

Nowcasting norwegian GDP: the role of asset prices in a small open economy

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Abstract This article finds that asset prices on Oslo Stock Exchange is the single most important block of data to improve estimates of current quarter GDP in Norway. We use an approximate dynamic factor model that is able to handle new information as it is released, thus the marginal impact on mean square nowcasting error can be studied for a large number of variables. We use a panel of 148 non-synchronous variables. The high informational content in asset prices is explained by reference to the small size of companies on Oslo Stock Exchange and the small and open nature of the Norwegian economy.

Keywords Forecasting · Financial markets · Monetary policy · Factor models · Small open economy

JEL Classification C33 · C53 · E52 · G14

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1 Introduction

Policy makers rely on indicators that compile information with a time lag and have few sources of contemporaneous information available when the current state of the economy is assessed. One candidate is asset prices. In particular equity prices react continuously to information about the current business climate for companies, as well as about expected future cash flows. In aggregate, an efficient market will reflect the current state of the economy insofar as that has relevance for the value of assets. The market clearing process can be seen as a filtering process for information that is lacking in statistically compiled indicators.

In this article, we use an approximate dynamic factor model to assess the current state of the Norwegian economy from a panel of 148 monthly variables. By using a model that builds on [Giannone et al. \(2008\)](#) we are able to assess the marginal impact from various categories of variables. We segment the different variables into 13 blocks sorted by release dates. Our main finding is that news about asset prices on Oslo Stock Exchange is the category that improves the nowcast the most.

In [Beaudry and Portier \(2006\)](#) it is found that innovations to stock prices are correlated with future productivity growth, i.e., that long-term changes in productivity growth are preceded by stock market booms. They argue that the type of model needed to explain these observations is one where agents recognize changes in technological opportunities well before the effect of such changes on productivity is observed. Thus, the recognition or expectation itself leads to a boom in consumption and investment, and thus real activity. [Jaimovich and Rebelo \(2008, 2009\)](#) suggest amendments to the neoclassical model that produce such effects. In the present article, we focus on changes in asset returns as signals about changes in real activity in the same quarter, i.e., there is an almost immediate impact to real activity. The cited articles lend some substance to ascribing such an impact to changes in expectations about the future reflected in asset prices. An additional advantage with asset prices is their timeliness. Relevant news about current business activity are immediately reflected in prices through the market clearing process.

The usefulness of asset prices in predicting real activity has been extensively studied for many countries; [Stock and Watson \(2003\)](#) survey this vast literature. While studies using interest rates, term spreads, and credit spreads abound, a more limited number of studies focus on the equity market. In general, results reported in [Stock and Watson \(2003\)](#) indicate a low predictive content of stock returns. Two more recent studies investigate the predictive power of stock returns in the euro area. [Panopoulou \(2007\)](#) find that equity returns are helpful in predicting a monthly industrial production index, and it performs better on a 1 month horizon than on longer horizons. While the studies above use methods involving single variables, [Forni et al. \(2003\)](#) use a factor model and study the effect of blocks of data on forecasting aggregate real activity (monthly industrial production). They find that financial variables are not important for forecasting real activity even at a 1 month horizon. Their financial block is however large, and includes several types of financial variables, such as real and nominal interest rates, spreads and exchange rates in addition to stock returns.

This article differs from these studies in two important ways. First, while the mentioned studies are investigating the forecasting properties of financial assets, we work

within a nowcasting framework. We study the effect of monthly variables on the concurrent quarterly real growth. Thus, we look at the simultaneous relationship between financial variables and the current state of the economy. Second, we use a factor model that can handle non-synchronous data; we can thus in a more precise way than [Forni et al. \(2003\)](#) detect the marginal impact of different variables, at the time they are released.

The reported result for asset prices is unique for this study. We use the same methodology as [Giannone et al. \(2008\)](#). They evaluate the marginal impact of different blocks of data for the U.S. economy and find that survey information carries the most information about concurrent GDP growth. In particular, in contrast to the current study they do not find similar effects of asset prices using the same methodology on U.S. data.

Our study differs from [Giannone et al. \(2008\)](#) in that the asset prices we are using are from companies that would be classified as between small cap and micro cap in the U.S.; in that we are using a broader block of financial data, i.e., industry level asset prices and dividend yield; and in that the economy we study is very small and open compared to the U.S.

Recent research in [Petkova \(2006\)](#) finds that the size factor as described in [Fama and French \(1992, 1993\)](#) proxy for innovations in a default spread, a finding that aligns with the intuition that small companies are more vulnerable in recessions than larger, perhaps more mature companies. In this context our finding of a higher informational content in asset prices with respect to the current state of the economy in Norway than in the U.S. is expected. In contrast, [Giannone et al. \(2008\)](#) do not focus on companies of a comparable size but use a broad, aggregated market index with a much larger median company in their article.

Norway is a small, open economy and a large petroleum exporter. It is reasonable to assume that both terms of trade shocks and other productivity/technology shocks play a more prominent role in Norway than in a larger, more diversified and less open economy like the U.S. Moreover it is reasonable to assume that shocks as, say a labor conflict, a change in foreign labor supply or news about a large contract being won by a large company traded on the stock exchange, will have an immediate effect on real activity. Hence, we would expect that timely news about such shocks, as reflected in exchange rates and equity returns, are more important in Norway than in the U.S. In line with such an assumption, both GDP growth and returns on the Oslo Stock Exchange are more volatile than similar measures for the U.S.

The article is organized as follows: The following section presents the model. Section 3 describes in detail the data set. Results are presented in section 4. Section 5 concludes.

2 Model

Consider the vector of n stationary monthly variables $X_t = (x_{1t}, \dots, x_{nt})'$, $t = 1, \dots, T$, which have been standardized to have mean equal to zero and variance equal to one. Assume that X_t can be described by an approximate dynamic factor model similar to [Giannone et al. \(2008\)](#). Let

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

where χ_t is a common component driving the variation in X_t and ξ_t is a non-forecastable idiosyncratic component.¹ Λ is an $(n \times r)$ matrix of factor loadings and $F_t = (f_{1t}, \dots, f_{rt})'$ are the factors. Typically the number of factors, r , is much smaller than the number of variables, n , thus securing a parsimonious model. The idiosyncratic component, $\xi_t = (\xi_{1t}, \dots, \xi_{nt})'$, has zero expectation and a covariance matrix equal to $\Psi = E[\xi_t \xi_t']$.

The factors evolve through time according to the vector autoregression

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

where A is an $(r \times r)$ parameter matrix and all roots of $\det(I_r - Az)$ lie outside the unit circle, B is an $(r \times q)$ matrix of full rank q , where q is the number of common shocks in the economy, i.e., the dimension of u_t . We assume that the vector of common shocks, u_t , follows a white-noise process and that the covariance matrix of Bu_t is given by $Q = E[Bu_t(Bu_t)']$. In this model an r larger than q captures the lead and lag relations between common factors and common shocks. Equations (1) and (2) together define a state-space representation of an approximate dynamic factor model. See e.g., [Forni et al. \(2009\)](#) for details.

In [Giannone et al. \(2008\)](#), Eqs. (1) and (2) are estimated by a two-step procedure. First, the parameters are estimated by OLS on principal components extracted from the balanced part of the data set, i.e., the data set up to the last date for which there exists observations of all variables. In the next step, the parameters are replaced with their consistent estimates obtained from the first step and the factors are re-estimated recursively using Kalman filtering techniques. The unbalanced part of the data set can be incorporated through the use of the Kalman filter, where missing observations are interpreted to have an infinitely large noise to signal ratio.² The ability to handle non-synchronized data makes it possible to evaluate the relative importance of blocks of new data releases in real time.³ The estimator yields consistent estimates of the factors under general assumptions and is feasible to use for a very large cross-section. There are no restrictions on the number of variables, n , relative to number of observations, T . An algorithm for the estimation procedure is given in Appendix A. See [Doz et al. \(2007\)](#) for additional details about the properties of the estimator.

Our task is to nowcast GDP growth which is a quarterly variable, using all available information from a large amount of monthly variables. We therefore need to build a bridge between the monthly variables and the quarterly variable. This is done by averaging the monthly observations to obtain quarterly series. The time aggregation

¹ The model is an approximate factor model, since in contrast to the strict factor model, the idiosyncratic terms in Eq. (1) are allowed to be weakly correlated. See [Chamberlain and Rothschild \(1983\)](#), [Forni et al. \(2000\)](#) and [Stock and Watson \(2002a\)](#) for details.

² This is done by parameterizing the variance of the idiosyncratic component of the missing observations to infinity at the end of the sample.

³ [Stock and Watson \(2002b\)](#) and [Schumacher and Breitung \(2008\)](#) suggest an alternative approach to handle unbalanced data. They estimate the factors applying an EM algorithm combined with a principal component estimator.

is such that the quarterly series corresponds to the third month of the quarter. More precisely, prior to the estimation we obtain monthly measures of 3 month aggregates by applying the following filter: $Z_{it} = (1 + 2L + 3L^2 + 2L^3 + L^4)z_{it}$, where z_{it} is assumed to be a stationary variable.⁴ In the case where z_{it} represents a variable of monthly growth rate, Z_{it} can be interpreted as a variable of quarterly growth rate. This will be consistent with defining quarterly GDP growth as the 3 month average of monthly latent observations.⁵ In the third month of a quarter, the 3 month difference will correspond to a quarterly difference. In this way the monthly factors obtained in the third month of a quarter will represent quarterly quantities. We refer to these quarterly factors as $\widehat{F}_\tau^{q_0}$, where $\tau = 3, 6, \dots, T - 3, T$. In the third month of a quarter one directly obtains $\widehat{F}_\tau^{q_0}$, while in the first 2 months of the quarter one obtains a forecast of the factors of the third month using the transition equation (2). The GDP growth nowcast after any monthly block release in the quarter, is then obtained as a projection of GDP growth on the factors

$$\widehat{y}_\tau^{q_0} = \widehat{\alpha} + \widehat{\beta}' \widehat{F}_\tau^{q_0} \quad (3)$$

where q_0 represents the current quarter and $\tau = 3, 6, \dots, T - 3, T$ indicates that only the monthly observations corresponding to a quarterly quantity are used. The coefficients of the projection are estimated by OLS. Note that in this specification, lagged values of GDP are not included as a predictor. Hence, we assume that the common factors capture the dynamic interaction among the independent variables in the large data set as well as the dynamics in GDP growth. We will return to this issue in Sect. 4.

The model is re-estimated when the non-synchronous variables in the data set are updated. That is, when new information arrives, the factors are re-estimated and a new OLS estimate for GDP growth is computed as a function of the new factors.⁶ The marginal impact of new information is thus immediate in the sense that factors change. However, the marginal impact also has a long-lasting effect because the presence of a variable in the data set affects the estimate of the factors and thus the impact of subsequent releases of other variables. For example, the presence of “Financials” early in the month affects the marginal impact of “Industrial Production” when those series are released later in the month.

Intuitively, adding a variable, or new observations of an existing variable, may change the allocation of variance in the data set to the common component and to non-forecastable idiosyncratic noise. New observations might bring noise relative to the factor extraction, thus impairing the common component and increasing the importance of idiosyncratic noise. Moreover, the factors are extracted based on the covariance structure between the explanatory variables only, and are not related to covariance with GDP growth at all.

⁴ The filter was introduced by [Mariano and Murasawa \(2003\)](#), in order to map unobservable measures of monthly GDP growth to observable measures of GDP growth in a state-space model. Several other authors, such as for instance [Schumacher and Breitung \(2008\)](#) and [Angelini et al. \(2008a\)](#) have applied the filter to similar problems.

⁵ See [Giannone et al. \(2008\)](#) and [Angelini et al. \(2008b\)](#) for details on this.

⁶ Note that the parameters in Eqs. (1) and (2) are only re-estimated once every quarter.

Factor models have long been established as a useful tool in economics, in particular where there is a need to distinguish between noise and valuable information in a large information set. Many authors such as Boivin and Ng (2005), Forni et al. (2005), Giannone et al. (2005), and Stock and Watson (2002b) have shown that such models are successful in economic forecasting. The setting in Giannone et al. (2008) is close to the real life decision-making process of a policy maker. This approximate dynamic factor model is able to exploit non-synchronous data releases so that the user can incorporate individual variables as soon as they are available. An alternative framework for real time estimates of GDP growth that also allows non-synchronous data releases is Evans (2005). This model is however not a factor model and only suitable for a limited number of variables.

3 Data

We have collected a panel of macroeconomic and financial variables for the Norwegian economy. In addition, we use macroeconomic and financial variables for Norway's main trading partners; the euro area, Sweden, U.K. and the U.S. In total we use a panel of 148 monthly variables. The sample starts in January 1990 and ends in January 2009.⁷ Series covering financial assets such as equity prices, dividend yields, currency rates, interest rates and commodity prices are constructed as monthly averages of daily observations. All variables are transformed to induce stationarity and normalized to have mean equal to zero and variance equal to one. The full details of the data set and the transformations are reported in Appendix G (see Electronic supplementary material).

Following the standard approach, data series that have similar release dates and are similar in content are grouped together in blocks. We have defined a total of 13 different blocks that are released on 8 different dates throughout the months, i.e., on some dates more than one block is released. The number of variables in each block varies from 38 in "Industrial Production" to only 2 in the "Commodity Prices" and "Mixed International 2" blocks. In Fig. 1 we depict how the 13 different blocks are released throughout any month and quarter. Note that data lag varies for different blocks, ranging from 4 months for the "Labour Market"⁸ block to 1 month lag for "Financials", "Interest Rates" and "Commodity Prices". Thus, the structure of the unbalancedness changes when a new block is released.

Figure 1 illustrates the data release calendar of a generic quarter, exemplified by the second quarter of 2007. The quarter is divided into 3 months and each month into 8 release dates. Horizontal bars indicate the release dates of the 13 different blocks of data. The color scheme of the bars indicate that when released, the data are lagging in varying degree as explained by the legend in the upper left corner (t refers to the second month of the quarter). Moreover, the date, year and month, of the latest available data

⁷ For variables that contain a seasonal pattern, we have used seasonal adjusted series published by Statistics Norway. Statistics Norway apply the X-12-ARIMA method for seasonal adjustment.

⁸ Note that unemployment data are lagging with 2 months while data on employment measures are lagging with 4 months.

the results, see Appendix C. However, financial variables are computed as monthly averages of daily observations and can in principle be included anytime during the month. We make the ad hoc assumption that these variables become available as monthly averages only once a month. Hence, to simplify the block structure in the model we are using less information than possible. In this sense we may understate the importance of the financial variables, as we do not take into account that the monthly average of these variables could have been included on a daily basis.

The marginal effect on the nowcast from including a new block of data is influenced by properties of the new block relative to the data that already are being used. If the new block is uncorrelated noise, the inclusion of the block has no effect. If the inclusion of the block changes the correlation structure of the augmented data set so that factors explain less of the total variance, or so that the factor dynamics becomes less related to GDP, then the marginal impact of including the block could worsen the precision of the nowcast. Hence, since the marginal impact is interrelated with the data that are being used, the ordering of blocks, when that is a discretionary decision, can have an impact on the performance of a specific block.

In the absence of economic arguments guiding the ordering of blocks of potentially high frequency data, one could argue in favor of using the ordering that works best. The caveat is that this is a feature of the model that is susceptible to data mining.

Financial variables like equity prices and interest rates are forward looking and thus should be included in the beginning of the month. That argument is perhaps less clear for currencies and commodities; however they are also functions of discounted expectations. We choose to include all financial variables in the beginning of the month.

The internal ordering of the “Financials” and “Interest Rates” blocks has no effect on subsequent performance during the quarter, but the information from interest rates are less useful when the financial block already is included in the data. Both blocks are included on the first day of each month. See Appendix C for details.

3.2 How many factors drive the Norwegian economy?

The main strength of factor models is that a large number of variables can be distilled into a few factors that capture the predictable common component of the data; the residual is non-predictable idiosyncratic noise. A question remains, however, in choosing the appropriate number of factors. This is a model selection problem.

A standard approach for choosing the number of factors is based on the degree of variance in the data set explained by the first r principal components.¹⁰ In Table 1 the percentage of the total variance explained by up to ten principal components is shown: We see that a small number of principal components explain a non-trivial fraction of the total variance in the data set, thus indicating a high degree of collinearity between

¹⁰ This is done by calculating the following ratio: $\frac{\sum_{i=1}^r d_i}{\sum_{i=1}^n d_i}$, where $\{d_1, \dots, d_n\}$ denotes the eigenvalues of the covariance matrix of our data set. The eigenvalues are ordered in descending order so that d_1 represents the largest eigenvalue and d_n the smallest eigenvalue.

Table 1 Percentage of total variance explained by the first r static principal components

Number of factors	1	2	3	4	5	6	...	10
10 block model	0.13	0.23	0.31	0.37	0.43	0.48	...	0.65
13 block model	0.17	0.28	0.35	0.41	0.46	0.51	...	0.66

Based on data from 1990 to 1998

the variables.¹¹ A cut-off for marginal explanation of the next consecutive factor of less than ten percentage points, implies a choice of two factors.

Table 1 describes variance of the factors divided by total variance among the dependent variables; it does not relate to the predictive power of the factors relative to GDP growth. [Koop and Potter \(2004\)](#) investigate alternative methods for choosing factors that incorporate the predictive power. They find that the optimal number of factors chosen is on average close to two, underlining the importance of parsimony.

We will in the following parameterize the model with two factors. Our findings are however robust with respect to different choices of number of factors, see Fig. 7 and Table 4 in Appendix B.¹²

4 Results

4.1 Marginal impact of block releases

We perform a pseudo-real-time out-of-sample simulation. “Real-time” means that all parameters in the model are estimated only on information that where available at the time. “Pseudo” means that we do not account for data revisions.¹³ Our out-of-sample evaluation begins in first quarter of 1998 and ends last quarter of 2008. As the sample begins first quarter of 1990, the first out-of-sample evaluation is based on 8 years of data.

We measure performance by mean square forecasting error between nowcast and subsequent realization of GDP growth.¹⁴ We choose a naive forecast as benchmark where a constant growth rate, computed on the available history of GDP at the time, is recursively estimated.¹⁵

¹¹ We only report the extracted principal components using data up to the end of 1997, since in the first quarter of 1998 we start our out-of-sample simulations.

¹² More results are available from the authors upon request.

¹³ Real time data are not available for the data set. [Aastveit and Trovik \(2008\)](#) show using U.S. data that factor models are robust to data revisions.

¹⁴ Note that we use observations for GDP growth from the last available data vintage as “final” realizations of GDP growth. Hence, we neglect the data revision problem. Typically, the last 3–4 years of data are revised.

¹⁵ The naive forecast performs better than forecasts from simple univariate AR models on our data set.

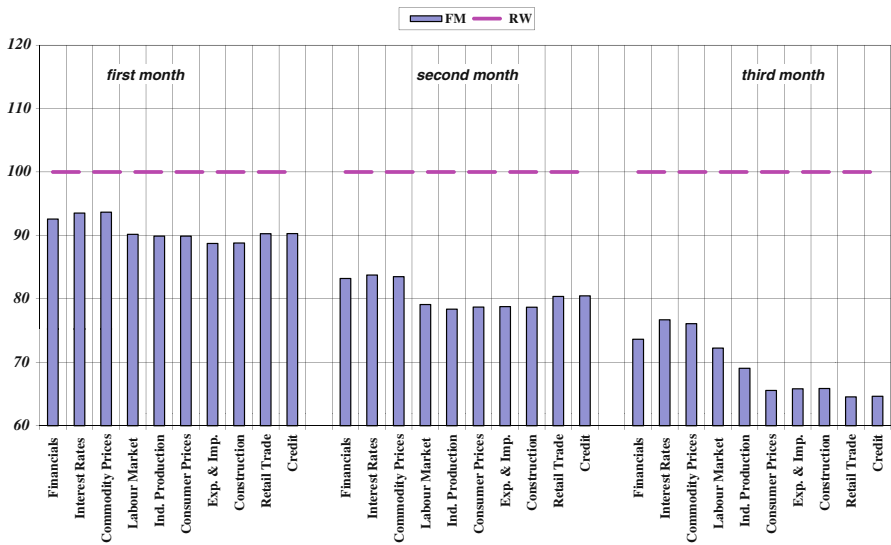


Fig. 2 MSFE across data blocks; relative to MSFE based on a constant growth rate. Depicting the first, second and third generic month of the quarter for which the nowcast is done. Out-of-sample nowcasts from 1998q1 to 2008q4. Data sample starts from 1990m1

In Fig. 2 we see how the relative nowcasting error is reduced as new information become available throughout the quarter in the 10-block version of the model.¹⁶ The bars represent the factor model (FM) and the dotted line is our constant growth benchmark, i.e., the naive forecast (RW).

We see that towards the end of the generic quarter the nowcasting error of the factor model is close to 60 percent of that of the naive nowcast. Furthermore, we see that the performance is steadily improving as new information is incorporated into the model, confirming our intuition that nowcasts of GDP growth by and large will benefit from using newly released information. Although the estimated factors are likely to be invariant to data revisions, revisions in GDP may distort the estimation of the regression coefficients in Eq. (3). Figure 10 in Appendix D compares the performance of the model when we estimate Eq. (3) using respectively the last vintage of GDP growth data and real time GDP growth data. The figure shows that the results are robust to the use of real time GDP data.¹⁷

¹⁶ This is measured as $MSFE = \frac{\text{mean}((\hat{y}_t^{FM} - y_t)^2)}{\text{mean}((\hat{y}_t^{RW} - y_t)^2)}$, where \hat{y}_t^{FM} denotes nowcasts from the factor model, \hat{y}_t^{RW} nowcasts from the naive model and y_t actual observations on GDP growth.

¹⁷ Real time GDP data are not available for Norway prior to the third quarter 2000. Note that the out-of-sample evaluation in Fig. 10 therefore starts in the third quarter 2000 and ends last quarter 2008.

A prominent feature of Fig. 2 is the large marginal gain when the “Financials” block is released. This effect is large and consistent in all 3 months of the quarter.¹⁸ The result is robust to different ordering of blocks with similar release date, see Appendix C. The “Labour Market” and “Industrial Production” blocks also have positive marginal impacts on the performance of the nowcast.

Some blocks have varying marginal impact through the quarter. For example, the “Consumer Prices” block seems to contain little information in the two first months of a quarter, but then become quite informative in the third month. Such changing impact of a block during the quarter may be indicative of a short sample problem. Note however that “Consumer Prices” is released with 1 month lag around the 10th of each month. Hence, only the number released for the two last months relates to inflation within the quarter for which we are nowcasting GDP.

In Eq. (3), quarterly GDP growth is regressed on the two factors. Note that we find evidence of first order negative residual autocorrelation in this regression, indicating that the factors do not capture all dynamics in quarterly GDP growth. An alternative specification is to include lagged values of quarterly GDP growth as a regressor. This would improve the model’s ability to capture dynamics in quarterly GDP growth, however it would make the marginal impact of new information more difficult to assess. The reason can be ascribed to scale. While a new observation of lagged GDP growth can be quite different from the backcast we need to use in the first part of the quarter, the change in the factors as a result of the release of a new block is on average less dramatic. This difference in scale carries over to the OLS estimated coefficients. Hence by including lagged GDP growth, the unified framework through which to compare information, i.e., the factor model, is lost.¹⁹ Further, the overall performance of the nowcast is not much affected by including lagged GDP growth, see Fig. 11 in Appendix E. We therefore decide to not include lagged GDP growth as a regressor in the predictive OLS regression.

The reported result for asset prices is unique for this study. In particular, [Giannone et al. \(2008\)](#) do not find similar effects of asset prices using the same methodology on U.S. data. In [Giannone et al. \(2008\)](#) the marginal impact of “Financials” in the U.S. is negligible. They find that in the U.S., surveys are the most important type of data in addition to labor market data. In Norway, surveys are only available on a quarterly frequency and are therefore not included in our model. One possibility is that surveys in the U.S. are capturing the information in asset prices and thus make the financial block redundant. To test for this we have run the model on a U.S. data set which is similar to the one used by [Giannone et al. \(2008\)](#), but without any survey variables.

¹⁸ The large positive effect for the third month is sensitive to whether we order “Financials” as the last block of the month or as the first block of the month. It is not obvious, which ordering to choose. However, bearing in mind that financial variables are forward looking variables, we find it reasonable to order them as the first block. The large positive effect for the two first months is not sensitive to this ordering.

¹⁹ In particular the marginal impact of the blocks following a new release of lagged GDP growth becomes hazardous to interpret. The picture is less robust with respect to the number of factors and less robust to the inclusion/exclusion of different blocks. When the alternative model is run with the model’s backcast as an estimate of lagged GDP growth, and without updating that estimate through the quarter, the results for the marginal effect of the blocks are very similar to results from our chosen model. See Fig. 11 in Appendix E for details.

We find that the marginal impact from the block of financial variables does not change much.²⁰

In general, although intuitively one should think that asset prices would contain information about the macro economy, such results have been empirically elusive. Thus, there is reason to ask whether there are special features of the Norwegian economy that can explain the affirmative results reported here.

4.2 The informational content of asset prices

This study differs from [Giannone et al. \(2008\)](#) in that we are applying their approach to a small, open economy and in that we are using a larger “Financials” block that contains industry specific returns as well as financial ratios. Moreover, the median size of companies on Oslo Stock Exchange is very small compared to the U.S. The size factor as described by [Fama and French \(1992, 1993\)](#) has been connected to business cycle risk in the literature. In the following we elaborate on these differences and seek to explain the high informational content of asset prices in Norway.

The median company on Oslo Stock Exchange has 0.18 billion USD in market capitalization while the median market capitalization is 0.79 billion USD for a company in the Russell-3000 Index, representing 98 percent of the total market capitalization of the U.S. equity market. The small cap segment in the U.S., represented by the Russell-2000 index has a median size company of 0.47 billion USD. The micro cap segment, represented by the Russell Microcap Index has a median size company of 0.15 billion USD. The small cap and micro cap segments constitutes 8 percent and 3 percent respectively of the total market capitalization of the U.S. equity market.

[Fama and French \(1992, 1993\)](#) found that smaller companies attracted a risk premium relative to large companies. They motivated their findings by reference to a [Merton \(1973\)](#) Intertemporal Capital Asset Pricing Model (ICAPM) framework, suggesting that investors might have different needs for hedging changes in the investment opportunity set and that their priced factors serve as proxies for state variables in such a setting. Small size companies could be more vulnerable in recessions and thus require a risk premium above the market average to attract investors. The finding in [Petkova \(2006\)](#) that the size factor proxy for a default spread surprise factor is consistent with such an explanation. [Liew and Vassalou \(2000\)](#) show that the size (and value) factor help forecast future rates of economic growth. [Lettau and Ludvigson \(2001\)](#) and [Vassalou \(2003\)](#) show that the informational content of the size factor is reduced when macroeconomic risk is accounted for.

In view of these findings it is not surprising that pricing of companies on a small to micro cap exchange like Oslo Stock Exchange contains more information with respect to current quarter GDP in Norway than what a broad market index does in the U.S., which is what is used in [Giannone et al. \(2008\)](#). Moreover, [Giannone et al. \(2008\)](#)

²⁰ To make the results for the U.S. comparable with the results for Norway, we deviate from [Giannone et al. \(2008\)](#) and run the model on the U.S. data set assuming that financial variables are the first block of data released in a month. However, results are also similar when including financial variables as the last block of data in a month.

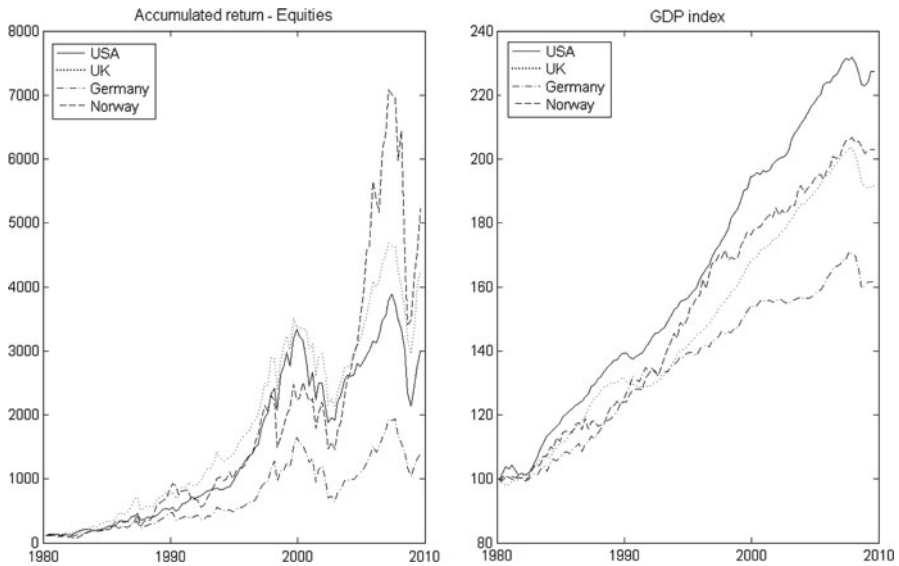


Fig. 3 Accumulated returns and GDP for some selected countries. Index 1979q4 = 100. The figure spans the data period from 1980q1 to 2009q4

used only a few aggregated market indexes to represent equities. The financial block in this study contains 21 series covering industry specific return and dividend yield. Factor estimation on a broader data set could benefit by potentially allocating larger weights to industries that are more cyclical, thus parts of the financial block could be better aligned with movements in macro data.

A recent study by Næs et al. (2010) show a strong predictive relation between illiquidity measures for equity prices and the business cycle both in Norway and in the U.S. They find that in the U.S. the illiquidity measure on small companies but not large companies, have a significant coefficient in a regression on GDP growth.²¹ This finding suggests that disaggregated financial data should be considered in the approach of this article when applied to the U.S.

The Norwegian economy is characterized by being small and open. One conjecture is that because of the openness and the small size, Norway experiences more significant shocks to productivity than what the U.S. does. Smaller size could mean that the economy is less diversified and that, e.g., a technology shock will have a larger impact on the aggregate economy. Examples could be a sudden change in availability of foreign labor, unexpected domestic labor market frictions, news about a large contract being won by one of Norway's few large companies, etc. The effect on real activity could be rather immediate for such shocks; hence the lags in macroeconomic statistics could be an important reason why equities are more informative for nowcasting. One observation that supports this conjecture is that both the volatility on Oslo Stock Exchange and the volatility of Norwegian GDP growth are larger than for comparable variables in most other countries, see Fig. 3 and Table 2.

²¹ See Table 15 in their internet appendix.

Table 2 Annualized volatility in percent

Country	USA	UK	Germany	Norway
Equities	16.8	17.1	21.0	26.9
GDP growth	1.6	1.5	1.9	2.6

Based on data from 1980 to 2009

In a recent study of the U.S. economy, [Beaudry and Portier \(2006\)](#) show that shocks to stock prices are strongly colinear with anticipated productivity shocks leading to a delayed but permanent change in productivity. Their results indicate that most of the productivity shocks are anticipated by the stock market long before they are materialized. In other words, shocks that affect future productivity will be immediately captured by the pricing in the stock market.

To check which variables within the “Financials” block are particularly important, we re-estimate the model with selected variables excluded. In [Fig. 4](#) we can see the effect of excluding the currencies or all equity variables, respectively. The third bars are the results when all equity variables are included but currencies are excluded. We see that results are not much affected by removing currencies from the “Financials” block. The last bars are the results when all equity variables are excluded, i.e., only currencies are left in the “Financials” block. Here we see that results deteriorate more, and across the entire quarter. Thus, we find that asset prices on Oslo Stock Exchange are much more important than the value of NOK versus other currencies. This finding is expected as the currency rate is a relative price involving the state of two economies, not only Norway. Prices of Norwegian equities are presumably more related to the absolute level of production and consumption in Norway. The currency market is also a truly global market while equity prices are determined by market participants on Oslo Stock Exchange that to a larger degree has a local presence.

Equities listed in different countries are strongly correlated, indicating the presence of a common international factor in the pricing of equities. Oslo Stock Exchange is no exception, however, a large fraction of the market cap in Oslo is positively exposed to the price of oil. Hence, OSE is more correlated with the price of oil than most other stock exchanges, and this may explain the somewhat lower correlation with other country indices.

[Table 3](#) shows correlation between key equity markets and changes in the price of oil. We see that Norway differ somewhat from the other markets. These effects are even stronger prior to the financial crisis in 2008 which had a large positive impact on correlations between equity markets and on correlation between equities and the price of oil. A possible explanation for the high informational content in Norwegian asset prices that we find in this article could be that the equity market is a proxy for either an oil price factor or an international factor. We proceed to check our results for such an effect.

With a view to the low informational content of the “Commodity Prices” block, it would be surprising if the good nowcasting performance of the “Financials” block was due to the high correlation between returns on OSE and the price of oil. To check for this we remove both the total market index for OSE and the sector index covering the

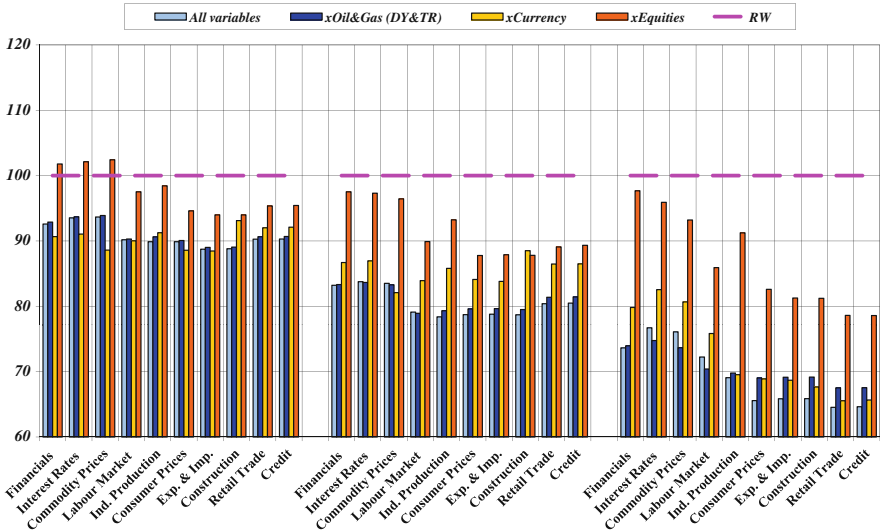


Fig. 4 MSFE across data blocks when excluding selected variables in the “Financials” block. Bars from left to right: All variables, excluding Market index and Oil & Gas sector both among total return series and among dividend yield series, excluding currencies as well, excluding all equities. Depicting the first, second and third generic month of the quarter for which the nowcast is done. Out-of-sample nowcasts from 1998q1 to 2008q4. Data sample starts from 1990m1

Table 3 Correlation between Norwegian equities and main markets and oil price changes

	Norway	U.S.	E.U.	U.K.	Germany
U.S.	0.64				
E.U.	0.67	0.81			
U.K.	0.72	0.79	0.81		
Germany	0.66	0.75	0.79	0.78	
Brent Blend	0.25	0.09	0.16	0.09	0.02

Local currencies; E.U. and oil price in USD. Based on data from 1990 to 2009

oil and gas industry on OSE, both for total return and dividend yield. We remove the total market index because of the high weight it allocates to the oil and gas sector. The results are shown in the second bars from the left in Fig. 4. They are almost the same as the original result, confirming the low informational content of the “Commodity Prices” block. As petroleum activities are capital intensive and incur substantial fixed costs, it is not surprising that the price of oil and the petroleum related content on the exchange do not have an immediate effect on real activity.

Turning to test for an international equity effect, in Fig. 5 we have included international equity data in block number 2, covering seven main trading partners to Norway.²²

²² Results are robust to including international equity data as the first block in the month. See Appendix C for details.

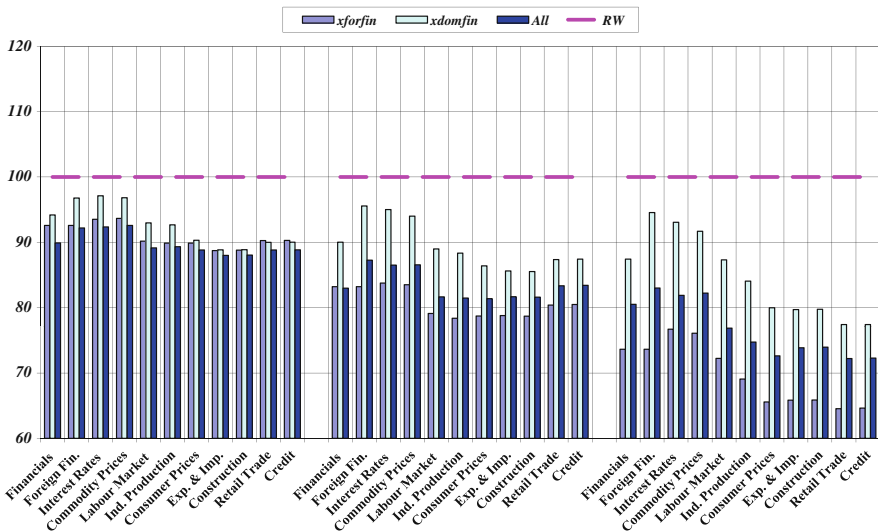


Fig. 5 MSFE across data blocks and the effect of foreign financials. Bars from left to right: All domestic variables, including foreign financials and excluding domestic financials, including both domestic and foreign financials. Depicting the first, second and third generic month of the quarter for which the nowcast is done. Out-of-sample nowcasts from 1998q1 to 2008q4. Data sample starts from 1990m1

International interest rates are not included. This inclusion has a negative impact on the performance, hence pricing of equities abroad represents noise relative to the nowcast. The strong performance of Norwegian equities are thus not a proxy for an international equity factor.

Lastly we include all 13 blocks in Fig. 6; here “Foreign Financials” contain both interest rates and equity data, and two mixed international blocks contain various macroeconomic series, see Appendix G (Electronic supplementary material) for details. The result is again substantially worsened when both international equity data and the “Mixed International 2” block, which contains survey data for the U.S., is included. “Mixed International 1”, containing consumer prices and industrial production for various countries, has little impact either way.

Keeping in mind that we are nowcasting current quarter GDP growth, this result is not surprising. While an open economy clearly is influenced by real activity in other countries, one would expect international changes to influence Norwegian real activity with a lag. Figure 6 indicates that the lag is longer than 1 month.²³ This result for the 13-block model is also robust to the number of factors included.

Even though including more information improves the factors in terms of explanatory power among the independent variables, see Table 1, it worsens the predictive

²³ Fig. 12 in Appendix F shows the performance for the different blocks when forecasting GDP growth four quarters ahead. The figure shows that the different blocks will not affect the forecasts in the same way as they affect the nowcasts. The reason is that the factors need to be forecasted using the transition equation (Eq. 2). The forecasted factors will then mostly be determined by the dynamics in the transition equation and much less affected by new information reflected in the factors used for nowcasting.

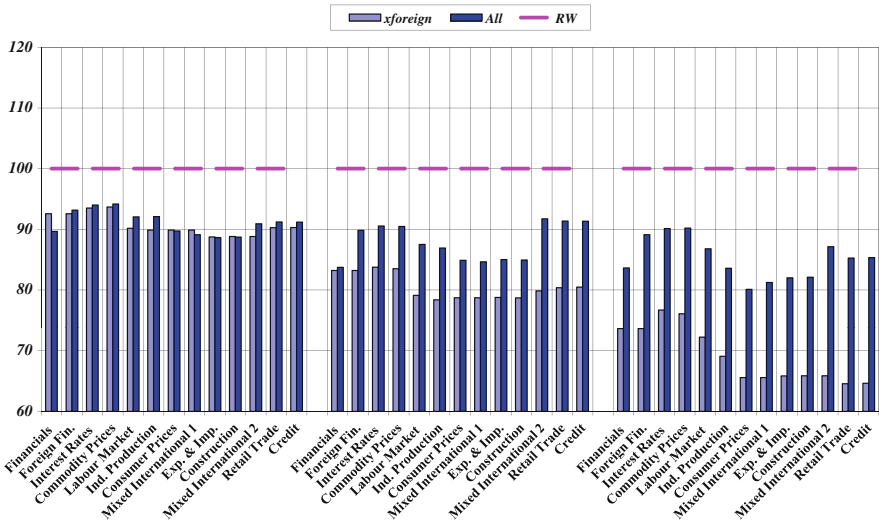


Fig. 6 MSFE across data blocks when including the three international blocks. *Bars from left to right:* All domestic variables (no international blocks), including foreign financials and international macro data. Depicting the first, second and third generic month of the quarter for which the nowcast is done. Out-of-sample nowcasts from 1998q1 to 2008q4. Data sample starts from 1990m1

power of the factors, indicating that the increased variability is not related to GDP growth. Hence, in this model more information is not always a good; it may destroy some of the structure in the existing information and thus harm the predictive power of the model. [Boivin and Ng \(2006\)](#) show that adding more variables or observations only improve forecasts if it leads to a tighter relationship between the components in the data set (X_t) on the one hand and between X_t and the variable to be forecasted (GDP growth) on the other hand. They provide examples where adding more data has perverse effects. See [Boivin and Ng \(2006\)](#) for further discussion on this topic.

5 Summary and conclusion

In this article, we have used an approximate dynamic factor model on Norwegian data to study the marginal impact on a nowcast of current quarter GDP growth from new data releases. We have found that financial data contribute the most to the precision of the nowcast, in particular data from Oslo Stock Exchange. Hence, financial data provide a valuable contribution in addition to statistically compiled indicators. We find that in particular labor market data and industrial production indicators also contribute favorably to the precision of the nowcast.

We ascribe the high informational content of asset prices in Norway partly to the small size of companies on Oslo Stock Exchange and partly to Norway being a small and open economy. These are features that distinguish our data from the U.S. data where broad market asset prices are less valuable in a similar model. We have shown that our results are not driven by the high petroleum content on the exchange or by

the high correlation between Oslo Stock Exchange and international markets. We find that the seven sector indices that are included in the data are all close to being equally important. However, sectors organized along other attributes have not been investigated. The strong results in the present article motivate further studies.

Results deteriorate sharply when international macro variables are included in the data set. Although Norway is an open economy this is not surprising as international conditions supposedly have an effect on activity in Norway with a time lag. Even though including international data bring about factors that explain more of the variance among the independent variables, this increased variance in the factors is of a nature that has low correlation to the current quarter GDP growth in Norway, thus reducing the predictive power of the factors.

A model establishing a link between asset prices and the current state of the economy is valuable from the point of view of the policy maker. The link presented here provides a source to real time information and a way for the policy maker to combine such information with a broader set of less timely data.

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Appendix

A Algorithm for the estimation procedure

- (i) Estimate the common factors, F_t , in Eq. (1) by extracting the first r principal components from the balanced part of the data set. The common factors can be consistently estimated by principal components provided that the idiosyncratic shocks exhibit, at most, “weak” cross-correlation, see [Forni et al. \(2000\)](#) and [Stock and Watson \(2002b\)](#).
- (ii) Compute all the parameters in the model. That is, estimate A , B , Λ and Ψ . First, estimate Eq. (1) for the balanced part of the data set using the estimated factors, \widehat{F}_t , from step (i) and obtain $\widehat{\Lambda}$ and $\widehat{\Psi}$. Then estimate the VAR model in Eq. (2), using the estimated factors, \widehat{F}_t , to obtain \widehat{A} and \widehat{B} .
- (iii) Replace the parameters with their consistent estimates obtained from step (ii). Re-estimate the factors, \widehat{F}_t , recursively using the Kalman filter and Kalman smoother, now on the basis of the unbalanced panel.

B Robustness to the number of factors

See Fig. 7 and Table 4



Fig. 7 Nowcasting performance using different number of factors. *Upper panel* describes the 10 block variant of the model. *Lower panel* contains the full 13 blocks

Table 4 Nowcasting performance at the end of the quarter using different number of factors

q / r	1	2	3	4
1	72.0	69.6	76.0	74.0
2	—	64.6	75.2	77.1
3	—	—	64.3	71.4
4	—	—	—	67.8

MSFE of the factor model relative to MSFE based on a constant growth rate. Out-of-sample nowcasts from 1998q1 to 2008q4

C Robustness to the ordering of blocks

See Figs. 8 and 9

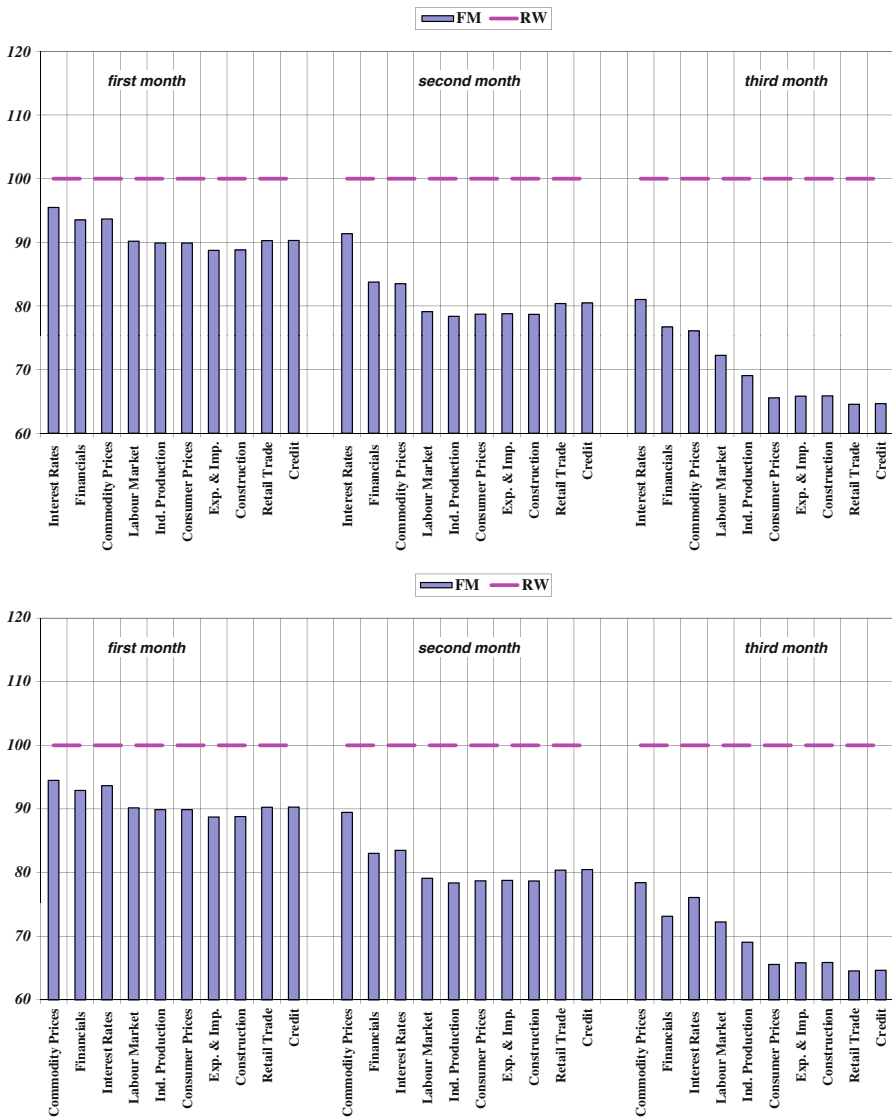


Fig. 8 Nowcasting performance using different ordering of the blocks. The *upper panel* describes the 10 block variant of the model when “Interest Rates” is ordered before “Financials”. The *lower panel* describes the 10 block variant of the model when “Commodity Prices” is ordered before “Financials”

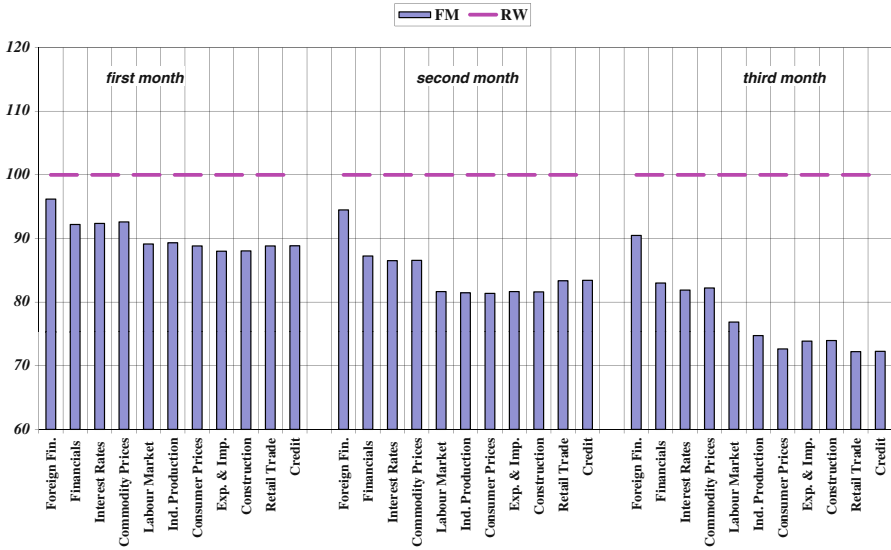


Fig. 9 Nowcasting performance using different ordering of the blocks. The panel describes a 11 block variant of the model when “Foreign Financials” is ordered before “Financials”

D Robustness to data revisions

See Fig. 10

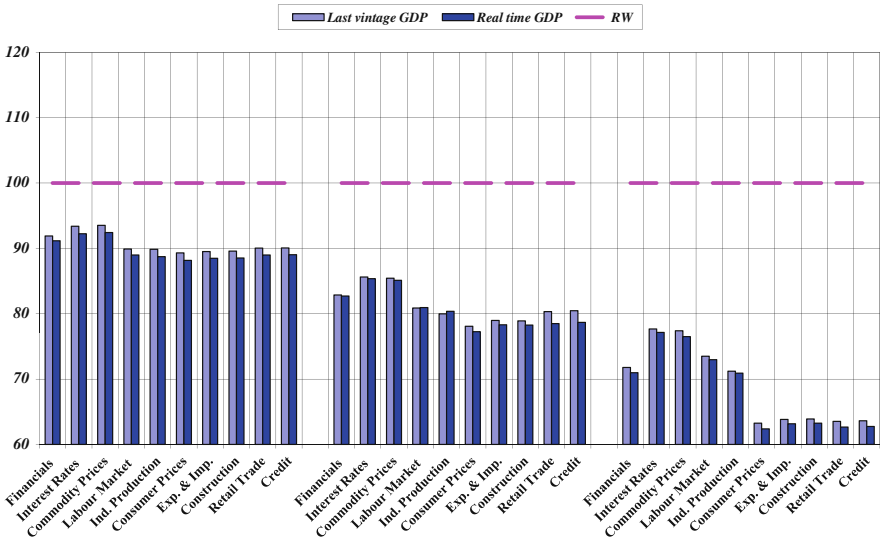


Fig. 10 Comparison of nowcasting performance using real time GDP and last vintage GDP. Out-of-sample nowcasts from 2000q3 to 2008q4. Data sample starts from 1990m1

E Effects of including lagged GDP as predictor

See Fig. 11

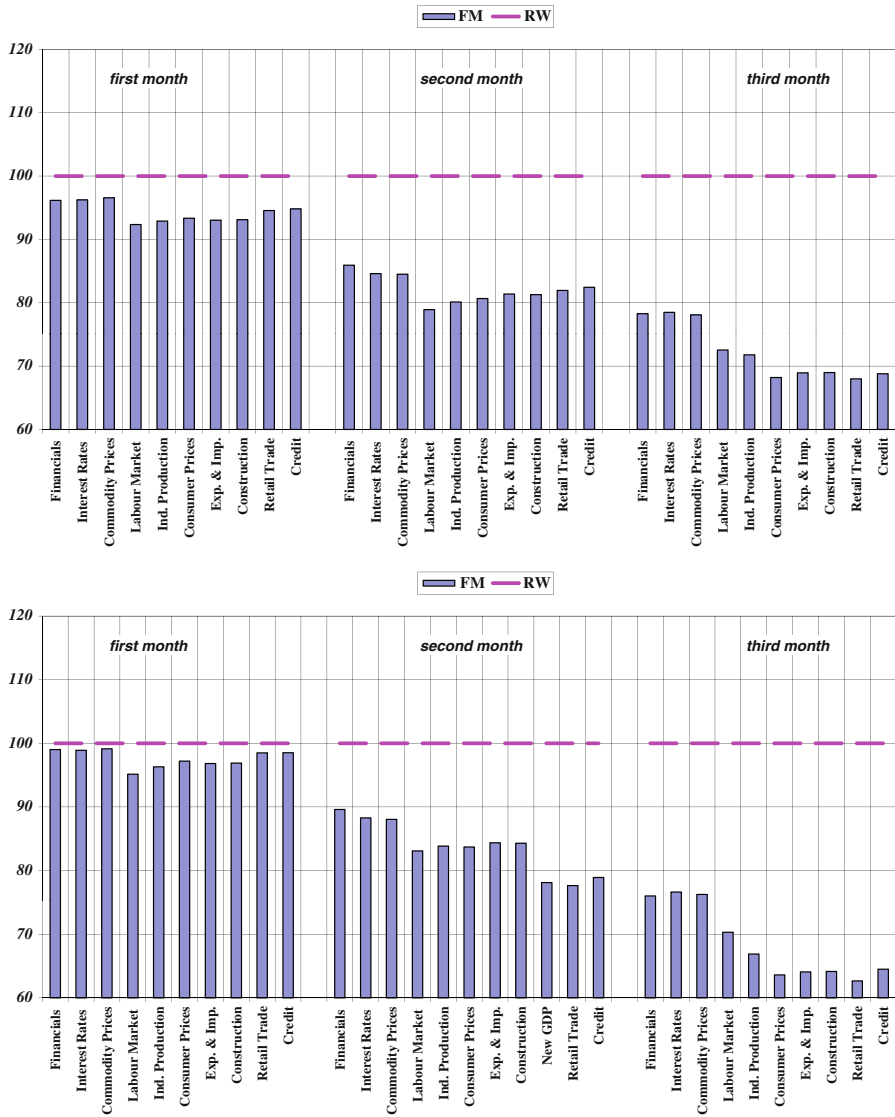


Fig. 11 Nowcasting performance when including lagged value of GDP as predictor. *Upper panel* describes variant using an estimate for lagged value of GDP as predictor. *Lower panel* describes variant where we update with the actual value of lagged GDP after it is released

F Forecasting performance

See Fig. 12

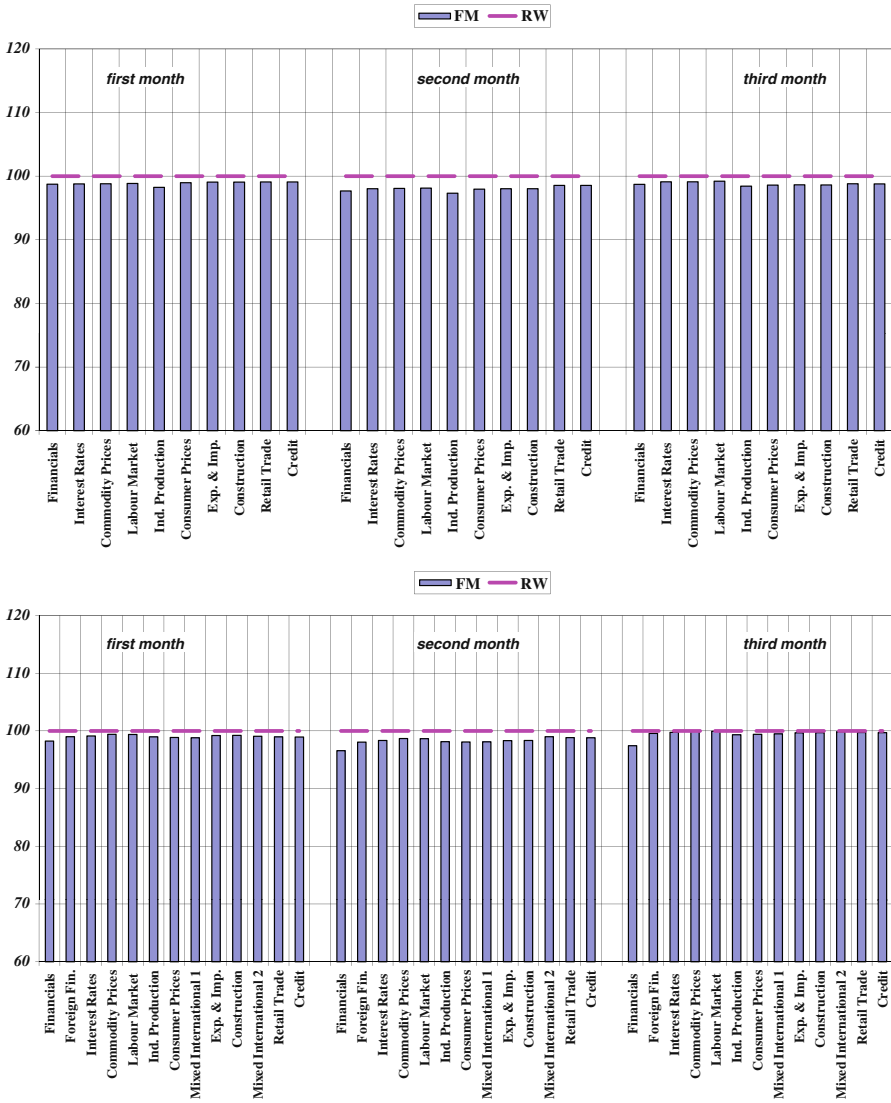


Fig. 12 MSFE across data blocks when forecasting GDP growth 4 quarters ahead. Upper panel describes the 10 block variant of the model. Lower panel contains the full 13 blocks

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