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Nowcasting Norwegian GDP

The Hard, the Soft and the Uncertainty Data

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Abstract

This Master thesis investigates nowcasting, or predicting real time GDP, power of the following series: i) hard data gauging real economy; ii) soft indicators reflecting business and financial markets' sentiment and iii) uncertainty measures depicting the overall uncertainty in Norway. I employ approximate dynamic factor model, a framework acknowledged by researchers and practitioners at central banks, to examine the predictive power of 209 variables sorted in 15 blocks according to their economic content and release time. This thesis documents that finance related variables are good in predicting the current state of the economy. Due to their timely release and forward looking nature, they also perform well in forecasting the economic growth over the following year. These findings suggest that finance related variables are useful inputs for conducting timely and adequate monetary policy. Uncertainty measures help to predict the contemporaneous economic growth rate as well. Real variables like industrial production, while released with a lag and at a later date, add to the precision of the nowcast the most.

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Contents

1. Introduction

Real time monetary policy decisions are crucial in ensuring adequate and timely response to economic disturbances. The policy decisions, however, are often based on assessments from incomplete data since GDP measures, reflecting economic activity and closely monitored by the central banks, are released with a lag and are subsequently revised. Contemporaneous policy response thus requires re-construction and prediction of the main macroeconomic variables, a task for which the central banks devote considerable resources (Giannone, Reichlin, & Small, 2005). Moreover, the short-term predictions are often used as inputs for long-run forecasts (Norges Bank, 2010), thus making them important also for planning structural policies and reforms.

The exercise of real time prediction is often labelled as *nowcasting*, reflecting a contraction for *now* and *forecasting*. The term has long been used in meteorology, while the interest in applications in economics have grown substantially more recently (Bańbura, Giannone, Modugno, & Reichlin, 2013). Methods to evaluate contemporaneous GDP currently vary from relatively simple *bridge equations*, projecting the GDP figure using a panel of higher frequency indicators, to more parsimonious *factor models*, involving compression of the information contained in a high number of potential predictors into few uncorrelated factors.

In this Master thesis, I rely on two-step procedure (Doz et al. 2006) or approximate dynamic factor model to nowcast Norwegian GDP using a panel of 209 monthly indicators over the period of 2013-2016. First step entails extraction of common factors from the balanced part of the monthly indicators and estimation of the model parameters by OLS. The second step involves re-estimation of the factors recursively with help of Kalman filter and smoother on an unbalanced panel basis. This method is thus not only parsimonious, but also suits the jagged edge structure of the input data. The method tolerates the fact that higher frequency data used for predicting GDP are released at various dates and with different lags (please see Table 1 for a Norwegian example). The method has been employed both by practitioners in centrals banks (e.g., Angelini et al. 2011) and researchers in several economies, including Norway (Aastveit & Tørres, 2012).

This methodological framework helps to seek answers to three empirical questions. First, *can a large information set help to obtain early and accurate estimate of economic activity in Norway during the period of 2013-2016?* The accuracy here is defined as being more precise, or resulting in a smaller RMSE, than naive models, e.g., *AR(1)* model where GDP growth is predicted by its own lag. Second, *what kind of information and which release of it matters in nowcasting the economic activity?* The type of information varies across *soft* or survey indicators and financials to *hard* data reflecting real economic activity. I group these indicators in 15 blocks based on their timeliness and economic content. An example of a block is labour market indicators or financials (please refer to section 5 for a detailed definition on grouping the data into blcoks). I explore the predictive power of releases of these blocks within each of the three months of a generic quarter. In this thesis, I investigate the predictive power of the whole blocks, not its granular constituents. Namely, I do not examine how good in nowcasting is, e.g., each component of industrial production. Rather, I focus on the whole block, including the total figure, containing figures on industrial production. Finally, I explore *to what extent uncertainty portrayed in the news help to nowcast the economic activity in Norway?* I proxy uncertainty by Vegard Larsen's (2017) uncertainty indicators constructed using textual analysis of *Dagens Næringsliv,* the Norwegian largest business newspaper.

The *economic activity* here is proxied by annual growth of both initial and final releases of mainland GDP of Norway. The final release allows assessing if more timely indicators can help to predict the real time economic developments, and thus help in conducting adequate short term and long-term policies. That is, it allows evaluating how good the indicators are in predicting the ultimate, presumably best/true figure of economic growth. Testing the predictive power of initial releases serves as a robustness check and also allows being in the shoes of policy makers and economists – trying to predict the upcoming figures using all the information up to the point of nowcast.

Robust across the GDP vintages, I find that the individual block doing the best job in predicting contemporaneous economic activity is industrial production indicators. Both domestic and foreign trade and credit data add noticeably to the nowcasting power as well, yet with releases towards the end of a generic quarter. Industry manager survey (PMI) data helps to predict the real time activity too. Besides, the marginal contribution of PMI data stems not only from the timeliness of the releases – since published at the first working day of the month, but also due to its informational content. Finally, uncertainty measures, especially about the most *hot* topics, and financial indicators perform relatively well in nowcasting the current state of the economy. Yet the contribution of the uncertainty measures varies across time periods and is not robust to changes in ordering within the blocks.

I contribute to the work of Aastveit & Tørres (2012) and the existing body of nowcasting literature in three areas. First, I extend the period under study by Aastveit & Tørres (2012) for Norway. Second, I test the predictive power of survey and unique uncertainty data. Finally, I take a slightly different methodological approach, which allows me to investigate if data released in the beginning of a general quarter can predict the economic activity better than releases towards the end of that quarter. Namely, by testing how well the first or second month releases predict the GDP directly, without projecting a third month figure, I can investigate the forward looking nature of the data, e.g., for financial indicators. It is important to outline that the findings of this thesis do not indicate any causality and fundamental drivers of economic growth. This thesis only identifies informational content useful for assessing the economic activity in real time.

The rest of the thesis is structured as follows. Section 2 overviews a reasonable approximation of monetary policy decision rule employed by Norwegian and many other central banks, justifying the importance of having a good estimate of the current GDP growth. Section 3 reviews the existing body of nowcasting literature, focusing particularly on papers employing the *two-step procedure*. Section 4 introduces the econometric model in more detail while section 5 describes the data used. Results are discussed in section 6, while section 7 outlines limitations and room for further research. Section 8 concludes.

2. Conceptual Framework

Nowcasting plays a crucial role in conducting real time monetary policy. Let us consider a formal approximation of the key policy rate decision rule to show how estimates of contemporaneous and short-term future GDP affect the monetary policy. This framework also allows arguing on the optimal loss function for the nowcast evaluation.

Perhaps the most well known and acknowledged interest rate rule is the one suggested by Taylor (1993). It is driven by two elements. First, the nominal rates should rise more than proportionally to jumps in inflation above the target. This allows for real interest rates to raise and thus cool down the economy when inflation rates are growing above the target. Second, interest rates should rise when output growth is above normal. *Taylor rule* takes the following form:

$$i_t = r^n + \phi_\Pi(\Pi_t - \Pi^*) + \phi_y(\ln Y_t - \ln Y_t^n),$$

where ϕ_Π >1 and ϕ_y >0. Time-invariant normal level of real interest rates is denoted by r^n. Π^* can be taught of inflation target while $\ln Y_t^n$ denotes normal output growth.

The initial version of the rule has been subject to critique. Among other, it was criticized since the equilibrium rate of real interest rate r^n presumably varies over time. Also, it was outlined that central banks react more on future values of output and inflation gap than on its past values. Moreover, some literature argues that the rule should be supplemented with measures on financial stability. It has, nevertheless, been acknowledged as a reasonable approximation of the key policy decision rule (Romer, 2012). Yet to address one of the drawbacks and to test the model capabilities of predicting developments of GDP in the short-term future and thus test the fit to forward looking version of Taylor rule (see, e.g., Clarida et al., 1999), I also apply it in the setting of forecasting. The forecasting capabilities of the model and the individual data blocks are discussed in section 6.5.

The rule highlights the importance of having a good estimate of the contemporaneous (and short-term forecast of) output growth. A precise estimate or nowcast of the GDP growth would ensure an adequate and timely response to economic disturbances. On top of that, Taylor rule also is related to a simple yet commonly used *loss function* used for guidance by central banks (e.g., Norges Bank, 2012) formalized as follows:

$$L = (\Pi_t - \Pi^*)^2 + \lambda(\ln Y_t - \ln Y_t^n)^2$$

The quadratic terms in the loss function reflect not only common sense view that fluctuations in business cycles and highly variable inflation are not desirable (Woodford & Friedman, 2011), but also can be derived from the welfare functions of representative agents (Woodford & Walsh, 2003). The solution to the second order approximation of the loss function implies that the central bank should aim to stabilize the output growth around a natural rate. That is, the objective takes into account only the rate of economic growth, or more precisely its distance from the natural rate. Other measures like historic variability of the growth are left out in this form of loss function. In this thesis I therefore focus on how precise the nowcasts are *on average*, i.e., by measuring the root mean squared errors between the actual and the nowcasted GDP values (see section 3 for more details).

3. Literature

Interest in nowcasting the economic activity has grown significantly among policy makers and researchers over the last decades, and several approaches to nowcasting have been developed. One of the earliest and relatively simple methods to empirically estimate the current state of the economy is *bridge equations*. The bridge equations (see e.g., Baffigi, Golinelli, & Parigi, 2004 or Ingenito & Trehan) involve regressing quarterly GDP figures on higher frequency data released prior to the initial estimates of the GDP. This approach commonly requires transformation of the indicators from higher to quarterly frequency, with the methods ranging from simple averaging or slightly more complex transformations to reflect quarterly figures at the last period of each quarter (see e.g., Giannone & Reichlin, 2008) to *mixed data sampling or MIDAS* (Ghysels, Santa-Clara, & Valkanov, 2004). The latter involves weighting of the higher frequency observations based on, e.g., their timeliness.

Due to the potential pool of predictors being rather large, the bridge models can easily suffer from lack of parsimony. Two general approaches have been practiced among policy makers and researchers to circumvent the lack of parsimony. First, the estimate is made by averaging a large number of bridge models with only one predictor. Second, nowcast is calculated as an average of multiple regressions with several selected indicators (Barhoumi, Darné, & Ferrara, 2010). Nevertheless, these approaches suffer from a couple of drawbacks too. The first approach is somewhat ineffective in the sense that it does not take into account the correlation among the individual predictors and could also lead to biased estimates due to averaging several models suffering from omitted variable bias. The second one requires some a priori judgement on which indicators to select, instead of just letting the data speak.

Factor models address the two aforementioned issues while keeping the model parsimonious. In essence, the factor model compresses the information variation of a high number of potential predictors into few, uncorrelated, factors. Principal component analysis is commonly used to obtain the common factors (see, e.g., Stock & Watson, 2002) which are further used to project the GDP growth. To integrate dynamics in forecasting, the factor model analysis has been also supplemented with autoregressive model describing the dynamics of the factors (Stock & Watson, 2002) or modelling the factor dynamics explicitly (e.g., Giannone & Reichlin, 2008).

The data releases of higher frequency indicators often happen at different times and reflect information with different time lags. To deal with missing observations at the end of the sample for some indicators, i.e., the unbalanced structure of the panel the dynamic factor models have been combined with Kalman filtering and smoothing techniques. This method is commonly called as *two step procedure* (Doz et al. 2006), and as outlined further in this section it has been used in a nowcasting setting by the central banks and researchers in several economies. The technicalities of the model are described in the following section.

It is important to note that despite their simplicity and potential drawbacks, the bridge models are found to perform fairly well in predicting the economic development. Ingenito & Trehan (1996) investigate bridge equations for combinations up to 30 variables and find that specification with only two predictors – monthly data on consumption and nonfarm payroll employment – provides relatively precise forecasts for US GDP. Barhoumi et al. (2010) concludes that bridge models outperform naive forecasting models. Moreover, when compared with factor models, the evidence is not clear-cut. Although a large body of literature (e.g., Stock & Watson, 2002 or Angelini et al., 2011) documents the superiority of factor models, some studies (e.g., Antipa et al., 2012) find the opposite.

In this Master thesis I chose to rely on the dynamic factor model and Kalman filtering technique described by Doz et al. (2006) for several reasons. First, it allows avoiding a somewhat subjective pre-selection of variables to be used in nowcasting, and just lets all the available data speak. Second, it maintains the parsimony by condensing large set of information into few common factors. Third, the dynamic nature of the model allows updating the model as soon as the new information is released. The Kalman filter and smoother allows dealing with the particularity of the different data releases happening at different times. Thus, the aforementioned conditions rather precisely match the setting of an economist attempting to nowcast or forecast economic developments.

The two-step procedure was first formally employed by the Board of Governors of Federal Reserve to nowcast US GDP and inflation, supplementing more simple models and qualitative judgement (Giannone, Reichlin, & Small, 2005). Utilizing over 200 indicators, both survey or soft data and hard data such as price and real variables, the practitioners investigate the predictive power of the model and further examine what types of information add to the precision of the nowcasts. Moreover, they also examine whether the marginal contribution to the forecast precision stems from the data content or quality, or rather just the timeliness of the data releases – i.e., the fact that a set of indicators helping to predict the economy is simply released before other variables with higher economic content. Interestingly, Giannone et al. find that survey data have a large marginal impact on nowcasts of both the inflation and GDP. Yet, when controlling for timeliness of the data by constructing the counterfactual series of vintage data where data do not differ in their release time and lags, hard data, and in particular industrial production, does bring much larger marginal contribution while the contribution from the soft data decreases. This indicates that survey data contributes to forecasting more due to its timeliness than its economic content.

The methodology of Doz et al. (2006) was also applied by the European Central Bank, and yielded similar conclusions (Bańbura & Rünstler, 2007). Exploring the role of hard versus soft data in nowcasting GDP of euro area, Bańbura & Rünstler find that differences in publication lags play a significant role in forecast evaluation. Namely, predicting in a real time setting, surveys and financial variables contribute significantly to the GDP nowcasts. Yet when ignoring the differences in publication lags, the real variables, particularly industrial production, provide the most contribution to the nowcast precision. The relevance of survey data, and to a smaller extent also the financial indicator data, becomes less pronounced when ingoring the publication lags. The authors also provide a critique on studies that attribute no predicting power of survey or financial data on real economic activity because the studies do not take into account the differences in publication lags. Generally, survey data are published faster and portray information with smaller time lag compared to real indicators like industrial production.

Angelini et al. (2011) compare the two-step procedure model to bridge equations in euro zone setting. ECB in their nowcasting practices rely both on combining multiple bridge equations of selected indicators (BES) as well as averageing large number of bridge equations with only one regressor each (BA). The authors document that the two step procedure helps to predict the final vintage of euro area GDP more precisely than the bridge equations – independently on the time horizon of the available data at hand and the selection of indicators for the BES models. Similarly to Bańbura & Rünstler (2007), the authors also find that survey data contributes to the precision of euro area GDP nowcasts.

Several authors have studied the precision of the model on an individual country level as well. Barhoumi et al. (2010) , for instance, employed the model to nowcast the French GDP. The authors find that the dynamic factor model generally outperforms naive and autoregressive models. Interestingly, they document that the forecasting power of the dynamic factor model decreases substantially when moving from nowcasting to forecasting. That is, the model predictive power declines considerably when forecasts are made for the GDP one to four quarters ahead. This indicates that the model is best suited for very short-term predictions rather than forecasts for more longer term economic developments. Also, the authors document that the performance of the dynamic factor model is satisfactory even with a rather small number of higher frequency indicators – as little as 40.

D' Agostino et al. (2011) nowcasts the Irish GDP using a panel of only 35 selected indicators. The authors rely on the timiliness of release of the monthly indicators and set the delay of the information to be no longer than 40 days. As a result, the panel used contains hard and soft data as well as financial variables. Examples of hard data are live register unemployment benefit claimants, retail sales and industrial production, housing statistics and car sales while soft data contain such series as consumer sentiment index. Even with somewhat slightly limited number of monthly indicators, authors document that the dynamic factor model performs much better than a standard benchmark model of GDP growth being equal to last four quarter average. Examining the improvements by individual data releases, D' Agostino et al. document that live register of unemployement claimants, housing statistics as well as monetary data contribute to the improvement of the nowcast most considerably. The study thus emphasizes that the number of higher frequency indicators is not the sole key to a better nowcast, and the model outperforms naive benchmarks even with a rather small number of indicators.

Siliverstovs & Kholodilin (2010) report that the two step procedure offers a substantial improvement in nowcasting the GDP of Switzerland, compared to naive constant growth models, at all available forecast horizons and vintages of GDP. They also report that survey data and stock market indices contribute the most to the increase in the precision of the model. The latter finding, however, changes with underlying transformation of the monthly indicators from which the factors are extracted. Conducting the transformation following Giannone & Reichlin (2008), where the indicators reflect the quarterly growth rates at third month of each quarter, the authors find that the extracted factors are correlated to much larger number of datablocks, and thus each additional data block predicts the GDP to a smaller extent. The finding indicates that the transformation of monthly indicators can influence the predictive power. The common practice, however, is to transform the variables following Giannone &

Reichlin (2008), which is in line of definition of GDP being the aggregate value of latent monthly observations.

The model has also been employed to predict economic development outside Europe. Matheson (2007) nowcasts the GDP of New Zealand and finds that soft data, particularly business opion surveys, contribute significantly to the predictive power of the model. What is more, the contribution holds irrespective of the timileness of the publications. That is, even after controlling for the release date of the publications of higher frequency indicators, the business opinion surveys are found to improve the predictive power of the dynamic factor model. This finding is differs from a considerable number of studies (e.g., Bańbura & Rünstler, 2007 or Giannone, Reichlin, & Small, 2005) concluding that the contribution from survey data stems from the timeliness, but not the quality of the data.

Closer to Norwegian market, the dynamic factor model's nowcasting capabilities were examined in Swedish context by Solberg & Spånberg (2017). Extracting two factors from a panel of 187 indicators - including hard, financials and survey data, the authors find that the model gets very close to the actual value of quarterly GDP growth for 2016Q3. Nevertheless, the authors do not investigate the predictive capabilities in other quarters and neither they explore the marginal contributions to each of the datablocks.

In a Norwegian setting, at least to the best of my knowledge from publicly avialable resources, the two step procedure has been employed to Nowcast GDP only by Aastveit & Tørres (2012). The authors investigate the predictive power of the model relying on a panel of 148 monthly variables over the period of 1998Q1 to 2008Q4. The survey data for Norway for the period covered is only available on a quarterly basis, so the author's panel contains only hard data and financial variables reflecting both the domestic economy and the economies of the largest trading partners. Aastveit & Tørres document that the block of asset prices is the category that improves the nowcast the most.

This finding contrasts that of Giannone et al. (2005) and (2008) for the U.S. setting, who find that asset prices do not improve the predictive power of the model significantly. One hypothesis for this finding is that survey data already contains predictive information of asset prices. Aastveit & Tørres test this by re-estimating the work of Giannone et al. in US setting, but without survey data. Authors, however, find that the marginal contribution of financials do not change after the exclusion of survey data. A potential explanation for the differences in results, as suggested by the authors, stems from the differences in structure of the economy. Namely, Norway is small and open economy, thus more prone to larger volatility of financial variables. Another reason stems from the fact that the financials data used for the Norwegian setting is broader and more detailed, thus proxying the economic developments better.

In this Master thesis, I contribute the existing body of the literature on nowcasting by exploring the predictive power of a set of 209 indicators in a Norwegian setting. First, I update the time frame studied by Aastveit & Tørres (2012) to explore if the asset prices add the most to predictive power of the nowcast model also in the post-crisis period. Second, as suggested by large body of empirical evidence, I gauge the predictive power of survey data as well. Particularly, I explore if the business sentiment (proxied by PMI index) adds to the model accuracy. These survey measures are available on a monthly basis, and were not available at the time for the forecasting window used by Aastveit & Tørres (2012). As documented, e.g., by Matheson (2007), business opinion surveys are found to be one of the most important predictors of economic activity.

In addition, I contribute by exploring the predictive power of the uncertainty measures constructed by Vegard Høghaug Larsen (2017). Kydland and Prescott (1982), among others, document that uncertainty affects economic growth[1], thus the marginal contribution of this data block is expected to be noticable as well. More recent literature also documents general counter-cyclicality of uncertainty measures. That is, spikes in uncertainty are found to be followed by downturns in economic activity (see, eg., Kliesen, 2013). Larsen (2017), in turn, finds that the impact of uncertainty shocks may vary depending on the source of the uncertainty. Technology related uncertainty, e.g., is found to be followed by improving economic conditions.

Finally, given the result of financials data improving the nowcasts more in the first rather than the third month of release, I contribute by exploring the Granger causality between common factors extracted from financial variables and the economic growth.

[1] Please refer to data section for description of the uncertainty data as well as the suggested hypothesis on how it affects the economic development.

4. Model

The main purpose of the nowcasting model is to evaluate the economic activity, measured by annual mainland GDP growth, in a current quarter using monthly indicators released within the quarter. The first estimate of contemporaneous mainland Norway GDP growth is released after 45-50 days of the end of the quarter while various monthly and daily indicators reflecting the economic activity are released on an ongoing basis during the quarter (Statistics Norway, 2018). The particularity of these data releases is that they happen at different times of the month and reflect information with varying time lags, so at times some indicators contain a relevant observation while others do not. That is, the evolving dataset has *jagged edge* structure. The nowcasting model, thus, should be of a dynamic nature and should be able to handle this particular feature of the indicators.

I rely on a model examined by Doz et al. (2006). The model's consistency in large panel setting is proven by Doz et al. (2011) and it was used for nowcasting, among others, by Giannone & Reichlin (2008) and Aastveit & Tørres (2012), as well as Solberg & Spånberg (2017). The model entails a two-step procedure. First, model parameters are estimated by OLS on the principal components obtained from the balanced part of the higher frequency dataset. Second, the factors are re-estimated recursively employing the Kalman filter and smoother, on the unbalanced panel basis. The model, therefore, suits the jagged edge structure of the data. The estimation procedures are described in detail in the following sub-sections.

4.1 The Two-Step Procedure

Let vector $X_t = (x_{1,t};\ x_{2,t};\ \dots\ ;\ x_{n,t})$ denote the n transformed (see section 4.2 on data transformation) stationary monthly time series for the period $t=1,\dots,T$ used for nowcasting. X_t can then be described by approximate dynamic factor model examined in Doz et al. (2011). That is, it can be assumed as a sum of two independent, unobservable components: i) a common component χ_t, which is driven by small number of factors that are common to all individual variables; ii) remaining non-forecastable idiosyncratic (individual specific) component ξ_t:

$$X_t = \chi_t + \xi_t = \Lambda F_t + \xi_t \qquad (1)$$

Λ is an *n * r* matrix of factor loadings while F_t is a *1 * r* vector of factors $f_{1t},..f_{rt}$. To ensure the parsimony of the model, i.e., to not to lose substantial part of degrees of freedom, the number of factors r is typically much smaller than number of series used for nowcasting, *n*. With a reasonable assumption that GDP is not highly dependent of individual variable-specific dynamics, this also provides a good approximation for the full but much less parsimonious model. The expectation value of individual-specific component, $\xi_t = (\xi_{1t,}, ..., \xi_{nt})'$ is zero and covariance matrix is equivalent to $\Psi = E \mid \xi_t, \xi_t^{'} \mid$.

4.1.1 Principal Component Analysis

Dynamic factor model places larger focus on the common component, while the idiosyncratic component is generally considered as a residual (Solberg & Spånberg, 2017). The unobserved common factors can be consistently estimated by *principal components* using the observable variables (Doz et al., 2006). The principal component analysis is relatively easy to compute, yields consistent estimates under general assumptions and when the cross-section and time dimension grows large. In simple words, the analysis can be described as compressing large amount of data into the essence of this data - or finding a smaller amount of components that explain a large variation in the original data. Note that estimation of principal components does not take into account GDP dynamics, rather only the variance of the higher frequency indicators.

Let Σ denote the covariance matrix of the vector X_t. Same as every covariance matrix, this matrix is positive semi-definite, thus can be decomposed as $\Sigma = V\Pi V'$, where

$\Pi = diag(\pi_1(\Sigma), \pi_2(\Sigma), ..., \pi_n(\Sigma))$ denotes a diagonal matrix with the ordered positive eigenvalues (the principal components) of Σ on its main diagonal. *V*, in turn, is a matrix with associated eigenvectors in the columns, such that $VV' = I_N$. With normalization (see data transformation in the next sub-section), the linear transformation $m_t = V' x_t$ is the population PC estimator of the factors f_t (Solberg & Spånberg, 2017). With $V = (v_1, v_2, ..., v_n)$, the first PC factor $\hat{f}_{1,t} = v'_1 x_t$ is the projection which maximizes the variance among all linear projections from unit vectors. Its variance is the first principal component $\pi_1(\Sigma)$. The second PC factor, $\hat{f}_{2,t} = v'_2 x_t$ maximizes the variance under the restriction of being orthogonal to the first PC factor and its variance is the second principal component, $\pi_2(\Sigma)$. Subsequent factors are calculated in a similar fashion, with restriction of them to be set orthogonal. The PC estimator of the factor loadings is found by setting $\hat{\Lambda}$ equal to the eigenvectors of Σ associated with its *R* largest eigenvalues (Solberg & Spånberg, 2017).

Balanced sample counterpart of covariance matrix $S = T^{-1}\Sigma_{t=1}^{T} x_t x'_t$ is used to estimate the sample PC estimators. Following Doz et al. (2011) , they are obtained similarly as described before. Let $\hat{D} = diag(d_1, d_2, ..., d_R)$ be defined as diagonal matrix with the *R* largest eigenvalues of *S* on its main diagonal. Let *R***R* matrix $\hat{P}$ contain the associated eigenvectors as columns. Under specific transformation (see Doz et al. (2011) for more detail on the transformation and consistency of the estimators) the PC estimators of the factors and the factor loadings are calculated as:

$$\hat{F}_t = \hat{D}^{-1/2} \hat{P}' x_t \quad \text{(a)}$$

$$\hat{\Lambda} = \hat{P} \hat{D}^{1/2} \quad \text{(b)}$$

4.1.2 Kalman Smoother

A large drawback of the principal component analysis in a nowcasting setting, however, is that it requires the sample to be balanced. The task of an economist or policy maker is to evaluate the economic activity in real time, which evolves dealing data releases at different points in time, and thus missing values for some of the observations at the end of the sample at times. To address this issue, the principal component analysis is combined with Kalman filter technique, where Kalman smoother is employed to compute recursively the expected value of the common factors (Giannone & Reichlin, 2008).

Kalman filtering technique requires further specification of the model structure in *a state-space representation*. Conceptually, the necessary setting for the filtering technique can be described by a system of two equations. First one, *the state equation*, describes the dynamics of state of the unobserved measure at interest. The state can be multi-dimensional, ie., described by a number of parameters forming the measurement space. Second one, *the measurement or signal equation*, describes the signal/measurement one obtains on the various dimensions characterizing the state of the measure. In our case, equation (1) can be taught of as the signal equation. Namely, it describes that the system obtains measures or signals on the values of monthly indicators, which consists of i) the common components or measures describing the states, ii) the idiosyncratic components, which for the purposes of the filtering technique can be taught of as measurement errors. Doz et al. (2011) show that ignoring the idiosyncratic component and thus possibly misspecifying the underlying model can still produce consistent estimates of the central parameters of the factor model. In essence, due to law of large numbers, when the cross-sectional dimension increases, the idiosyncratic component becomes negligible.

I further supplement the model with a state equation, ie., one describing evolvement of the common component of the monthly indicators. Following Aastveit & Tørres (2012) and Solberg & Spånberg (2017), I describe the dynamics of the common factors as a VAR process with one lag:

$$F_t = AF_{t-1} + Bu_t \quad (2)$$

Parameter matrix A is of size ($r*r$), and all roots of $det(I_r\text{-}Az)$ lie outside the unit circle. Matrix B is of size ($r*q$) and is of full rank q - the number of common shocks in the economy, i.e., the dimension of u_t. The vector of common shocks, u_t, follows a white-noise process and the covariance matrix Bu_t is given by $Q = E[Bu_t(Bu_t)']$. Larger r than q in this model captures lead and lag structure between common factors and common shocks. Refer to Forni et al. (2009) or Solberg & Spånberg (2017) on properties of this specification.

Equations (1) and (2) together form a state-space representation of the dynamic factor model. In addition, following Doz et al. (2011) and Giannone & Reichlin (2008) several assumptions supplement the model. First, for all available vintages, the idiosyncratic components in Eq. (1) are cross-sectional orthogonal white noises:

$$E(\xi_{t|v_j}\xi'_{t|v_j}) = \psi_{t|v_j} = diag(\tilde{\psi}_{1,t|v_j},...,\tilde{\psi}_{n,t|v_j})$$

$$E(\xi_{t|v_j}\xi'_{t-s|v_j}) = 0 \text{, s>0 for all v, j}$$

Also, the idiosyncratic components are assumed to be orthogonal to shocks in Eq. (2)

$$E(\xi_{t|v_j}u'_{t-s|v_j}) = 0 \text{, for all s,v, j.}$$

Errors are assumed to be Gaussian. Despite not allowing for-cross sectional and serial correlation in the idiosyncratic component, the model is still consistent (Doz et al., 2011 and

Giannone & Reichlin, 2008). The key reasoning follows from the law of large numbers, which makes the idiosyncratic component negligible when cross-sectional dimension grows large. Consequently, the model consistency is not compromised due to the misspecification of the idiosyncratic component.

Finally, to handle the real-time data flow and thus missing observations at the end of the sample, following the conventional practice, I parameterize the variance of the idiosyncratic component as:

$$\tilde{\psi}_{i,t|v_j} = \begin{cases} \psi_i & \text{if } x_{it|v_j} \text{ is available} \\ \infty & \text{if } x_{it|v_j} \text{ is not available} \end{cases}$$

This way of handling missing observations implies that during the signal extraction process the filter will put zero weight on missing observations when calculating the common factors. When an observation is missing, the filter will produce a forecast on the common factors.

The aforementioned setting characterizes the model fully. The common factors are consistently estimated in two steps. In the first step, preliminary parameter estimates are computed by PC. That is, one estimates A, B, Λ and Ψ. That requires estimating Eq. (1) for the balanced part of the dataset using the obtained factors from PC analysis, $\hat{F}_t$, to obtain $\hat{\Lambda}$ and $\hat{\Psi}$. Then one estimates the VAR model of Eq. (2) using the estimated factors, $\hat{F}_t$, and obtains $\hat{A}$ and $\hat{B}$. In the second step, one re-estimates the factors, $\hat{F}_t$, recursively (backward looking, using information up to the date of the estimation) using the Kalman filter and Kalman smoother. The recursive estimation now allows dealing with unbalanced panel and thus fits the jagged edge structure of the data.

Following the standard procedures, I obtain the annual GDP growth nowcast as a projection of common factors each month and time when a new data block is released (please refer to

Table 1 for Norwegian example on data releases). The nowcast is estimated by OLS on a quarterly basis:

$$\hat{y}_{\tau}^{q0} = \hat{\alpha} + \hat{\beta}' \hat{F}_{\tau}^{q0} \quad (3)$$

,where $q0$ denotes the current quarter. Assuming that factors capture dynamic interaction among independent variables and also capture the dynamics of GDP, the lagged values of GDP are not included in the model. Inclusion of GDP lags would make the assessment of marginal impact from inclusion of an extra data block more difficult due to change in the factors becoming less noticeable (Aastveit & Tørres, 2012). Section 4.2 describes how the common factors are transformed from monthly to quarterly frequency while section 4.3 describes how the estimates are updated each time a new data block is released.

4.2 Data Transformation and Frequency Bridging

As outlined in the model description, the inputs for vector X_t require stationary and normalized series. First, to achieve stationarity of the monthly indicators, I conduct differencing of the time series that are originally in levels (see Appendix G for list of transformations). More precisely, I do it in a manner that the transformed series reflect annual growth rates of 3-month aggregates. That is, I obtain monthly series, which can be thought of as 3-month moving average annual growth rates. At the third month of each quarter, the growth rate will exactly coincide with the annual growth rate of the particular quarter, matching the format of the GDP data at hand. More formally, I apply the following filters to monthly series z_{it}:

$$Z_{it}=(1-L^{12})(1+L+L^2)z_{it}, \text{ when original series are in percentage points}$$

$$Z_{it}=\ln\left(\frac{1+L+L^2}{L^{12}+L^{13}+L^{14}}z_{it}\right), \text{ when original series are in levels}$$

This way the series are consistent with defining annual GDP growth rate as annual growth rate of 3 month latent observations.

I further check the stationarity of the transformed series using Augmented Dickey Fuller test. After visual inspection, the majority of the untransformed data seem to be fluctuating around some constant value, instead of zero, thus I allow for a constant option in the test specification. I do not evaluate the optimal lag length for each individual series using information criteria, yet a visual inspection of individual lag significance suggests that 3 lags is sufficient for the test of the absolute majority of the series. If the time series of a particular indicator are found not to be stationary, I do a second differencing of the series (please refer to appendix G for a description of which series are transformed in what way). As a result of the transformations, all of the input indicators used for the model are found to be stationary. Additionally, I normalize the obtained series to have a mean equal to zero and variance equal to one.

The transformed series are further grouped into a vector X_t and used as inputs for the nowcasting model. The output of the two-step procedure, the factor estimates $\hat{F}_t$, are further used to produce the fitted values of the current GDP growth. Each month and each time a new series set is released; I re-estimate the factors given all the information up to that particular month.

In order for the factor series to be used in Eq. (3), they must be transformed to a quarterly frequency. Given the nature of the transformation, the monthly data at the third month of the quarter coincides with annual growth of each quarter. So each last month of a quarter, there is no need for a transformation. As for the first two months of the quarter, I chose to simply use the last available observation. In this manner, I can evaluate the exact marginal contribution of data releases in each of these months.

The approach is slightly different from the one taken by Aastveit & Tørres (2012) , who forecast the factor as if at the third month using the bridge Eq. (2). I choose not to rely on forecasted values, but rather exact values estimated for the particular month, so that they reflect the given information at the particular point in time as precisely as possible. That is, I re-estimate equations (1) and (2) on a monthly basis and re-run the equation (3) each of the three months of the quarter. Aastveit & Tørres (2012), on the other hand, re-estimate the equation (3) using factors as if at the third month of the quarter. The third month values are in turn predicted by the bridge equation (2). I argue that this transformation thus not allow to capture the exact predictive power and forward-looking manner of the data at the first and the second month of a generic quarter. It therefore does not reflect precisely reflect the forward looking nature of the data released at the first or second month of a generic quarter.

As the data is transformed in a manner that reflects figures of 3 month moving average, the results I obtain suggest the annual economic growth, on a quarterly basis, given information up to the particular month. This also allows evaluating the forward looking manner of the data releases. I.e., compare the precision of the predicted values in first, second and third month of the quarter. If, for instance, the first month nowcasts of a particular data block release are more precise than the third month forecasts, this might indicate that the indicators are somewhat forward looking.

4.3 Forecast Evaluation

To evaluate the predictive power of the nowcasting model, I compare it to the fitted values of a naive *AR(1)* model of the annual mainland GDP growth estimated by OLS:

$$\hat{y}_{\tau}^{q0} = \hat{\alpha} + \hat{y}_{\tau-1} \quad (4)$$

Each time within a month a new data block is released, I re-calculate the factors, estimate the Eq. (3) and obtain the *squared forecast error* from the nowcast model, $(\hat{y}_{\tau}^{NOW} - y_{\tau})^2$. Note that parameters in Eq.(3) are only estimated once every quarter. That is, I recalculate the factors every month, but for the projection of the current GDP growth I use $\hat{\alpha}$ and $\hat{\beta}$ obtained from the information available up to the last full quarter. I then compare it to the forecast error for the consecutive month obtained from the naive model in Eq. (4),

$(\hat{y}_{\tau}^{AR} - y_{\tau})^2$. I further evaluate the relative precision of the nowcasting model by computing RMSEs over the forecasting window, which is chosen to be 2013Q1-2016Q4:

$$\text{RMSE}=\frac{\sqrt{\text{mean}(\hat{y}_{\tau}^{NOW} - y_{\tau})^2}}{\sqrt{\text{mean}(\hat{y}_{\tau}^{AR} - y_{\tau})^2}}$$

The choice of RMSE as an evaluation measure is motivated by the quadratic approximation of the central bank loss function presented in section 2. Other, higher order loss functions would also require testing for higher moments, e.g., *log scores* or *probability density transformation.*

A value of 1, e.g., thus means that the nowcasting model is as precise as the naive model. A value smaller, e.g., 0.7, means that the root mean squared errors of the nowcasting model are by 30% smaller.

4.4 Granger causality

Given the interesting result of financial variables adding to the forecast precision more in the first month of the quarter, rather than in the final month of the quarter, I test whether the financial indicators are predicting the economic activity in a forward looking manner. More precisely, I investigate if the common factors extracted from the financials block are good predictor of GDP, or vice versa. I follow the commonly used procedure for these types of tests by performing a *Granger causality test*. That entails running bivariate regressions to explore if lagged values of one variable help to explain the other (Granger, 1969). In this particular case, the two equations are defined as:

$$GDP_t = \alpha_0 + \alpha_1 GDP_{t-1} + \alpha_2 GDP_{t-2} + \beta_1 \hat{F}_{t-1}^{FIN} + \beta_2 \hat{F}_{t-2}^{FIN}$$

$$\hat{F}_t^{FIN} = \alpha_0 + \alpha_1 \hat{F}_{t-1}^{FIN} + \alpha_2 \hat{F}_{t-2}^{FIN} + \beta_1 GDP_{t-1} + \beta_2 GDP_{t-2}$$

Where $\hat{F}_t^{FIN}$ is the common factor extracted from the panel of indicators of financial data up to time *t* using Eq (1) The Granger causality test then involves examining if coefficients before the lags of the other variable are jointly significant, with F-statistics for each equation on:

$$\beta_1 = \beta_2 = 0$$

If, for instance, the lags of $\hat{F}_t^{FIN}$ are found to be significant in explaining GDP_t, then it can be claimed that $\hat{F}_t^{FIN}$ is a good predictor of GDP_t.

5. Data

As a starting point, I gather a panel of macroeconomic and financial indicators employed by Aastveit & Tørres (2012) to nowcast GDP of Norway over the period of 1998-2008. Following their standard approach, I group the higher frequency data with similar economic content and release dates together in 13 *blocks*: financials, foreign financials, interest rates, commodity prices, labour market, industrial production, consumer prices, foreign trade, construction, retail trade, credit as well as two blocks contained mixed international data. A *data block* is therefore defined as a sub-set of indicators with similar economic content, often containing measures of the total figures (e.g., total industrial production) and its constituents (e.g., breakdown by sub-industries).

Complete replication of the set of variables used by the authors, however, is limited due to SSB discontinuing such series as CPI by delivery sector (as of 2015) and two indicators characterizing the participants in labour market schemes (as of 2014). Another limitation stems from very short time series or some missing values for a few variables – one variable in trade block, a couple of indicators in the financial and foreign financial block[2]. The common factors of the dataset are first estimated from the balanced part of the dataset, thus having very short time series or time series with missing observations considerably reduces the time window available for estimation and forecasting. I prefer to exclude these few variables in order to have larger time window and therefore more robust results of my analysis. Slight mismatch in the data used also comes from the granularity of variables describing some of the blocks differing due to changes in the SSB statistics methodology. For instance, the set of variables I collect is less detailed for industrial production block while slightly more granular for retail trade block, compared to the corresponding blocks used by the authors. Finally, I exclude two variables from retail block and one from the import block since they exhibit very persistent trend and are not stationary even after second-differencing.

Given the outlined limitations, I obtain a panel of 124 monthly variables (Macrobond, SSB and Norges Bank, 2018 and Larsen, 2017), compared to 148 used by the authors. See Appendix G for more detailed description of the variables gathered. The panels are,

[2] The variables excluded are i) imports of ships; ii) dividend yields for basic materials and consumer goods industry and iii) dividend yields for US and Euro area. The latter are rather correlated with other interest rate measures, while the other form only a very small part of the total block they represent, thus not posing serious missmatch problems.

nevertheless, very similar and comparable. Namely, the exclusion a couple of variables in the financials and trade block should not significantly influence the behaviour of the common factors extracted from the blocks since most of the constituents are highly correlated. Moreover, the differences in the granularity of the data blocks for, e.g., industrial production should not affect the factors significantly as well. The purpose of this Master thesis is to estimate the overall predictive power of the different sectors/blocks, not its very granular constituents. Both panels include the totals (e.g., total industrial production figure) as well as various constituents, thus the factor dynamics for the overall block should not be significantly different.

Admittedly, there is a substantial variation in the labour market blocks. More precisely, because of discontinuation of the series I only obtain 2 out of 7 variables for the block used by the authors. The limited availability of monthly indicators describing labour market might be the reason why I get somewhat unexpected results from including the block as described in the results section.

All of the data blocks with exception of foreign trade are not subject to systematic revision after first release. Revision of the foreign trade data can inflate their predictive power of final release of GDP, therefore these results might be taken with caution. For a robustness check, I also exclude the foreign trade data block from my analysis (see appendix A, figures A1 – A3).

I further supplement the analysis by examining the predictive power of the uncertainty. To test how well the uncertainty predicts the economic fluctuations, I employ a unique dataset of 80 uncertainty indicators constructed by Vegard Høghaug Larsen (2017). The uncertainty measures are obtained from analysing the textual content of Norway’s largest business newspaper, *Dagens Næringsliv*. Very simply put, the measures reflect the relative frequency of words signalling uncertainty in the newspaper at the given period of time. The indicators reflect both bad (e.g., uncertainty related to financial and economic distress) and good (e.g., uncertainty related to technology and firm expansion) uncertainty signals. The overall uncertainty is categorized in 80 reasonably narrow topics, which are labelled by visual inspection of distribution of words that describe the topic and picking one that describes the topic well. The uncertainty measures are available on a working day frequency and are highly volatile. Thus I construct monthly figures by calculating simple averages.

When determining the marginal effect on the forecasting power of each of the individual blocks, the ordering of the inclusion of the blocks can matter. Namely, an inclusion of a particular block could either have no effect – in case it only adds white noise, or could affect the correlation structure of the new dataset. In case the correlation is affected in such manner that either factors explain less of the augmented dataset or the factors are less capable to predict the GDP, the predictive power of the model decreases. The model improves if the opposite holds. Thus, the marginal forecasting power is not only determined by the information contained in the new block, but also in the existing dataset to which the block is added.

Following the approach of Aastveit & Tørres (2012), I order the data blocks based on the time of their release as well guiding by economic arguments on the time horizon the variables in the block reflect. This portrays the task of economists and policy makers most realistically – the nowcasts have to be made by employing all available information at the particular point in time. It is quite less realistic, if a forecaster would ignore particular indicators when they get released and take them into account only later.

Table 1 illustrates the release order of various data blocks in a general quarter, and 2016Q2 is chosen as an example. Within a general quarter, the data is released at different dates and contain measures with a different time lag. For example, data on consumer prices is released around 10th date of each month and contain the figure for the previous month. Industrial production data is released slightly faster, yet depict the figures with a two months lag. That is, statistics on industrial production in February 2016 is released on 8th of April.

Table 1. Generic release order of higher frequency data-blocks

Nowcasting 2016Q2 (2016m4: days 1, 2, 8, 10, 15, 22, 27, 30 | 2016m5: days 1, 2, 8, 10, 15, 22, 27, 31 | 2016m6: days 1, 2, 8, 10, 15, 22, 27, 30 | 2016m7 | 2016m8 | 2016m9)

Block number	Numb. Series		Releases
1	20	Financials	16m3, 16m4
2	18	Foreign Financials	16m3, 16m4
3	6	Interest Rates	16m3, 16m4
4	2	Commodity Prices	16m3, 16m4
5	80	Uncertainty	16m3, 16m4
6	2	Labour Markets	16m3, 16m4
7	24	Industrial Production	16m2, 16m3
8	12	Consumer Prices	16m3, 16m4
9	5	Mixed International 1	16m2, 16m3
10	18	Exports & Imports	16m3, 16m4
11	3	Construction	16m3, 16m4
12	2	Mixed International 2	16m3, 16m4
13	8	Retail Trade	16m3, 16m4
14	4	Credit	16m3, 16m4
	204		
		First release of GDP	2015Q4, 2016Q1, 2016 Q2
		Revised release of GDP	2015Q4, 2016Q1

Source: Statistics Norway (2018), Norges Bank (2018). The table depicts a general illustration of the ordering of data releases, which may vary slightly across quarters, depending on whether the exact date is a working day. It illustrates the timing and lag of different data releases. As an example, consumer price data (8th column) for the previous month is released on around 10th date of the each month. Consumer price block contains 12 different indicators and is added as the 8th block in the model. The bottom line reflects the time lag of GDP releases. The first release of the particular quarter is published only 45-50 days after the end of the quarter. After that, it is revised when the figure for the consecutive quarter is released.

Data on financials, interest rates, exchange rates and commodity prices are released on a daily basis. Following Aastveit & Tørres (2012), I first convert them to monthly frequency using simple averaging. Next, given the forward looking nature of the financial, interest rate (see e.g., Ang et al., 2006) as well as exchange rate and to a lesser extent commodity price data[3] (Chen, Rogoff, & Rossi, 2010), I proceed with an assumption that these data are released at the very beginning of the month. More precisely, as soon as particular month ends, the data on it is immediately released in the consecutive month. Therefore, I include financial, interest rate and commodity price blocks first in the model. Following a similar logic, I treat the uncertainty data in the same manner. That is, the daily news are to large extent reflecting events with some forward looking window – e.g., expansion plans of the company or beliefs of further developments on economic or financial situation. Thus, the monthly figures calculated as simple average over the month are assumed to be released at the very beginning of the month.

Although treated with a forward looking manner to an upcoming month, the effect on economic growth from these indicator sets can still be happen with a delay - if the forward looking window is longer than just the forthcoming month. It could particularly hold for the uncertainty block, assuming, e.g., that the channel goes as follows: higher uncertainty leads to lower investments, which in turn hampers economic growth. As argued and documented by Kydland and Prescott (1982), it takes a period of time until capital becomes productive due to time to build. Namely, it takes time to construct new productive capital, and thus the effect from uncertainty on investments might materialize with a time lag. The ordering of daily indicators within the daily indicator group is less clear-cut, and is tested as well (see appendix C).

I test the predictive power of the nowcast model on two types of GDP data. I am grateful to have quarterly dataset containing GDP vintages of annual growth over 2005Q1-2014Q4 provided by assistant professor Ole-Petter Moe Hansen. That is, data containing first, revised and final estimate of GDP growth in each quarter over the aforementioned period. I first extract the initial vintages of mainland GDP growth by following the guidelines of Statistics Norway (2018), stipulating that first release is published within 45-50 days after the end of the

[3] While the empirical evidence is mixed, one can clearly argue that commodity prices still reflect a function of discountend expectations, i.e., investors base their decision on expectations on future commodity returns, which, in turn, affects the spot prices.

particular quarter. The second type of data I test the nowcasting model is on final mainland GDP annual growth figures obtained from Statistics Norway.

The parsimony of the nowcasting model lies in an opportunity to compress large number of potential predictors of economic growth into a few common factors. The exact number of the factors is, however, rather debatable – both formal (see, e.g., By & Ng, 2002) and rule of thumb criteria (e.g., Aastveit & Tørres, 2012) exist. Upon deciding, I follow the conventional approach and begin by examining the variance of the data explained by the first *r* principal components. Note that data here refers only to the monthly indicators used for nowcasting. The test is not related to the structure of the GDP data. Table 2 depicts the cumulative variance explained by first 10 factors. First two factors, for instance, explain around half of the variance in the indicators used for the nowcasting purposes.

Relatively small number of factors explaining a rather significant part of the variance in the dataset suggests a high correlation between the monthly indicators. This is not surprising given the nature of the data. That is, considerable part of the indicators within a block reflects different constituents of the same measure, which is often moving in a similar direction. Also, the effects in the economy rather often tend to spill over across different sectors, thus inducing larger correlation among different measures. I follow the common rule of thumb in choosing the number of factors – the marginal explanatory power of the next consequtive factor of less than 10 percentage points should be chosen as the cut-off value. This suggests a choice of two factors. The result is equivalent to Aastveit & Tørres (2012), whose analysis also suggest a choice of two factors for the period of 1990-1998.

Table 2. Percentage of total variance explained by the first 10 principal components.

Number of factors	**1**	**2**	**3**	**4**	**5**	**..**	**10**
10 Blocks	0.35	0.52	0.61	0.69	0.77	..	0.92
11 Blocks	0.35	0.55	0.64	0.72	0.79		0.93
14 Blocks	0.29	0.49	0.57	0.62	0.68	..	0.83

Obtained from data as of 2006Q1-2012Q4

10 Blocks denote the set of domestic indicators. Supplementing it with PMI indicators, I obtain the 11 Block set. 14 Blocks reflect the domestic indicators supplemented with foreign data and unique set of uncertainty measures (Larsen, 2017).

As a robustness test, I also explore the predictive power of the data blocks if the number of common factors is set to be slightly larger, to 3. The marginal contribution of the third factor is close to the cut off value, thus suggesting that it could be tested as well. I do not, however, find any substantial differences in the general findings (see appendix F figures F1-F3), except that the nowcasts are now generally more imprecise, with exceptions of few data blocks. This evidence hints towards possible over-fitting problems in larger models with a substantial number of predictors. The finding also reflects the fact that the third factor is usually found to be insignificant in the bridge equation, and suggests that the optimal number of common factors is as small as two. This is in line with the findings of, among others, Aastveit & Tørres (2012) and (Giannone & Reichlin, 2008), who find the optimal number of factors to be two.

As for the time window, the setting of the nowcasting task requires a *training sample* during which the factors are extracted and the parameters in Eq. (3) estimated. Also, the first part of extraction of the factors by principal component analysis requires a balanced panel. Given the structure of the dataset, where the shortest time-series start as of mid 2002, and properties of the principal component analysis estimators requiring a relatively large panel, I begin the training sample as of 2006Q1. To test the predictive power of the model by calculating RMSEs, I also need to have a time window for out-of-sample forecast evaluations. The uncertainty data at hand is available until January 2017, so for consistency of estimating addition of different data blocks I restrict my sample end point to 2016Q4.

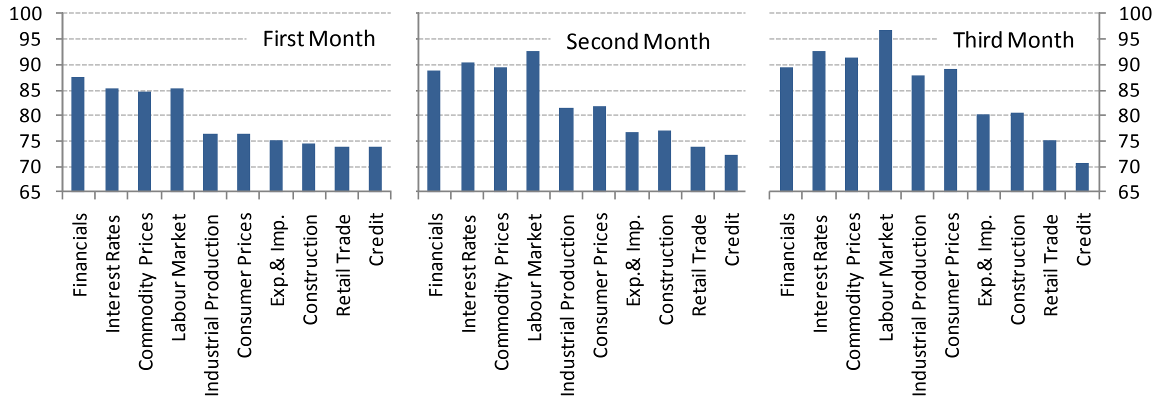
I choose the border between the training sample and evaluation sample between the two endpoints, ie., I start my out-of-sample nowcasts as of 2013Q1. This means that the first nowcast is based on 7 years long training sample (2006Q1-2012Q4).

6. Results

6.1 Marginal impact of domestic releases

In the first part of the analysis, I update the panel of indicators examined by Aastveit & Tørres (2012) with more recent observations. This allows comparing marginal contributions of different data blocks to the predictive power in 2013-2016 with the initial sample used by the authors: 1998 to 2008. I begin by testing the predictive power of the final release of the mainland GDP. The results of 10 block panel consisting of domestic data are reported in Figure 1. As a robustness check (see appendix A, figures A1 – A3), I also exclude the foreign trade figures, which are subject to systematic revision and thus potentially could have an overestimated predictive power of final release of GDP.

Figure 1. RMSE across data blocks relative to a naive *AR(1)* model of final release of mainland GDP, 2013-2016.



A value of 80, for instance, means that RMSE of the nowcasting model is by 20% more precise. The figure depicts the first, second and the third generic month of the quarter for which the nowcasting is done. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

The general findings of Aastveit & Tørres hold in the period of 2013-2016 as well. That is, adding more information blocks gradually reduces the forecast error and the forecasts for the full 10 block model become more precise from first to the third month of a quarter. Similar to the main findings of the authors, I document that financials block noticeably contributes to the nowcasting power of the model. However, I find two significant differences in the updated period. First, the contribution of the financials as well as interest and commodity block is decreasing from first to the third month. If I exclude these blocks, the predictions based only on hard data consistently improve over months (see Appendix B figures B1 and B2). Second, the contribution of financials block are not robust to the changes of the ordering with interest rate block (see appendix C figure C1).

There could be a couple of reasons for the marginal contribution power declining over the months. At least partly, it could be explained by the forward looking nature of the financials block. Namely, asset prices and exchange rates, the constituents of the financial block, could be taught as reflecting discounted expectations and generally are found to be forward looking (see e.g., Ang et al., 2006). In case it holds also in the sample at hand, it can be that the first month release predicts the generic quarter better than releases in later months. The later month releases, in turn, can do a better job in explaining the consecutive quarter (see section 6.5 and figure E3 on forecasting properties of the model).

I test if the financial, interest rate and commodity data are forward looking by Granger causality test. First, I extract the two common factors from the panel of these indicators and then test it together with mainland GDP over the forecasting period of 2013-2016. The results are reported in Table 3.

Table 3. Granger causality test on factors extracted from finance related data.

Null Hypothesis:	**F-Statistic**	**Prob.**
GDP does not Granger cause Financials 2	0.484	0.629
Financials 2 does not Granger cause GDP	3.630	0.062*
Financials 1 does not Granger cause GDP	10.727	0.003***
GDP does not Granger cause Financials 1	0.065	0.937

Sample: 2013Q1 2016Q4; Lags: 2

Financials 1 denote the first factor extracted from the financials, interest rate and commodity price block data. Financials 2 denote the second. A probability value smaller than the significance level suggests that the hypothesis of one variable being a good predictor for the other cannot be rejected.
Significance levels: * 10%, ** 5%, *** 1%.

The test results clearly suggest that panel of finance related indicators is a good predictor of GDP, while not the opposite. This is in line with the reasoning that financial variables are typically forward-looking, thus reflecting the future economic developments. The conclusion is robust to changes in the number of lags for the test specification. Also, the findings hold in different time-periods available for the study[4]. This, at least partly, explains why the predictive power of the finance related variables is better in the beginning of the quarter. Additional evidence of finance related indicators are provided by examining the model in a forecasting setting in section 6.5.

Another reason, at least partly, why finance related variables are not documented to be forward looking to such extent by Aastveit & Tørres (2012) could stem from a change in the decision rule of Norges Bank on optimal interest rate. Since 2012 Norges Bank has formally included financial imbalances criteria for an appropriate interest rate path setting (Norges Bank, 2012). More precisely, the decision on the key rate was supplemented with a criterion on key rate volatility and its deviation from a normal level. The key interest rate path thus in theory has become less volatile and the decision rule rather more forward looking. Since the key rate is highly correlated with other interest rates as well as asset returns included in the finance block, one can argue that this contributed to the finance related data to become more forward looking and somewhat less correlated with the current disturbances in GDP.

Additional reason why the marginal contribution is declining over months might stem from the extra information added to the higher order moments of the forecast – e.g., standard deviation or kurtosis. Relying on a quadratic approximation of the central bank loss function, I only study the performance of the mean error. The analysis of the entire predictive density of the errors is beyond the scope of this Master thesis.

Finally, this finding might differ due to slight differences in methodology. Please refer to section 4 for more detailed description of how the approach differs, compared to Aastveit & Tørres (2012). It could be the case that since estimating the factors as of third month using the transition equation (2), Aastveit & Tørres (2012) obtain more precise estimates of the economic growth towards the end of a generic quarter. But at the same time, this does not allow investigating if, for instance, the finance variables have a better predictive power already in the beginning of a generic quarter.

[4] Unfortunately due to limitations described in the data section, I am not able to run the Granger causality test on the sub-sample of 1998-2008 studied by Aastveit & Tørres. The findings, however, hold for different sub-samples in the period of 2006-2016.

Labour market indicators worsen the predictive power over the months as well. Labour market measures are usually found to be rather lagging than leading the economic activity (e.g., Whitta-Jacobsen & Sorensen, 2010), thus suggesting a puzzling result. I account these results to rather poor contents of the data block – due to data availability it only includes two indicators. I would treat these results with caution.

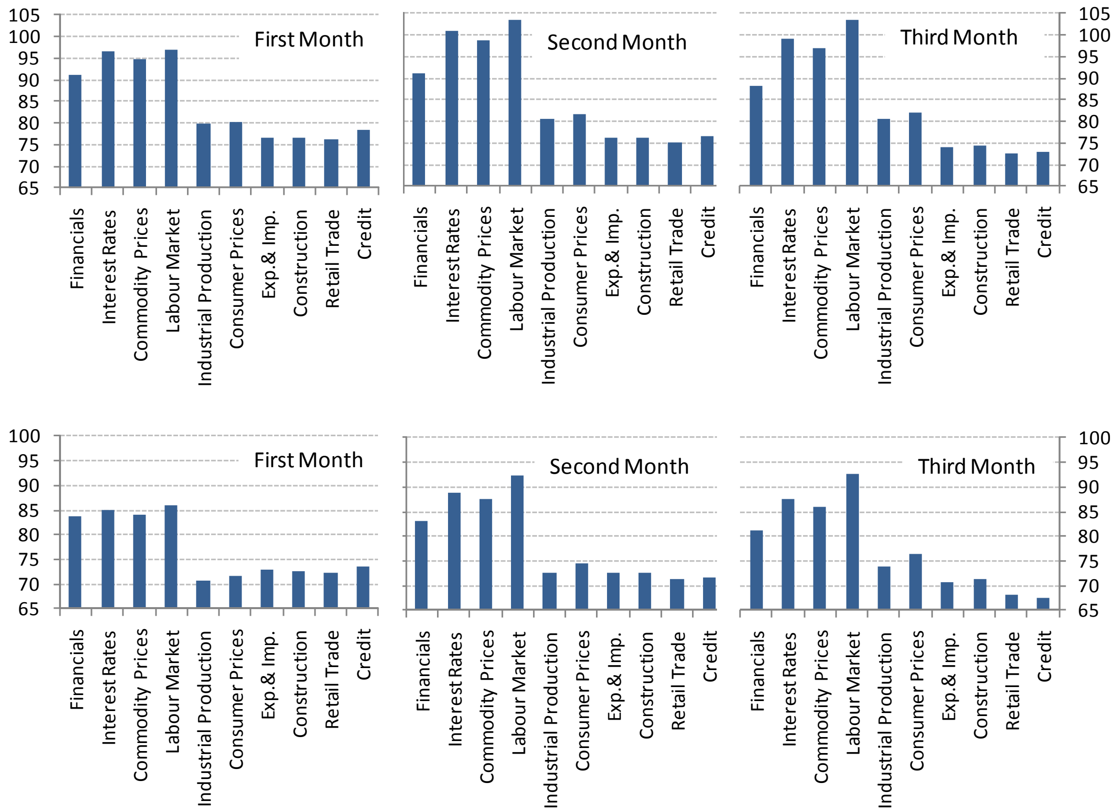
Interestingly, the contribution of industrial production data block (please refer to section 5 for a definition of a data *block*) seems to have increased compared to the period of 1998-2008, and now adds to the forecasting power the most among single blocks. This is despite a steady decrease of the share of value added in industry and manufacturing in total GDP over the period of 2008-2016 (Eurostat, see appendix D), a general trend among developed countries. The finding suggests that industry still plays a crucial role in Norwegian economy. There could be at least two channels how the industry maintains an important role in the economic development while decreasing its share in GDP: i) providing the capital for other industries that are growing and becoming more productive; ii) through spillover effects from investments in R&D on the productivity of other sectors (Los & Verspagen, 2000). This result is also in line with evidence that hard data, especially industrial production, adds to the predictive power substantially in developed countries (see, e.g., Giannone, Reichlin, & Small, 2005 or Bańbura & Rünstler, 2007).

Lastly, trade (both domestic and foreign) and credit data noticeably improves the predictive power of the current state of the economy as well, yet mostly with the second and third month releases. A potential explanation for why the first month data adds relatively less might come from the lagging nature of these data (see, e.g., Whitta-Jacobsen & Sorensen, 2010). Namely, better economic conditions gradually facilitate more credit growth, more investments and thus more exports and domestic trade. Therefore, these higher frequency indicators reflect the economic conditions with a slight delay – in this case, of at least a month.

6.1.1 Robustness to data revisions in GDP and Foreign Trade

To test if the findings above differ between final and initial vintages of GDP, I further explore the predictive power of the various data blocks for the first release of the mainland GDP. First estimate of GDP is released with a 45-50 day delay after the end of a generic quarter. The series of the first estimates of GDP provided by SSB via assistant professor Ole-Petter Moe Hansen allow this comparison. Unfortunately, the end date of the provided time series is limited to 2014, which do not allow ideal setting. For the conclusions not to be affected by time period, I perform nowcasts over the period of 2013-2014 for both initial and final releases of the mainland GDP. Top panel of Figure 2. depicts the predictive performance of various data blocks on the initial release of mainland GDP. Bottom panel, in turn, portrays how well the blocks predict the final release.

Figure 2. RMSE across data blocks relative to a naive AR(1) model. 2013-2016.
Top panel – initial release; Bottom panel – final release of mainland GDP.



A value of 80, for instance, means that RMSE of the nowcasting model is by 20% more precise. The figure depicts the first, second and the third generic month of the quarter for which the nowcasting is done. The top panel portrays the predictive power on the initial release of mainland GDP, while the bottom panel portrays final release. Out of sample forecasts over the period of 2013Q1-2014Q4, training sample starts as of 2006Q1.

The general findings remain robust with initial release of mainland GDP and also with the shortened nowcasting period of 2013-2014. First, finance related variables do a better job in the first rather than the two last months of a generic quarter – indicating forward looking nature. Second, industrial production adds most to the predictive power over the three months of a quarter. Third, domestic and foreign trade as well as credit data increases the predictive power noticeably towards the end of the quarter, suggesting lagging nature of the data.

Interestingly, the predictive power of the whole 10 block is better in absolute terms when the final release of mainland GDP is nowcasted. This could be partly due to one block of input indicators being revised as well – foreign trade figures for the previous release can be revised when a current release is published. It could be the case that model does a better job in predicting final release of GDP only because final figures of input data are used. Unfortunately, the data on initial releases of foreign trade are not publicly available, and thus I cannot test if the conclusions would change in case they are used as inputs.

As a robustness test, I exclude them from the analysis. Figure A1 in Appendix A suggests that this decreases the overall predictive power of the 10 block model slightly[5]. Also, it seems that the marginal contribution of retail trade data increases a bit – suggesting that some of the predictive power of foreign trade is captured by the domestic trade. The rest of the general findings remain the same, also in case of initial release of GDP and over the period of 2013-2014 as suggested by the figures *A2* and *A3*, respectively. Therefore, even accounting for changes in foreign trade data, the model seems to predict final releases of GDP better. This finding works in favour of the model nowcasting capabilities – predicting the true value of economic growth more precisely than just its initial estimates.

6.2 Marginal impact of foreign data and uncertainty

Following Aastveit & Tørres (2012), I supplement the domestic dataset with three blocks of macroeconomic and financial indicators describing Norway's main trading partners: Sweden, the euro area, United Kingdom and the United States. Being small and open economy, Norway is affected by the developments in these markets and thus inclusion of these data blocks theoretically might improve the model's nowcasting power. I denote the new data set as 13 block model.

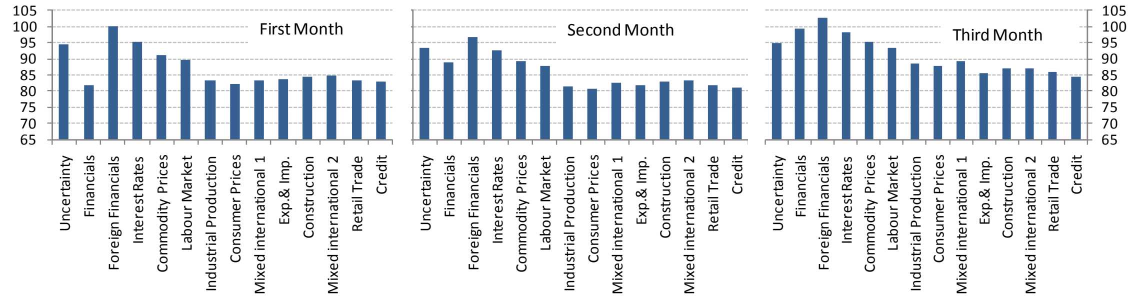
In addition, I supplement the input variables with an uncertainty index constructed by Vegard Høghaug Larsen (2017) using Norway's largest business newspaper, *Dagens Næringsliv*. I

[5] Please refer to section 5,

Table 1 for a description of different sets of blocks used for nowcasting. Sub-sections 6.2-6.4 describe the results also for the case of 13 and 14 blocks (i.e., adding foreign, uncertainty and sentiment indicators).

denote the new data set as 14 block model. The uncertainty index reflects prevailing uncertainty in both domestic and international context. Assuming that daily news are reflecting events with some forward looking window, and it is the financial markets that react to the news not vice versa, I include the uncertainty measure as the first data block in the model. As a robustness test, I also swap the ordering with the finance related variables (see appendix C). Figure 3 depicts the results for the final release of mainland GDP over the period of 2013-2016.

Figure 3. RMSE across data blocks relative to a naive *AR(1)* model of final mainland GDP, 2013-2016.



A value of 80, for instance, means that RMSE of the nowcasting model is by 20% more precise. The figure depicts the first, second and the third generic month of the quarter for which the nowcasting is done. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

First, it can be seen that predictions based only on the uncertainty measure do slightly better than a naive model as indicated by the first bar of the figure. However, the marginal contribution to the predictive power is noticeably smaller than that of financials block. Moreover, as shown in Appendix C Figures C2-C4, the uncertainty block adds to the forecasting power only if blocks on foreign financials and interest rates are not yet included. It thus seems that uncertainty measures do help predicting the current state of the economy, yet partly only by proxying the informational content contained in domestic and financial markets. Presumably, it points that *Dagens Næringsliv* writes about topics that are eventually reflected in the real economy or prices in the financial data. If added after foreign financial or interest rate block, the uncertainty block deteriorates the predictive power. These results might be due to part of the uncertainty block measures reflecting the developments in the foreign financial markets – e.g., the newspaper describing changes in the foreign stock market or depicting the same developments already reflected in the financial markets, i.e., something already captured in the foreign financial data block. I explore the nowcasting power of the uncertainty measures on a more granular level in the sub-section 6.3.

Second, there is a noticeable decrease in the predictive power in the first two months after adding the foreign financial block. Part of this could be attributed due to overlap in information with the uncertainty measure. As discussed above and shown in Appendix C, adding uncertainty block on top of foreign financials or vice versa might simply deteriorate the forecasting power because the informational content between the two blocks is to some extent equal, and adding non-overlapping part might simply add extra noise.

Nevertheless, if added right after financials block (see appendix C figure C3), the foreign financials, although to a much smaller extent, still deteriorate the predictive power. To explore this in more detail, I examine the tendencies in the constituents of the foreign financial block, and compare them to developments in the Norwegian economy. Dividend yields and stock returns in the euro area countries, constituting a large part of the foreign financial block, seem to have recovered after the financial crisis in 2015-2016. Moreover, since large part of the euro-area economies were oil consumers or net importers (Eurostat, 2017), the economies and stocks of large firms were to some extent benefiting from lastingly low oil prices. Norway, as a net exporter of oil, on the contrary experienced more gloomy developments in the economy during 2015-2016. These discrepancies in the business cycles might account for at least a part of the weak predictive power of foreign financials when years 2015-2016 are added to the model.

Third, similar to of Aastveit & Tørres (2012), I arrive at a conclusion that mixed international blocks do not add or even deteriorate the predictive power of the nowcasting model. As claimed by the authors, this might be due to time delay during which developments in consumer prices or industrial production in Norway's trading partners materialise in the domestic economy. The results suggest that the developments in the trading partner consumer prices and industry do not help to predict the Norway's GDP within the same quarter. Figure E3 in the Appendix E suggests that a delay of one quarter helps to improve the predictive power of mixed international figures slightly.

Finally, the general results obtained from the panel of domestic indicators still hold. Finance related variables seem to be forward looking. Industrial production is the best among single predictors of the current state of the economy. Trade and credit data add to the forecasting power as well, but more towards the end of a generic quarter. A slight difference is present in marginal contribution of consumer price block. It now improves the precision of the model slightly, while deteriorating it in the case if only domestic variables are used. This might suggest some correlation between foreign financial and consumer price data blocks.

6.2.1 Robustness between GDP vintages

A comparison of the results between final and initial vintages of GDP over the nowcasting period of 2013-14 seem to support the idea of predictive power of foreign financials depending on the differences in the position in the business cycle between large part of euro area and Norway. Namely, unlike if the period of 2015-2016 is included, foreign financial block improves the predictive power for both the initial and final releases of mainland GDP (see appendix C figures C5 and C6). Majority of euro area economies and Norway were on a somewhat similar business cycle over the period of 2013-2014. This was also partly reflected by similar developments in asset returns and dividend yields – major part of foreign financial block constituents. Towards 2015-2016, the trends started to diverge due to Norwegian economy being more negatively and deeply affected by prolonged oil price drop, thus deteriorating the predictive power of the foreign financials block.

Interestingly, GDP nowcasts based solely on the uncertainty block are more precise relative to the naive model for the forecast window of 2013-2014 than forecast window of 2013-2016. Moreover, it is not only due to the naive model becoming relatively less precise during 2013-2014. In fact, while the forecast error of the naive model increases by 21%, the error of the uncertainty indicators decreases by 3% in absolute terms in 2013-2014 compared to 2013-2016. This finding remains somewhat puzzling. More careful examination of the two factors extracted from uncertainty block indicate that the uncertainty has been, on average, higher during the period of 2015-2016 due to a couple of spikes – fuelled, e.g., by OPEC decision not to cut down oil production as of end 2014 and the BREXIT vote on mid-2016 (Larsen, 2017). It seems that the slowdown of the Norwegian economy during the period was more moderate than predicted by the spikes in the uncertainty (see section 6.3 for more detailed analysis).

In addition, changes in the ordering of financials and uncertainty blocks (see appendix C figures C7 and C8) show that the combination of first month releases of financials, foreign financials and uncertainty block produce the most precise prediction over the period of 2013-2014. Adding the measures on real economy gradually worsens the predictive power – with exception of industrial production as well as trade and credit data releases towards the end of a quarter. Importantly, the financials block on its own does not improve the nowcasting power noticeably over 2013-2014, compared to 2013-2016. But the combination of the three blocks – financials, foreign financials and uncertainty - reduces the forecast error by around 40% relative to the naive model.

This finding is important in the context of the results of Aastveit & Tørres (2012), who find that financials are the single most important predictor of the current state of Norwegian economy. Similarly to the authors, I find that financials block does improve the estimates of current GDP noticeably, yet I document that this block is not the best performing one. First, as outlined above, a combination of financials, foreign financials and uncertainty measures contributes to the predictive power considerably more. Second, among the individual data blocks, I find the industrial production to be the best performing. Moreover, if ignoring the timeliness of the financial data release and examining the data releases of real economic variables, I find that a combination of industrial production, domestic and foreign trade as well as credit data predicts the currents GDP the best (see appendix B figure B1). This is in line with evidence that financial variables contribute to the predictive power more through their timiliness rather than informational content (see, e.g., Giannone, Reichlin, & Small (2005) among others).

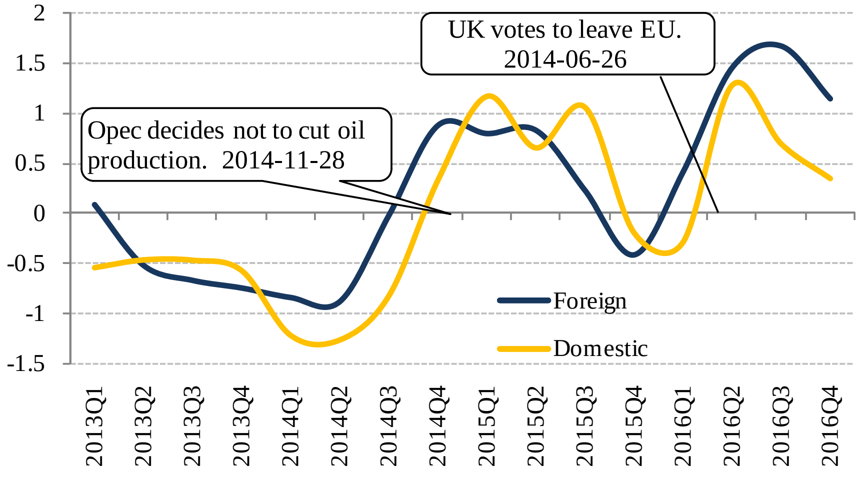
6.3 Marginal impact of the uncertainty block

I further examine the nowcasting power of the uncertainty block in more detail by testing the contribution of different sub-sets of the 80 uncertainty indicators. To label the 80 indicators, Larsen (2017) first obtains word distributions describing each indicator. After visual inspection of individual distributions, the author picks a title/theme that best describes the given indicator. As argued by the author, most of the indicators convey a clear theme or category. Nevertheless, caution is needed when defining the various sub-sets. I refrain from categorizing topics on a very granular level since it is sometimes ambiguous if a detailed topic is reflected by one of the 80 indicators or not. *Oil* related uncertainty, for instance, is clearly captured by *oil production* and *oil price* indicators, but it is less clear cut to what extent it is covered by *engineering* indicator.

Therefore, I group the indicators only in three rather broad categories. First, the indicators directly describing the uncertainty on foreign matters form one group. Topics in this sub-set include *Europe, USA, UK, Foreign* among others[6]. Such classification is not perfect as well, since some of the seemingly *domestic* indicators might partly reflect issues of a foreign nature, yet I argue that the chosen set gives a good proxy on uncertainty stemming from abroad. Second, I classify all the rest of the indicators as *domestic*. Third, I group the 10 most frequent uncertainty indicators as another sub-set. Namely, I pick the topics where the share of words related to uncertainty is the highest. The topics include: monetary policy, stock markets and macroeconomics among others (please refer to table 1 in Larsen (2017) for more details).

Events related to *foreign* uncertainty seem to account for a large part of the reason why uncertainty increases and to some extent why predictive power of the uncertainty block deteriorates if years 2015-2016 are added to the nowcasting window. Figure 4 depicts that both foreign and, to a lesser extent, domestic uncertainty was on average higher during 2015-2016, fuelled by some spikes related to foreign events. The following slowdown of the Norwegian economy seems to have been less pronounced as predicted by the spikes.

Figure 4. Foreign and Domestic uncertainty, 2013-2016

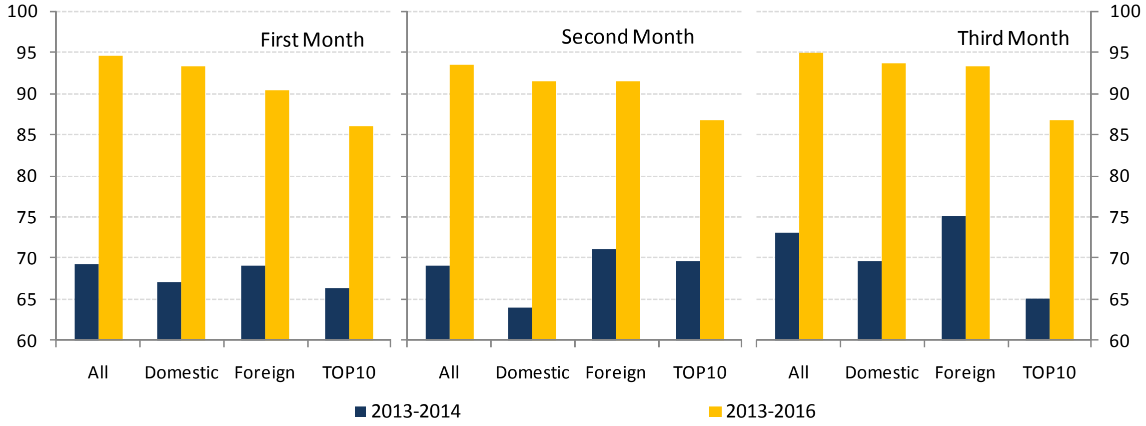


"Foreign" reflect the common factor extracted from uncertainty measures describing uncertainty on foreign matters. "Domestic" reflects the factor extracted from remaining indicators. Only first factor is depicted since it explains the majority of the variance in the data. The second factor is more noisy yet generally portrays the same developments of being higher during 2015-2016.

[6] More precisely, the group consitutes the following numbers of the 80 topics: 11, 25, 29, 33, 48, 56, 64, 79

Figure 5 portrays how the predictive power changes if 2015-2016 are added to the nowcasting window across different blocks. One can observe that during 2013-2014 domestic uncertainty did a relatively good job in explaining the current economic developments. Adding higher uncertainty, largely driven by foreign matters, in 2015-2016 has deteriorated the predictive power of both the *domestic* and *foreign* blocks. This finding is somewhat similar to foreign financial block worsening the precision of the model during 2015-2016, implying that usefulness of the foreign indicators in predicting Norwegian economy can change over time.

Figure 5. RMSE across different uncertainty measure blocks relative to a naive *AR(1)* model of final mainland GDP, 2013-2016.



A value of 80, for instance, means that RMSE of the nowcasting model is by 20% more precise. The figure depicts the first, second and the third generic month of the quarter for which the nowcasting is done. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

Finally, the block of top most frequent uncertainty topic performs best among all sub-groups. This indicates that some of the 80 uncertainty indicators do not add any positive marginal contribution in nowcasting the current economy, and that the current developments can be predicted relatively well with as little as 10 uncertainty indicators.

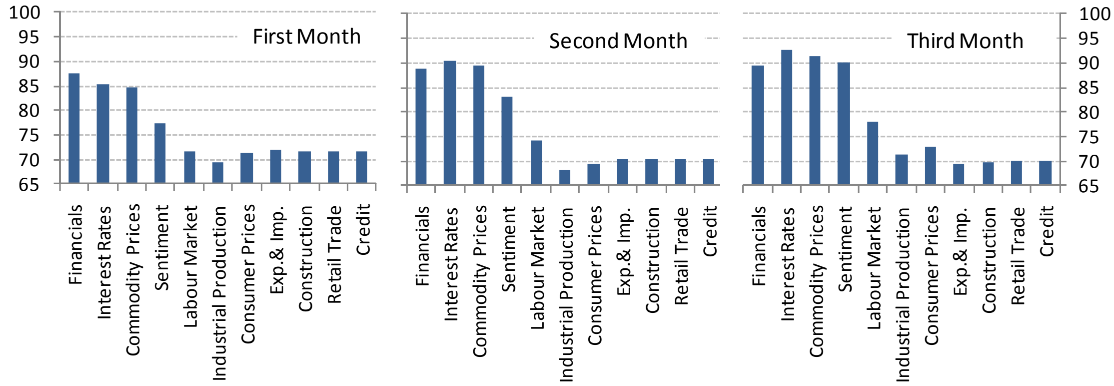
6.4 Marginal impact of the survey block

Empirical evidence suggests that sentiment indicators, particularly business confidence, perform well in predicting the current state of the economy (e.g., Bańbura & Rünstler, 2007 or Giannone, Reichlin, & Small, 2005). To test if the finding holds also in the Norwegian context, I supplement the indicator set with a block containing PMI index and its constituents. Moreover, to test if the contribution of the survey data stems only from its timeliness or also informational context (latter documented, e.g., by Matheson, 2007), I do a robustness check where I place the survey data after hard data releases like industrial production. Data on PMI indices was not available at the period examined by Aastveit & Tørres (2012), therefore the inclusion of this datablock also allows to contribute by examining the predictive power of sentiment data in Norway.

The Norwegian PMI indicators are released around the first working day of a month, and the exact ordering relative to financial indicators is thus somewhat unclear. I place the sentiment block right after financials, interest rate and commodity block in the base scenario. First, I argue that the business sentiment is affected by interest rates and commodity prices, while less likely other way around. Second, some of the finance related data are also available on the weekends, thus in theory could be released faster than the sentiment data. Nevertheless, I do a robustness checks where I switch the ordering of the sentiment indicators relative to the finance releated blocks (see appendix C figure C9).

Figure 6 includes the marginal contribution of the PMI block. One can observe that sentiment indicators do add to the predictive power of the nowcasting model noticeably. The contribution is also robust in changes relative to other finance related variables. The results suggest that surveys of business managers, released at the very beginning of the month, are a good indicator on current economic performance in Norway. Moreover, unlike documented by e.g., Bańbura & Rünstler (2007) this contribution stems not only from the timeliness of the data release. Placing the sentiment indicators after the industrial production block still noticeably adds to the predictive power (see figure C10 in appendix C). This suggests that survey data have also some informational content on the current state of the Norwegian economy on top of the hard data.

Figure 6. RMSE across data blocks relative to a naive *AR(1)* model of final mainland GDP, 2013-2016.



A value of 80, for instance, means that RMSE of the nowcasting model is by 20% more precise. The figure depicts the first, second and the third generic month of the quarter for which the nowcasting is done. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

6.5 Forecasting Power of the Model

It is commonly argued that the central banks react also on future values of the output gap, not only on its present developments. I thus test the forecasting power of the model and data blocks. As for the forecast horizon, I keep it rather short with one quarter and one year horizon. The key policy rate is usually set taking rather short-term forecast values of the macroeconomic variables, instead of long-run predictions (see, e.g., Norges Bank, 2012), thus in this framework it is more important to evaluate the predictive power in a short term.

Figure 7 compares the predictive power of the model in a nowcasting setting to a one quarter ahead forecast. The bars indicate the percentage increase (one quarter ahead forecasts are less precise) or decrease (forecasts are more precise) of RMSEs. It repeatedly confirms the forward looking property of finance related indicators – one quarter ahead forecasts are more precise than the nowcasts if financials, interest rates and commodity prices are used to predict the economic development. PMI indicators, although to a lesser extent, are more forward looking too.

Figure 7. One quarter ahead RMSE across data blocks relative to a nowcasting model of final mainland GDP, 2013-2016.

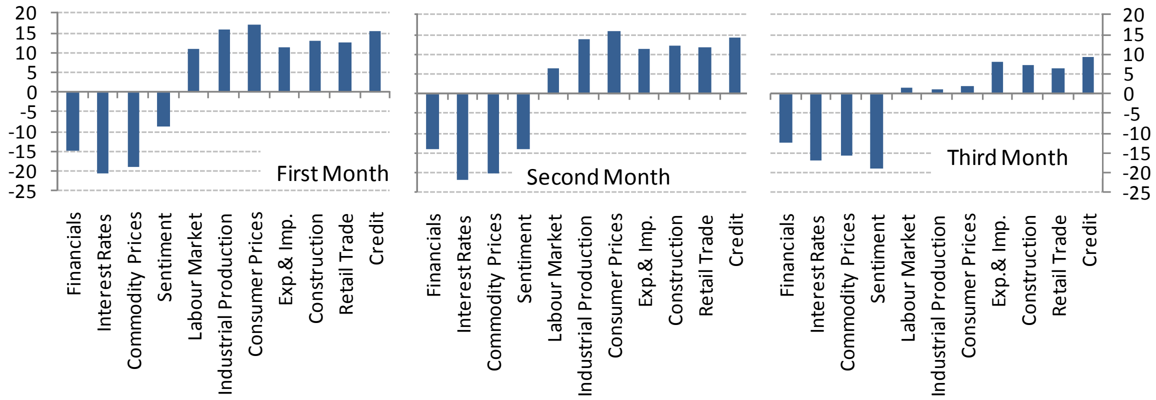


Figure depicts how precise are the one quarter ahead forecasts relative to nowcasts. Negative value, of, for example, -10 means that the RMSE of the forecast is by 10% more precise than the nowcast. Positive values imply that the forecast is less precise. If the bar is coloured red, then the model is less precise than a naive *AR(1)* model too. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

Interestingly, all of the blocks of the model perform better than the naive *AR(1)* model of the sample of 2013-2016. This is, however, explained by the ordering the blocks. Since the forward looking data are released first, they decrease the forecast error by quite a large margin at the very beginning of the procedure of adding subsequent data blocks. Supplementing the model with hard data increases the error, yet to a relatively smaller extent and all 11 blocks do an overall better job in forecasting than a naive *AR(1)* model. Performing the same procedure only on selection of hard data with largest marginal contribution in the nowcasting setting portrays that the model does much worse both compared to nowcasting setting and in some instances also compared to a naive *AR(1)* model – as figure 8 depicts.

Figure 8. One quarter ahead RMSE across data blocks relative to a nowcasting model of final mainland GDP, 2013-2016.A selection of indicators describing the real economy.

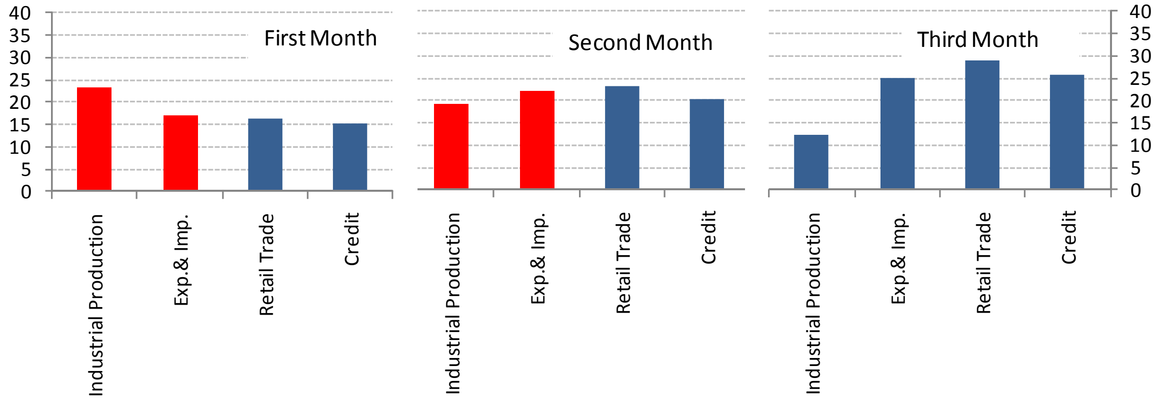


Figure depicts how precise are the one quarter ahead forecasts relative to nowcasts. Negative value, of, for example, -10 means that the RMSE of the forecast is by 10% more precise than the nowcast. Positive values imply that the forecast is less precise. If the bar is coloured red, then the model is less precise than a naive *AR(1)* model too. Out of sample forecasts over the period of 2013Q1-2016Q4, training sample starts as of 2006Q1.

The predictive power of the hard indicators decreases even more if one year ahead forecasts are considered (see appendix E figure E1 and figure E2). This is in line with the general evidence that the performance of the two-step procedure is deteriorating rather fast if switching from nowcasting to forecasting and increasing the forecasting window (Barhoumi, Darné, & Ferrara, 2010).

Finance related variables, nonetheless, still perform slightly better than in a nowcasting setting, suggesting that their predictive power is still non-negligible even for one year ahead forecasts. Uncertainty measures, in turn, seem to add less to the predictive power of one quarter and one year window forecasts, compared to nowcasts (see appendix E figure E3 and figure E4). The third month release of the uncertainty measures adds most to the predictive power, suggesting that the forward looking window, if any, is possibly rather short for this indicator set.

7. Limitations and Potential Extensions

In this thesis, the nowcasting performance was evaluated from the perspective of conduct of monetary policy with a simple quadratic loss function. This implied that the sole criterion for evaluating the model and the data blocks was the average of the forecast errors, RMSE. It is plausible that the key decision rules might take into account also higher order moments, thus suggesting that variance, skewness, etc of the forecasts might be of interest as well. The analysis of the entire predictive density of the forecast errors is beyond the scope of this thesis and gives fruitful ground for further research.

Additional room for research stems from the limits of data availability at the time of the study. First, at least to my knowledge, there is no publicly available data on consumer confidence available at the monthly or higher frequency for Norway. It would useful to investigate if consumer sentiment, on top of the business sentiment proxied by PMIs, helps to predict the economic developments. If yes, this would provide another timely and frequent indicator for contemporaneous GDP growth. Second, there is no publicly available data on the initial estimates of foreign trade data. Investigating its predictive power on the initial releases would allow getting into the shoes of a policy maker properly, using all available information up to the date. Measuring the impact differences of the vintages of foreign trade data would allow precise gauging if initial figures might be trusted. Exclusion of final releases as a robustness test yet seem to suggest that the predictive value of final releases is not inflated, and there are no substantial revisions.

Finally, it is important to outline that in this thesis I investigate which higher frequency indicators and to what extent are correlated with real time economic growth. These findings do not imply causality. Study of what factors determine short term and long term economic growth are outside of the scope of this study, and would likely require structural models based in economic theory.

8. Conclusions

In this Master thesis, I evaluated how well the latest releases of soft, hard and uncertainty data with higher frequency can predict contemporaneous economic growth rate in Norway. For the purposes of evaluating the predictive power of a panel of 207 monthly indicators and its different sub-sets, I relied on approximate dynamic factor model (Doz, Giannone, & Reichlin, 2011) acknowledged among researchers and employed by practitioners at the central banks. This framework allowed contributing to the existing body of nowcasting literature in several areas. First, I extended the period under study of Aastveit & Tørres (2012) and supplemented the panel of higher frequency indicators with more recently produced PMI measures. Second, by taking a slightly different methodological approach, I could investigate the forward looking nature of first and second month releases of data in a generic quarter more precisely. Third, I investigated the predictive power of a unique panel of uncertainty measures (Larsen, 2017).

By employing the methodological framework, I searched for an answer to three research questions. First, I find that a set of monthly indicators can produce more timely and accurate estimate of real time economic growth, compared to a naive model in Norway over the period of 2013-2016. This highlights the importance of the nowcasting models in predicting the real time economic developments, and hence adds to conducting more adequate monetary policy, among other benefits.

Second, I document that the nowcasted growth rate is not becoming more precise with each information block and its subsequent release added to the model. I find that the data block contributing to the precision of the nowcast the most is industrial production. This suggests that industry is still playing an important role in Norwegian economy, despite a gradual decrease of its share in the total value added over the last decade. A combination of third month releases of hard data like industrial production as well as domestic and foreign trade produces an average forecast error by 40% smaller than the naive model, suggesting that a mix of hard indicators describing real economy can predict the economic developments very well.

Industrial production and other hard data describing the real economy, however, are released with some lag, which might partly be the reason why the nowcasts improve towards the third month of a generic quarter. Finance related variables like asset returns, interest rates and commodity prices, in turn, are available on a daily basis and in real time. Surveys on purchasing managers sentiment are available on a monthly basis, but are released in a very timely manner. Testing the predictive power of these datasets, I obtain noticeable marginal contribution as well. Moreover, the business survey data contributes not only due to its timeliness, but also due to its informational content. In addition, I find that finance related variables are even better predictors in a short term forecast setting than in estimating the contemporaneous growth. These findings suggest that the economic growth rates in Norway are well reflected by timely and also forward looking high frequency data releases. Such indicators are very useful to look at for the purposes of conducting monetary policy, also in a forward looking decision rules.

Importantly, the contribution of finance related variables is not constant over time. How well financial indicators of the Norwegian main trading partners describe the Norwegian economy seem to largely depend on the similarities in the business cycles. When on a similar business cycle, the foreign financials do considerably better job in nowcasting compared to times where the differences in the cycles are more pronounced.

Third, I learn that uncertainty measures constructed by textual analysis of Norwegian largest business newspaper (Larsen, 2017) can also provide some hint on the current economic developments. This underlies the complex structure of economic drivers, which cannot simply be captured only by hard data. The informational content of the uncertainty measures seem to be partly reflected in finance related indicators since adding uncertainty measures on top of finance variables does not improve the nowcast. Additionally, the contribution of the uncertainty measures, similarly to foreign financials, varies over time periods under study.

It is important to outline that in this thesis, I have investigated which data types could be used for predicting the economic activity and thus conducting adequate monetary policy in real time. I find that the aforementioned indicators seem to be well correlated with the GDP growth. Claims of causality, however, our outside of the scope of this research and would require more structural models and arguments.

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Appendix

A. Robustness to Revisions in GDP and Higher Frequency data

Figure A1. Final Release of Mainland GDP, 2013-2016. Foreign Trade Excluded.

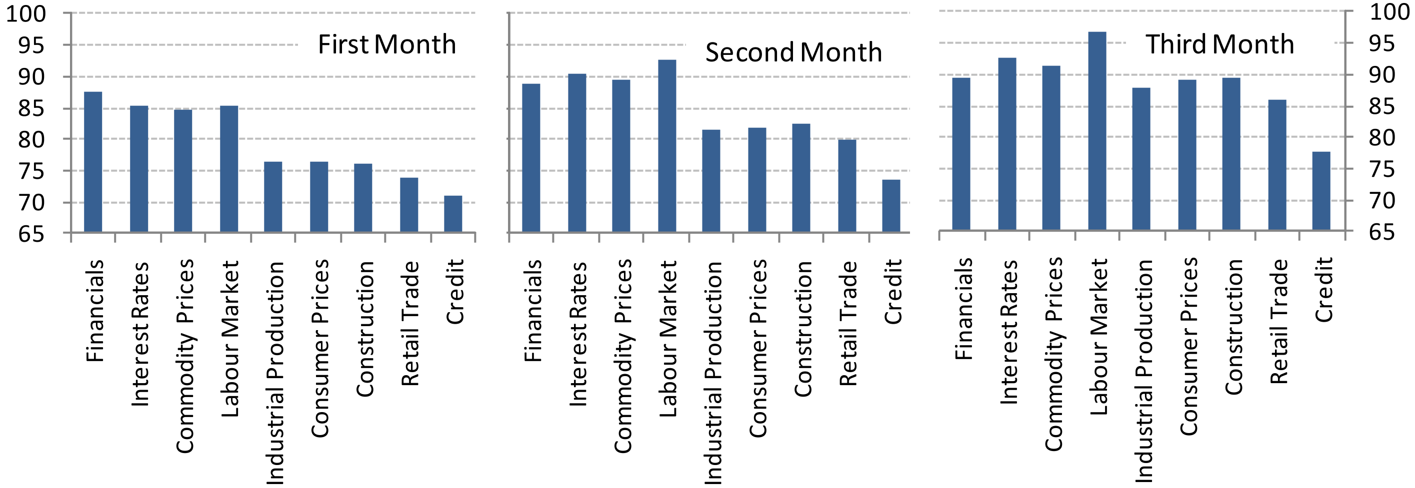


Figure A2. Final Release of Mainland GDP, 2013-2014. Foreign Trade Excluded.

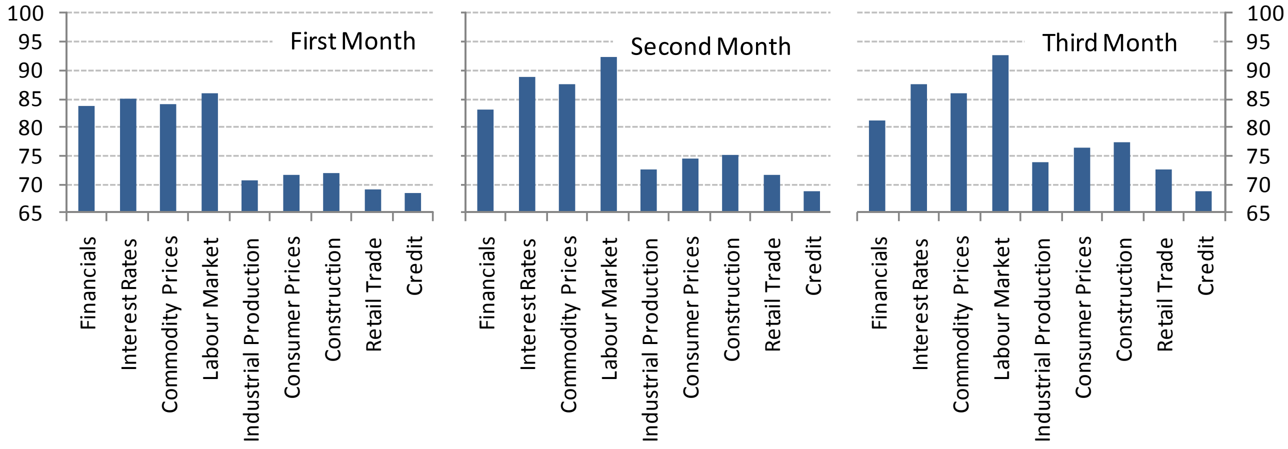
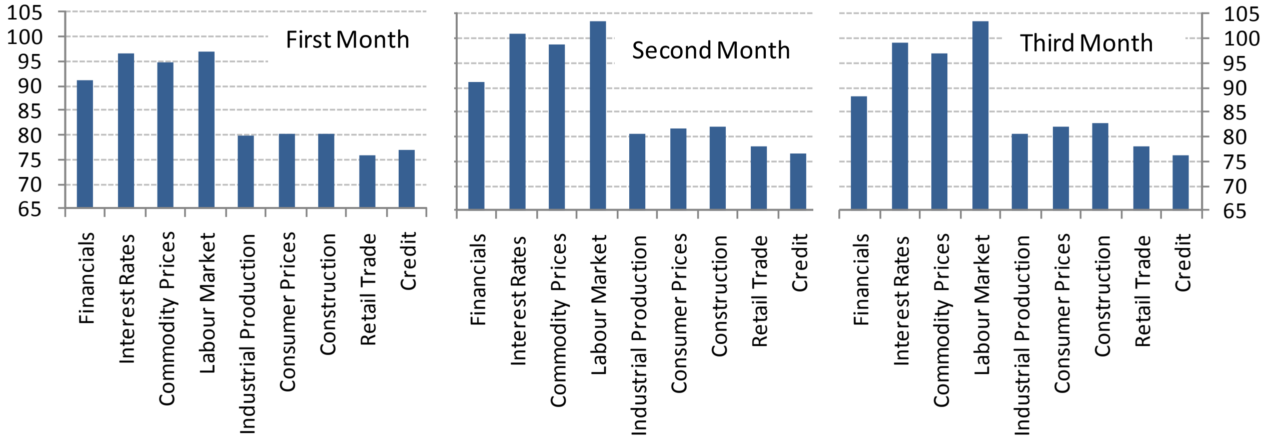


Figure A3. First Release of Mainland GDP, 2013-2014. Foreign Trade Excluded.



B. Predictive Power of Selected Data Blocks Describing Real Economy

Figure B1. Final Release of Mainland GDP, 2013-2016. Data Blocks with Highest Marginal Contribution.

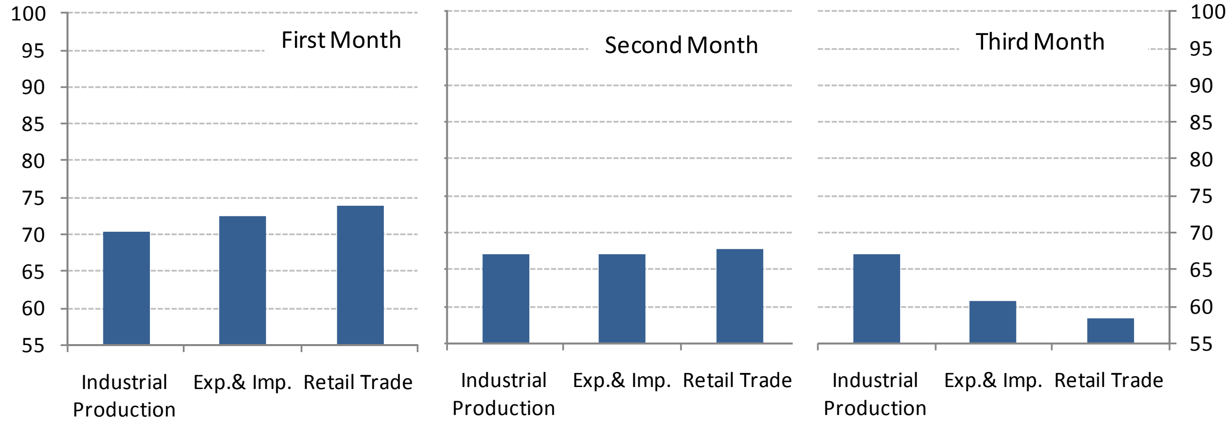
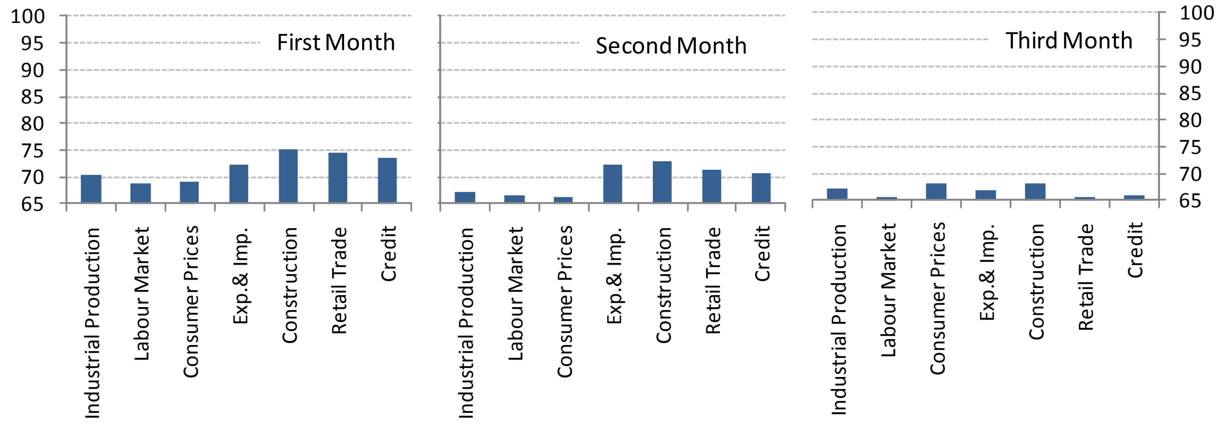


Figure B2. Final Release of Mainland GDP, 2013-2016. Data Blocks with Highest Marginal Contribution.



C. Robustness to the Ordering of Data Blocks

Figure C1. Final Release of Mainland GDP, 2013-2016. Swap in the Order of Financials and Interest Rates.

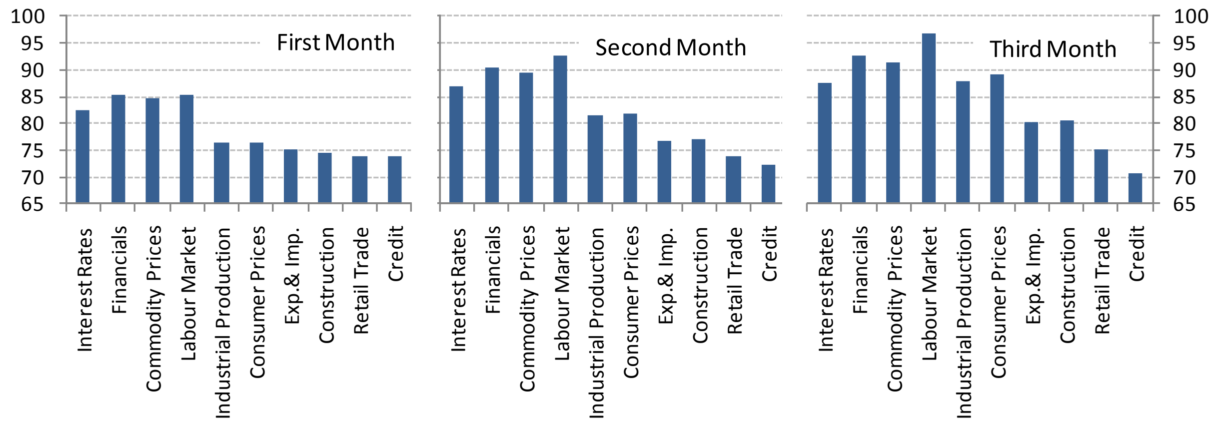


Figure C2. Final Release of Mainland GDP, 2013-2016. Swap in the Order of Uncertainty and Financials.

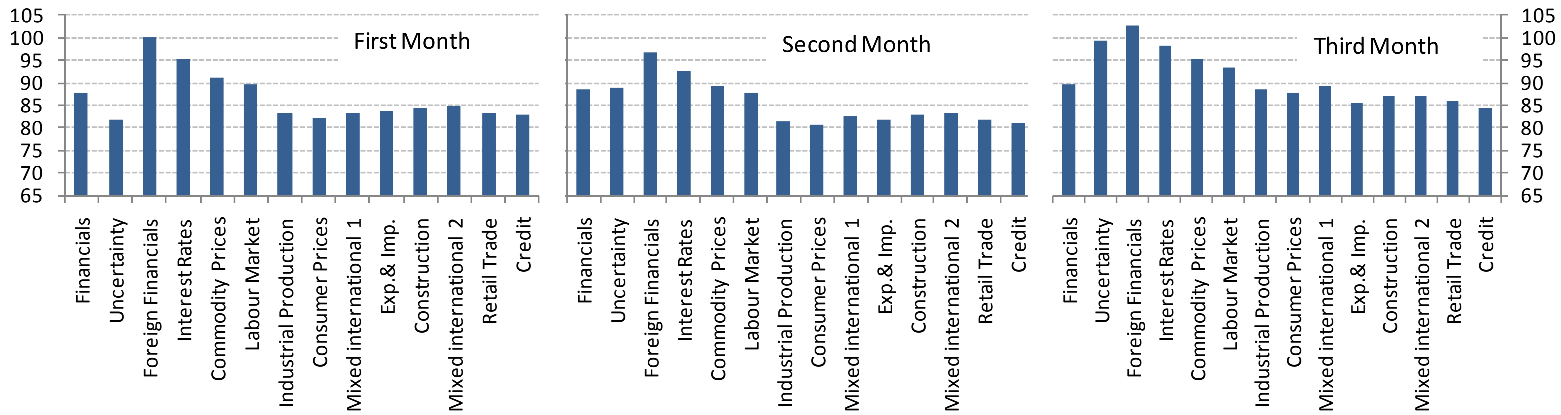


Figure C3. Final Release of Mainland GDP, 2013-2016. Swap in the Order of Uncertainty and Foreign Financials.

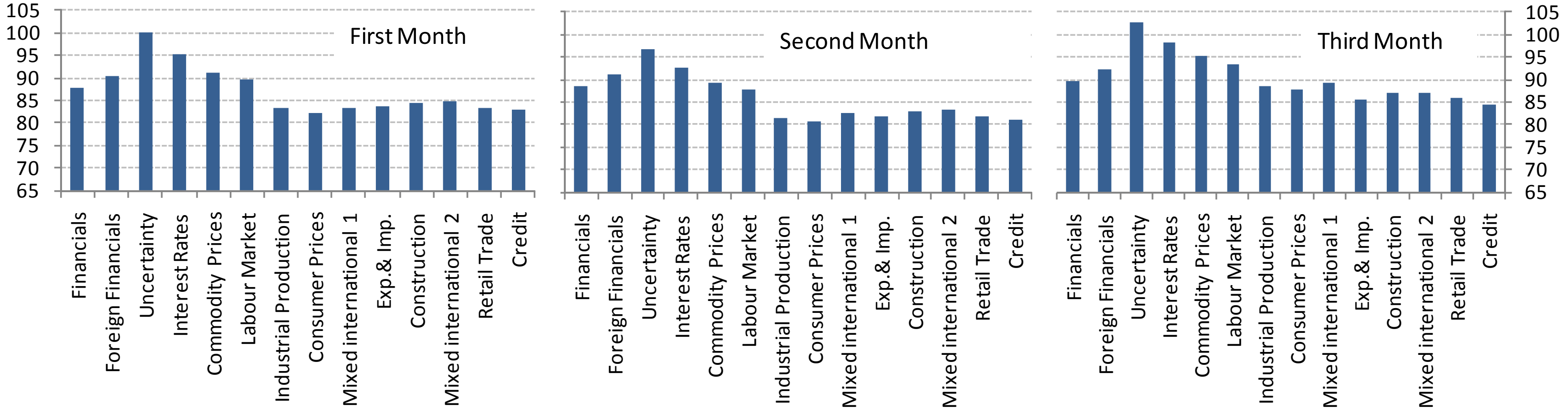


Figure C4. Final Release of Mainland GDP, 2013-2016. Swap in the Order of Uncertainty and Interest Rates.

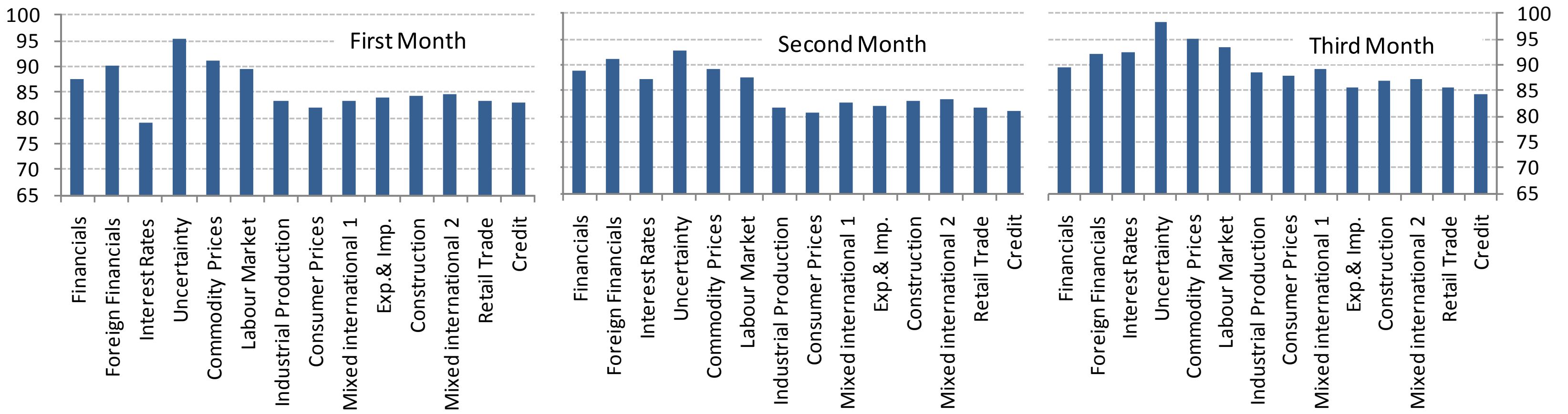


Figure C5. Initial Release of Mainland GDP, 2013-2014.

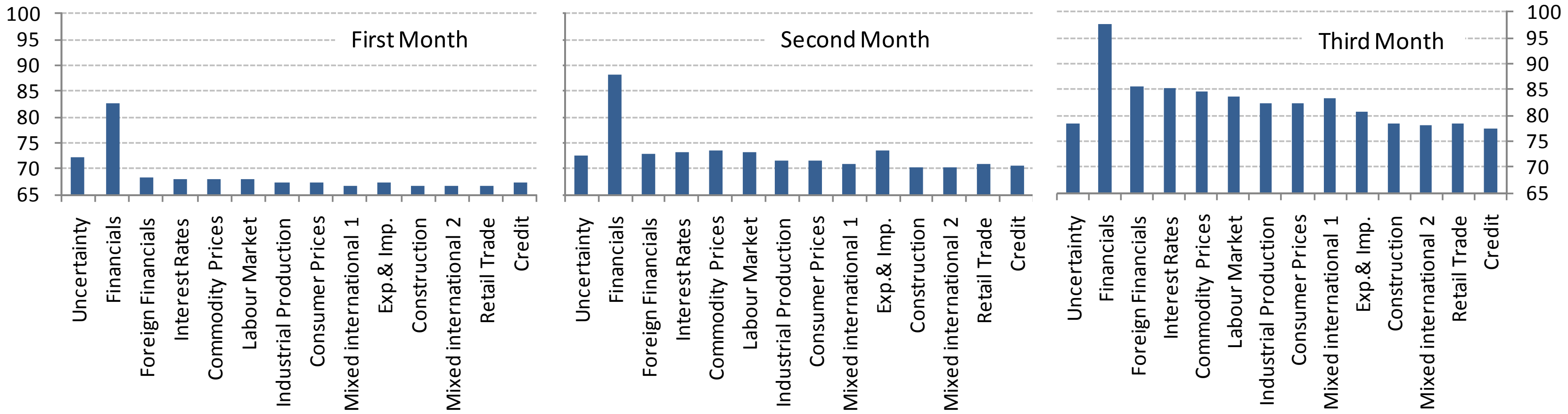


Figure C6. Final Release of Mainland GDP, 2013-2014.

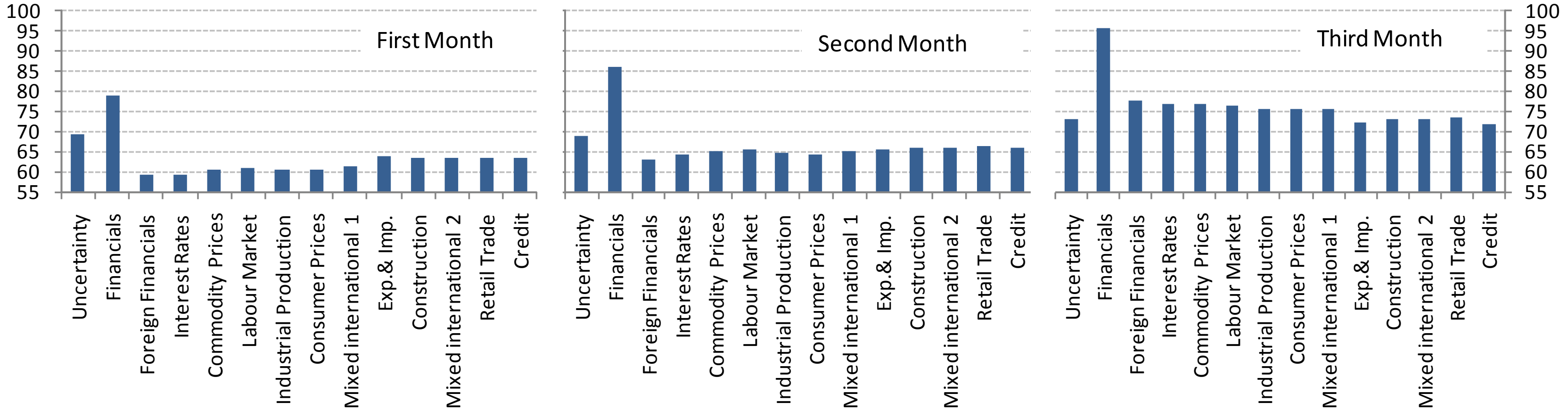


Figure C7. Final Release of Mainland GDP, 2013-2014. Swap in Financials and Uncertainty Block.

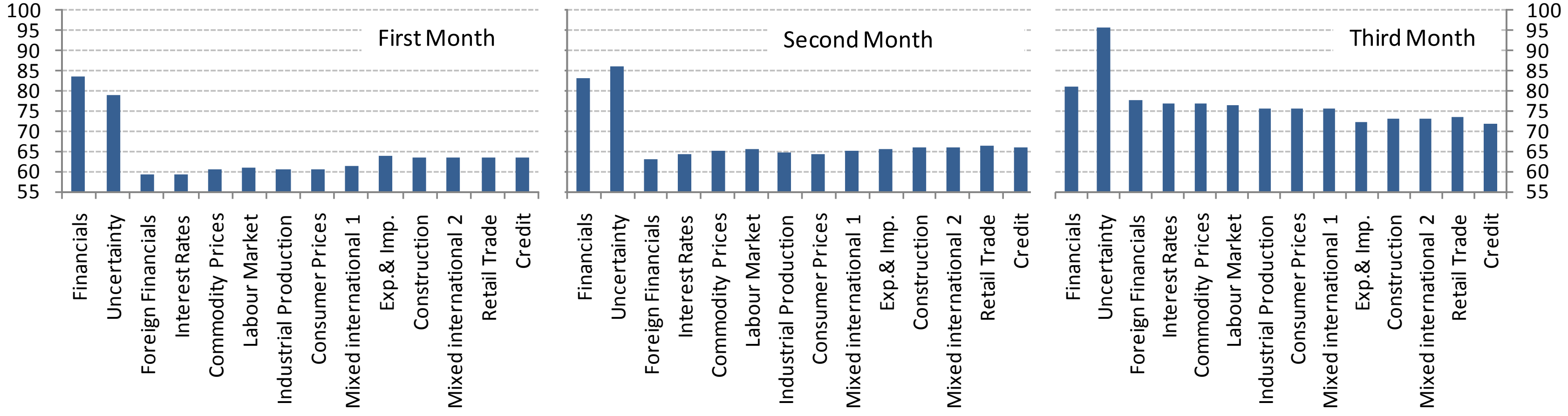


Figure C8. Final Release of Mainland GDP, 2013-2014. Swap in Foreign Financials and Uncertainty Block.

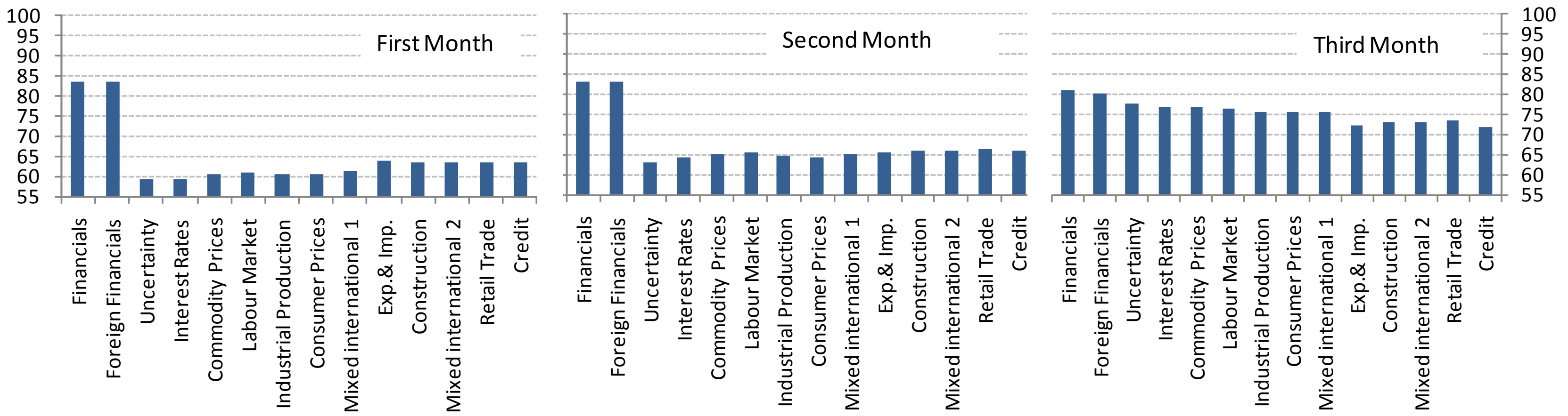


Figure C9. Final Release of Mainland GDP, 2013-2016. Swap in Sentiment and Commodities Block.

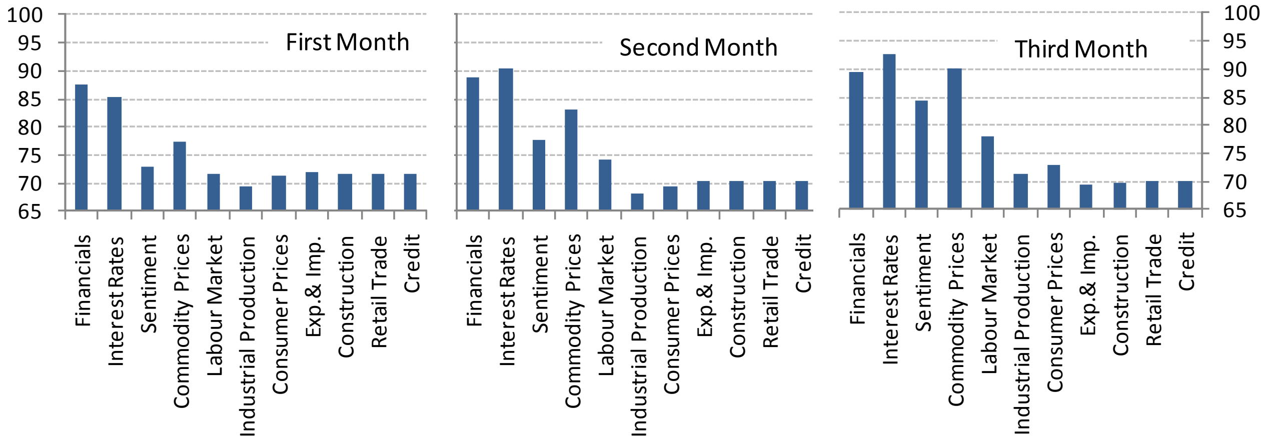
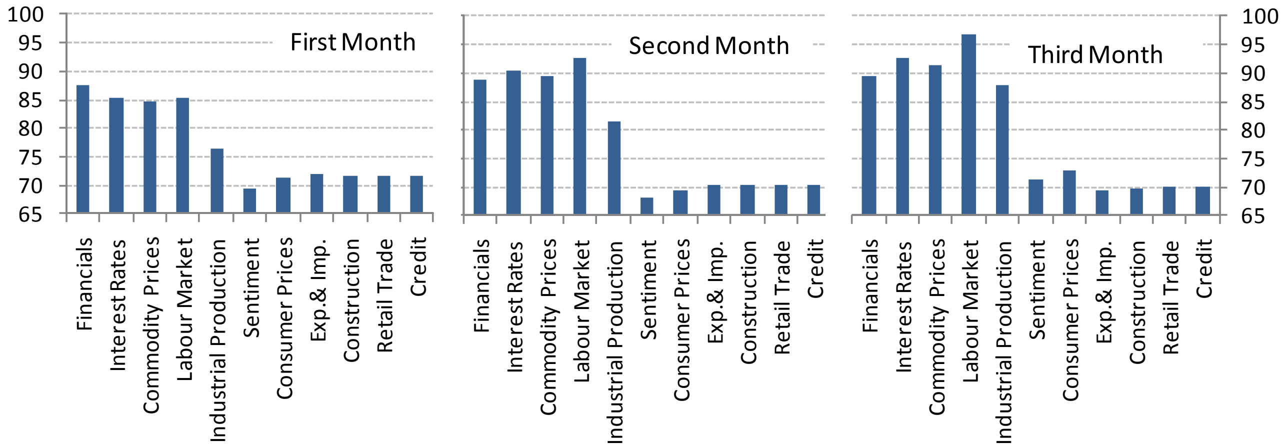
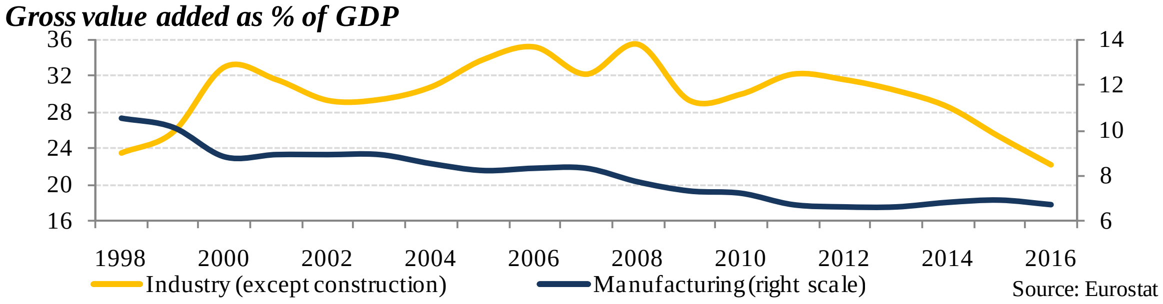


Figure C10. Final Release of Mainland GDP, 2013-2016. Swap in Sentiment and Industrial Production Block.



D. Share of Industry in the Norwegian Economy, 1998-2016



E. Forecasting Performance

Figure E1. Final Release of Mainland GDP, 2013-2016. One year ahead forecasts relative to nowcast.

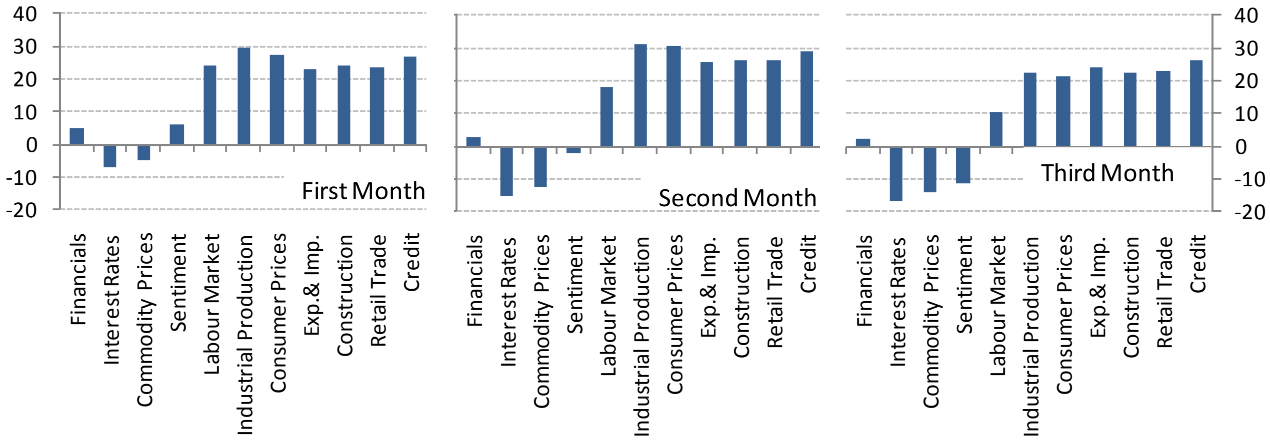


Figure E2. Final Release of Mainland GDP, 2013-2016. One year ahead forecasts relative to nowcast. Selection of hard indicators.

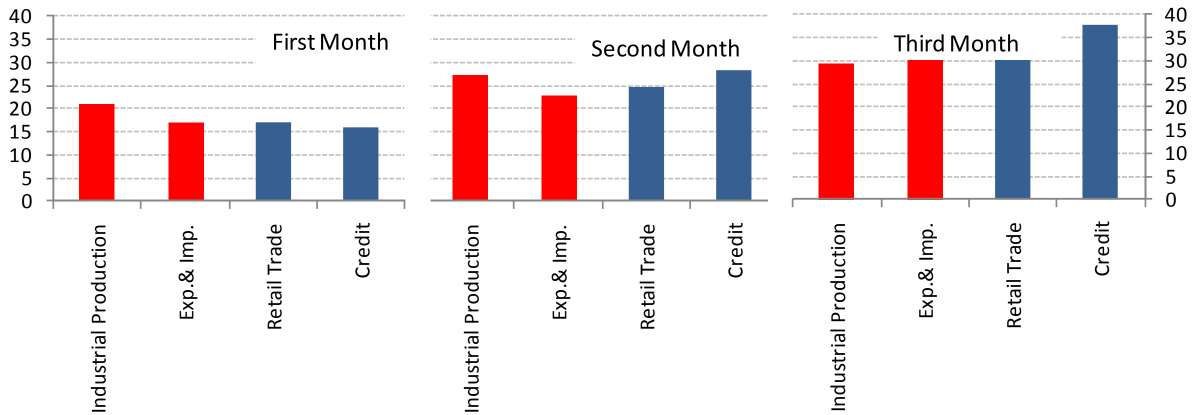


Figure E3. Final Release of Mainland GDP, 2013-2016. One quarter ahead forecasts relative to nowcast. Uncertainty Measures.

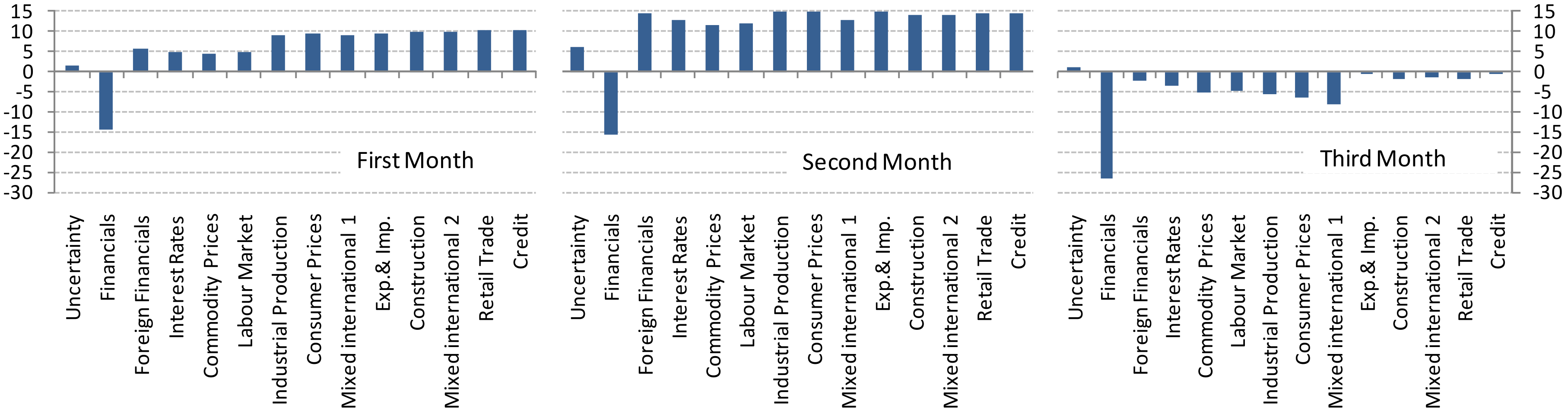
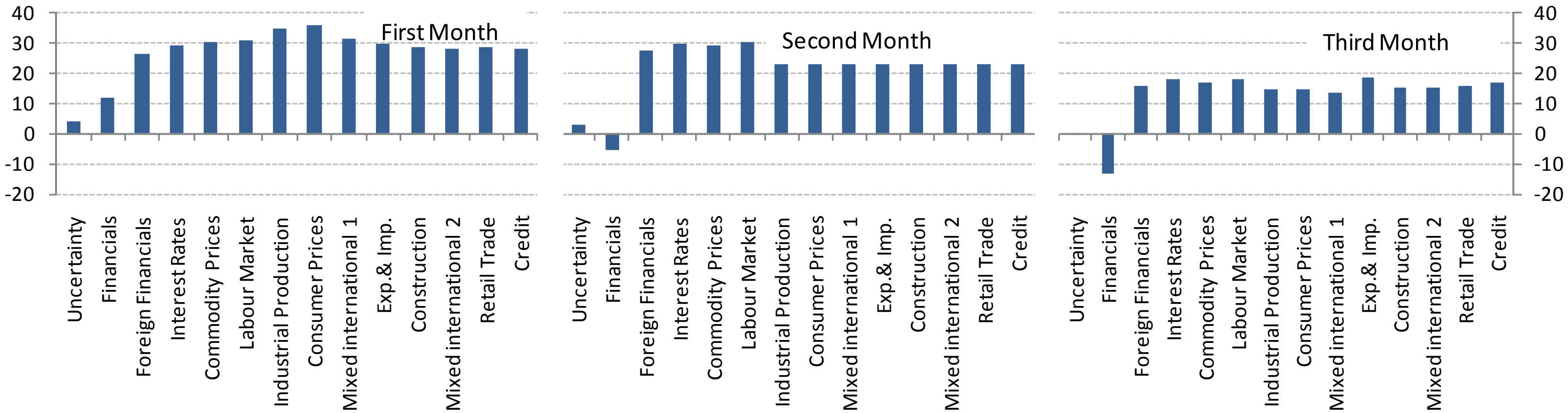


Figure E4. Final Release of Mainland GDP, 2013-2016. One year ahead forecasts relative to nowcast. Uncertainty Measures.



F. Robustness to Number of Factors

Figure F1. Final Release of Mainland GDP, 2013-2016. 10 Block Model of Domestic Indicators.

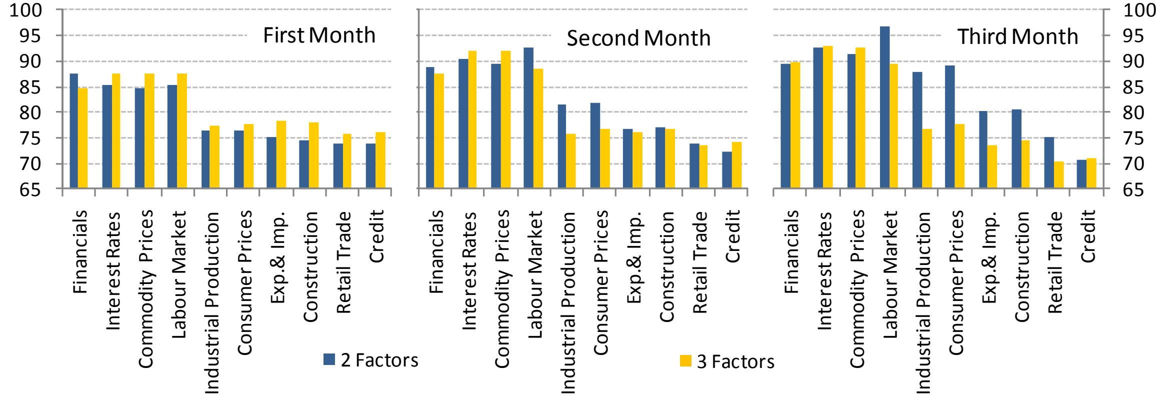


Figure F2. Final Release of Mainland GDP, 2013-2016. 11 Block Model with Sentiment Indicators.

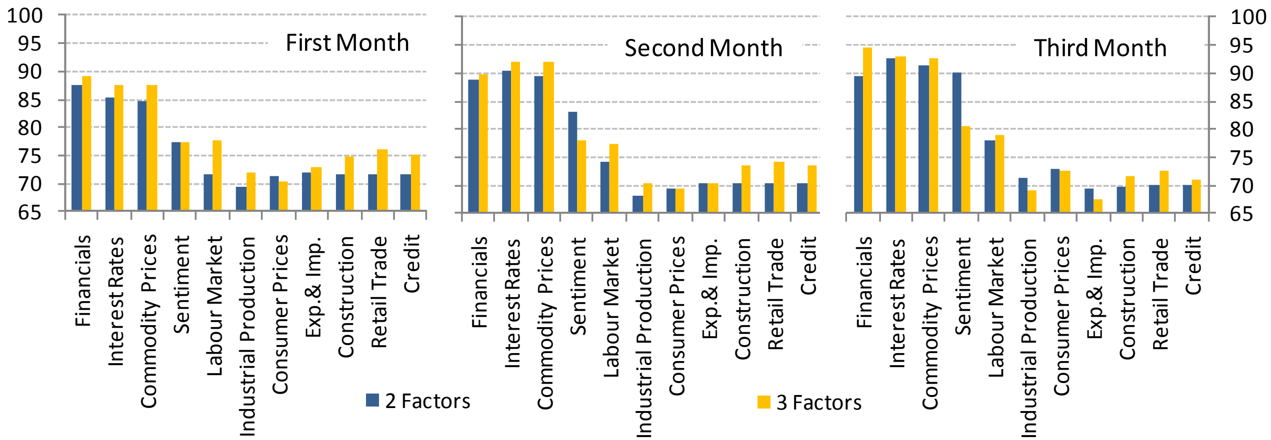
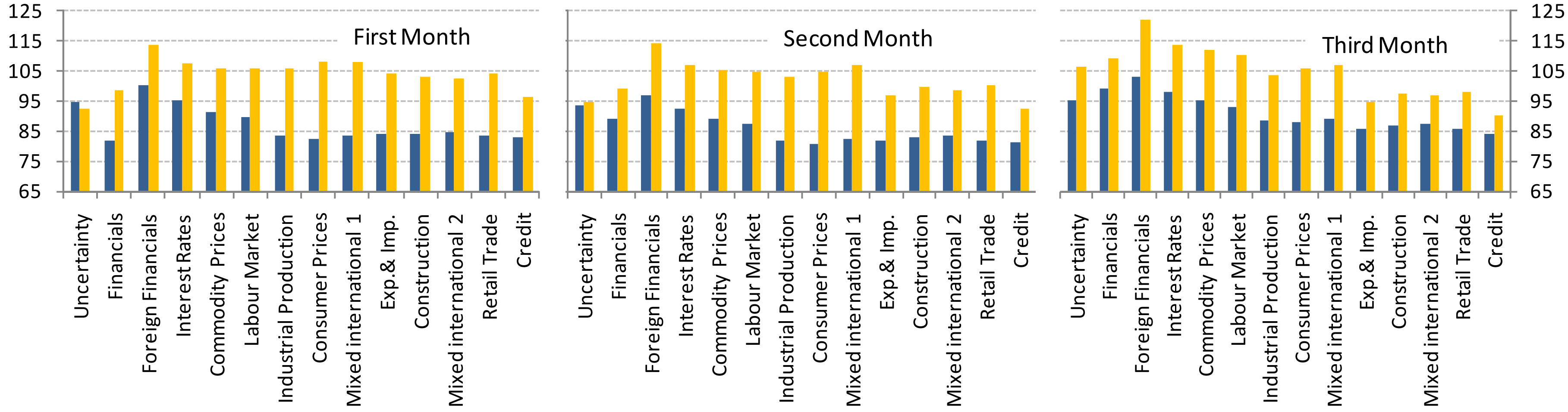


Figure F3. Final Release of Mainland GDP, 2013-2016. 11 Block Model with Foreign and Uncertainty Measures.



G. List of Higher Frequency Indicators

I apply the following transformations to raw data in order to make the series stationary. 1 = No transformation; 2 = First differences; 3 = First differences in logs; 4 = Second differences in logs.

#	Database	Block	Description	Transformation	Revised
1	Macrobond	Labour Market	Registered unemployment rate	2	No
2	Macrobond	Labour Market	Employed Persons, Total 15-74 Years	4	No
3	Macrobond	Consumer Prices	Total	3	No
4	Macrobond	Consumer Prices	Food & Non-Alcoholic Beverages	3	No
5	Macrobond	Consumer Prices	Alcoholic Beverages & Tobacco	3	No
6	Macrobond	Consumer Prices	Clothing & Footwear	3	No
7	Macrobond	Consumer Prices	Housing	3	No
8	Macrobond	Consumer Prices	Furnishings & Household Equipment	3	No

9	Macrobond	Consumer Prices	Health	3	No
10	Macrobond	Consumer Prices	Transport	3	No
11	Macrobond	Consumer Prices	Communication	3	No
12	Macrobond	Consumer Prices	Recreation & Culture	3	No
13	Macrobond	Consumer Prices	Restaurants & Hotels	3	No
14	Macrobond	Consumer Prices	Miscellaneous Goods & Services	3	Yes
15	Macrobond	Exports & Imports	Export of Animal & Vegetable Oils	3	Yes
16	Macrobond	Exports & Imports	Export of Beverages & Tobacco	3	Yes
17	Macrobond	Exports & Imports	Export of Commodities & Transactions	3	Yes
18	Macrobond	Exports & Imports	Export of Crude Materials, Inedible, except Fuels	3	Yes
19	Macrobond	Exports & Imports	Export of Food & Live Animals	3	Yes
20	Macrobond	Exports & Imports	Export of Machinery & Transport Equipment	3	Yes
21	Macrobond	Exports & Imports	Export of Manufactured Goods Classified Chiefly by Material	3	Yes
22	Macrobond	Exports & Imports	Export of Mineral Fuels	3	Yes
23	Macrobond	Exports & Imports	Export of Miscellaneous Manufactured Articles	3	Yes
24	Macrobond	Exports & Imports	Export of Crude Oil	3	Yes
25	Macrobond	Exports & Imports	Import of Animal & Vegetable Oils	3	Yes
26	Macrobond	Exports & Imports	Import of Beverages & Tobacco	3	Yes
27	Macrobond	Exports & Imports	Import of Commodities & Transactions	3	Yes
28	Macrobond	Exports & Imports	Import of Crude Materials	3	Yes
29	Macrobond	Exports & Imports	Import of Food & Live Animals	3	Yes
30	Macrobond	Exports & Imports	Import of Manufactured Goods Classified Chiefly by Material	3	Yes
31	Macrobond	Exports & Imports	Import of Machinery & Transport Equipment	3	Yes
32	Macrobond	Exports & Imports	Import of Mineral Fuels	3	Yes
33	Macrobond	Construction	Number of dwellings initiated building	3	No
34	Macrobond	Construction	Total area of dwellings initated building	3	No
35	Macrobond	Construction	Total area of commercial buildings initiated building	3	No
36	Macrobond	Industrial Production	Industry, Energy Goods, Constant Prices Index	3	No
37	Macrobond	Industrial Production	Industry, Durable Consumer Goods, Constant Prices Index	3	No
38	Macrobond	Industrial Production	Industry, Intermediate Goods, Constant Prices Index	3	No
39	Macrobond	Industrial Production	Industry, Non-Durable Consumer Goods, Constant Prices Index	3	No
40	Macrobond	Industrial Production	Industry, Capital Goods, Constant Prices Index	3	No
41	Macrobond	Industrial Production	Industry, Total, Constant Prices Index	3	No
42	Macrobond	Industrial Production	Manufacturing, Printing and Reproduction, Constant Prices Index	3	No
43	Macrobond	Industrial Production	Manufacturing, Rubber, Plastic & Mineral Products, Constant Prices Index	3	No
44	Macrobond	Industrial Production	Manufacturing, Furniture & Manufacturing N.E.C., Constant Prices Index	3	No
45	Macrobond	Industrial Production	Manufacturing, Ships, Boats & Oil Platforms, Constant Prices Index	3	No
46	Macrobond	Industrial Production	Manufacturing, Fabricated Metal Products, Constant Prices Index	3	No

47	Macrobond	Industrial Production	Manufacturing, Textiles, Wearing Apparel, Constant Prices Index	3	No
48	Macrobond	Industrial Production	Manufacturing, Refined Petroleum, Chemicals, Pharmaceuticals, Constant Prices Index	3	No
49	Macrobond	Industrial Production	Manufacturing, Basic Metals, Constant Prices Index	3	No
50	Macrobond	Industrial Production	Manufacturing, Computer & Electrical Equipment, Constant Prices Index	3	No
51	Macrobond	Industrial Production	Manufacturing, Transport Equipment N.E.C, Constant Prices Index	3	No
52	Macrobond	Industrial Production	Manufacturing, Wood & Wood Products, Constant Prices Index	4	No
53	Macrobond	Industrial Production	Manufacturing, Non-Ferrous Metals, Constant Prices Index	4	No
54	Macrobond	Industrial Production	Manufacturing, Food Products, Constant Prices Index	3	No
55	Macrobond	Industrial Production	Manufacturing, Basic Chemicals, Constant Prices Index	3	No
56	Macrobond	Industrial Production	Manufacturing, Paper & Paper Products, Constant Prices Index	3	No
57	Macrobond	Industrial Production	Manufacturing, Food, Beveradges and Tobacco, Constant Prices Index	3	No
58	Macrobond	Industrial Production	Manufacturing, Repair, Constant Prices Index	3	No
59	Macrobond	Industrial Production	Manufacturing, Total, Constant Prices Index	3	No
60	SSB	Retail Trade	Total except of motor vehicles and motorcycles, Constant Prices Index	4	No
61	SSB	Retail Trade	Automotive fuel in specialised stores, Constant Prices Index	4	No
62	SSB	Retail Trade	Information and communication equipment in specialised stores, Constant Prices Index	4	No
63	SSB	Retail Trade	Other household equipment in specialised stores, Constant Prices Index	4	No
64	SSB	Retail Trade	Cultural and recreation goods in specialised stores, Constant Prices Index	4	No
65	SSB	Retail Trade	Other goods in specialised stores, Constant Prices Index	4	No
66	SSB	Retail Trade	Retail trade not in stores, stalls and markets, Constant Prices Index	4	No
67	SSB	Retail Trade	Retail sale, except of motor vehicles and motorcycles and automotive fuel, Constant Prices Index	4	No
68	Macrobond	Commodity Prices	LME Official Prices - Aluminum, USD	3	No
69	Macrobond	Commodity Prices	Crude Oil - Brent, Spot, USD per BBL	3	No
70	Macrobond	Interest Rates	NIBOR, 3 Month, Fixing	2	No
71	Macrobond	Interest Rates	NIBOR, 6 Month, Fixing	2	No
72	Macrobond	Interest Rates	NIBOR, 1 Month, Fixing	2	No
73	Macrobond	Interest Rates	Government Bonds, 2 Year, Yield	2	No
74	Macrobond	Interest Rates	Government Bonds, 5 Year, Yield	2	No
75	Macrobond	Interest Rates	Government Bonds, 10 Year, Yield	2	No
76	Macrobond	Financials	Spot Rates, NOK per EUR	3	No
77	Macrobond	Financials	Spot Rates, NOK per GBP	3	No
78	Macrobond	Financials	Spot Rates, NOK per USD	3	No
79	Macrobond	Financials	Spot Rates, NOK per SEK	3	No
80	Macrobond	Financials	Spot Rates, NOK per SDR	3	No
81	Macrobond	Financials	Spot Rates, NOK per JPY	3	No
82	Macrobond	Financials	Spot Rates, NOK per DKK	3	No
83	Macrobond	Financials	Central Bank of Trade Weighted Krone Index (TWI)	3	No

84	Macrobond	Financials	Central Bank of Import-Weighted Krone Index (I-44)	3	No
85	Macrobond	Financials	Oslo Stock Exchange, All-Share Index (OSEAX), Total Return, Close, NOK	3	No
86	Macrobond	Financials	Oslo Stock Exchange, Consumer Discretionary, Index, Total Return, Close, NOK	3	No
87	Macrobond	Financials	Oslo Stock Exchange, Consumer Staples, Index, Total Return, Close, NOK	3	No
88	Macrobond	Financials	Oslo Stock Exchange, Energy, Index, Total Return, Close, NOK	3	No
89	Macrobond	Financials	Oslo Stock Exchange, Financials, Index, Total Return, Close, NOK	3	No
90	Macrobond	Financials	Oslo Stock Exchange, Health Care, Index, Total Return, Close, NOK	3	No
91	Macrobond	Financials	Oslo Stock Exchange, Industrials, Index, Total Return, Close, NOK	3	No
92	Macrobond	Financials	Oslo Stock Exchange, Information Technology, Index, Total Return, Close, NOK	3	No
93	Macrobond	Financials	Oslo Stock Exchange, Materials, Index, Total Return, Close, NOK	3	No
94	Macrobond	Financials	Oslo Stock Exchange, Telecommunication Services, Index, Total Return, Close, NOK	4	No
95	Macrobond	Financials	Oslo Stock Exchange, Utilities, Index, Total Return, Close, NOK	4	No
96	Norges Bank	Credit	Domestic Debt in NOK (C1), Actual Stock, SA, NOK	4	No
97	Norges Bank	Credit	Domestic Debt (C2), Non-Financial Corporations, Total, Actual Stock, SA, NOK	4	No
98	Norges Bank	Credit	Domestic Debt (C2), Households, Total, Actual Stock, SA, NOK	4	No
99	Norges Bank	Credit	Domestic Debt (C2), All Sectors, Total, Actual Stock, NOK	4	No
100	Macrobond	Mixed International 1	United States, Industrial Production, Industry Group, Manufacturing, Volume Index	3	No
101	Macrobond	Mixed International 1	Sweden, Manufacturing, Total, Volume Index	3	No
102	Macrobond	Mixed International 1	Euro Area 19, Industrial Production, Total Excluding Construction, Volume Index	3	No
103	Macrobond	Mixed International 1	United States, Consumer Price Index, Average, All Items Less Food & Energy	3	No
104	Macrobond	Mixed International 1	Sweden, Consumer Price Index, Total, Index	3	No
105	Macrobond	Mixed International 2	United States, Business Outlook Survey, Manufacturing, Current General Activity	2	No
106	Macrobond	Mixed International 2	United States, Consumer Surveys, Conference Board, Consumer Confidence Index, Total	2	No
107	Macrobond	Foreign Financials	United States, Government Bonds, 10 Year, Yield	2	No
108	Macrobond	Foreign Financials	Sweden, Government Bonds, 10 Year, Yield	2	No
109	Eurostat	Foreign Financials	Euro Area, Government Bond, 10 Year, Yield	2	No
110	Macrobond	Foreign Financials	United States, Interbank Rates, LIBOR, 3 Month, Fixing	2	No
111	Macrobond	Foreign Financials	Sweden, Interbank Rates, STIBOR, 3 Month, Fixing	2	No
112	Macrobond	Foreign Financials	Euro Area, Interbank Rates, LIBOR, 3 Month, Fixing	2	No
113	Macrobond	Foreign Financials	United States, Equity Indices, S&P, 500, Index, Price Return, Close, USD	3	No
114	Macrobond	Foreign Financials	Euro Area, Equity Indices, STOXX, 50, Index, Price Return, Close, EUR	3	No
115	Macrobond	Foreign Financials	United Kingdom, Equity Indices, FTSE, 100, Index, Price Return, Close, GBP	3	No
116	Macrobond	Foreign Financials	Germany, Equity Indices, Deutsche Boerse, DAX, 30 Index, Total Return, Close, EUR	3	No
117	Macrobond	Foreign Financials	France, Equity Indices, Euronext Paris, CAC 40 Index, Price Return, Close, EUR	3	No
118	Macrobond	Foreign Financials	Italy, Equity Indices, FTSE Italia, MIB Index, Total Return, Close, EUR	3	No
119	Macrobond	Foreign Financials	Sweden, Nasdaq OMX, All-Share, OMX Stockholm Index, Price Return, Close, SEK	3	No
120	Macrobond	Foreign Financials	United Kingdom, Equity Indices, FTSE, 350, Index, Dividend Yield	2	No
121	Macrobond	Foreign Financials	Germany, Equity Indices, FTSEurofirst, 300 Index, Dividend Yield	2	No

122	Macrobond	Foreign Financials	France, Equity Indices, FTSEurofirst, 300 Index, Dividend Yield	2	No
123	Macrobond	Foreign Financials	Italy, Equity Indices, FTSE Italia, All-Share, Index, Dividend Yield	2	No
124	Macrobond	Foreign Financials	Sweden, Equity Indices, FTSEurofirst, 300 Index, Dividend Yield	2	No
125	Macrobond	Sentiment	Business Surveys, NIMA, Purchasing Managers' Index, Total	1	No
126	Macrobond	Sentiment	Business Surveys, NIMA, Purchasing Managers' Index, New Orders	1	No
127	Macrobond	Sentiment	Business Surveys, NIMA, Purchasing Managers' Index, Employment	1	No
128	Macrobond	Sentiment	Business Surveys, NIMA, Purchasing Managers' Index, New Orders, Export Market	1	No
129	Macrobond	Sentiment	Business Surveys, NIMA, Purchasing Managers' Index, New Orders, Domestic Market	1	No
130	Larsen (2017)	Uncertainty	Calendar	1	No
131	Larsen (2017)	Uncertainty	Family business	1	No
132	Larsen (2017)	Uncertainty	Institutional investing	1	No
133	Larsen (2017)	Uncertainty	Justice	1	No
134	Larsen (2017)	Uncertainty	Surroundings	1	No
135	Larsen (2017)	Uncertainty	Housing	1	No
136	Larsen (2017)	Uncertainty	Movies/Theater	1	No
137	Larsen (2017)	Uncertainty	Argumentation	1	No
138	Larsen (2017)	Uncertainty	Unknown	1	No
139	Larsen (2017)	Uncertainty	Agriculture	1	No
140	Larsen (2017)	Uncertainty	Automobiles	1	No
141	Larsen (2017)	Uncertainty	USA	1	No
142	Larsen (2017)	Uncertainty	Banking	1	No
143	Larsen (2017)	Uncertainty	Leadership	1	No
144	Larsen (2017)	Uncertainty	Negotiation	1	No
145	Larsen (2017)	Uncertainty	Newspapers	1	No
146	Larsen (2017)	Uncertainty	Health care	1	No
147	Larsen (2017)	Uncertainty	IT systems	1	No
148	Larsen (2017)	Uncertainty	Stock market	1	No
149	Larsen (2017)	Uncertainty	Macroeconomics	1	No
150	Larsen (2017)	Uncertainty	Oil production	1	No
151	Larsen (2017)	Uncertainty	Wage payments	1	No
152	Larsen (2017)	Uncertainty	Regions	1	No
153	Larsen (2017)	Uncertainty	Family	1	No
154	Larsen (2017)	Uncertainty	Taxation	1	No
155	Larsen (2017)	Uncertainty	EU	1	No
156	Larsen (2017)	Uncertainty	Industry	1	No
157	Larsen (2017)	Uncertainty	Unknown	1	No
158	Larsen (2017)	Uncertainty	Mergers and acquisitions	1	No
159	Larsen (2017)	Uncertainty	UK	1	No

160	Larsen (2017)	Uncertainty	Narrative	1	No
161	Larsen (2017)	Uncertainty	Shipping	1	No
162	Larsen (2017)	Uncertainty	Projects	1	No
163	Larsen (2017)	Uncertainty	Oil price	1	No
164	Larsen (2017)	Uncertainty	Sports	1	No
165	Larsen (2017)	Uncertainty	Organizations	1	No
166	Larsen (2017)	Uncertainty	Drinks	1	No
167	Larsen (2017)	Uncertainty	Nordic countries	1	No
168	Larsen (2017)	Uncertainty	Airline industry	1	No
169	Larsen (2017)	Uncertainty	Entitlements	1	No
170	Larsen (2017)	Uncertainty	Employment	1	No
171	Larsen (2017)	Uncertainty	Politics	1	No
172	Larsen (2017)	Uncertainty	Funding	1	No
173	Larsen (2017)	Uncertainty	Literature	1	No
174	Larsen (2017)	Uncertainty	Statistics	1	No
175	Larsen (2017)	Uncertainty	Watercraft	1	No
176	Larsen (2017)	Uncertainty	Results	1	No
177	Larsen (2017)	Uncertainty	TV	1	No
178	Larsen (2017)	Uncertainty	International conflicts	1	No
179	Larsen (2017)	Uncertainty	Elections	1	No
180	Larsen (2017)	Uncertainty	Music	1	No
181	Larsen (2017)	Uncertainty	Oil service	1	No
182	Larsen (2017)	Uncertainty	Tourism	1	No
183	Larsen (2017)	Uncertainty	Unknown	1	No
184	Larsen (2017)	Uncertainty	Engineering	1	No
185	Larsen (2017)	Uncertainty	Fishery	1	No
186	Larsen (2017)	Uncertainty	Europe	1	No
187	Larsen (2017)	Uncertainty	Law and order	1	No
188	Larsen (2017)	Uncertainty	Weekdays	1	No
189	Larsen (2017)	Uncertainty	Supervision	1	No
190	Larsen (2017)	Uncertainty	Retail	1	No
191	Larsen (2017)	Uncertainty	Startups	1	No
192	Larsen (2017)	Uncertainty	Food	1	No
193	Larsen (2017)	Uncertainty	Stock listings	1	No
194	Larsen (2017)	Uncertainty	Asia	1	No
195	Larsen (2017)	Uncertainty	Art	1	No
196	Larsen (2017)	Uncertainty	Disagreement	1	No
197	Larsen (2017)	Uncertainty	Debate	1	No

198	Larsen (2017)	Uncertainty	Life	1	No
199	Larsen (2017)	Uncertainty	Goods and services	1	No
200	Larsen (2017)	Uncertainty	Telecommunication	1	No
201	Larsen (2017)	Uncertainty	IT technology	1	No
202	Larsen (2017)	Uncertainty	Monetary policy	1	No
203	Larsen (2017)	Uncertainty	Education	1	No
204	Larsen (2017)	Uncertainty	Regulations	1	No
205	Larsen (2017)	Uncertainty	Trade organizations	1	No
206	Larsen (2017)	Uncertainty	Fear	1	No
207	Larsen (2017)	Uncertainty	Fiscal policy	1	No
208	Larsen (2017)	Uncertainty	Energy	1	No
209	Larsen (2017)	Uncertainty	Foreign	1	No
210	Macrobond	GDP	Annual GDP growth Mainland-Norway. Constant prices, NSA. Final and initial releases	1	Yes
			Initial release: 45-50 days after the end of a particular quarter.	1	
			Figures for quarter in year t are considered to final only in year t+2	1	