. (2011) evaluate the density forecast produced with different weighting scheme, and Aastveit, Gerdrup, and Jore (2011) show that the nowcasting performance of SAM improves steadily as new data are released.

Finally, there are also a few papers on *forecasting/nowcasting* Norway with dynamic factor models. Martinsen, Ravazzolo, and Wulfsberg (2014) estimate a DFM on disaggregate survey data to forecast national aggregate macroeconomic variables. They found that the DFM beats a standard autoregressive benchmark when forecasting both inflation and unemployment rate, but also that the DFM is most successful in forecasting GDP growth. Finally, Aastveit and Trovik (2012), which is the paper most similar to ours, estimate a DFM on a large database. They found that unemployment, industrial production, and asset prices are crucial for producing accurate nowcasts of Norwegian GDP.

Compared with this literature, this paper differs in two main aspects. The first aspect is the use of a Bayesian dynamic factor model (BDFM). The BDFM is an extension to the Bayesian framework of the dynamic factor model introduced by Forni et al. (2000) and Stock and Watson (2002a). The intuition and the working of the BDFM is exactly the same as that of the DFM. The difference is that, compared with a DFM, there is more dynamics in the BDFM introduced in order to accommodate the dynamic heterogeneity of different variables. However, in order to introduce more dynamics, the BDFM requires estimation of a large number of parameters, which can easily lead to very volatile predictions due to estimation uncertainty. This is why the model is estimated with Bayesian methods, which, by shrinking the factor model toward a simple naive prior model, are able to limit estimation uncertainty.

The second aspect is the use of a small data set. A common feature of the literature on dynamic factor models is the use of large data sets. This practice is mainly a consequence of the asymptotic theory of DFM, which was derived for both the number of variables and the number of observations, going to infinity. However, there is a literature that has shown how, for the purpose of forecasting, DFMs can be estimated on a small/medium number of appropriately selected variables (Bai and Ng 2008; Bańbura, Giannone, and Reichlin 2010, 2011; Camacho and Perez-Quiros 2010). We follow this approach and, as in Bańbura et al. (2013), we select only those few variables that are followed closely by the market—that is, those variables that market participants monitor in order to form expectations on Norwegian GDP.

The rest of the paper is organized as follows: in section 2, we illustrate the econometric framework, while in section 3, we describe the database, including the variable-selection process. Then, in section 4, we present the results, and finally, in section 5 we conclude.

## 2. The Bayesian Dynamic Factor Model

Factor models are based on the idea that macroeconomic fluctuations are the result of a small number of macroeconomic/structural shocks, which affect all the variables, and of a large number of sectorial/regional shocks that affect one or a few variables. Therefore, each variable in the data set can be decomposed into a common part and an idiosyncratic part, where the common part is assumed to be characterized by a small number of common factors that evolve over time as a VAR process driven by the common shocks.

Formally, let $\mathbf{x}_t$ be a vector of $n$ stationary variables observed at month $t$; the dynamic factor model is defined as follows:

$$x_{it} = \boldsymbol{\lambda}_i \mathbf{f}_t + \xi_{it} \qquad i = 1, \ldots, n \tag{1}$$

$$\mathbf{f}_t = \sum_{s=1}^{p} \mathbf{A}_s \mathbf{f}_{t-s} + \mathbf{u}_t \tag{2}$$

$$\xi_{it} = \sum_{s=1}^{p} \rho_s \xi_{it-s} + e_{it}, \tag{3}$$

where $\mathbf{f}_t$ and $\mathbf{u}_t \sim \mathcal{N}(0, \mathbf{I}_r)$ are $r \times 1$ vectors containing, respectively, the common factors and the common shocks, while $\boldsymbol{\xi}_t$ and $\mathbf{e}_t$ are, respectively, the idiosyncratic components and the idiosyncratic shocks. The common shocks and the idiosyncratic shocks are assumed to be uncorrelated at all leads and lags, while the idiosyncratic shocks are allowed to be cross-sectionally correlated, albeit by a limited amount (approximate factor structure).[2]

There exists a large literature showing how, by simply forecasting the common factors, it is possible to outperform standard univariate benchmark forecasts, in particular, when forecasting GDP.[3] The idea is that by capturing the co-movement in the data—i.e., the business cycle, or, in other words, "the signal" in the data—factor models are able to forecast accurately GDP. Moreover, since model (1)–(3) can be estimated with the Kalman filter (Doz, Giannone, and Reichlin 2011), factor models proved successful also in nowcasting. The usual procedure adopted for nowcasting with DFM can be summarized as follows:

1. Let $x_{gt}$ be GDP growth rate at time $t$.
2. Let $\hat{x}_{gt}^{v} = \widehat{\boldsymbol{\lambda}}_i \hat{\mathbf{f}}_t^{v}$ be the prediction of GDP growth rate at time $t$ obtained by using the $v$-th vintage of data.
3. Suppose that today new data are released (e.g., purchasing managers' index, or PMI).
4. Then by running the Kalman filter on the new vintage of data $\mathbf{x}_t^{v+1}$, we can update our estimate of the factors, $\widehat{\mathbf{f}}_t^{v+1}$, where the Kalman filter gives us the most likely factors given the available information.
5. Finally, we can update our prediction as $\hat{x}_{gt}^{v+1} = \widehat{\boldsymbol{\lambda}}_g \widehat{\mathbf{f}}_t^{v+1}$.

The main intuition of the Bayesian dynamic factor model used in this paper is exactly the same. The difference is that there is more dynamics in the model introduced in order to accommodate the dynamic heterogeneity of different variables, where by "dynamic

[2]This is the model studied in Doz, Giannone, and Reichlin (2011, 2012), which is a special case of the model studied in Forni et al. (2009). Doz, Giannone, and Reichlin (2011) propose to estimate (1)–(3) with the Kalman filter, while Doz, Giannone, and Reichlin (2012) suggest maximum-likelihood estimation through the expectation-maximization (EM) algorithm. Bańbura and Modugno (2014) further extended the EM algorithm proposed in Doz, Giannone, and Reichlin (2012) to the case of missing data.

[3]This literature includes, among others, Stock and Watson (2002a, 2002b), Forni et al. (2003, 2005), Marcellino, Stock, and Watson (2003), Artis, Banerjee, and Marcellino (2005), Boivin and Ng (2005, 2006), Schumacher (2007), Giannone, Reichlin, and Small (2008), Bańbura, Giannone, and Reichlin (2011), and D'Agostino and Giannone (2012).

heterogeneity of different variables" we refer to the possibilities that some variables may be contemporaneously correlated with quarter-on-quarter GDP growth, while others may be correlated with different transformations of GDP. A perfect example is PMI, though this is true for all the survey indicators in our database. If we plot monthly PMI with quarter-on-quarter GDP growth, we see that PMI tracks GDP decently (figure 1A). However, if we plot PMI against yearly GDP growth (i.e., the growth rate from a year ago), we can see that PMI tracks GDP very well (figure 1B). This means that PMI not only is a very timely indicator (i.e., it is released few days after the reference period) but also contains a lot of information on the business cycle. These two properties are the most desirable for real-time forecasting, and hence accounting for these different dynamics may be crucial.

Formally, the BDFM is defined as follows:[4]

$$x_{it} = \sum_{s=0}^{p} \boldsymbol{\lambda}_{is} \mathbf{f}_{t-s} + \sum_{s=1}^{p} \rho_{is} x_{it-s} + e_{it} \tag{4}$$

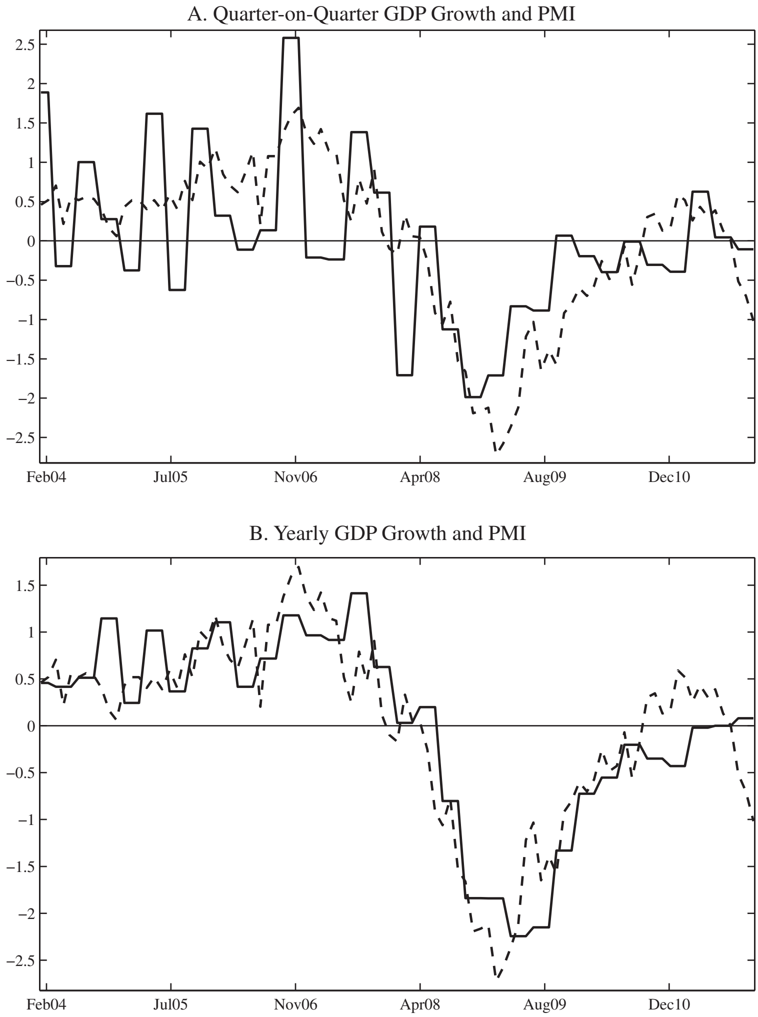
$$\mathbf{f}_t = \sum_{s=1}^{p} \mathbf{A}_s \mathbf{f}_{t-s} + \mathbf{u}_t, \tag{5}$$

where $\mathbf{u}_t \sim \mathcal{N}(0, \mathbf{I}_r)$ and $e_{it} \sim \mathcal{N}(0, \psi_{it})$.

Compared with model (1)–(3), the main difference here is that the factors are allowed to have an impact on the variables not only contemporaneously but also dynamically through the polynomial $\boldsymbol{\lambda}_i(L) = \sum_{s=0}^{p} \boldsymbol{\lambda}_{is}$. This is the feature that allows us to take into account the dynamic heterogeneity shown in figure 1. However, model (4)–(5) requires us to estimate a large number of parameters, which can easily lead to very volatile predictions due to estimation uncertainty. This is why the model is estimated with Bayesian methods, which, by shrinking the factor model toward a simple naive prior model, are able to limit estimation uncertainty. In particular, the priors on the coefficients are set to have mean zero and such that the variance is smaller for higher-order lags, so that posterior

[4]Note that, although the model is specified and estimated at the monthly frequency, we include also quarterly variables by constructing partially observed monthly counterparts. This procedure was originally proposed by Bańbura, Giannone, and Reichlin (2011, 2012) and Bańbura and Modugno (2014) and is explained in appendix 1.

**Figure 1. Example of Dynamic Heterogeneity**




**Notes:** In both panels, the solid line is GDP, while the dashed line is PMI. Both variables are plotted at the monthly frequency so that the value of GDP growth is repeated three consecutive times.

coefficients of high-order lags are different from zero only if the data strongly point in that direction.

The model is estimated by means of likelihood-based Gibbs sampling techniques as in Bernanke, Boivin, and Eliasz (2005). Suppose that the algorithm was run $j-1$ times, then at the $j$-th iteration estimation is divided into two steps:[5]

- Step 1: We draw the factors $\mathbf{f}_t^j$ using the algorithm proposed by Carter and Kohn (1994) from the state space (4)–(5) parameterized by using $\rho_i^{j-1}(L)$, $\boldsymbol{\lambda}_i^{j-1}(L)$, $\mathbf{a}^{j-1}(L)$, and $\psi_{it}^j$. However, in order to account for missing observations, we replace $\psi_{it}^{j-1}$ with $\tilde{\psi}_{it}^{j-1} = \psi_{it}^{j-1}$ if $x_{it}$ is available, and $\tilde{\psi}_{it}^{j-1} = \infty$ otherwise.
- Step 2: We draw the parameters $\boldsymbol{a}^j(L)$, $\boldsymbol{\lambda}_i^j(L)$, $\rho_i^j(L)$, and $\psi_{it}^j$ from their posterior distribution using the Gibbs sampling. Note that since $\mathbf{e}_t$ and $\mathbf{u}_t$ are independent, (4) and (5) can be treated separately. Moreover, since the idiosyncratic components are orthogonal, we can apply standard Bayesian regressions to (4) variable by variable. Similarly, since (5) has a standard VAR form, it can thus also be estimated equation by equation.

Finally, we impose relatively flat priors on the coefficients, that is, $\psi_i \sim \mathcal{IW}(1,3)$, $\lambda_{ik} \sim \mathcal{N}(0, \tau\frac{1}{(k+1)^2})$, $\rho_{ik} \sim \mathcal{N}(0, \tau\frac{1}{(k+1)^2})$, and $a_{ik} \sim \mathcal{N}(0, \tau\frac{1}{(k+1)^2})$, where $\tau$, the parameter governing the level of shrinkage, is set to 5.[6]

## 3. The Data Set

Factor models are usually estimated on a large number of variables. This practice is a consequence of the asymptotic theory of approximate dynamic factor models, which was derived for a double asymptotic in both $n$ and $T$. The intuition for this is simple: since what distinguishes factors from idiosyncratic components is the fact that the former are pervasive (i.e., are common to *all* variables), whereas the latter are non-pervasive, for the number of variables growing to

[5]The algorithm is initialized by principal components, which is equivalent to maximum likelihood of the model $x_{it} = \boldsymbol{\lambda}_i \mathbf{f}_t + e_{it}$, with $\mathbf{f}_t \sim \mathcal{N}(0, \mathbf{I}_r)$ and $e_{it} \sim \mathcal{N}(0, \psi_i)$ (Doz, Giannone, and Reichlin 2012). That is, we impose $\lambda_{ik} = \rho_{ik} = a_{ik} = 0$ for $k > 0$, and we set $\mathbf{f}_t^0 = \hat{\mathbf{f}}_t^{PC}$, $\boldsymbol{\lambda}_i^0 = \hat{\boldsymbol{\lambda}}_i^{PC}$, and $\psi_i^0 = \mathrm{var}(\hat{\xi}_i^{PC})$, where superscript $PC$ stands for estimated by principal components.

[6]Robustness analysis for the level of shrinkage can be found in appendix 2.

infinity, the only thing surviving to an aggregation of all the variables (such as, for example, that performed by principal components) are the common factors.

However, there is a literature that has shown how, for the purpose of forecasting, DFM can be estimated on a small/medium number of appropriately selected variables. Specifically, Bańbura, Giannone, and Reichlin (2010, 2011) and Barhoumí, Darné, and Ferrara (2010) show that medium-size models (i.e., including 10–30 variables) perform equally well in forecasting as large-size models (about 100 variables), while Luciani (2014) shows that aggregate variables are enough to produce a good forecast of GDP, but when forecasting more disaggregated variables, sectoral information matters.

In summary, the conclusion of this literature is that, unless one needs to comment on many data releases (as can be the case, for example, of a policy report), there is no need for a large database when forecasting. This conclusion supports our approach of relying on a small/medium database.

Of course, the conclusion of this literature is true as long as the variables are appropriately selected. The obvious question then is how to select variables. A first strand of the literature suggests using statistical methods (Bai and Ng 2008; Camacho and Perez-Quiros 2010).[7] A second strand of the literature (Bańbura, Giannone, and Reichlin 2010, 2011) suggests selecting variables with "economic judgment," which, essentially, amounts to including only aggregate variables. Finally, a third possibility—pioneered by Bańbura et al. (2013)—consists in considering only those variables that are followed closely by the market. The rationale of this approach is that market participants can be viewed as nowcasters. Market participants monitor macroeconomic data, form their expectations on current and future fundamentals of a given country, and also, based on these data/expectations, allocate their investments. Since we believe that they know what are the relevant series to monitor in order to form appropriate expectations on current GDP, it make sense to include in the model only those variables that are followed by them.

[7]Bai and Ng (2008) suggest selecting only those variables that are really informative for forecasting the target variable with the LARS algorithm. Camacho and Perez-Quiros (2010) suggest first selecting a core group of variables and then evaluating if other possible predictors are useful.

Practically, we proceed as follows: first, we look at the Bloomberg calendar for Norway. Second, we look at the "news" section of both the Statistisk Sentralbyra (SSb) and the Norges Bank websites. We assume that if a variable is on the Bloomberg calendar, then it is followed closely by market operators and is considered to be informative of the Norwegian business cycle. In addition, given that SSb and the Norges Bank produce hundreds of series, the few series that enter the "news" section are those considered the most important by them. We assume that these few series in the "news" section are also followed by market operators. Finally, we use some "expert judgment," meaning that if the data set is missing a variable that, based on our experience and on the literature, is believed to be a good indicator of the business cycle, then we include it.

By following this strategy, we end up with a data set of fourteen macroeconomics indicators ranging from January 1990 to June 2011. The data set includes indicators representing the main sectors of the real economy as well as survey indicators, while it does not include nominal or financial indicators. This choice is justified by the results in Bańbura et al. (2013), according to which a DFM estimated only on real variables does as well as a DFM estimated on a larger data set including also nominal and financial variables. All variables are seasonally adjusted and, where necessary, are transformed to reach stationarity. The data set was downloaded on May 2, 2012 from Haver. The complete list of variables and transformations is available in table 1.

Columns 9 and 10 of table 1 give information on the publication delay of each series. The column labeled "Day" shows (approximately) in which day of the month the series is released, while the column labeled "M" shows after how many months the data is published. For example, PMI is released three days after the end of the reference month, which means that on February 3 we know the value of January, while the unemployment rate is published almost three months after the reference month (on March 23 we know the value of January).[8] As we can see from table 1, there are substantial

[8] In the case of quarterly series, when "M" = 0, it means that the data are released the last month of the reference quarter (e.g., March for the first quarter); when "M" = 1, it means that the data are released the month after the end of the reference quarter (e.g., April for the first quarter); and when "M" = 2, the data are released two months after the end of the reference quarter.

**Table 1. Data Description and Data Treatment**

| Haver | Variable | Source | F. | Unit | SA | T. | Init. Date | Day | M. |
|---|---|---|---|---|---|---|---|---|---|
| S142VPMI@INTSRVYS | PMI | NIMA | m | % | 1 | 0 | 2-2004 | 3 | 1 |
| S142R@EUDATA | Unemployment Rate | EURO | m | % | 1 | 0 | 1-1989 | 23 | 2 |
| NOSD@NORDIC | Industrial Production | SSb | m | 2005=100 | 1 | 1 | 1-1960 | 7 | 2 |
| NOSELE@NORDIC | Employment | SSb | m | Thousands | 1 | 1 | 1-1989 | 23 | 2 |
| NOSTR47C@NORDIC | Retail Sales[a] | SSb | m | 2005=100 | 1 | 1 | 1-1979 | 31 | 1 |
| NOSTEN@NORDIC | Turnover[b] | SSb | m | 2005=100 | 1 | 1 | 1-1998 | 7 | 2 |
| NOSIX2@NORDIC | Merchandise Exports[c] | SSb | m | Mil. Kr. | 1 | 1 | 1-1989 | 17 | 1 |
| NOSIM2@NORDIC | Merchandise Imports[c] | SSb | m | Mil. Kr. | 1 | 1 | 1-1973 | 17 | 1 |
| S142VZ@INTSRVYS | Consumer Confidence | TNS | q | % | 1 | 0 | 3-1992 | 6 | 0 |
| S142QFQ@EUDATA | Construction Output | EURO | q | 2005=100 | 1 | 1 | 1-1995 | 17 | 2 |
| NOSNGPMC@NORDIC | GDP Mainland Norway | SSb | q | † | 1 | 1 | 1-1978 | 22 | 2 |
| NOSDU@NORDIC | Capacity Utilization | SSb | q | % | 1 | 0 | 1-1987 | 29 | 0 |
| NONVNIS@NORDIC | Industrial Confidence Indicator[d] | SSb | q | % | 1 | 0 | 1-1990 | 27 | 0 |
| NONTO@NORDIC | New Orders[e] | SSb | q | 2005=100 | 0 | 1 | 1-1990 | 7 | 2 |

**Notes:** From left to right, *Haver* shows the code to retrieve the series from the Haver Database; *Variable* reports the name of the variable; *Source* reports the original source of the data; *F*. specifies whether a variable is monthly (m) or quarterly (q); *Unit* reports the unit of measure of each variable; *SA* specifies whether a variable is seasonally adjusted (1) or non-seasonally adjusted (0) by the original source; *T*. specifies whether a variable has been transformed to growth rates as $\Delta$ log to reach stationarity (1) or is considered in levels (0); *Init. Date* specifies since when a variable is available (the format is either month-year or quarter-year); *Day* reports the approximate day of release of each variable; and, finally, *M*. indicates how many months after the end of the reference period the data are released.

[a]Volume: Trade ex Motor Veh & Motorcycles. [b]Energy Mining/Manufact/Distrib. [c]Excl. Ships and Oil Platforms. [d]BTS: Mfg/Mining/Quarrying. [e]All Industries. †Mil. Chn. 2009.NOK

Abbreviations used for *Source*: TNS = TNS Gallup; EURO = Statistical Office of the European Communities; SSb = Statistisk Sentralbyra; NIMA = Norsk Forbund for Innkjop og Logistikk.

differences between series in terms of their publication delay. On the one hand, surveys are very timely and are available at the end of the reference period; on the other hand, data on real activity are available one or two months after the reference period, with GDP and labor market indicators experiencing the longest delay.

## 4. The Forecasting Exercise

To evaluate the performance of our model, we perform a *pseudo* real-time out-of-sample exercise. *Backcasts*, *nowcasts*, and *forecasts* are produced according to a recursive scheme (described below), where the first sample starts in January 1990 and ends in December 2005. More specifically, starting from January 2006, we construct real-time vintages by replicating the pattern of data availability implied by the stylized calendar. Every time new data are released, the model updates the *backcast*, the *nowcast*, and the *forecast* of GDP growth rate based only on information actually available at that time; that is, in each quarter, the model produces a sequence of predictions, where the prediction of GDP growth rate is obtained from the Kalman smoother. The exercise is repeated until the end of June 2011 for a total of 419 *backcasts/nowcasts/forecasts*. Notice that, since data were downloaded on May 2, 2012, we are not able to track data revisions.[9]

The model is estimated at the beginning of each quarter using only information available as of the first day of the quarter, and then the parameters are held fix until the next quarter. More specifically, we follow D'Agostino, Gambetti, and Giannone (2013) and for the first window we compute the posterior distribution as described in section 2 by running the Gibbs sampler for 12,000 iterations, by discarding the first 10,000, and by accepting 1 out of 5 of the remaining 2,000 for a total of 400 accepted draws. From the second quarter onwards, since the algorithm is initialized with the median from the previous quarter's estimation, we compute the posterior distribution by running the Gibbs sampler for 2,500 iterations, by discarding the

[9]However, it is well known that factor models are robust to data revisions (Giannone, Reichlin, and Small 2008) since revision errors, which by nature are idiosyncratic, do not affect factor estimation. This issue is discussed also in section 4.4.

first 500, and by accepting 1 out of 5 of the remaining 2,000 for a total of 400 accepted draws.

The model is estimated by including one factor ($r = 1$) and twelve lags ($p = 12$), thus being able to account for a whole calendar year when forecasting. The choice of including one factor has both a theoretical and an empirical motivation. From a theoretical point of view, the literature on factor models has shown that for forecasting, it suffices to include a small number of factors (Stock and Watson 2002b; Forni et al. 2003). Often, a few factors means just two factors—one "real" factor and one "nominal" factor (Stock and Watson 2005). Hence, given that we include only real variables and surveys, we need just one factor to capture the co-movement in the real economy. From an empirical point of view, the first eigenvalue of the covariance matrix of the data accounts for more than 50 percent of the variance, thus signaling that the bulk of the co-movement is captured by the first factor.[10]

### *4.1 Univariate Benchmark*

We compare the performance of our model with several standard benchmark models: a random-walk model, a bridge model, and a MIDAS (mixed-data sampling) model.

Let $y_t^Q$ and $x_t$ be, respectively, quarterly GDP growth and a monthly variable, both observed at month $t$, so that GDP is observed at month $t = 3, 6, 9, \ldots$; then the bridge model (Parigi and Schlitzer 1995; Baffigi, Golinelli, and Parigi 2004) is defined as follows:

$$y_t^Q = \mu + \sum_{s=0}^{3} \beta_s x_{t-3s}^Q + \varepsilon_t, \tag{6}$$

where $x_t^Q = \sum_{j=1}^{3} \frac{1}{3} x_{t-j}$ is the monthly indicator aggregated at the quarterly frequency by a simple average.[11]

[10] This is the case when considering both real variables and surveys. Indeed, if we look at the covariance matrix of real variables only, then the first eigenvalue accounts for more than 90 percent of the variance.

[11] Equation (6) is typically estimated by OLS. Moreover, in case of missing observations in the target period, an auxiliary model such as ARMA is used.

In MIDAS models (Ghysels, Sinko, and Valkanov 2007; Andreou, Ghysels, and Kourtellos 2013), the aggregated variable $x_t^Q$ is replaced with the variable at the original frequency:

$$y_t^Q = \mu + \sum_{s=0}^{4} \beta_s \Gamma(L, \theta) x_{t-s} + \varepsilon_t, \tag{7}$$

where $\Gamma(L, \theta) = \sum_{m=1}^{M} \gamma(m, \theta) L^m$, and $\gamma(m, \theta) = \frac{\exp(\theta_1 m + \theta_2 m^2)}{\sum_m \exp(\theta_1 m + \theta_2 m^2)}$. Equation (7) together with the polynomial $\Gamma(L, \theta)$ is estimated by non-linear least squares.

In this paper, the predictions from the bridge model and the MIDAS model are obtained as follows: first we estimate a model for each monthly indicator in the database, and then we average the forecast.

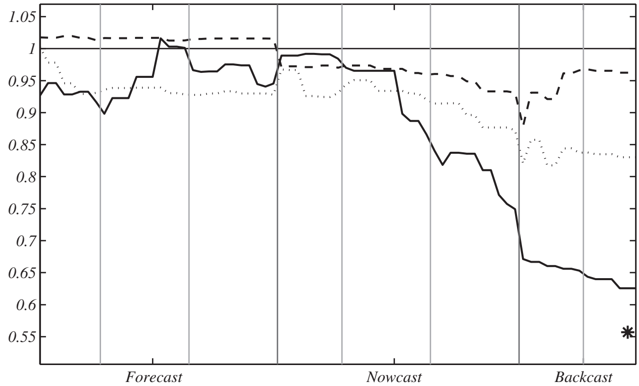
Finally, we compare our predictions with those of the Bloomberg survey (BS). The BS consists of the median GDP prediction provided independently by a number of specialists a few days before GDP is released. Both the number of specialists that provide a prediction (thirteen on average) and the day of release of the survey (on average six days before GDP is released) vary from quarter to quarter. Note that, since the Bloomberg survey is released a few days before previous-quarter GDP, according to our terminology the BS is a *backcast.*

### *4.2 Prediction Accuracy: Point Forecast*

In this sub-section, we evaluate the forecasting accuracy of the BDFM by looking at the point forecast (i.e., the median of the predictive density). Figure 2 shows the mean squared error (MSE) of the BDFM, of the bridge model, and of the MIDAS model. The MSE reported in figure 2 is relative to that of the random-walk (RW) model, hence a value smaller than 1 means that the BDFM on average is doing better than the RW model.

Figure 2 shows, in more detail, the evolution over time of the MSE in correspondence to each release in the stylized calendar during a period of almost eight months. The figure is divided into three sections delimited by a vertical solid line. The first section, labeled "forecast," reports the MSE of the prediction of the next quarter; the

**Figure 2. Relative Mean Squared Error**




**Notes:** In this plot, the horizontal line at level 1 is the MSE of the RW model, the solid line is the MSE of the BDFM, the dashed line is the MSE of the MIDAS model, the dotted line is the MSE of the bridge model, and the asterisk (*) is the MSE of the Bloomberg surveys.

second section, labeled "nowcast," reports the MSE of the prediction of the current quarter; finally, the last section, labeled "backcast," reports the MSE of the prediction of the previous quarter obtained before GDP is actually released. Moreover, the first two sections are divided into three other sections (delimited by a vertical grey line) representing the three months within each quarter, while the third section is divided into two sections since GDP is released the twenty-second of the second month after the end of the quarter.[12]

By looking at figure 2, four main conclusions can be drawn: (i) One quarter ahead, there is no predictability of Norwegian GDP growth, and lack of predictability continues for the first month and a half of the current quarter. (ii) The BDFM starts providing good predictions in correspondence with the release of previous-quarter GDP (twenty-second of the second month of the current quarter), and from that point on the MSE decreases as new data are released.

[12]For example, in the case of predicting Q2 GDP, the first section reports the MSE of the prediction done from January to March, the second section reports the MSE of the prediction done from April to June, and the third section reports the MSE of the prediction done between June and July 17, the last day before GDP is released.

(iii) At the end of the current quarter, the BDFM does 25 percent better than the RW model, while before GDP is released it does 35 percent better. (iv) The MSE of the Bloomberg survey denoted by an asterisk in figure 2 is just 11 percent smaller than that of the BDFM.

The column labeled "MSE" in table 2 shows in detail the MSE in correspondence of each data release, whereas the column labeled "Reduction in MSE" shows the reduction in the MSE accounted for by each data release: GDP previous quarter, survey indicators (PMI, consumer confidence, industrial confidence indicator), retail sales, and unemployment rate are the most important variables in predicting Norwegian GDP.

The performance of our model is very similar to that of Aastveit and Trovik (2012), who use a large DFM similar to (1)–(3). Their model has a relative MSE at the end of the current quarter of approximately 0.65–0.70, while the relative MSE of the BDFM is 0.75. Moreover, similar to them, we found a great role for unemployment rate. The main difference with Aastveit and Trovik (2012) is the role of survey indicators. Aastveit and Trovik (2012) do not include surveys in their database, and they found a great role for financial variables. This is so because financial variables are the only timely variables in their database. In our database, instead, timely information about the current state of the economy is provided by surveys, and thanks to the dynamic loadings in equation (4) we are able to capture properly the signal contained in the surveys.

We conclude the evaluation of the point forecast by comparing our predictions with the predictions of the year-on-year (YoY) GDP growth published by the Norges Bank in the Monetary Policy Report. The Norges Bank updates three times a year its predictions of the YoY GDP growth rate for the current year. Since our model produces quarter-on-quarter (QoQ) GDP growth rate predictions, we need to transform these QoQ predictions into YoY predictions. As is explained in appendix 3, this can be easily done by applying the approximation suggested by Mariano and Murasawa (2003).

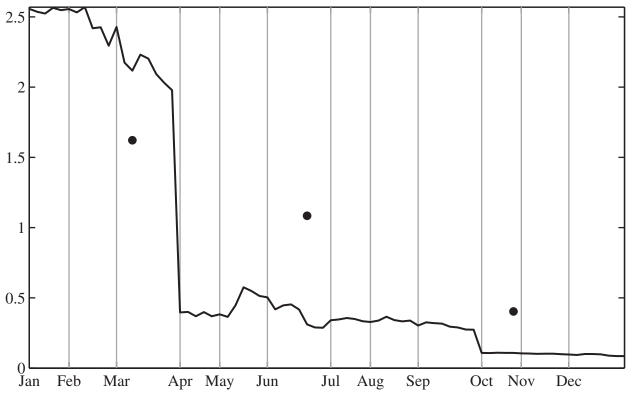
The black line in figure 3 is the MSE at each data release during a whole calendar year of the BDFM, while the black dots are the MSE of the Norges Bank predictions in correspondence of the day of release of the Monetary Policy Report. As we can see, the MSE of the Norges Bank decreases monotonically and so does that of the

## Table 2. The Contribution of Data Releases

| Variable | Day | MSE | | | Reduction in MSE | | |
|---|---|---|---|---|---|---|---|
| Month 1 | | | | | | | |
| PMI | 1 | 0.853 | 0.912 | 0.658 | | 0.042 | −0.032 |
| Industrial Production | 3 | 0.871 | 0.912 | 0.654 | 0.018 | 0.000 | −0.005 |
| Turnover | 6 | 0.871 | 0.912 | 0.654 | 0.000 | 0.000 | 0.000 |
| Merchandise Exports | 7 | 0.854 | 0.914 | 0.647 | −0.016 | 0.002 | −0.006 |
| Merchandise Imports | 8 | 0.854 | 0.914 | 0.647 | 0.000 | 0.000 | 0.000 |
| Unemployment Rate | 2 | 0.858 | 0.913 | 0.643 | 0.004 | −0.001 | −0.004 |
| Employment | 4 | 0.858 | 0.913 | 0.643 | 0.000 | 0.000 | 0.000 |
| Retail Sales | 5 | 0.843 | 0.907 | 0.640 | −0.015 | −0.006 | −0.003 |
| Month 2 | | | | | | | |
| PMI | 1 | 0.827 | 0.894 | 0.631 | −0.016 | −0.013 | −0.009 |
| Industrial Production | 3 | 0.849 | 0.890 | 0.627 | 0.022 | −0.004 | −0.004 |
| Turnover | 6 | 0.849 | 0.890 | 0.627 | 0.000 | 0.000 | 0.000 |
| New Orders | 14 | 0.849 | 0.890 | 0.627 | 0.000 | 0.000 | 0.000 |
| Merchandise Exports | 7 | 0.880 | 0.890 | 0.613 | 0.031 | 0.000 | −0.014 |
| Merchandise Imports | 8 | 0.880 | 0.890 | 0.613 | 0.000 | 0.000 | 0.000 |
| Construction Output | 10 | 0.880 | 0.890 | 0.613 | 0.000 | 0.000 | 0.000 |
| GDP: Mainland | 11 | 0.935 | 0.828 | | 0.055 | −0.062 | |
| Unemployment Rate | 2 | 0.923 | 0.818 | | −0.012 | −0.010 | |
| Employment | 4 | 0.923 | 0.818 | | 0.000 | 0.000 | |
| Retail Sales | 5 | 0.921 | 0.798 | | −0.002 | −0.019 | |
| Month 3 | | | | | | | |
| PMI | 1 | 0.889 | 0.775 | | −0.032 | −0.023 | |
| Consumer Confidence | 9 | 0.887 | 0.754 | | −0.003 | −0.021 | |
| Industrial Production | 3 | 0.888 | 0.772 | | 0.001 | 0.017 | |
| Turnover | 6 | 0.888 | 0.772 | | 0.000 | 0.000 | |
| Merchandise Exports | 7 | 0.898 | 0.770 | | 0.010 | −0.001 | |
| Merchandise Imports | 8 | 0.898 | 0.770 | | 0.000 | 0.000 | |
| Unemployment Rate | 2 | 0.896 | 0.747 | | −0.001 | −0.024 | |
| Employment | 4 | 0.896 | 0.747 | | 0.000 | 0.000 | |
| Industrial Confidence Indicator | 13 | 0.869 | 0.711 | | −0.027 | −0.035 | |
| Capacity Utilization | 12 | 0.866 | 0.698 | | −0.004 | −0.013 | |
| Retail Sales | 5 | 0.870 | 0.691 | | 0.004 | −0.008 | |

**Notes:** The column labeleed "MSE" shows in detail the MSE in correspondence of each data release, whereas the column labeled "Reduction in MSE" shows the reduction in the MSE accounted for by each data release.

**Figure 3. Year-on-Year Mean Squared Error**




**Notes:** The black line is the MSE at each data release during a whole calendar year of the BDFM, while the black dots are the MSE of the Norges Bank predictions in correspondence of the day of release of the Monetary Policy Report.

BDFM. The BDFM performs worse than the Norges Bank during the first quarter; however, starting from the second quarter onwards, the BDFM consistently outperforms the Norges Bank.

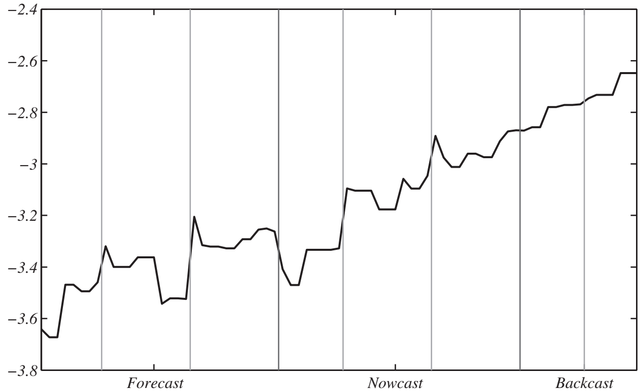
### *4.3 Prediction Accuracy: Predictive Density*

In this sub-section, we evaluate the forecasting accuracy of the BDFM by looking at the whole predictive density, that is, we account for uncertainty around our predictions, a line of research that is becoming increasingly popular in this literature (see, e.g., Gerdrup et al. 2009; Aastveit et al. 2014; Mazzi, Mitchell, and Montana 2014).

To evaluate the predictive density, we begin by looking at the average log-predictive score. The predictive score is the probability that the predictive density had assigned to the actual value. Hence, the higher the value of the average log-predictive score, the higher on average is the probability assigned by our model to the actual GDP release.

Similarly to figure 2, figure 4 shows the evolution over time of the average log-predictive score of the BDFM in correspondence to each release in the stylized calendar during a period of almost eight

**Figure 4. Log-Predictive Score**




**Notes:** The figure shows the evolution over time of the average log-predictive score (LPS) of the BDFM in correspondence to each release in the stylized calendar during a period of almost eight months. The figure is divided in three sections delimited by a vertical solid line. The first section, labeled "forecast," reports the LPS of the prediction of the next quarter; the second section, labeled "nowcast," reports the LPS of the prediction of the current quarter; finally, the last section, labeled "backcast," reports the LPS of the prediction of the previous quarter obtained before GDP is actually released. The first two sections are further divided into three other sections (delimited by a vertical grey line) representing the three months within each quarter, while the third section is divided into just two sections since GDP is released the twenty-second of the second month after the end of the quarter.

months. The main result in figure 4 is that starting from the second month of the current quarter, the log-probability score is clearly upward sloping, indicating that as new data arrive, the model not only reduces on average its error (figure 2), but it also assigns a higher and higher probability to the actual GDP release.

We continue the evaluation of the predictive density by looking at the probability integral transform (PIT), an approach originally introduced by Rosenblatt (1952) and recently proposed by Diebold, Gunther, and Tay (1998), which nowadays is commonly used for evaluating density forecasts (see, for example, Jore, Mitchell, and Vahey 2010; Mitchell and Wallis 2011). The PIT is the probability that the predictive density we are assigning to GDP growth is equal to or smaller than the actual value, hence PIT$\in [0,1]$. Intuitively, if the predictive density is well calibrated, then the PITs should be uniformly distributed; if that is not the case, it means that the predictive density is constantly over- or under-estimating GDP growth.

There exist a number of tests and formal procedures to investigate whether the predictive density is correctly calibrated (see D'Agostino, Gambetti, and Giannone 2013 and Rossi and Sekhposyan 2014, among others, and Corradi and Swanson 2006 for a review). In this paper, however, we follow none of these procedures. As we discuss in the next section, we have too few observations for obtaining reliable results from a formal testing procedure, and hence we resort to less-sophisticated visual inspection as in Diebold, Gunther, and Tay (1998).

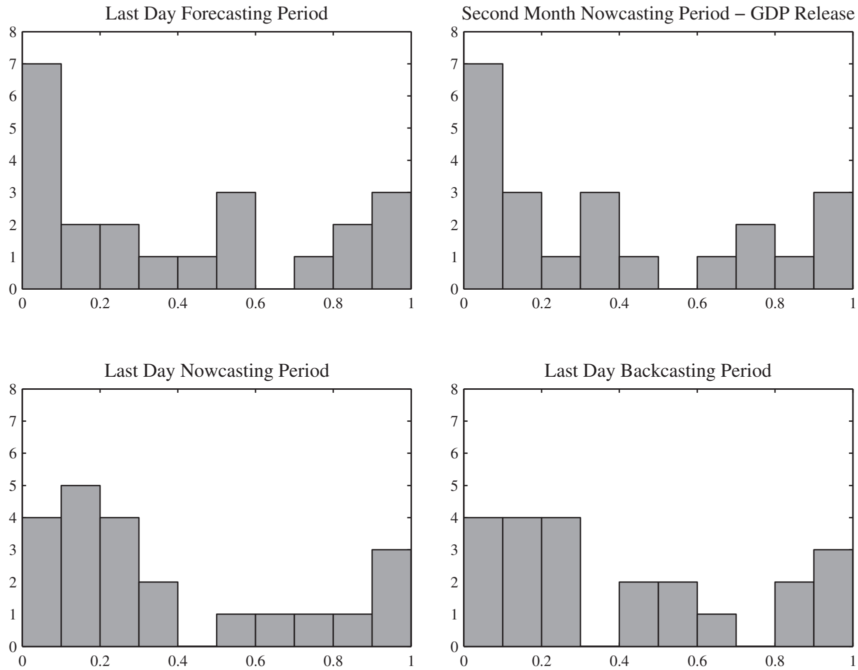
Figure 5 shows the distribution of the PIT at select dates. Results clearly point out how for all of the previous quarter, and most of the current quarter, the density forecast is upward biased, while starting from the end of the current quarter, the predictive density seems to be well calibrated.

### *4.4 Caveats*

The overall conclusion of the previous sub-sections is that the BDFM performs well both in terms of point forecast and in terms of density forecasts. Results indicate that the BDFM outperforms the benchmark models, that it performs as well as the Bloomberg survey, and that it outperforms the predictions that the Norges Bank publishes in its Monetary Policy Report. However, there are two main caveats that we must stress.

The first caveat is related to the fact that our forecasting exercise is *pseudo* real time. As we explained at the beginning of this section, we consider the stylized calendar of data releases, meaning that each time we produce a prediction we use only information actually available that day. However, we do not use real-time data vintages. Since factor models are robust to data revisions (Giannone, Reichlin, and Small 2008), we can still assume that the performance of the BDFM should be almost the same even when considering real-time data vintages. We must point out, though, that the comparison with the Norges Bank and the Bloomberg survey is not completely fair. Indeed, since we observe data revision, we use an information

**Figure 5. Probability Integral Transform Test**

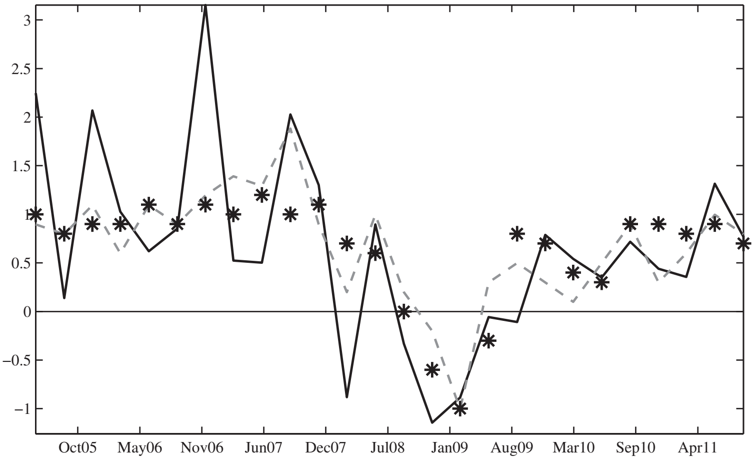



**Notes:** The figure shows the distribution of the PIT at select dates. "Last Day of Forecasting Period" means the twenty-ninth of the last month of the previous quarter, "Second Month Nowcasting Period—GDP Release" means the twenty-second of the second month of the current quarter, "Last Day of Nowcasting Period" means the twenty-ninth of the last month of the current quarter, and, finally, "Last Day of Backcasting Period" means the twenty-second of the second month of the next quarter. For example, in the case of predicting Q2, the four plots would identify the following dates: March 29, May 22, June 29, and August 22.

set that is superior to the one that was available to the Bloomberg specialists and to the Norges Bank when they made their prediction.

Moreover, we must notice that these data revisions may be important. Figure 6 shows GDP growth final release together with the first release, from which we can clearly see that revisions are sometimes huge. In addition, in figure 6 we also plot the prediction of the Bloomberg survey (asterisks), from which we can clearly see that Bloomberg specialists are predicting much better (and perhaps targeting) the first GDP release.

**Figure 6. First and Final Release of GDP Growth**

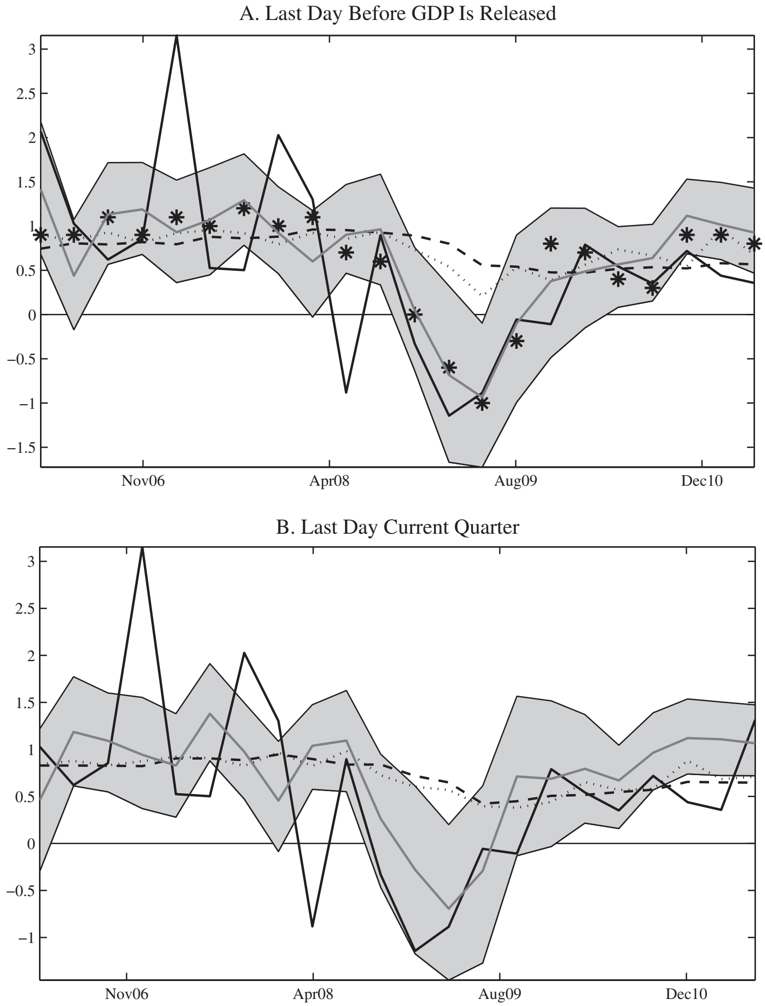



**Notes:** The figure shows GDP growth final release (black line) together with the first release (gray dashed line) and the prediction of the Bloomberg survey (black asterisks).

The second caveat is related to the fact that the evaluation sample is short. Indeed, the evaluation of QoQ GDP growth predictions is done on the basis of (just) twenty-two quarters (i.e., predictions), and similarly the evaluation of YoY GDP growth predictions is done on the basis of (just) five years (i.e., five predictions). This implies that average results should be taken cautiously. However, despite being short, this sample comprises a lot of action, including the downturn and the recovery. Moreover, by looking at the predictions (figures 7 and 8), it is still possible to appreciate the merit of the BDFM.

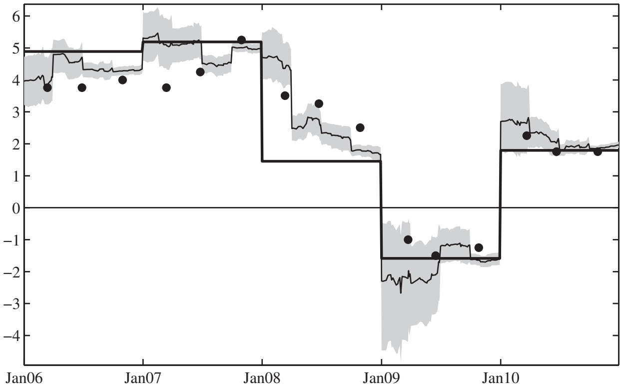
In figure 7A we show the predictions obtained in the last day of backcast. As we can see, compared with the other benchmark models, the BDFM is the only model able to capture the downturn of 2009. Moreover, the prediction of the BDFM is very close to that of the BS, thus strengthening the statement that the BDFM does a good prediction and that it is comparable to the BS. A similar conclusion can be reached when looking at the nowcast (figure 7B). Finally, from figure 8 we can see that the predictions obtained with the BDFM are very close to that published by the Norges Bank,

**Figure 7. Predicting Quarter-on-Quarter GDP Growth Rate**




**Notes:** The solid black line is the actual GDP growth rate. The gray solid line is the point prediction obtained with the BDFM, while the shaded areas are the 80 percent confidence band. The dashed line is the prediction obtained with the MIDAS model, while the dotted line is the prediction obtained with the bridge model. Finally, in panel A the asterisks are the Bloomberg survey.

**Figure 8. Predicting Year-on-Year GDP Growth Rate**




**Notes:** The thick solid black line is the actual GDP growth rate. The thin solid black line is the prediction obtained with the BDFM, while the shaded areas are the 80 percent confidence band. Finally, the black dots are the Norges Bank's predictions.

with the only exception being the year 2008, which is the year that drives the MSE shown in figure 3.

## 5. Conclusions

In this paper, by estimating a Bayesian dynamic factor model (D'Agostino et al. 2014), we produce predictions of the previous, the current, and the next quarter growth rate of Norwegian GDP. Compared with the factor model typically used in the nowcasting literature, the model used in this paper contains more dynamics in order to accommodate the dynamic heterogeneity of different variables. However, since the model has a large number of parameters, Bayesian shrinkage is employed to limit estimation uncertainty.

The model is estimated on a panel of fourteen variables ranging from 1990 to 2011. These fourteen variables have been selected because they are all followed closely by the market, meaning that those are the variables that market participants monitor in order to form expectations of Norwegian GDP.

By means of a *pseudo* real-time exercise, we show that the Bayesian dynamic factor model performs well both in terms of point forecast and in terms of density forecast. Results indicate that our model outperforms standard univariate benchmark models such as bridge models and MIDAS models, and that it performs as well as the Bloomberg survey, which is the median forecast provided independently by a number of specialists few days before GDP is released. In particular, we show that our model was the only model able to capture timely the downturn of the Norwegian economy in 2009. Finally, we show that our model outperforms the predictions of the year-on-year GDP growth published by the Norges Bank in its Monetary Policy Report.

## Appendix 1. Modeling Quarterly and Monthly Variables

In section 2 we said that although the model is specified and estimated at the monthly frequency, we include also quarterly variables by constructing partially observed monthly counterparts. In this appendix, we explain how practically this was done. The interested reader is referred to Bańbura, Giannone, and Reichlin (2011), Bańbura et al. (2013), and Bańbura and Modugno (2014) for more details.

The issue of mixed frequency (i.e., monthly and quarterly) is solved by treating quarterly series as monthly series with missing observations and by assigning the quarterly observation to the third month. The problem then is how to relate the monthly factors and the monthly idiosyncratic components with quarterly series.

The starting point is to understand the relationship between monthly and quarterly growth rates. Let $t$ denote months, and let $Y_t^Q$ be the log-level of a quarterly variable. The quarter-on-quarter growth rate is then equal to $Y_t^Q - Y_{t-3}^Q$, and we will denote it as $y_t^Q$. Then, let $Y_t^M$ be the monthly log-level of $Y$, and let $y_t^M = Y_t^M - Y_{t-1}^M$ be the month-on-month growth rate. Note that both $Y_t^M$ and $y_t^M$ do not exist, since $Y$ is observed only at the quarterly frequency. What matters for us is to understand what would have been the relationship between $y_t^M$ and $y_t^Q$ had we observed $Y_t^M$. In order to link $y_t^Q$ and $y_t^M$ we follow Mariano and Murasawa (2003), and we make use of the approximation $Y_t^Q \approx Y_t^M + Y_{t-1}^M + Y_{t-2}^M$ which, after some algebra, allows us to write

$$y_t^Q = y_t^M + 2y_{t-1}^M + 3y_{t-2}^M + 2y_{t-3}^M + y_{t-4}^M. \tag{8}$$

Once we know how to link quarter-on-quarter growth rates with month-on-month growth rates, we are also able to relate the monthly factors and the monthly idiosyncratic components with quarterly series. Suppose that we have a vector of monthly growth rates $\mathbf{x}_t^M$ described by a factor model:

$$\mathbf{x}_t^M = \boldsymbol{\lambda}_m \mathbf{f}_t + \boldsymbol{\epsilon}_t^M. \tag{9}$$

Suppose that we have a vector of quarterly growth rates $\mathbf{x}_t^Q$. How can we construct a factor model for $\begin{bmatrix} \mathbf{x}_t^M \\ \mathbf{x}_t^Q \end{bmatrix}$?

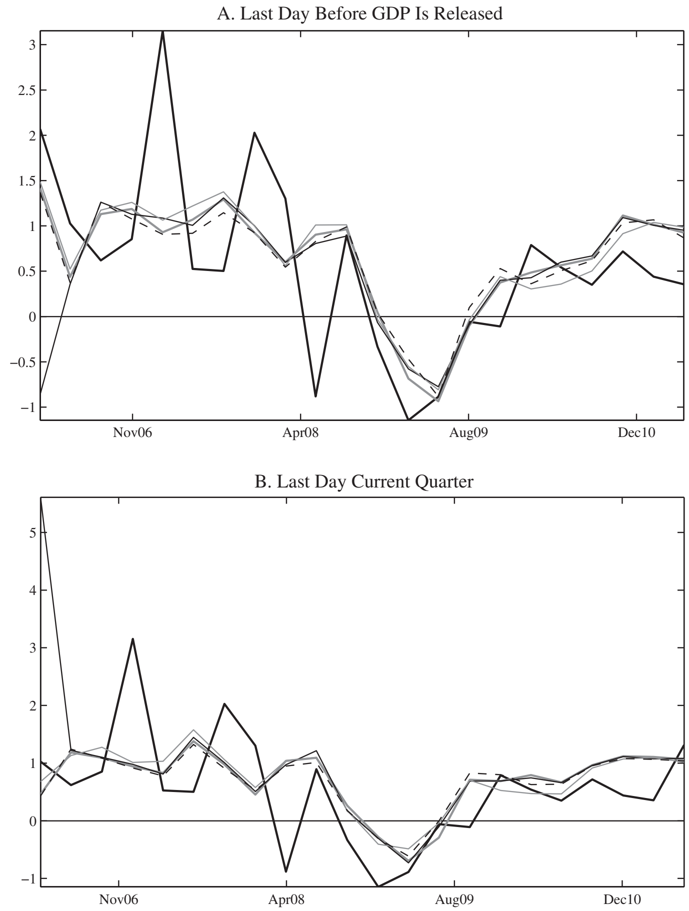
To do this we have to modify (9) in order to let coexist $\mathbf{x}_t^M$, $\mathbf{x}_t^Q$, $\mathbf{f}_t$, and $\boldsymbol{\epsilon}_t$. How to do this is given in equation (8). Namely,

$$\begin{bmatrix} \mathbf{x}_t^M \\ \mathbf{x}_t^Q \end{bmatrix} = \begin{bmatrix} \boldsymbol{\lambda}_m & 0 & 0 & 0 & 0 \\ \boldsymbol{\lambda}_q & 2\boldsymbol{\lambda}_q & 3\boldsymbol{\lambda}_q & 2\boldsymbol{\lambda}_q & \boldsymbol{\lambda}_q \end{bmatrix} \begin{bmatrix} \mathbf{f}_t \\ \vdots \\ \mathbf{f}_{t-4} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \\ 0 & 1 & 2 & 3 & 2 & \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon}_t^M \\ \boldsymbol{\epsilon}_t^Q \\ \vdots \\ \boldsymbol{\epsilon}_{t-4}^Q \end{bmatrix}. \tag{10}$$

## Appendix 2. Robustness Analysis

In this appendix, we show robustness analysis with respect to $\tau$, the parameter governing the level of shrinkage. As we said in section 2, in our benchmark specification we choose $\tau = 5$. When $\tau = 5$, the variance of the prior for the coefficient at lag 6 is still 0.1, while at lag 9 and lag 12 it is, respectively, 0.03 and 0.01. This is a relatively flat prior, meaning that we are leaving some space to the data for telling us what is the value of the coefficient of higher-order lags. In figure 9, we show the nowcast and the backcast obtained by setting $\tau = 1$, $\tau = 2.5$, and $\tau = 10$. When $\tau = 10$ or $\tau = 2.5$, we are shrinking either two times as much as or half of the benchmark scenario. These are two reasonable levels of shrinkage and can still be classified as relatively flat priors. When $\tau = 1$, instead, we are

**Figure 9. Robustness Analysis**




**Notes:** The thick black line is the actual GDP growth rate. The thick gray line is the point prediction obtained with the benchmark level of shrinkage, the thin gray line is the prediction obtained by setting $\tau = 10$, and the thin black line is the prediction obtained by setting $\tau = 2.5$.

shrinking much more than in the benchmark scenario. This is a high level of shrinkage, but not a limiting case in the sense that there is still room for the data to speak. As can be seen from figure 9, the performance of the BDFM is nearly identical independently from the level of shrinkage.

**Table 3. Variance of the Priors**

| $\tau$ | 1 | 2.5 | 5 | 10 | 100 |
|---|---|---|---|---|---|
| Lag 3 | 0.0625 | 0.1562 | 0.3125 | 0.6250 | 6.2500 |
| Lag 6 | 0.0204 | 0.0510 | 0.1020 | 0.2041 | 2.0408 |
| Lag 9 | 0.0100 | 0.0250 | 0.0500 | 0.1000 | 1.0000 |
| Lag 12 | 0.0059 | 0.0148 | 0.0296 | 0.0592 | 0.5917 |

**Notes:** This table shows the variance of the prior on the coefficients $\lambda_{ik}$, $\rho_{ik}$, and $a_{ik}$, for different levels of $\tau$. Recall that all these coefficients are normally distributed with zero mean and a variance equal to $\tau/(k+1)^2$, where $k$ is the lag order.

To conclude, we repeat the exercise for the case $\tau = 100$. This is an extreme case in which we are not shrinking at all (table 3). The results (not reported here) indicate that without any shrinkage, estimation uncertainty kills completely our predictions. The predictions have a huge variance and are often completely unrealistic.

## Appendix 3. Constructing Annual Nowcast

As we discussed in section 4, the Norges Bank publishes three times a year projections of the annual GDP growth rate for the current year. In order to compare our predictions with Norges Bank's projections, we need to transform our quarter-on-quarter (QoQ) predictions in annual values. In this appendix, we explain how we do it.

Let $X_q^y = 100 \times \log(GDP_q^y)$ be GDP of the $q$-th quarter of year $y$, and let $Z^y = 100 \times \log(GDP^y)$ be GDP of year $y$. Then, by definition $x_q^y = X_q^y - X_{q-1}^y$ is the quarter-on-quarter growth rate, while $z^y = Z^y - Z^{y-1}$ is the annual growth rate.

Following Mariano and Murasawa (2003), we make use of the approximation $Z^y \approx X_1^y + X_2^y + X_3^y + X_4^y$, which allows us to write the annual growth rate as a function of QoQ growth rates:

$$\begin{aligned} z^y = Z^y - Z^{y-1} &\approx (X_1^y + X_2^y + X_3^y + X_4^y) \\ &\quad - (X_1^{y-1} + X_2^{y-1} + X_3^{y-1} + X_4^{y-1}) \\ &= x_4^y + 2x_3^y + 3x_2^y + 4x_1^y + 3x_4^{y-1} + 2x_3^{y-1} + x_2^{y-1}. \end{aligned} \tag{11}$$

**Table 4. Constructing Annual Nowcast**

| Day | Month | $x_4^y$ | $x_3^y$ | $x_2^y$ | $x_1^y$ | $x_4^{y-1}$ | $x_3^{y-1}$ | $x_2^{y-1}$ |
|---|---|---|---|---|---|---|---|---|
| 1 | January | $3s$ | $2s$ | $f$ | $n$ | $b$ | | |
| 22 | February | $3s$ | $2s$ | $f$ | $n$ | | | |
| 1 | April | $2s$ | $f$ | $n$ | $b$ | | | |
| 22 | May | $2s$ | $f$ | $n$ | | | | |
| 1 | July | $f$ | $n$ | $b$ | | | | |
| 22 | August | $f$ | $n$ | | | | | |
| 1 | October | $n$ | $b$ | | | | | |
| 22 | November | $n$ | | | | | | |

**Notes:** This table shows how the nowcast of $z^y$ is obtained as more GDP data are released. $b$ indicates that that specific quarter-on-quarter growth rate is obtained with the *backcast*, $n$ with the *nowcast*, $f$ with the *forecast*, $2s$ with the two-step-ahead forecast, and $3s$ with the three-step-ahead forecast. An empty cell means that the data are available.

Suppose we are in January of year $y$ and we want to forecast $z^y$ with the BDFM, which produces QoQ growth rate forecasts. We can do it by using equation (11). In January of year $y$ we know only $x_3^{y-1}$ and $x_2^{y-1}$, while we need to estimate the other terms of equation (11). But this is easily done since $x_4^{y-1}$ can be estimated with the *backcast*, $x_1^y$ can be estimated with the *nowcast*, $x_2^y$ can be estimated with the *forecast*, and $x_3^y$ and $x_4^y$ can be easily obtained as two-step- and three-step-ahead forecasts. As time passes by and more data become available, the forecast of $z^y$ is updated. For example, on February 22 the data for $x_4^{y-1}$ are released and it is no longer necessary to estimate it. Moreover, as time goes by, also $x_1^y$, $x_2^y$, and $x_3^y$ will be available and hence it will no longer be necessary to rely on the three-step-ahead forecast, on the two-step-ahead forecast, and on the *forecast* (table 4).

## References

Aastveit, K. A., K. Gerdrup, and A. S. Jore. 2011. "Short-Term Forecasting of GDP and Inflation in Real-Time: Norges Bank's System for Averaging Models." Staff Memo No. 9/2011, Norges Bank.

Aastveit, K. A., A. S. Jore, K. R. Gerdrup, and L. A. Thorsrud. 2014. "Nowcasting GDP in Real-Time: A Density Combination Approach." *Journal of Business & Economic Statistics* 32 (1): 48–68.

Aastveit, K. A., and T. Trovik. 2012. "Nowcasting Norwegian GDP: The Role of Asset Prices in a Small Open Economy." *Empirical Economics* 42 (1): 95–119.

Andreou, E., E. Ghysels, and A. Kourtellos. 2013. "Should Macroeconomic Forecasters Use Daily Financial Data and How?" *Journal of Business & Economic Statistics* 31 (2): 240–51.

Angelini, E., G. Camba-Mendez, D. Giannone, L. Reichlin, and G. Rünstler. 2011. "Short-Term Forecasts of Euro Area GDP Growth." *Econometrics Journal* 14 (1): C25–C44.

Artis, M. J., A. Banerjee, and M. Marcellino. 2005. "Factor Forecasts for the UK." *Journal of Forecasting* 24 (4): 279–98.

Baffigi, A., R. Golinelli, and G. Parigi. 2004. "Bridge Models to Forecast the Euro Area GDP." *International Journal of Forecasting* 20 (3): 447–60.

Bai, J., and S. Ng. 2008. "Forecasting Economic Time Series Using Targeted Predictors." *Journal of Econometrics* 146 (2): 304–17.

Bańbura, M., D. Giannone, M. Modugno, and L. Reichlin. 2013. "Nowcasting and the Real Time Data Flow." In *Handbook of Economic Forecasting*, ed. G. Elliott and A. Timmermann. Amsterdam: Elsevier-North Holland.

Bańbura, M., D. Giannone, and L. Reichlin. 2010. "Large Bayesian Vector Auto Regressions." *Journal of Applied Econometrics* 25 (1): 71–92.

———. 2011. "Nowcasting." In *Oxford Handbook on Economic Forecasting*, ed. M. P. Clements and D. F. Hendry. New York: Oxford University Press.

Bańbura, M., and M. Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Data Sets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29 (1): 133–60.

Bańbura, M., and G. Rünstler. 2011. "A Look into the Factor Model Black Box: Publication Lags and the Role of Hard and Soft Data in Forecasting GDP." *International Journal of Forecasting* 27 (2): 333–46.

Barhoumi, K., O. Darné, and L. Ferrara. 2010. "Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP?" *Journal of Forecasting* 29 (1–2): 132–44.

Bernanke, B. S., J. Boivin, and P. S. Eliasz. 2005. "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach." *Quarterly Journal of Economics* 120 (1): 387–422.

Bjørnland, H. C., K. Gerdrup, A. S. Jore, C. Smith, and L. A. Thorsrud. 2008. "Improving and Evaluating Short Term Forecasts at the Norges Bank." Staff Memo No. 4/2008, Norges Bank.

———. 2011. "Weights and Pools for a Norwegian Density Combination." *North American Journal of Economics and Finance* 22 (1): 61–76.

Boivin, J., and S. Ng. 2005. "Understanding and Comparing Factor-Based Forecasts." *International Journal of Central Banking* 1 (3): 117–51.

———. 2006. "Are More Data Always Better for Factor Analysis?" *Journal of Econometrics* 132 (1): 169–94.

Camacho, M., and G. Perez-Quiros. 2010. "Introducing the Euro-Sting: Short-Term Indicator of Euro Area Growth." *Journal of Applied Econometrics* 25 (4): 663–94.

Carter, C. K., and R. Kohn. 1994. "On Gibbs Sampling for State Space Models." *Biometrika* 81 (3): 541–53.

Corradi, V., and N. Swanson. 2006. "Predictive Density Evaluation." In *Handbook of Economic Forecasting*, ed. G. Elliott, C. Granger, and A. Timmermann. North Holland: Elsevier.

D'Agostino, A., L. Gambetti, and D. Giannone. 2013. "Macroeconomic Forecasting and Structural Change." *Journal of Applied Econometrics* 28 (1): 82–101.

D'Agostino, A., and D. Giannone. 2012. "Comparing Alternative Predictors Based on Large Panel Factor Models." *Oxford Bulletin of Economics and Statistics* 74 (2): 306–26.

D'Agostino, A., D. Giannone, M. Lenza, and M. Modugno. 2014. "Forecasting Uncertainty: Models versus Judgement." Université libre de Bruxelles.

D'Agostino, A., K. McQuinn, and D. O'Brien. 2012. "Nowcasting Irish GDP." *OECD Journal: Journal of Business Cycle Measurement and Analysis* (2): 21–31.

Diebold, F., T. Gunther, and A. Tay. 1998. "Evaluating Density Forecasts with Applications to Financial Risk Management." *International Economic Review* 39 (4): 863–83.

Doz, C., D. Giannone, and L. Reichlin. 2011. "A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering." *Journal of Econometrics* 164 (1): 188–205.

———. 2012. "A Quasi Maximum Likelihood Approach for Large Approximate Dynamic Factor Models." *Review of Economics and Statistics* 94 (4): 1014–24.

Evans, M. D. D. 2005. "Where Are We Now? Real-Time Estimates of the Macroeconomy." *International Journal of Central Banking* 1 (2): 127–75.

Forni, M., D. Giannone, M. Lippi, and L. Reichlin. 2009. "Opening the Black Box: Structural Factor Models with Large Cross Sections." *Econometric Theory* 25 (5): 1319–47.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin. 2000. "The Generalized Dynamic-Factor Model: Identification and Estimation." *Review of Economics and Statistics* 82 (4): 540–54.

———. 2003. "Do Financial Variables Help Forecasting Inflation and Real Activity in the Euro Area?" *Journal of Monetary Economics* 50 (6): 1243–55.

———. 2005. "The Generalized Dynamic Factor Model: One Sided Estimation and Forecasting." *Journal of the American Statistical Association* 100 (471): 830–40.

Gerdrup, K., A. Jore, C. Smith, and L. Thorsrud. 2009. "Evaluating Ensemble Density Combination—Forecasting GDP and Inflation." Working Paper No. 2009/19, Norges Bank.

Ghysels, E., A. Sinko, and R. Valkanov. 2007. "MIDAS Regressions: Further Results and New Directions." *Econometric Reviews* 26 (1): 53–90.

Giannone, D., L. Reichlin, and D. Small. 2008. "Nowcasting: The Real-Time Informational Content of Macroeconomic Data." *Journal of Monetary Economics* 55 (4): 665–76.

Jore, A. S., J. Mitchell, and S. P. Vahey. 2010. "Combining Forecast Densities from VARs with Uncertain Instabilities." *Journal of Applied Econometrics* 25 (4): 621–34.

Luciani, M. 2014. "Forecasting with Approximate Dynamic Factor Models: The Role of Nonpervasive Shocks." *International Journal of Forecasting* 30 (1): 20–29.

Marcellino, M., and C. Schumacher. 2010. “Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP.” *Oxford Bulletin of Economics and Statistics* 72 (4): 518–50.

Marcellino, M., J. H. Stock, and M. W. Watson. 2003. “Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information.” *European Economic Review* 47 (1): 1–18.

Mariano, R. S., and Y. Murasawa. 2003. “A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series.” *Journal of Applied Econometrics* 18 (4): 427–43.

Martinsen, K., F. Ravazzolo, and F. Wulfsberg. 2014. “Forecasting Macroeconomic Variables Using Disaggregate Survey Data.” *International Journal of Forecasting* 30 (1): 65–77.

Matheson, T. D. 2010. “An Analysis of the Informational Content of New Zealand Data Releases: The Importance of Business Opinion Surveys.” *Economic Modelling* 27 (1): 304–14.

Mazzi, G. L., J. Mitchell, and G. Montana. 2014. “Density Nowcasts and Model Combination: Nowcasting Euro-Area GDP Growth over the 2008–09 Recession.” *Oxford Bulletin of Economics and Statistics* 76 (2): 233–56.

Mitchell, J., and K. F. Wallis. 2011. “Evaluating Density Forecasts: Forecast Combinations, Model Mixtures, Calibration and Sharpness.” *Journal of Applied Econometrics* 26 (6): 1023–40.

Parigi, G., and G. Schlitzer. 1995. “Quarterly Forecasts of the Italian Business Cycle by Means of Monthly Economic Indicators.” *Journal of Forecasting* 14 (2): 117–41.

Rosenblatt, M. 1952. “Remarks on a Multivariate Transformation.” *Annals of Mathematical Statistics* 23 (3): 470–72.

Rossi, B., and T. Sekhposyan. 2014. “Evaluating Predictive Densities of US Output Growth and Inflation in a Large Macroeconomic Data Set.” *International Journal of Forecasting* 30 (3): 662–82.

Rünstler, G., K. Barhoumi, S. Benk, R. Cristadoro, A. Den Reijer, A. Jakaitiene, P. Jelonek, A. Rua, K. Ruth, and C. Van Nieuwenhuyze. 2009. “Short-Term Forecasting of GDP Using Large Datasets: A Pseudo Real-Time Forecast Evaluation Exercise.” *Journal of Forecasting* 28 (7): 595–611.

Schumacher, C. 2007. "Forecasting German GDP Using Alternative Factor Models Based on Large Datasets." *Journal of Forecasting* 26 (4): 271–302.

Stock, J. H., and M. W. Watson. 2002a. "Forecasting Using Principal Components from a Large Number of Predictors." *Journal of the American Statistical Association* 97 (460): 1167–79.

———. 2002b. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20 (2): 147–62.

———. 2005. "Implications of Dynamic Factor Models for VAR Analysis." NBER Working Paper No. 11467.