Inflation indicators

The Inflation Report describes the forecasts for the macro economy made by the Riksbank for the coming two to three years. These forecasts are produced by means of expert assessments and various types of macroeconomic models. This Box provides more detailed information on one of these components, namely forecasts of the inflation path produced using the Riksbank's indicator models. These models have proven to be useful for forecasts of up to around one year ahead. However, there is a significant degree of uncertainty in the forecasts produced by these models, as in forecasts produced by competing models and assessments. In certain particular circumstances, indicator models may contribute significantly to the precision of forecasts as they can capture complicated patterns in large amounts of data.

The inflation forecasts are based on both assessments and models

The Riksbank's Inflation Report currently includes forecasts for more than 50 variables in the Swedish and international macro economy. Given the large number of forecast variables, it is necessary to use some form of structural macro model to arrive at a coherent basic scenario.[22] The advantage of a structural model is that a number of theoretical relationships are assumed to apply, which makes it easier to interpret the model's forecasts. However, these theoretical relationships can also impose restrictions on the model, impairing its ability to forecast specific variables, particularly in the short term. It is therefore necessary to make adjustments to the structural model's forecasts. This may be achieved with the help of expert assessments and alternative forecasts produced by models that do not to the same extent require that the variables fulfil the criteria of the theoretical relationships, in other words, models that to a greater degree allow data to "speak for itself". Different assessments suggest that the latter type of model – which in principle merely extrapolates the patterns found in historical data – is above all useful for forecasts in the short term.[23] These indicator models can thus be regarded as a complement to traditional assessment forecasts for shorter horizons. This Box describes the Riksbank's indicator models for inflation.

The database currently includes 88 inflation indicators

The database used to estimate the indicator models contains 88 quarterly observed indicators at present. A general description of the variables included is given in Table B2. The data period currently covers the first quarter of 1991 up to the second quarter of 2006. This choice of period is due to the length of available series and to the fact that older data often reveal other relationships than those which currently apply.[24]

Table B2. Inflation indicators 1991:3-2006:2

Variables
11 labour market
11 other real
12 price development
13 financial
9 international
32 business tendency surveys
88 total

Source: The Riksbank

Three different model approaches are used

In the analysis, three different model approaches are used, all of which are ultimately based on the vector autoregressive method (VAR). These consist of classical VAR models, Bayesian VAR models and VAR models based on statistical

22 Over the years, the Riksbank has used a number of macro models. The model currently used is a Dynamic Stochastic General Equilibrium model, see Adolfson, M., S. Laséen, J. Lindé and M. Villani, "Bayesian Estimation of an Open Economy DSGE Model with Incomplete Pass-Through", Sveriges Riksbank Working Paper Series No. 179, 2005.

23 See, for example, Galbraith, J. and G. Tkacz, "Forecast Content Horizons for Some Important Macroeconomic Time Series", Bank of Canada Working Paper, forthcoming.

24 The Riksbank also uses a database comprising monthly observations. In this case, the number of indicators is 37. The results for monthly data are approximately the same as for quarterly data in terms of the precision of forecasts and longest applicable forecast horizons.

factors, known as Factor-Augmented models (FAVAR).[25] Research in this field indicates that all approaches work well for short-term forecasts in particular.[26] Below is a brief description of the principles underlying each of the approaches.

1. Classical VAR models. Vector autoregression is a system of equations where today's observations are dependent on all variables included in the system at earlier points in time. In one particular case – when only one variable is included – the model is called AR (AutoRegression). In this case the variable is explained (forecast) solely on the basis of its own historical pattern. In the application in this Box, VAR models with two to four variables included are estimated. This will render a large number of estimated models from the given data set.

2. Bayesian VAR models. These are VAR models that have been charged with some form of subjective information prior to estimation. Examples of such subjective information might include the forecaster's view of the long-term sustainable level of growth in the economy and opinions on the nature of different relationships between variables. In the context of the Bayesian analysis, the importance attached to the subjective information can vary depending on how convinced one is of its accuracy. Bayesian VAR models with up to three variables included are used in the forecasting exercise.

3. FAVAR models. VAR models cannot be estimated with too many variables included. In FAVAR models, the information in a large amount of data is summarised with a small number of statistical factors that describe common components in the data. The factors and inflation are then modelled in a small VAR model. In this way, the information in a very large amount of data can be used without necessarily losing too much of the information in the data set.

A useful method for establishing how well the various models perform on average can be obtained by carrying out a simulated forecast evaluation where data is saved for a particular period at the end of the sample and the models' forecasts are then evaluated against the outcomes during that particular period. Forecasts for each model are made for one to eight quarterly periods ahead. The mean value (M) of all forecasts is then calculated for each model approach as well as the best forecast (B).[27] The estimation period is then extended with an observation and the exercise is repeated in the same way. When new mean value forecasts and best forecasts have been calculated, a further observation is added to the estimation period, and so on. This produces a set of M and B forecasts for which the average accuracy can be estimated. This is done using the root mean square error (RMSE), a measure which summarises the standard deviation in the forecast errors and how forecasts systematically misjudge outcomes. The lower the estimated RMSE, the better the forecasting ability (a forecast that is always correct has an RMSE of zero).

The models' short-term forecasting ability is relatively good

Table B3 shows the RMSE for the mean of all models (M) and for the ex ante best model

25 In the Box entitled "GDP indicators" in Inflation Report 2005:3, models based on forward-looking information are also used. These models cannot be used here since inflation statistics are among the first to be published every month and those statistics which are forward-looking (e.g. in the National Institute of Economic Research's business tendency survey) consist of very short series.

26 See, for example Robertson, J. and E. Tallman, "Vector Autoregressions: Forecasting and Reality", Federal Reserve Bank of Atlanta Economic Review 84, first quarter 1999, 4–18; Stock, J. and M. Watson, "Macroeconomic Forecasting Using Diffusion Indexes", Journal of Business and Economic Statistics 20, 2002, 147–162; Wright, J., "Forecasting U.S. Inflation by Bayesian Model Averaging", International Finance Discussion Papers No. 780, 2003; Hansson, J., P. Jansson and M. Löf, "Business Survey Data: Do they Help in Forecasting GDP Growth?", International Journal of Forecasting 21, 2005, 377–389.

27 Best forecast means the forecast model which, according to an evaluation, is best at each given point, in other words, the model which ex ante may be regarded as best. However, this does not mean that this model produces the best forecast outside the sample. The evaluation studies the forecasting abilities of the models outside the sample.

(B). The table shows that all model approaches produce forecasts with similar accuracy, at least as regards short-term forecasts. This amounts to around 0.4 percentage points for UND1X forecasts one quarter ahead and around 0.5-0.6 percentage points for forecasts two quarters ahead. If the forecast errors follow the normal distribution, a forecast interval with the breadth 1.6 percentage points will in 95 per cent of cases typically include the outcome for the inflation rate for the next quarter. The RMSE can be compared with the standard deviation for UND1X, which during the evaluation period has been 0.8 percentage points. By way of comparison, Table B3 also shows the forecasting precision for a random walk model, where the forecast for all horizons is always equal to the latest inflation outcome. All evaluated models consistently show higher accuracy than random walk forecasts.

The size of the indicator models' forecast error is thus appreciable, but is nevertheless smaller than for corresponding forecasts from structural models. For example, the RMSE for forecasts one quarter ahead in the Riksbank's structural model is around 0.5 percentage points. The indicator models offer approximately the same precision as the Riksbank's published forecasts one to four quarters ahead.[28]

In line with the results from research in the field, we can say that forecasts in the form of mean values are often more accurate than individual forecasts, as illustrated in the table, where the RMSE for M forecasts is generally lower than that for B forecasts.[29] For a good model, the forecast RMSE should theoretically increase with the forecast horizon and when the model no longer contributes any information, the RMSE should stabilise at the standard deviation of the series. For the evaluation of the indicator models, the RMSE of the forecasts more or less coincides with the standard deviation for UND1X when the forecast horizon is around three to four quarters. Time series and indicator models thus have their main area of use in short-term forecasts, at best one year ahead.

Indicator models can be particularly useful in particular cases

Table B3 illustrates that the simple autoregressive model (see the AR column) displays on average a forecasting ability that is comparable with the

Table B3. Forecast evaluation for UND1X 1999:1 to 2006:2
Root Mean Square Error (RMSE)

	Classical VAR		Bayesian VAR		Factor VAR			
Forecast horizon (quarter)	**M**	**B**	**M**	**B**	**M**	**B**	**AR**	**RW**
1	0.38	0.42	0.38	0.39	0.40	0.38	0.38	0.55
2	0.53	0.62	0.55	0.59	0.60	0.59	0.54	0.75
3	0.67	0.81	0.71	0.76	0.76	0.79	0.67	0.93
4	0.82	0.99	0.89	0.98	0.97	1.02	0.83	1.07
5	0.84	1.04	0.90	1.02	1.00	1.09	0.84	1.10
6	0.85	0.97	0.92	1.06	1.03	1.11	0.84	1.13
7	0.85	0.95	0.94	1.13	1.01	1.09	0.84	1.17
8	0.85	0.96	0.97	1.20	0.99	1.05	0.84	1.30

Note. M is the mean value of all forecasts in each approach and B is the ex ante best forecast. AR is an autoregression and RW is a random walk forecast where the most recently known outcome serves as the forecast.

Source: The Riksbank

28 See Adolfson, M., M. K. Andersson, J. Lindé, M. Villani, and A. Vredin, "Modern Forecasting Models in Action: Improving Analyses at Central Banks", Sveriges Riksbank Working Paper Series 188, 2005.

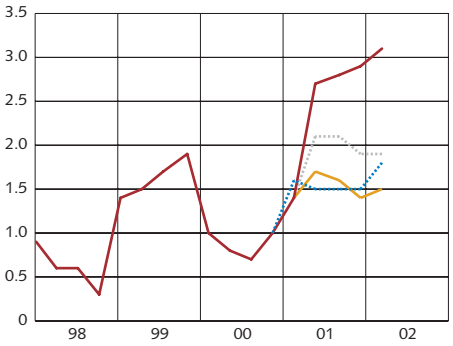
29 See, for instance, Stock, J. and M. Watson, "Combination Forecasts of Output Growth in a Seven-Country Data Set", Journal of Forecasting 23 (Issue 6), 2004, 405–430.

other model approaches. This result is borne out by the research in the field. Research findings also indicate that information from other variables not captured by an autoregression can be particularly useful in particular cases.[30]

Figure B13 shows UND1X forecasts based on quarterly data up to the first quarter of 2001. The first forecast is for the second quarter of the same year.[31] During the second quarter, UND1X inflation rose quite dramatically, partly in consequence of significant and unexpected fluctuations in food prices following mad cow disease and foot and mouth disease. The increase in UND1X came as a surprise, also for the indicator models and the forecast error was significant. However, in Figure B13 it is clear that those models which took into account information in addition to UND1X produced a noticeably better forecast than the autoregression, which means that the indicators contained information that suggested a rising inflation rate. The figure also shows forecasts from the first Inflation Report of 2001. In this case, the assessment made by the Riksbank reveals forecast errors similar to those shown by the autoregressive model.

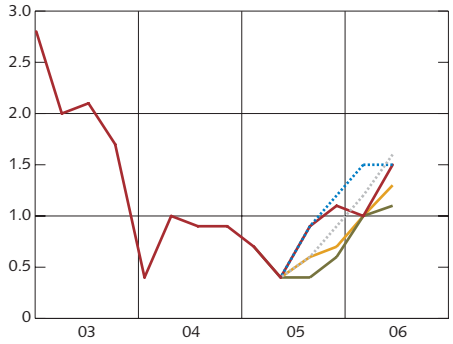
A more recent example of how information in a large volume of data can be useful is in the forecasts from the second quarter of 2005 (see Figure B14). In this case as well, one can see that the autoregressive model forecast a lower inflation than the actual outcome and that those models which take other information into consideration produced far better forecasts. The timing of the forecast coincides with a period of economic upturn. By way of comparison, the UND1X forecasts from Inflation Reports 2005:2 and 2005:3 are shown. In the first of these forecasts, not all outcomes for the second quarter were known and in the later forecast, two out of the three months in the outcome for the third quarter were known at the time of publishing the report.

Figure B13. UND1X forecasts 2001:2 to 2002:1
Annual percentage change



Source: The Riksbank

Figure B14. UND1X forecasts 2005:3 to 2006:2
Annual percentage change



Source: The Riksbank

Naturally there will be occasions when the autoregression will have produced better forecasts than those models that take other information into consideration, since the average forecasting ability compared with the RMSE is similar. These examples merely serve to illustrate the benefits of studying the results from many different models when making assessments of future inflation.

Summary

The results in this Box show that there is appreciable uncertainty in inflation forecasts. Further, the results suggest that the simple autoregressive model produces forecasts that on average fare well compared to other more sophisticated forecast methods. However, it should be noted that the indicator approaches

30 See Stock, J. and M. Watson, "Combination Forecasts of Output Growth in a Seven-Country Data Set", Journal of Forecasting 23 (Issue 6), 2004, 405–430 and Stock, J and M. Watson, "An Empirical Comparison of Methods for Forecasting Using Many Predictors," manuscript, 2005, for a discussion of the significance of using information in other variables in addition to the actual forecast variable.

31 At the time of publication of the first Inflation Report in 2001, only the inflation outcome for two of the first quarter's three months was known, which explains the minor deviation in the first quarter of 2001 in Figure B13.

presented in this Box may, during certain periods, contribute to more precise forecasts than an autoregression. This is due to the fact that the indicator models take into consideration a large amount of information that is not included in the actual inflation series. This is a fairly significant limitation of the autoregression, since in practice, one never knows when such periods might occur.

Even if time series models have proven useful as forecasting instruments, they lack the capability to provide explanations of the economics underlying the forecasts. For this reason, it is also necessary to use models based on economic theory to enable economic interpretations of the forecasts. Furthermore, one earlier evaluation shows that the Riksbank's structural model produces relatively good forecasts for the slightly longer term.[32]

Both indicator models and structural models are important instruments of forecasting and analysis, but they are of course gross simplifications of reality. This means that they cannot possibly be expected to take into consideration all the information that affects the economy, and it is therefore necessary to adjust the model forecasts for both short-term and long-term forecast horizons.

32 See Adolfson, M., M. K. Andersson, J. Lindé, M. Villani, and A. Vredin, "Modern Forecasting Models in Action: Improving Analyses at Central Banks", Sveriges Riksbank Working Paper Series 188, 2005.