Short-term forecasting methods as instruments of business cycle analysis

Forecasts are of major importance in the monetary policy decision-making process, not least on account of the lagged effects in the transmission of monetary impulses. Over the past few years, a number of econometric forecasting models have been developed, especially for short forecast horizons, which take due account of both the incomplete availability of data at the current end of the sample and the differing frequency with which data are published.

A large number of indicators are available for assessing current economic conditions. These indicators may send contradictory and unclear signals. The key tasks facing the forecaster are therefore selecting the economic indicators and weighting them appropriately. In this context, too, model-based procedures – such as factor models – can be a valuable aid, especially if the contributions of various groups of economic indicators to the forecast can be quantified.

When examining macroeconomic developments at the current end, the inherent limitations of forecasting procedures soon become apparent, too, however, as forecasts based on past patterns of experience can be derived only with distinctly greater uncertainty.

Monetary policy and forecasts

Forecasts as instruments for underpinning...

Forecasts play a major role in central banks' monetary policy decision-making process. As there is usually a certain time lag in monetary policy taking effect, it can, in the short term, have no more than a marginal impact on real activity and prices in an economy. This means that monetary policy has to have a medium-term orientation, which must be based on a reliable assessment of developments in the economy in a forward-looking manner. Furthermore, publishing central bank forecasts can help to anchor, in particular, the longer-term expectations of firms and households and thus make monetary policy more effective. Consequently, projections of price developments, real activity and other key macroeconomic variables form an important basis for monetary policy decisions and for communicating them.

In the Eurosystem, the staff of the ECB and the national central banks regularly prepare projections for the most important macroeconomic variables. In the twice-yearly rounds of projections involving experts from the entire Eurosystem, the national central banks prepare country-level macroeconomic projections. These are then aggregated in a multistage process to form a projection for the euro area.[1] The projections serve as an input for the monetary policy decisions of the Governing Council of the ECB.

...and communicating monetary policy decisions

These projections for the euro area are published regularly in the Monthly Bulletin of the ECB. Since December 2007, the Bundesbank also publishes the individual macroeconomic projections for the German economy which it contributes in this context.[2]

Forecasting methods at central banks

Model uncertainty requires a variety of methods

Central banks use a large number of models and methods to prepare forecasts.[3] One major feature of the forecasting process is that it involves forecasts that rely on expert knowledge as well as model-based projections. Neither approach is independent of the other. When preparing a consistent projection scenario, both are, in fact, closely integrated.

The econometric forecasting models display major differences with regard to the incorporated variables, the theoretical coherence of the model structure, and the econometric estimation procedures.[4] In addition, central banks generally maintain "suites of models", ie groups of models, which are used in parallel for forecasting purposes. It is true that, in most cases, a macroeconomic core model is used for forecasting all key variables and for economic policy analyses (simulations). However, since even sophisticated models are an oversimplification of the complex reality, alternative models with different structural

1 See European Central Bank, A Guide to Eurosystem Staff Macroeconomic Projection Exercises, June 2001.
2 See, for example, Deutsche Bundesbank, Outlook for the German economy: macroeconomic projections for 2008 and 2009, Monthly Report, December 2007, pp 17-29.
3 See O Issing (2004), The role of macroeconomic projections within the monetary policy strategy of the ECB, Economic Modelling 21, pp 723-734.
4 See A Pagan and J Robertson (2002), Forecasting for Policy, in M Clements, D Hendry (eds), A Companion to Economic Forecasting, Blackwell, pp 152-176; G Fagan and J Morgan (eds), Econometric Models of the Euro-Area Central Banks, 2005, Edward Elgar.

characteristics are also applied. By doing so, it is possible to counter the problem of model uncertainty. Furthermore, incorporating a large number of data and taking due account of correlations between various classes of models can reduce the risk of projections being inaccurate because of undetected structural breaks. Many empirical studies have shown that combinations of models perform well in forecast comparisons.[5]

Structural models as key forecasting instruments

Structural models play a key role in forecasting. They aim to model economic relationships in a closed framework on the basis of economic theories and empirical data. They are used mainly for medium and longer projection horizons. There are two different classes of structural models. First, there are econometric multi-equation models which are estimated on the basis of quarterly national accounts data.[6] The long-term relationships are largely modelled by theoretically founded behavioural equations, while the short-term dynamics are specified on empirical grounds. Second, central banks are making increasing use of dynamic stochastic general equilibrium (DSGE) models as forecasting instruments, too. These models mostly have a stronger microeconomic foundation than the traditional multi-equation models.[7]

The structural models are not applied purely mechanically for forecasting purposes. Rather, expert knowledge is used to adjust the model projection if, for instance, reliable information on future discretionary policy measures is available which cannot be explained endogenously from within the model. Examples of this might be changes in tax or social security contribution rates and in tax depreciation rules. Furthermore, in structural models, not all the variables which are relevant to the projection can be explained endogenously. Rather, for key variables, experts set out a list of assumptions about, say, global economic growth, commodity prices or public finances.

Short-term forecasting methods

Short-term forecasting requires special procedures

Short-term forecasting methods play a particular role in preparing forecasts. As a rule, short-term forecasts cover horizons of up to two quarters and therefore serve as the basis or starting point for longer-term projections which are compiled using other methods. The need for preparing a forecast for the short term is due, moreover, to the incomplete availability of data for key macroeconomic variables at the current end of the sample and to the differing frequency with which data are published. This means that special methods have to be applied, especially with regard to forecasting gross domestic product (GDP). GDP, as a comprehensive measure of real activity in an economy, is available as a quarterly figure only with a certain time lag. In Germany, for example, a flash estimate is published some six weeks after the end of the reporting quarter. This necessitates the

5 See A Timmermann (2006), Forecast Combinations, in G Elliot, C Granger and A Timmermann (eds), Handbook of Economic Forecasting, Vol 1, pp 135-196.
6 See B Hamburg, K-H Tödter (2005), The macroeconometric multi-country model of the Deutsche Bundesbank, in G Fagan and J Morgan (eds), Econometric Models of the Euro-Area Central Banks, pp 119-136.
7 For an overview, see Deutsche Bundesbank, Development and application of DSGE models for the Germany economy, Monthly Report, July 2008, pp 31-46.

use of forecast models for the short term in order to be able to make an assessment of GDP in the current quarter as soon as possible. Short-term forecasts therefore do not cover just the immediate future. Rather, even a sound assessment of the current macroeconomic situation requires the use of forecasting instruments. The estimations of GDP for the current quarter are generally called "nowcasts" and represent one of the key areas in which short-term forecasting methods are applied.[8]

Forecast preparation as an iterative weighting of expert opinion ...

Despite the widespread application of formal-statistical procedures, the preparation of short-term forecasts is an iterative process involving a relative weighting of the forecaster's empirical knowledge and professional expertise. The approach used in the short-term projection of GDP based on expert opinion takes the national accounts as a starting point. In line with the classification in the accounts, a disaggregated approach is adopted to conduct a detailed analysis of developments in demand and value-added components. Finally, an assessment of their short-term development is made with the help of the historically observed relationship between certain economic indicators and national accounts components. In this forecast, knowledge of institutional and regulatory factors is of crucial importance. In contrast to a pure model-based projection, for example, it is possible with this procedure to take account of the fact that the announcement of discretionary policy measures has an impact on the short-term profile of GDP and its components. As a rule, an analysis of this kind is performed for both the demand and supply sides of GDP, although the forecast results do not necessarily match initially. The expert opinion is of particular importance when reconciling the supply and demand sides since knowledge of special developments at the current end make it easier to assess the extent to which developments in certain components might be especially fraught with uncertainty. In the current setting, for example, the macroeconomic effects of fiscal stabilisation measures cannot be assessed adequately without recourse to assessments by experts.

... and econometric models

Econometric short-term forecasting models are mostly based on times series analysis approaches. These rest on certain ideas about economic interactions but generally do not have any explicit relationship to economic theories. Rather, the models aim at capturing the observed dynamic relationships of the past in the current data using purely statistical criteria and to utilise them for forecasting. Unlike structural multi-equation models – which, in most cases, are based on quarterly national accounts data – econometric models for short-term forecasting can also take account of monthly or more frequent indicator information. In the interests of a comprehensive utilisation of information, the short-term forecasting methods therefore complement the structural models.

Bridge equations and factor models

Bridge equations and factor models are two classes of models which are often used for short-term forecasting in the Eurosystem. The

8 On the terminology, see D Giannone, L Reichlin and D Small (2008), Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases, Journal of Monetary Economics 55, pp 665-676.

concept of the bridge equation adopts a single-equation approach which establishes a statistical relationship between quarterly national accounts variables and monthly economic indicators. To solve the problem of differing frequencies, the more frequent data are converted to quarterly frequency. The specified single equations serve in the end as instruments for the model-based short-term projection. What the single-equation methods have in common is their reliance on a small number of economic indicators selected by experts with the aid of statistical tests. By contrast, large factor models access a large number of economic indicators simultaneously. These models are based on the empirical observation that movements of many economic variables are correlated over the business cycle. Using statistical procedures, the data from a multiplicity of individual indicators is condensed into a small number of factors so that they represent this common development as accurately as possible. In the forecasting process, the estimated factors can, like observable variables, also be used as determinants of the projection. Further details of the various classes of models may be found in the annex to this article.

Expert and model projections complement each other...

Although the approach of the expert forecast initially appears to differ from that of the econometric short-term projection, both approaches follow a similar logic. The data available from very heterogeneous sources at the time the forecast is prepared should be used in the best possible way to assess the current economic situation. Differences consist, for example, in the number of variables included in each of the procedures and in the possibility of incorporating subjective assessments and judgements.

In the case of methods supported by expert knowledge, the focus is on the empirically based analysis of meaningful individual indicators and on incorporating determinants that are difficult to capture within the model framework. The use of statistical methods, on the other hand, is designed to ensure that a broad information base is exploited for the projection. Dynamic correlation structures among a large number of variables cannot be evaluated using a purely descriptive analysis, however. Since modern econometric methods of short-term forecasting make it possible to analyse a large number of variables with regard to, say, their leading indicator properties for the target variable, there is also a reduced risk of important information being neglected in the forecasting process.

... and serve as a cross-check for plausibility

Nevertheless, the results of purely statistical methods are often not immediately open to an economic interpretation. Moreover, the information content of econometric methods may be limited by structural breaks. In the event of especially far-reaching structural changes, it may be the case that the models estimated on the basis of historical information has only very little information value for future economic developments. Furthermore, policy measures which have been announced but will not take effect until a later date are modelled inadequately as expectations are not explicitly incorporated into these models. In such cases, it is especially important to subject the outcome of the econometrically based projection to a critical examination and to supplement it with expert knowledge.

Seen in this light, the two approaches should not be construed as competing with each other but rather as complementary. For this reason, central banks frequently perform short-term forecasts on the basis of both expert knowledge and econometric models. Their joint application makes it possible to cross-check the results for plausibility. This means that, as a rule, both approaches as applied in practice are closely linked to each other.

Selection and weighting of economic indicators for the short-term projection

Selection of variables ...

The short-term forecasting methods described above try in different ways to allow current time series information on economic indicators to be used for forecasting GDP. To do this in practice, it is necessary to select the indicators that are deemed to be relevant. For forecasting purposes, economists can nowadays make use of a large number of economic indicators from a wide variety of sources. These include, for example, monthly industry statistics with an in-depth breakdown by sector covering a major part of macroeconomic value added. Survey data are also available. These reflect households' and firms' assessment of the current situation as well as their expectations about future economic activity. Furthermore, readily available and very frequent financial market data as well as data from many other sectors of the economy can be used. This means that there are several hundred time series are available from which to select variables.

... and weighting of information as forecaster's key tasks

Besides selecting the indicators which are relevant to the forecasting process, the forecaster also has to reach a conclusion about the relative importance of the chosen indicators, ie decide which indicators are regarded as having particular information content for current GDP. It is necessary to gauge the relevance of information because individual indicators can generate conflicting signals for the overall assessment of economic activity. In this instance, it is the job of the forecaster to weight the signals – both qualitatively and quantitatively – with regard to the projection of GDP and thus separate cyclically relevant information from potentially misleading signals.

Information content ...

Generally, indicators that have a close statistical relationship with GDP are extremely important for forecasting GDP. For example, production data from monthly reports on industry and construction are used as primary statistics for calculating GDP. Data from surveys on the assessment of the current situation and the short-term outlook for firms and households, however, are assumed to have a weaker correlation with GDP in theoretical terms owing to the subjective character of the individual responses. This is why industrial statistics, for example, are called "hard" economic indicators, while survey data are termed "soft" indicators.

... and near-time availability as key assessment criteria

In terms of the indicators' relative importance – besides the leading indicator properties – it is not only the indicators' information content that is relevant but also their near-time availability. For example, certain economic indicators become available only with a time lag. Many primary statistics, such as retail sales and production data, are published much later than survey data. For example, statistics on industrial output are usually not published until nearly six weeks after the end of the reporting month, while survey data are generally available in the same month. Financial market data can be used for the projection even sooner.

Moreover, the selection and weighting of the variables is made more difficult by the fact that the explanatory power of individual indicators for GDP varies over time.[9] This means that the selection and weighting of the indicators have to be scrutinised constantly.

Various methods of selecting and weighting the variables

In the methods of short-term forecasting described above, the indicators are selected and weighted in a variety of ways. In short-term forecasting which relies on expert opinion, the selection and weighting of the variables is, first and foremost, based on experience. When econometric methods are applied, the indicators are first pre-selected; in the case of factor models, a large number of time series can be analysed simultaneously, while a small group of selected indicators is generally used in bridge equations. In economic models, the chosen indicators are weighted by means of empirical estimation techniques giving due regard to the underlying model structure. In this context, the statistically quantifiable relationships observed between the variables in the past are projected into the future.

Empirical illustration using a factor model

Relative weighting of model outcome and expert opinion

Below, the weighting of various groups of economic indicators for short-term forecasting of German GDP is illustrated empirically based on an econometric procedure. Here, a large factor model is used to assess the relevance of monthly economic indicators to the forecast. The econometric results are compared with an expert-based analysis. This comparison is intended to demonstrate the relative weighting given in the business cycle analysis to the outcome of the model and expert judgement.

In short-term projections using factor models, it is not initially apparent what importance individual indicators have for the forecast. The difficulty in interpreting a factor-based projection is that the extracted common factors summarise the relationships between the large number of variables in the dataset but ultimately represent synthetic aggregates which are not easily open to an economic interpretation. In other words, it is not initially possible to reach a conclusion about the relative importance of individual indicators or groups of indicators merely by looking at the factors. Especially for communicating the projection, however, it is extremely important that the statistically based projection result can also be interpreted in terms of what it has to say about the driving forces behind economic activity and the forecast.

9 See, for example, A Banerjee, M Marcellino and I Masten (2005), Leading Indicators for Euro Area Inflation and GDP Growth, Oxford Bulletin of Economics and Statistics 67, pp 785-814.

Methods for factor forecasting have now been developed, however, that make it possible to quantify the contributions which the individual time series make to the projected figure.[10] This means that the forecast value – for the quarter-on-quarter rate of seasonally and calendar-adjusted GDP – can be broken down additively into the contributions (measured in percentage points) of the individual variables or groups of variables. An analysis of this kind puts an explicit figure on the relative importance of variables and, at the same time, makes the factor forecast accessible to an economic assessment by experts.

Breakdown of historical forecast figures…

Below, such a breakdown of historical forecast figures for German GDP growth is used to show which time series have had the strongest influence on the forecast result in each case. The analysis uses a factor model in which the quarterly rate of change in seasonally and calendar-adjusted GDP is explained by 105 monthly economic indicators. The data include industrial and construction statistics, survey data as well as labour market and financial market data. In selecting the indicators, a disaggregated approach is taken in an attempt to adequately capture possibly diverging developments in some subsectors of the economy. It is thus possible, as a general tendency, to prevent the forecast being led into error by false signals from individual economic indicators.

… using the Kalman filter…

The factor model used here is based on a state-space representation and, by applying the Kalman filter, can be used for forecasting GDP.[11] GDP is interpolated at the monthly level and explained by the monthly factors, which are likewise estimated simultaneously by the Kalman filter. In the model's estimation and the preparation of the forecast, due account is taken of the fact that observations of the economic indicators at the end of the sample are not complete. The instruments can also be used to break down the forecast figures into contributions by individual variables or groups of variables, using the characteristics of the Kalman filter as a linear filter.[12]

…allows assessment of quantitative relevance of variables groups…

Condensing to groups of variables has the advantage that interpreting the results is made considerably easier in view of the large number of indicators. The relative levels of the forecast contributions make it possible to assess the quantitative significance of groups of economic indicators in the context of the chosen model. When breaking down the forecast figure into the sum of contributions made by the groups of variables, negative contributions are also possible in principle if most of the indicators within one group have a sufficiently dampening impact on GDP.

Recursive estimation and "nowcasting"

When applied empirically, the model is estimated recursively with the estimation period beginning in the second quarter of 1992 and the end of the estimation period being moved forward successively from the third

10 See, for example, M Camacho and G Perez-Quiros, (2008), Introducing the EURO-STING: Short Term INdicator of Euro Area Growth, Bank of Spain Working Paper 0807.
11 Large sections of the model are consistent with the proposal by M Banbura and G Rünstler (2007), A look into the factor model black box – publication lags and the role of hard and soft data in forecasting GDP, ECB Working Paper Series 751.
12 See S J Koopman and A Harvey (2003), Computing observation weights for signal extraction and filtering, Journal of Economic Dynamics & Control 27, pp 1317-1333.

quarter of 2007 to the fourth quarter of 2008. This takes account of the fact that the economic indicators – as in real time – are only incompletely available at the end of each estimation period, which means that the missing observations have to be added or estimated using the model. This analysis is confined here to the typical situation in preparing a "nowcast" at the start of the third month of the quarter to be forecast. In these circumstances, the provisional figure for GDP in the preceding quarter is generally available, while the flash estimate for the current quarter cannot be expected until two and a half months after the forecast has been prepared.

Breakdown of forecast results into contributions by variables groups

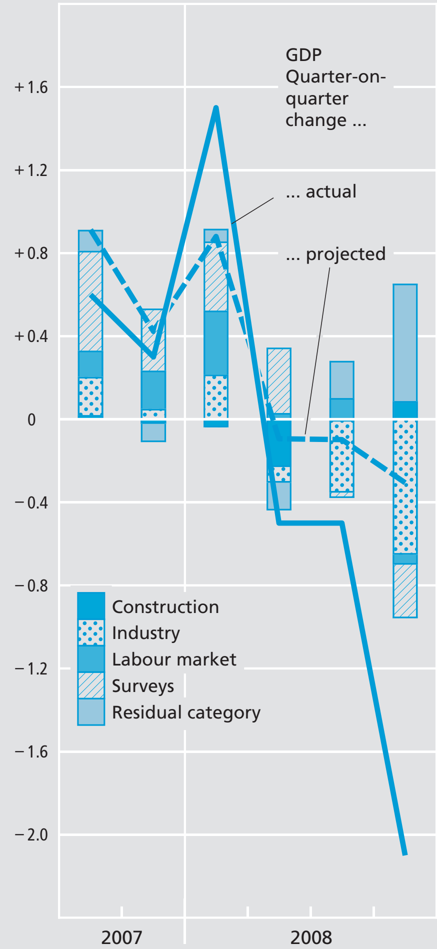
The adjacent chart shows the results for the recursive projections of the quarter-on-quarter rate of change in GDP and their breakdown into forecast contributions by individual groups of variables. For reasons of clarity, the chart shows only the groups of industry, construction, surveys and the labour market, while the other variables are combined in a residual category. The positive and negative forecast contributions of the groups of variables are depicted as bars. In the chart, besides the contributions, the projection is represented by a dashed line and actual observations by a solid line.

Plausibility check of the model result with regard to economic activity...

As the next step, the forecasts prepared using the factor model can now be made accessible for a plausibility check by breaking down the forecast figures into quantitative contributions by individual groups of variables. The second half of 2007 was characterised by positive GDP growth rates, which were, in fact, clearly surpassed in the first quarter of

Breakdown of GDP forecast into contributions by groups of variables*

As a percentage/in percentage points, seasonally and calendar-adjusted



* Results based on factor model.

Deutsche Bundesbank

2008. This surge in growth was evident from many indicators. Above all, survey data, the "hard" industrial indicators and the labour market were sending out distinctly positive signals, as is evident from their positive contributions to the model forecast. Looking at the published rate of change in GDP, the contribution breakdown and the overall projection provide a fairly accurate description of actual economic activity for this period. Although actual GDP growth was underestimated, this is likely to be attributable mainly to the special factor of a relatively mild winter.

In the second quarter of 2008, a countermovement set in. This was due essentially to a technical adjustment in the construction sector following the mild winter. The decline in GDP is captured in the factor model mainly by the "construction" category and, to a lesser extent, also by the "industry" group of variables, which points to the fact that the cyclical downturn had already started. At the same time, the surveys make positive contributions to the forecast, reflecting, above all, the fact that many survey figures were still at a high level in the second quarter. Their contribution is so large that the negative signals of the "hard" indicators for the construction and industrial sectors are considerably weakened, which means that the observed fall in GDP can be explained only to a very limited extent by the model.

The negative forecast figure of the factor model for the third quarter of 2008 is explained by the negative contribution of the "industry" category, which directly reflects the observed marked weakening of industrial activity. An even sharper decline in GDP is predicted for the fourth quarter of 2008, which can be attributed not only to developments in industry but also to the deterioration in the survey data. Comparing this with the observed data, it is apparent that the scale of the decline in GDP in the fourth quarter was clearly underestimated.

... indicates potential need for correction

The example illustrates how, by breaking down the forecast figures into the contributions made by the individual groups of variables, it is possible to identify those determinants which have led to the forecast outcome. In this way, causes of forecast errors can also be analysed after the event, which should, in principle, lead to an improvement in the forecast methods. It is striking, for example, that the contributions made by the survey figures were extremely large in the past upswing. This reflects the fact that a number of survey indicators reached new peaks during this period, while the international setting was already noticeably deteriorating. If, given those circumstances, the contribution made by the survey data to the factor forecast had been regarded as exaggerated, a downward revision would have been indicated.

Major forecast uncertainty at the current end

Given the current economic situation, it should be noted, however, that forecasts are currently subject to very large uncertainty. Looking at the general forecast quality of the model in the example, it is evident that the positive development in GDP up to and including the first quarter of 2008 was predicted much better than developments at the current end. In particular, the final quarter of 2008, with a 2.1% decline in GDP compared with the previous quarter, represents an extreme value which had not been observed for more than 20 years. There are two main factors that constitute outstanding challenges from a forecasting perspective. First, the global financial crisis has introduced an additional determinant of international economic activity. In the past, this was either not a factor at all or it played no more than a very subordinate role in explaining the usual cyclical patterns. Second, the dramatic escalation of the financial crisis in the autumn of 2008 was accompanied by a global shock to confidence. As a result, the dampening of global activity that set in around the middle of the year evolved into an abrupt downward correction in international trade and real activity.

Concluding remarks

Parallel application of various short-term forecasting models …

Using forecast models is regarded as more indispensable than ever for underpinning monetary policy decisions. As a rule, central banks use a wide variety of methodological approaches to prepare forecasts. Recently, econometric models have also been developed for the near-time assessment of the economic situation. These models take due account of the specific demands with regard to short-term forecasting stemming, in particular, from the asynchronous publication of data and different sampling frequencies. These methods can make a contribution to corroborating an economic assessment based on expert judgement. Divergent results from the two approaches suggest that the existing economic forecast and/or the models used should be subjected to a critical examination.

… makes it easier to prepare and corroborate an economic forecast

The exemplifying empirical analysis conducted with a factor model highlighted how model and expert forecasts can be used to complement each other. It was also made clear that a factor forecast is generally open to an economic, objective interpretation by analysing the quantitative contributions to the forecast by individual groups of variables. By comparing the arguments derived from each of these approaches, the forecasting process can gain in analytical clarity. The parallel application of different approaches to short-term forecasting thus assists in the creation and testing of an assessment of economic conditions and allows a better founded and more broadly supported judgement on short-term developments in macroeconomic activity.

That statement is valid despite the marked forecasting errors at the current end. Nevertheless, the events of the past months highlight the fact that, in particular problematic situations, forecasts of macroeconomic developments are subject to considerable margins of uncertainty. That is especially true if the premise underlying the model forecasts – that patterns of economic relationships derived from the past form a sustainable basis for drawing conclusions about the future – can no longer claim unqualified validity. For example, in the current environment it is no longer possible simply to uphold without qualifications the assumption – which was justified for the past – that developments in the financial markets have no serious effects on cyclical developments in the economy. Model-based forecasts are therefore to be used with particular caution at present. Nevertheless, forecasts which rely to a greater degree on incorporating subjective empirical knowledge are also currently faced with exceptional challenges. If there are no historical yardsticks for comparison when assessing the underlying economic conditions because singular events are exerting a crucial influence, forecasts' susceptibility to error inevitably increases, too.

One of the forecaster's main tasks is to understand the causes and effects of this higher degree of uncertainty, point out the limitations of point forecasts – which are of primary interest to the general public – and stress the importance of risk analyses as an integral component of macroeconomic forecasts.

Annex

Alternative econometric models for short-term forecasting of GDP

Central banks use a wide variety of methods to prepare short-term forecasts. Some of the methods most commonly used by the Eurosystem and the Bundesbank are presented below. These include, first and foremost, bridge equations and large factor models.

Bridge equations

Bridge equations describe the correlation between quarterly variables such as GDP (or its components) and monthly economic indicators.[13] A forecast can be prepared using a bridge equation as follows. The quarter-on-quarter rate of change in the seasonally and calendar-adjusted GDP is defined as y_{t_q}, with observations available for the quarterly periods $t_q = 1, ..., T_q$. The forecast is described as $y_{T_q+h_q|T_q}$ and is based on a forecast horizon of h_q quarters and on information up to quarter T_q. As explanatory variables, k monthly indicators x^m_{j,t_m} are used for $j = 1, ..., k$. However, the time index t_m now refers to months.

The bridge equation is formulated at quarterly frequency and can be represented in simplified form as

$$y_{t_q} = \sum_{j=1}^{k} \delta_j(L) x^{mq}_{j,\,t_q} \; + \; \varepsilon_{t_q}.$$

The indicators in the bridge equations are time-aggregated in line with their characteristics as stock and flow variables. The observations of the monthly indicator $x^m_{j,\,t_m}$ must therefore be converted into quarterly observations before the equation is estimated. The indicator $x^{mq}_{j,\,t_q}$ is, like the GDP data, therefore available at a quarterly frequency for estimation. The polynomial $\delta_j(L)$ with the lag operator L contains the coefficients of the lagged indicator.

In the bridge equation, the dynamic correlation is estimated first with the quarterly data. In addition, a dynamic monthly model is estimated for the indicator $x^m_{j,\,t_m}$, which provides monthly forecasts for the indicator $x^m_{j,\,T_m+h_m|T_m}$. This is often a simple autoregressive model. The forecast horizon for the monthly forecast must be adjusted in line with the time lag in publishing the respective indicator, ie the larger the publication time lag is, the longer the forecast horizon has to be. The monthly forecasts are, in turn, time-aggregated according to the indicator's stock or flow properties in order to

13 See, for example, A Baffigi, R Golinelli and G Parigi (2004), Bridge models to forecast the euro area GDP, International Journal of Forecasting 20, pp 447-460, or European Central Bank, Short-term forecasts of economic activity in the euro area, Monthly Bulletin 2008/4, pp 69-74.

form a quarterly indicator forecast $x^{mq}_{j,\,T_q+h_q|T_q}$ and inserted into the quarterly bridge equation, which ultimately delivers the GDP forecast.

If, as an initial step, bridge equations for demand or value added components are estimated rather than a bridge equation for aggregate GDP, the bridge equations must be condensed into the GDP forecast by (weighted) addition.

The indicators in the bridge equations may vary depending on the target variable. For methodological reasons, there is a limit on the number of explanatory variables to be included, however. This means that the relevant variables have to be pre-selected. Ultimately, the key to high forecast accuracy in a bridge equation is the selection of suitable indicators. In practice, experts' selection of variables for bridge equations is often based on descriptive statistical analyses.

Factor models

Factor models are based on the fundamental consideration that many economic variables show similar developments over the business cycle. The information obtained from a large number of individual indicators is condensed into factors in such a way that they represent these common developments as accurately as possible. Let us assume that the information content of a large number N of monthly indicators in vector X_{t_m} is bundled through r factors F_{t_m} in accordance with

$$X_{t_m} = \Lambda F_{t_m} + \zeta_{t_m}.$$

Here, ΛF_{t_m} is the common component of X_{t_m}, ie that part of the variables explained by the common factors. The variable ζ_{t_m}, by contrast, denotes the idiosyncratic component that is interpreted as the variable-specific part of X_{t_m}. The variable reduction in factor models is evident from the fact that a large number of N indicators is explained by merely $r << N$ factors. In the literature, it has been shown that the majority of variations in several hundred macroeconomic time series can be modelled by only a small number of factors.[14] The factors can be estimated using procedures which take into account the particular data properties discussed above, in particular the lack of observations at the current end of the sample.[15]

Various procedures can be used to forecast GDP with estimated factors. One approach is to treat the estimated factors as observable indicators and to make forecasts using individual equations.[16] Alternatively, the forecast can be prepared within a closed model framework. For this purpose, a state space model is estimated in which GDP is explained and interpolated using monthly factors.

The estimation techniques of the factor models permit the inclusion of a large number of variables and are therefore not subject to an econometric restriction in terms of the number of time series used. When applying the factor models empirically, however, due account should be taken of the fact that the forecaster has to take decisions about the specification of the forecast model, such as the number of factors to be estimated and the estima-

14 See J Bai and S Ng (2007), Determining the Number of Primitive Shocks in Factor Models, Journal of Business & Economic Statistics 25, p 58f.
15 For a comparison of various factor models for short-term forecasting, see M Marcellino and C Schumacher, Factor-MIDAS for now- and forecasting with ragged-edge data: A model comparison for German GDP, Deutsche Bundesbank Research Centre, Discussion Paper, Series 1, No 34/2007.
16 See C Schumacher and J Breitung (2008), Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data, International Journal of Forecasting, 24, pp 368-398.

tion method. In principle, misspecifications may occur just as with bridge equations.

Similarities and differences between the models

Bridge equations and factor models are both capable of meeting the specific challenges posed by short-term forecasting. High-frequency indicators, which are available to forecasters in near time, can therefore be used to forecast low-frequency variables such as GDP in both model types. In particular, both model categories avoid a loss of information in terms of the indicators as the latest information at the current end of the sample is taken into account.

Factor models are purely econometric models which do not initially make provision for expert opinions. Unlike in bridge equations, a large number of data can be analysed simultaneously. Moreover, it has been shown in the literature that factor estimates are relatively robust to structural breaks, as these estimates are based on a multiplicity of different variables, which makes them robust, to a certain extent, to misleading signals from individual indicators.[17]

Other approaches

In comparative studies, both bridge equations and factor models have demonstrated their value as instruments for short-term forecasting of GDP.[18] Owing to their specific advantages and drawbacks, both classes of model are used at central banks as instruments of ongoing economic analysis and forecasting. Other types of model are also employed, however.[19] Examples of these are vector autoregressive models, which can also be estimated to incorporate mixed-frequency data,[20] non-linear models and regressions that take direct account of mixed-frequency data (mixed data sampling: MIDAS), where, in contrast to bridge equations, a separate forecast of the indicators and their time aggregation can be dispensed with.[21]

In addition to the separate application of alternative forecasting instruments, the results of various models are also combined in a forecast pooling process. In the literature, combinations of forecasts have proved robust to structural breaks.[22] Furthermore, pooling short-term forecasts can also be regarded as a suitable strategy for reducing uncertainties in the specification of the individual models – for example, the selection of variables.[23]

17 See J Stock and M Watson (2007), Forecasting in Dynamic Factor Models Subject to Structural Instability, Working Paper, Harvard University.
18 For a comparison of short-term methods for forecasting German GDP, see K Barhoumi, S Benk, R Cristadoro, A Den Reijer, A Jakaitiene, P Jelonek, A Rua, G Rünstler, K Ruth and C Van Nieuwenhuyze (2008), Short-term forecasting of GDP using large monthly datasets: a pseudo real-time forecast evaluation exercise, ECB Occasional Paper 84; S Eickmeier and C Ziegler (2008), How successful are dynamic factor models at forecasting output and inflation? A meta-analytic approach, Journal of Forecasting 27, pp 237-265.
19 An impression of the wide variety of approaches is given, for example, by G Kapetanios, V Labhard and S Price (2008), Forecast combination and the Bank of England's suite of statistical forecasting models, Economic Modelling 25, pp 772-792; M Andersson and M Lof (2007), The Riksbank's new indicator procedures, Riksbank Economic Review 1/2007, pp 76-95.
20 See S Mittnik and P Zadrozny (2005), Forecasting German GDP at Monthly Frequency Using Monthly IFO Business Conditions Data, in J-E Sturm and T Wollmershäuser (eds), Ifo Survey Data in Business Cycle and Monetary Policy Analysis, Springer, pp 19-48.
21 See M Clements and A Galvão (2008), Macroeconomic Forecasting With Mixed-Frequency Data: Forecasting Output Growth in the United States, Journal of Business & Economic Statistics 26, pp 546-554.
22 See A Timmermann (2006), Forecast Combinations, in G Elliot, C Granger and A Timmermann (eds), Handbook of Economic Forecasting, Vol 1, pp 135-196.
23 See V Kuzin, M Marcellino and C Schumacher, Pooling versus model selection for nowcasting with many predictors: An application to German GDP, Deutsche Bundesbank Research Centre, Discussion Paper, Series 1, No 03/ 2009.