Nowcasting

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Nowcasting refers to methods for forecasting the current state of the economy and developments in the short term. For example, the National Accounts are published with a time lag and consequently no statistics are usually available for GDP growth in the current and preceding quarters when making a forecast. However, more up-to-date indicators are available and can be used in forecasting models to determine the current level of GDP growth. This article presents two ways of using large amounts of information to make forecasts in the short term, namely by aggregating many models and methods in which the weighting of series takes place prior to modelling. Particular focus is placed on how a dynamic factor model, with the help of more than 100 indicator variables at a monthly frequency can forecast quarterly percentage changes in GDP. We show that the model makes accurate forecasts. The factor model is also useful in understanding how the flow of information over time affects the forecasts for a macro variable. An application shows how GDP forecasts during the fourth quarter of 2008 were gradually revised downwards because the availability of new indicators changed the assessment of how the global financial crisis affected the Swedish economy.

1. Introduction

The repo rate affects the economy with a certain time lag. Forecasts therefore play an important role in the monetary policy decision-making process. In order to be able to make good decisions on the repo rate the Executive Board of the Riksbank must have quick access to reliable information on the current state of the economy and the most likely developments in the period immediately ahead, including uncertainties concerning the accuracy of the forecasts. A sound understanding of the macroeconomic situation is also a prerequisite for being able to make good assessments of developments in the long term. A forecast is built up by estimating where the economy is at present and is likely to be in the near future and then forming a view of where it is heading going forward. Depending on the forecast horizon, the Riksbank uses different models and methods to gain a good understanding of the development of the economy. In the case of the long forecast horizon, the Riksbank uses structural economic models that are based on theoretical economic links. For the shortest forecasts, the Riksbank uses statistical models that utilise empirical links in a large volume of available data.

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A large amount of indicator information is published at different frequencies. For example, financial market data, such as share prices and exchange rates, is available in real time, while the expectations of economic agents are observed every month, for example in the form of consumer confidence surveys and the purchasing managers' index. Another variable that is observed on a monthly basis is industrial production. Figures on this are published with a time lag of six weeks as it takes time to compile the data. Together, all the indicator variables comprise a large volume of time series at different frequencies that can be used, for example, to forecast GDP.

New statistical models that make use of this considerable flow of information have been developed over the last 10 years. In the case of the shortest forecast horizons, the forecasting performance of the statistical models improves when current indicators are included. As this improved forecasting performance relates to the current situation and the immediate future, these specific forecast models are usually referred to as nowcast models[1] in the world of central banking and in the research field. The Riksbank has reviewed its nowcast models, which we discuss in this article. In the first section of the article we discuss forecasts at different horizons. We then focus on nowcast models that are used for the shortest forecast horizons. In conclusion, we provide an example of how one of the nowcast models, the dynamic factor model, uses the flow of data to update the GDP forecast.

2. Different forecasting methods for different horizons

A forecast is built up by estimating where the economy is at present and then forming a view of where it is heading. It is normally assumed that the economy is moving towards a state of equilibrium, with normal resource utilisation, in which inflation is in line with the central bank's target. Due to publication time lags, that is the time it takes before new outcomes are published, we must also often make forecasts for the current situation and the immediate future. The current situation is the starting point for the forecast path that describes how the economy is expected to get from the current situation to the state of equilibrium. This three-step procedure for forecasting is described by Faust and Wright (2013) and comprises the following components (see Figure 1):

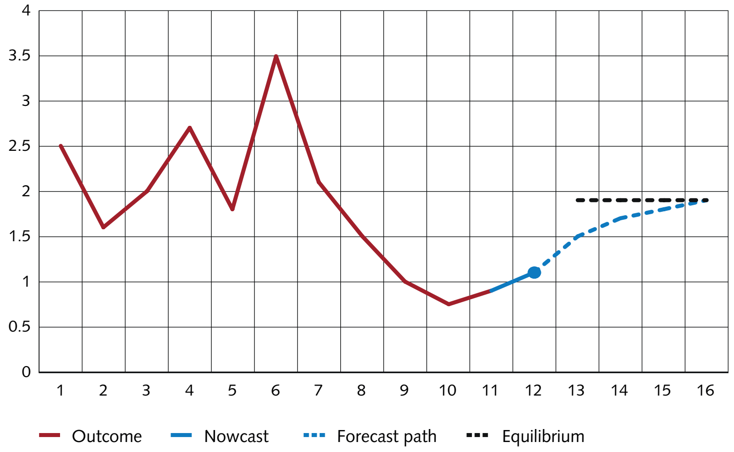
1. The current situation – *where* the economy is,
2. Long-term equilibrium – *where* the economy is going,
3. The path – *how* the economy will get from the current situation to equilibrium.

Usually, economic theory and estimated correlations in the data are used to understand and generate forecasts. In the case of the current situation, statistical models that utilise the historical correlations in the data are used. In the case of long-term equilibrium and the path that leads there, structural economic models that are more based on theoretical links

1 Nowcasting is used in meteorology as a term for weather forecasts for the next 12 hours. The term was introduced in the field of economics by Giannone et al. (2008).

are used. The economic and statistical models generate model forecasts with the help of a computer-based econometric programme. Even a very sophisticated model represents a simplification of reality and its results therefore need to be interpreted. Consequently, model forecasts are always complemented by analyses and assessments by sector experts. By using information that is not included in the models and insights that the models are not able to capture, these experts play an important role in the forecasting work.

Figure 1. Outline of a forecast showing nowcast, equilibrium and the forecast path between them



LONG-TERM EQUILIBRIUM AND THE PATH TO IT

In simple terms, we can say that long-term equilibrium in the economy arises when we ignore temporary seasonal and cyclical effects. In structural economic models, the long-term equilibrium[2] is determined by growth theory. There are two different categories of structural economic models and the Riksbank uses both.

The first is econometric models consisting of several equations that are often estimated on quarterly data from the National Accounts. In these models, the various components of the economy are described by single equations. The system of equations then simulates how the different components of the economy interact with each other. The assessment of the development of the economy in the long term is largely based on theoretical analysis, while the path taken is determined by patterns in the data. Moses[3] is one such model that is used by the Riksbank.

The other category of modern economic models are Dynamic Stochastic General Equilibrium models (DSGE[4]) of the new-Keynesian type. These models are based on the optimal behaviour of forward-looking consumers and producers. In such a model, the

2 Equilibrium should be understood as the state the economy is in when the effects of all shocks have faded. A shock is an unexpected disruption to the economy.
3 See Bårdsen et al. (2012).
4 DSGE models are based on the assumption that all markets return to equilibrium after the economy has been exposed to a shock that led away from equilibrium.

economy returns to its state of equilibrium because individual agents adapt their supply and demand. The Riksbank's main macroeconomic model is such a DSGE model and is named Ramses.[5]

FORECASTS OF THE CURRENT SITUATION

According to the approach in Figure 1, forecasts of the initial position differ from those for other horizons due to the access to indicator information. The horizon for nowcasts is usually the current and next quarters. Sometimes, however, the horizon may be six months after the latest National Accounts' outcome, as this is normally published with a time lag of six weeks. Such publication time lags thus mean that nowcasts sometimes have to be made after the event. This means that the term nowcast is somewhat misleading as it refers to describing the current situation. A forecast for the future, even if we mean the very near future, should really be called a "nearcast" and a forecast for an earlier period should be called a "backcast". Despite the fact that a backcast is conceptually different from a nowcast and a nearcast, the same statistical models are used for all three types of model forecasts. We can therefore view these models as one category and discuss them together. For this reason, we hereinafter refer to all these models as nowcast models.

A typical feature of nowcast models is that they use a large quantity of data and information from indicators that are available before the outcome of the forecast variable. An application with Swedish GDP as the forecast variable is presented later in the article. Nowcast models usually consist of statistical time series models that focus on regularities in economic and financial data. The good availability of a large amount of data has contributed to the development of new statistical procedures for exploiting this data. One such procedure is a factor model that compresses a large amount of data into a summarising measure, which makes it possible to estimate a relation between this measure and the forecast variable.

Nowcast models that use large amounts of data have become very popular at central banks.[6] This can be explained by the fact that powerful computers make it possible to make advanced and time-consuming calculations, but also by the fact that these models often produce a good forecast.

Publication time lags may lead to indicator information being published before an outcome for the forecast variable is published. Such complementary data therefore represents important input to short-term models if it is published at more frequent intervals than the forecast variable. One way of using information of this type is in bridge equations in which the higher frequency (for example a month) is bridged (converted) to the lower (for example a quarter). The bridging procedure is described in more detail in the section below.

5 See Adolfson et al. (2013)
6 See for example Norges Bank (2014).

3. Two nowcast models that can mix different frequencies

Here we will present two different types of nowcast model that can use a large amount of indicator information to improve forecasting performance. The first type consists of bridge equations that estimate many small models and then aggregate their forecasts. The second type consists of factor models that weigh together information in several series and then make a forecast based on the aggregate variable or factor.

BRIDGE EQUATIONS

Bridge equations are used to convert variables that are observed at different frequencies. Assume that we have a variable Y that is measured once a quarter and an indicator variable x_1 that is measured once a month. In order to forecast Y we must first convert x_1 to a quarterly frequency. In addition, the observations of x_1 usually stretch over a longer period than the observations of Y, but not always an entire quarter longer. Bridging takes place in two steps.

1. x_1 is extended with forecasts where necessary to "fill out" the quarter.
2. x_1 is converted to a variable (X_1) at a quarterly frequency with the help of the mean value or sum of the monthly observations carried out during the quarter.

With the bridged monthly variable one can then make a new model for the forecast of Y

(1) $$Y=a+b\times X_1+e,$$

where e is a (randomly distributed) error term. Using the equation, we can then forecast the next value of Y.[7] MIDAS[8] is a development of the bridge equation and makes it possible to estimate the equation without first converting the monthly indicator variable x_1 to the quarterly frequency X_1. The MIDAS equation relates the quarterly variable Y directly to the monthly variable x_1.

If more indicator variables are used we will get more forecasts for Y, one from each bridge equation. From the total number of model forecasts we can either try to select the "best" model or use information from all the models[9]. In the latter case, it is usual to calculate the mean value of the model forecasts or to study the entire distribution.

FACTOR MODELS

Another type of nowcast model is the factor model, which compresses the information in a large number of indicator variables into a few summarising factors. In order to illustrate the factor concept we posit two indicator variables x_1 and x_2 and that they have a common underlying, non-observable factor f in accordance with the following model

7 Note that the bridged variable X_1 (due to outcomes and projections) can be treated as observed a quarter beyond Y.
8 MIDAS stands for MIxed DAta Sampling, see Ghysels et al. (2007)
9 See Kuzin et al. (2013)

(2) $x_1 = c \times f + e_1$
$x_2 = d \times f + e_2$

where e_1 and e_2 is the variation that is unique for x_1 .respectively x_2, while the factor f is common. The estimated factor $\hat{f}$ can be seen as a weighted aggregate of the observed variables

(3) $\hat{f} = L_1 x_1 + L_2 x_2$

where the weights L_1 and L_2 are estimated with the help of principal component analysis[10]. Although we show two variables in the example there is no limit on the number of variables. The factor model is used to reduce the information in hundreds of indicator variables to a few common factors. For example, a common factor can be interpreted as a business cycle. The starting point then is that there is only one common cycle whose cyclical variation affects the different sectors of the economy. It is also the case, however, that even if the business cycle is clearly expressed in many macroeconomic variables it is in actual fact not possible to observe it. One way of capturing the business cycle is by using the estimated common factor $\hat{f}$. The Riksbank's indicator of resource utilisation, the RU-indicator[11], is one example of this. The RU-indicator is estimated as a non-observable factor with the help of labour market data and survey data from the Business Tendency Survey of the National Institute of Economic Research. This measure of the business cycle can then be used in, for example, bridge equation (1). In this way, we can use the information in a large number of macroeconomic variables to make forecasts for the variable Y.[12] We can also model the interaction and the dynamics between the variable Y and the measure $\hat{f}$. The interaction means that Y and $\hat{f}$ mutually affect each other. Dynamics here means that Y and $\hat{f}$ are affected by their own histories. One example of such a multiple equation system is the Factor-Augmented Vector Autoregressive model (FAVAR).[13]

MORE THAN JUST FORECASTS

The forecasting performance of the factor model that calculates a statistical measure of the economic situation is normally good. Understanding the underlying economic forces that govern the forecasts is also important, not least for the decision-makers. This has led to the development of methods[14] that that make it possible to quantify the underlying driving forces. Forecasters can themselves define a driving force as a single indicator variable or as a group of indicator variables. If we continue with the example in which we have a forecast

10 Principal component analysis is a statistical method that calculates the linear combination of the variables that explain as much as possible of the variance in the data. The first principal component then follows the direction in which the data varies most. By using the principal components that summarise the main part of the variation we can represent a large proportion of the information in a few components.

11 http://www.riksbank.se/sv/Statistik/Makroindikatorer/Resursutnyttjandeindikatorn-RU-indikatorn/

12 See Stock and Watson (2002) and Marcellino and Schumacher (2010) for the MIDAS factor.

13 See Bernanke et al. (2005) for an application to monetary policy.

14 See Bańbura and Modugno (2014).

variable Y and an estimated factor $\hat{f}$ based on two indicator variables x_1 and x_2, we can with the help of the factor model (3) above substitute in the indicator series.

$$4) \quad Y = \alpha + \beta\hat{f} + \vartheta = \alpha + \underbrace{\beta L_1 X_1}_{\substack{\text{Contribution} \\ \text{from } x_1}} + \underbrace{\beta L_2 X_2}_{\substack{\text{Contribution} \\ \text{from } x_2}} + \vartheta.$$

This is the simplest way to divide up the indicator variables' contributions to the forecast for the variable Y. The forecast for the variable Y is then gradually updated as new observations of the indicator variables become available. To do this, we need data from two different points in time. Assume that the later body of data is the previous body of data plus new observations for some of the indicator variables (for example variable X_1 in equation 4). If the new observations are exactly in line with those that the factor model predicted, then the forecast is not revised. If, on the other hand, the outcome for an indicator variable deviates from the earlier forecasts of the factor model, then the forecast for Y will be revised.[15] The size of the revision depends on how big a surprise the indicator is (that is the forecasting error for X_1) and how relevant the indicator is for the forecast variable (that is the term βL_1 in equation 4).[16] The division of the factor model in (4) can therefore quantify news contributions, that is how surprises in the flow of information from one or more indicator variables lead to forecast revisions for the variable Y. Such news interpretation can be formulated as follows: "As the growth rate for industrial production was lower than expected (according to the model) the GDP forecast has been revised downwards by x percentage points".

4. A factor model for Swedish GDP

Above we discussed two different types of nowcast model that can use a large amount of indicator information to improve forecasting performance. In this section we provide an example of how one can use the dynamic factor model. In the example, quarterly percentage changes in seasonally-adjusted GDP are forecast and analysed.

We first study how accurate the factor model's forecasts have been on average.[17] We then use the model to study the fourth quarter of 2008, when GDP growth was surprisingly low due to the global financial crisis.

15 If X_1 and also X_2 are included in the model above then it will be natural to measure how Y changes when X_1 and X_2 deviate from the model's forecasts of them.

16 In the empirical example below we also correct for the indirect effect of the forecasting error for X_1 affecting the contribution of X_2 even if there is no new observation for X_2.

17 As the model was not in use at the Riksbank we have conducted a study "as though we had" used the model.

INDICATORS OF GDP

126 indicator variables that are measured every month are used for the illustration of GDP. The indicators come from different parts of the economy:

i) indicators that affect the business cycle (such as monetary policy, fiscal policy, developments abroad and terms of trade),

ii) variables that react at an early stage to the business cycle (such as corporate profits and stocks of manufactured goods),

iii) series that measure the beginning of a production chain (such as incoming orders and approved building permits),

iv) the expectations of economic agents (such as consumer and producer confidence, the purchasing managers' index and the share index).[18]

Category iv) differs from the others as it consists of the survey responses of various economic agents. In its Business Survey[19], for example, the Riksbank attempts to acquire up-to-date information on developments in the business sector by interviewing companies that predominate in their sectors and then quantifying the responses to form an indicator of economic activity. This means that the information is available long before the official statistics are published.

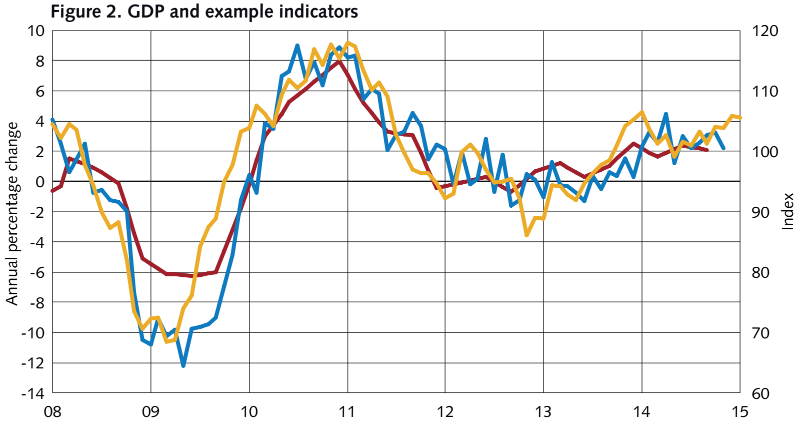
Survey responses are sometimes referred to as soft data, while hard data may for example be the statistics included in Statistics Sweden's calculation of GDP. Survey data becomes available before hard data, but hard data is considered to contain more reliable information. Figure 2 shows GDP together with two indicators: a hard data series, namely production in the business sector (BP), and a soft data series, the Business Tendency Survey (BTS). The first thing we can see in Figure 2 is that there is a lot of background noise[20] in the indicators. Neither of the two series can explain GDP. This shows that it is difficult to forecast GDP, but it also demonstrates the importance of studying many indicators and trying to extract the common information embedded in them. Figure 2 also shows that the indicator information stretches further into the future than GDP does. We can also see that BTS stretches a month further than BP.

18 The points describe a conceptual division of available indicators. In the empirical example below we have dived the indicators into the categories real, financial, surveys, foreign and prices as this provides a clear way for the forecaster to interpret the flow of information.

19 See Hokkanen et al. (2012).

20 The term background noise refers to movements in the indicators that do not help to explain movements in GDP.

Figure 2. GDP and example indicators



Note. All three series are at a monthly frequency. GDP and BP (production in the business sector) are published by Statistics Sweden. BTS (the Business Tendency Survey) is an index series that is shown on the right axis and is published by the National Institute of Economic Research. BP and GDP are shown on the left axis in terms of the annual percentage rate of change. GDP is a time series at a quarterly frequency that is linearly interpolated to a monthly frequency.

Other examples of indicators used in the factor model for Swedish GDP are financial variables and international variables. The financial markets are a rich source of highly-frequent information where data on expectations of the future is continually updated. The international situation is important to Sweden and it is therefore also important to study variables from other countries, both for the forecasts themselves and in order to understand the economic situation. All-in-all, we have compiled a database consisting of 126 leading indicator variables at a monthly frequency.

FORECASTING ACCURACY

Based on this database, we have carried out a forecast evaluation for the dynamic factor model with regard to the quarterly growth of GDP. The evaluation period covers 28 quarters from the first quarter of 2005 until the fourth quarter of 2011. For each quarter during this period we have re-estimated the factor model from several points in time before and after the quarter the forecast relates to. For example, in the forecast for the first quarter of 2005 we used data that was available at the beginning of September 2004. The next forecast for the first quarter of 2005 is based on information from October 2004. As a month has passed between the two forecasting occasions an additional observation is available for each indicator variable that can be used to forecast GDP for the first quarter of 2005. Then a further month passes before we make yet another forecast for the same variable. Forecasts based on an increasing amount of data are made eight times until Statistics Sweden publishes the actual outcome for GDP growth in the first quarter of 2005 in May 2005. This means that we will have produced four forecasts from September to December that are thus made between six and three months before the end of the quarter in March 2005. Then we have a further three nowcasts from January to March. These will thus have been produced in the period between the two months preceding the end of the quarter and the actual end of the quarter. Finally, we have a backcast produced in April, that is one month after the end of the quarter. All-in-all, we have therefore produced eight different forecasts for the first quarter of 2005. Replicating this pattern, we have produced eight different forecasts for all of the 28 quarters in the period 2005 to the end of 2011.

In order to get an idea of the forecasting performance of the dynamic factor model we compare it with a simple model[21] that delivers a forecast that is the mean value of GDP during the period. We calculate the factor model's relative forecasting performance with the square root of the ratio between both of the models' root mean square error – relative RMSE.[22] In this measure, a value less than 1 means that the forecasting performance of the dynamic factor model is better than that of the simple model. The RMSE measure has several advantages. One is that positive and negative errors do not "cancel each other out" as the forecasting errors are squared. Another advantage is that bias (mean forecasting error) and the distribution of the forecasting errors are summarised in the measure.[23] This means that a forecaster who constantly has a small forecasting error is punished just as much as a forecaster who makes a significant forecasting error just once.

Figure 3 shows the forecast evaluation for the factor model in the example. The three lines refer to the average relative RMSE for the factor model compared to the simple model. The unit on the x axis is the number of months before the end of the quarter, which relate to the eight forecasting occasions for each quarter in the example. The average of the relative RMSE is calculated during three different periods. The yellow line shows the relative RMSE throughout the evaluation period from 2005 to the end of 2011. The yellow line is below 1 for eight months, which means that the forecasting performance of the dynamic factor model is better than that of the simple model. This result is explained by the fact that the factor model uses the information provided by observations of the indicator variables, while the simple model only takes the historical data on GDP into account. Moreover, the yellow line slopes upwards, which means that forecasting performance improves during the nowcasting months when there is better access to already published data than during the forecasting months when there is limited access to such data.

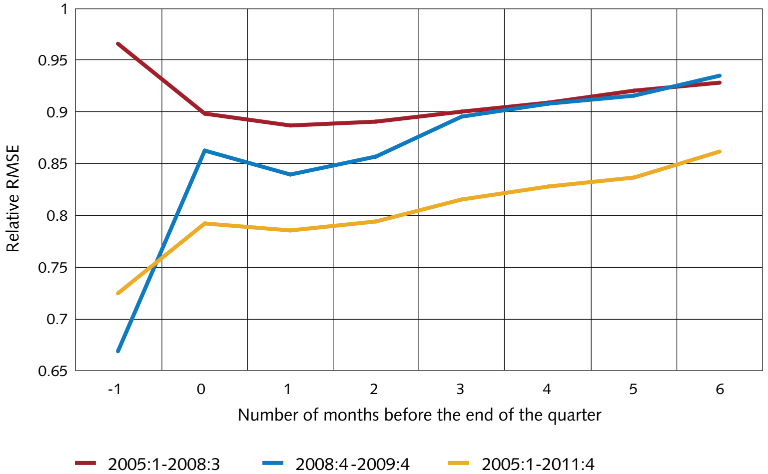
21 The simple model is univariate and uses only historical GDP outcomes. A better comparison is made against other methods that also use indicators such as the bridge equation (1). The forecasting performance of the dynamic factor model is better according to studies by Kuzin et al. (2013), Marcellino and Schumacher (2010) and Rünstler et al. (2009).

22 The RMSE (Root Mean Square Error) is calculated as the root of mean squared forecasting errors. The forecasting error is defined as the outcome minus the forecast. The relative RMSE for forecasts A and B is RMSE(A)/RMSE(B).

23 Bias (or the mean forecasting error) is an important statistic to study as it tells us something about the forecasts' systematic deviation from the outcomes. However, for means of comparison it is more reasonable to use the RMSE as this measure summarises bias and the variation in forecasting errors. It is not enough to be right on average if one nevertheless has significant individual forecasting errors. Both bias and the RMSE (and/or some other measure) are normally reported.

In addition to the entire period, averages have also been calculated for the stable period prior to the financial crisis and the most turbulent period during the crisis when GDP exhibited relatively substantial fluctuations. The first period refers to the first quarter of 2005 to the third quarter of 2008 and is illustrated by the red line in the figure. The second period refers to the fourth quarter of 2008 to the fourth quarter of 2009 and is illustrated by the blue line. The blue line shows that the dynamic factor model made best use of the indicator information in the nowcasting months during the turbulent period.[24]

Figure 3. The forecasting performance of the dynamic factor model



GDP FOURTH QUARTER 2008 – FORECASTS AND EXPLANATION OF REVISIONS

In the section above we studied the average performance of the factor model. We will now examine how the model performed for the final quarter of 2008 in a little more detail. With the new information and the updated forecast for the fourth quarter we can determine the news contributions from five groups.[25] The model is then re-estimated each month until Statistics Sweden publishes the actual outcome for GDP growth in the fourth quarter, which it does in February 2009.[26] The five groups are real indicators, financial indicators, surveys, international indicators and price indicators.[27] The division partly follows the availability of data. Financial data is available in real time while survey and price data become available with a certain time lag, although they are published much earlier than real data. Real data mostly consists of industrial production. Financial is data on interest

24 Note, however, the Figure 3 shows relative RMSE. The forecasting performance of both models deteriorates during the financial crisis, although the deterioration in the performance of the dynamic factor model is relatively less.

25 Decomposition is carried out using the method outlined by Bańbura and Modugno (2014).

26 We use the same data as in the forecast evaluation, except that we use real time data for GDP.

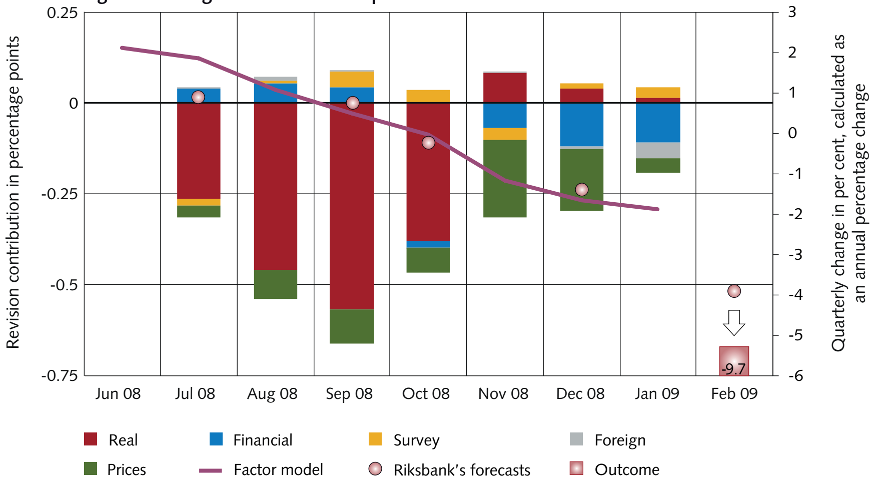
27 The indicators are taken from Swedish and foreign national accounts, consumer price indexes and surveys. Examples of such surveys in Sweden are the Labour Force Survey and the surveys of the National Institute of Economic Research.

rates at different maturities, interest rate spreads and exchange rates. Survey data refers to the surveys of the National Institute of Economic Research and various purchasing manager indexes. Statistics of various types are taken from abroad, particularly the euro area and the United States. Price indicators, finally, consist of both consumer and producer prices and world market prices.

Figure 4 shows forecasts from the various points in time together with news contributions from the five indicator groups. The factor model's forecasts are shown in the unbroken line, which refers to the quarterly rate of growth calculated as an annual rate on the right axis. The red rings refer to the forecasts that the Riksbank published between July 2008 and February 2009 in its Monetary Policy Reports. News contributions from revisions of the indicators are shown in percentage points on the left axis. The total sum of the five indicator groups represents how much the forecast has changed since the previous month. The forecast in July (2.1 per cent) was for example 0.3 percentage points lower than in June (1.8 per cent), which is shown as a downward sloping unbroken line between the two months on the right axis. The forecast revision of minus 0.3 percentage points is also shown on the left axis as the net sum of the individual columns. We can also see that the major part of the news contributions, that is –0.27 percentage points, comes from the red column, which refers to real variables. This can be interpreted to mean that the economic downturn was more severe than the factor model predicted. This pattern is repeated throughout the third quarter. The forecasts from the summer of 2008 predicted moderate growth. The factor model forecast was thereafter gradually revised downwards and the largest contribution during the autumn came from the hard real indicators. The factor model forecast predicted zero growth in September and shrinking GDP in October. Lehman Brothers went bankrupt at the middle of September 2008, which led to a financial and real shock wave that swept through the global economy. The reactions of the financial markets, in the form of interest rate cuts and weaker exchange rates, can be seen in negative contributions from financial data after October. Similarly, the collapse in oil prices provided a negative contribution from price indicators. All-in-all, the factor model led to a further downward revision of the forecast, to –1.9 per cent, in January 2009. The model's forecast from January is nevertheless far above the outcome that was published at the end of February 2009, which was –9.7 per cent.

It is worth noting that the factor model has been estimated on the basis of historical correlations between GDP and the indicators as they have been in "normal" times. Events such as the bankruptcy of Lehman Brothers and its widespread consequences are highly unusual. Both standard forecasting models and professional forecasters made historically large forecasting errors when the attempted to estimate GDP growth in the fourth quarter of 2008.

Figure 4. Change in GDP in fourth quarter of 2008: forecasts and new contributions



Note. The line in the figure shows factor model forecasts for GDP in 2008:4 at various points in time. The circles show the forecasts that the Riksbank published between July 2008 and February 2009. The square presents the outcome that Statistics Sweden published at the end of February 2009. The columns show new contributions to revisions of the model forecast and add up to the difference in "the line" between two points in time. Note that the forecasts (the line and the circles) are shown on the right axis and the revision contributions on the left axis.

Sources: National Institute of Economic Research, Macrobond, national statistics agencies and the Riksbank

Figure 4 also compares the factor model's GDP forecasts with the assessments the Riksbank published in five monetary policy reports during the period July to February. The Riksbank's forecast in the first report, in February 2009, was historically speaking very low, but the outcome was significantly lower.[28] Other Swedish forecasters made assessments similar to those of the Riksbank during this period.[29] The factor model forecasts and the Riksbank's published forecasts were relatively concordant, apart from during the summer when the model forecasts were slightly more optimistic. The example suggests that the forecasting performance of the factor model holds up well compared with that of professional forecasters. In addition, the factor model quantifies how news in the flow of data lead to forecast revisions.

28 Note that the figure –9.7 per cent shown in Figure 4 is the quick estimate that Statistics Sweden published in February 2009. The actual figure for the fourth quarter of 2008 is –15.4 per cent.

29 See Figure 2.9 in Riksbank 2009.

5. Summary

In order to gain a quick impression of how the economy can be expected to develop in the period ahead, central banks use models of different types. One particular type is nowcast models, which focus on regularities in the data and are used to forecast the current situation and the immediate future. The current situation is the starting point for the forecast path that describes how the economy is expected to get from the current situation to the state of equilibrium.

The Riksbank's nowcast system has recently been extended with models that explicitly take into account the fact that indicator variables are observed at different frequencies and are published with different time lags. A further feature of the new forecasting methods is that they enable interpretations of the economic driving forces that lie behind a model forecast or a revision.

The dynamic factor model is one of the models that has been introduced as part of the Riksbank's nowcast system. In an evaluation of GDP forecasts during the period 2005-2011, we have shown how the model's use of indicator variables helped to improve forecasting performance. We have also shown in the article how the factor model forecasts for Swedish GDP in the fourth quarter of 2008 have been revised in line with the Riksbank's published forecasts. In addition, we have illustrated how one can quantify the news contributions coming from different sectors of the economy to forecast revisions.

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