Forecasting models in short-term business cycle analysis – a workshop report

Econometric methods play a central role in the short-term business cycle analysis carried out by the Bundesbank. Short-term forecasting models provide estimates for the growth in gross domestic product (GDP) and in the components thereof for the two quarters following publication of the latest national accounts. These estimates feed into the reports on economic conditions in Germany. The short-term forecasts also form the basis for the macroeconomic projections which are drawn up in the spring and autumn.

Short-term econometric business cycle analysis makes use of automated statistical methods to evaluate large volumes of data in a systematic way. Unlike with traditional structural models, these methods take their lead from empirical correlations between the economic indicators which are already available and the national accounts metrics, which are published with a certain time lag. Expert knowledge is also brought to bear on these short-term econometric forecasts. The final product, predicated on the individual quantitative results produced by the models, is an analytically well-founded overall assessment of macroeconomic trends.

The forecasting models used at the Bundesbank (factor models and bridge equation models for GDP and models for industrial production) can be said to produce reasonable assessments for a time horizon of two quarters. The quality of the forecasts typically improves as new information becomes available. This also suggests that earlier publication of the official national accounts figures would entail risks to their accuracy because of the larger proportion of estimation earlier publication would involve.

An evaluation of different forecasting models leads to the conclusion that it is not possible to identify a model ex ante which will consistently deliver forecasts that are superior to those from other models in an ex post assessment. For that reason, a variety of models is used, and the results they produce are averaged or juxtaposed in a suitable manner. The differences between the forecasts provide pointers for an overall evaluation by the economists.

The forecasts for the first half of 2013 may be used as an example of this. Unusual weather conditions towards the end of the first quarter led to a fall in output which was largely made up in the next quarter. The first-quarter reduction in value added in particular was not captured well by the models. By contrast, some of the models proved very robust with regard to a relatively large reporting error for industrial production, which is probably the most important monthly economic indicator for Germany. This robustness resulted from the fact that a variety of indicators feed into the calculations, and discrepancies between the model results served to make inconsistencies visible.

Business cycle analysis with incomplete information

Comprehensive information on economic conditions takes time to become available …

Information on current macroeconomic conditions derives from indicators for specific factors which take varying amounts of time to become known. For instance, the Federal Statistical Office publishes the industrial production index almost six weeks after the month to which the figures apply. Similar information for many services sectors is subject to an even longer time lag. The most important overall indicator, GDP, is available to economists in the form of a flash estimate six weeks after the end of the relevant quarter. Detailed national accounts figures follow a week later, although the initial national accounts results are made up of estimates to a considerable extent, and these are later modified if necessary after further information has become available.

… so short-term forecasts are a key component of business cycle analysis

The purpose of business cycle analysis is to use the information already available to form as accurate a picture as possible of macroeconomic conditions and prospects. This includes providing a quantitative gauge of the overall economic trend. As well as assessing how the current quarter looks, the analyst is also generally required – owing to the time lag in the availability of data – to estimate the GDP result for the quarter just ended, since the statistics are not yet complete.[1] A rounded economic picture needs to give an idea, too, of how things will develop in the near future, which, in short-term economic analysis, is usually limited to the next quarter. These three categories of quarterly forecasting, the backcasts, nowcasts and forecasts,[2] also cover the period on which the Bundesbank's monthly economic reports focus.

Econometric models and traditional business cycle analysis

In traditional business cycle analysis, detailed information in the shape of business and financial indicators is put together with the help of historical values and expert knowledge. This form of analysis is increasingly supported by automated, econometric forecasting models. The Bundesbank, too, has for some time now been producing model-based short-term forecasts in addition to traditional business cycle analysis.[3] To do this, a number of monthly indicators are evaluated in a systematic way in order to derive quarterly GDP projections. These methods can be used to produce relatively accurate forecasts for two quarters following the last published GDP figure, ie either for the quarter just ended and the one just begun or for the quarter in progress and the forthcoming quarter. However, the information value for periods beyond this has proved to be very limited.

Data used in model-based business cycle analysis

The indicators analysed by the models cover activities in various parts of the economy, such as industrial production, or reflect assessments of the situation garnered through surveys. These different kinds of information are referred to as "hard" economic data and "soft" sentiment or confidence indicators. Many indicators also include forward-looking information. This includes, amongst other things, new orders in industry and the volume of construction permits, as hard data, and surveys on business, production and export expectations, as soft data.

At the Bundesbank, the forecasting models mainly make use of the indicators brought together in the Statistical Supplement to the Monthly Report entitled "Seasonally adjusted business statistics" as well as survey results from the Ifo Institute. These data have proved their worth in traditional business cycle analy-

1 The methods may even be of use in ascertaining macroeconomic trends in periods for which the GDP data, though published, are still very provisional. This applies if the model results can enable systematic prediction of subsequent revisions to GDP. See Deutsche Bundesbank, Reliability and revision profile of selected German economic indicators, Monthly Report, July 2011, pp 49-62.
2 For the terms backcast, nowcast and forecast, see M Banbura, D Giannone and L Reichlin (2011), Nowcasting, in M P Clements and D F Hendry (eds), The Oxford Handbook of Economic Forecasting, pp 193-224.
3 For a detailed examination of the interaction between model-based forecasts and expert evaluation, see Deutsche Bundesbank, Short-term forecasting methods as instruments of business cycle analysis, Monthly Report, April 2009, pp 31-44.

sis. The data are adjusted to reflect seasonal and calendar effects.[4] The GDP growth variable is also a seasonally and calendar-adjusted number. In addition, financial market data are included. A change in the yield curve, for instance, may point to a change in the overall macroeconomic dynamic.[5]

Choice of indicators

As well as being relevant to the economy, the indicators selected also need to be available for a sufficiently long period of time. New indicators, such as the production index for the finishing trades or the motorway toll statistics, are therefore not included in the modelling at this stage. Weather data, too, are considered only in rudimentary form, although unusual weather conditions in Germany have a considerable influence on short-term GDP movements. Nonetheless, it is difficult to capture the effects of weather peculiarities – especially the indirect effects in the subsequent quarter – in a suitable manner in short-term forecasting models.

Requirements for short-term forecasting models

The successive publication of different indicators means that new information is always coming in over the course of a quarter. As the body of information available broadens, forecasts can be progressively firmed up, given suitable methods, up until the initial publication of GDP data for the relevant quarter. The models used for this are based on approaches from econometric time series analysis, which capture the dynamic interrelations between the data as observed in the past and render them usable for the forecast.

This is primarily a matter of taking appropriate account of the staggered inflow of new data. For instance, the Ifo economic indicators and the financial market data become available at the end of the month under review, whilst the latest industrial production report relates to the month before last. There is therefore a gap of two months' data vis-à-vis the financial market and survey indicators, and suitable methods are needed to bridge this gap. Moreover, in the forecast for quarterly GDP using the monthly indicators, the right interplay between low-frequency and higher-frequency data must be ensured.

Forecast combination versus single forecasts

Single forecasts often unstable – combined forecasts a "robust" alternative

In view of the multiplicity of economic indicators, models and specifications which may potentially be of use in a short-term forecast, the question arises as to what a suitable selection might be. One option would be to apply statistical criteria such as an error metric and then select the model and the set of indicators which have proved most reliable in the past. However, because different specifications perform well depending on the conditions prevailing at particular stages in the business cycle, a selection on this basis would change over time. Nor is it generally known what conditions currently prevail or will prevail in the near future. An alternative to this, therefore, is to use a combination of forecasts which is calculated as a weighted average of single forecasts deriving from different models and indicators.[6] Although this has the disadvantage that the best model for a given situation is never in operation on its own, the risk of major forecast errors is also reduced.[7]

Composition of the forecast pool

When the forecast pool is put together, models with specific advantages are targeted for inclusion. For instance, some of the models may

4 For details on seasonal adjustment methods, see Deutsche Bundesbank, Seasonally adjusted business statistics, Statistical Supplement 4 to the Monthly Report, Explanatory notes, pp 19-21. See also Deutsche Bundesbank, Calendar effects on economic activity, Monthly Report, December 2012, pp 51-60, and Deutsche Bundesbank, The whole and its parts: problems with the aggregation of seasonally adjusted data, Monthly Report, June 2010, pp 59-67.
5 For past experience in this regard, see Deutsche Bundesbank, Estimating yield curves in the wake of the financial crisis, Monthly Report, July 2013, pp 33-45.
6 See K Lees (2009), Overview of a Recent Reserve Bank Workshop: Nowcasting with Model Combination, Reserve Bank of New Zealand Bulletin 72(1), pp 31-33.
7 See A Timmermann (2006), Forecast Combinations, in G Elliot, C Granger and A Timmermann (eds), Handbook of Economic Forecasting, Vol 1, pp 135-196.

take on board changes in economic structure in a flexible way. Competing theoretical approaches and different indicator sets may also be experimented with. Choices may be made, too, in terms of the dynamic structure of the models or the decision as to whether long-term trends in the variables should be explicitly modelled. Differencing is usually a suitable means of dealing with variables subject to trends, although this may potentially mean that information of relevance to the forecast is left out of consideration. In marginal cases, therefore, the variables may be left in levels. From the range of modelling options a pool of single forecasts is derived, from which a combined forecast can be drawn up using suitable weightings.

Straightforward weighting schemes have proved their worth

The weighting can either be provided by the forecaster or optimised with reference to a given criterion. For instance, one may wish to minimise the historical forecast errors of the combined forecast – focusing either on the recent past or a longer-term average. In this way, models with a demonstrably good forecasting record would acquire greater importance. In practice, however, straightforward weighting schemes[8] predominate, such as ones which attach the same weighting to all models that remain after an initial selection process. The reasons for this are twofold. First, it has proved difficult to infer the present quality of an individual model from historical forecast errors, particularly in the event of structural instability. Second, estimating a weighting structure creates a further source of uncertainty, and the detrimental influence of this uncertainty on the quality of the forecast often proves greater than the added value to be expected from an optimised weighting. Thus, an equal weighting, potentially including forecasts believed to be poor, often produces results which are just as good as those delivered by more complex methods.[9]

Helpful not to condense all forecasts into one single forecast

It has also proved helpful not to condense all available model forecasts into a single result, but instead to juxtapose different classes of models. In this way, the benefits of a combined forecast are utilised, while at the same time providing reference points for an overall evaluation by economists on the basis of the specific model properties.

Three model types, many model variants

Three groups: factor models, bridge equations and models for industrial production

The models used at the Bundesbank for short-term economic assessments and forecasts may be divided into three groups. Factor models and bridge equations are used for forecasts of GDP. Variants of bridge equations are also applied to the forecast for components of GDP. For industry – which accounts for only about one-fifth of overall gross value added in the economy but is the source of much of the fluctuation in the business cycle and is a key determinant in shaping activities in other areas of the economy – the Bundesbank makes use of very detailed models for production forecasts. This section describes the three types of model; details may be found in the Annex (see pages 81 to 83).

Factor models: bundled information

Factor models bundle information from a variety of monthly economic indicators into a small number of factors, by means of statistical procedures involving a great deal of computation. This bundling of information makes use of the fact that many macroeconomic variables are observed to move in the same direction at a given stage in the business cycle. The individual factors represent the shared trends. The process of breaking down the factors also allows gaps in the data at the current end – arising from time lags in the publication of economic indicators – to be automated and filled in a way consistent with the model. In a

8 See T E Clark and M W McCracken (2010), Averaging Forecasts from VARs with Uncertain Instabilities, Journal of Applied Econometrics 25, pp 5-29.
9 See M Marcellino, V Kuzin and C Schumacher (2012), Pooling versus Model Selection for Nowcasting GDP with Many Predictors: Empirical Evidence from Six Industrialized Countries, Journal of Applied Econometrics 28, pp 392-411.

second step, the estimated factors are fed into the actual forecast equation. This aims to use the factors available on a monthly basis to produce the forecast for quarterly GDP with minimum loss of information. The two steps in the computation may also be integrated. At present, more than 100 monthly indicators are included in the Bundesbank's factor models, and almost 70 model variants are calculated.

Bridge equations: zooming in on the national accounts …

With bridge equations, the quarterly variable to be forecast, such as GDP or the components thereof, is first put together using time-aggregated economic indicators which originally appear on a monthly basis. In a separate model, the monthly economic indicators are forecast. These forecasts are in turn fed into the previously estimated bridge equation. In contrast to the factor models, the individual equations are based on only a small number of economic indicators. The latter are selected by applying statistical tests or theoretical considerations. A number of variants are calculated and averaged in an appropriate way. In determining GDP within the context of the Bundesbank's short-term forecasts, eight variants are currently calculated on the supply side and ten on the demand side.

… provides reference points for medium-term business cycle analysis

The straightforward structure of the bridge equations also provides for a disaggregated forecast approach. In this, independent forecasts for individual components on the supply and demand side of GDP are first drawn up using the procedure described above. In a second step, weighted addition of the individual forecasts gives an estimate for GDP. This may happen at different levels of aggregation. Specifically, at the first level four components are used on each side[10] followed by seven and eight components on the supply and demand side respectively at the second level.[11]

Advantages of a disaggregated approach

The advantage of the disaggregated approach is that suitable indicators for specifically targeted areas of the economy or demand components can be used, and thus the resulting GDP forecast benefits to a certain extent from the advantages of a combined forecast. This more differentiated approach also creates added value for the Bundesbank's macroeconomic projections, which are fed into the Eurosystem's projections. The focus in this is not just on GDP as a whole, but also on changes in the composition of GDP.

Challenges of the disaggregated approach

One disadvantage, however, is that a number of components are difficult to forecast. That applies in particular to inventory changes, which are merely an estimated adjustment item in the GDP flash estimate issued by the Federal Statistical Office because of a lack of primary statistical backing.[12] In addition, the bridge equations, unlike a structural macroeconometric model, take no account of the interdependencies between the individual variables in the national accounts. This is of particular importance for imports. Conflicting errors in key demand-side components on the one hand and in imports on the other may significantly distort the GDP forecast through the combination of independent single equations on the demand side. That is one reason for looking at the supply and demand side of GDP separately.

Industrial production forecasts: a theory-based approach

In addition to the forecasts for GDP and its components, produced using factor models and bridge equations, there are also forecasting models for industrial production. Although value added in the manufacturing sector is also forecast by the bridge equations, this takes place in a rather simple framework typical for this type of model. Because economic stimuli from abroad, which are particularly important

10 Supply side: agriculture and forestry; production sector; services; net taxes on products. Demand side: consumption; gross fixed capital formation; exports; imports.
11 Supply side: agriculture and forestry; production sector excluding construction; construction sector; wholesale and retail trade, hotels and restaurants, and transport; private-sector services; public-sector services; net taxes on products. Demand side: private consumption; government consumption; plant and equipment; construction sector; other fixed capital formation; exports; imports; inventory changes.
12 See T A Knetsch (2005), Evaluating the German Inventory Cycle Using Data from the Ifo Business Survey, in: J-E Sturm and T Wollmershäuser (eds), Ifo Survey Data in Business Cycle and Monetary Policy Analysis, pp 61-92.

in Germany, are transmitted mainly via industry, the latter's importance goes beyond its approximately one-fifth share of national product, and justifies particularly sophisticated modelling. This is made possible by extremely good data availability in the industrial sector. Both the monthly production index and the corresponding index of new orders usually meet high quality standards.[13] Since a considerable share of output in industry – unlike in many areas of the service sector, for instance – is not produced at short notice, but, rather, orders are progressively worked through, future production can be inferred from orders.

Various modelling options

This basic relationship can be modelled in different ways. In the simplest form, a change in order volume leads to a change in production volume with a certain time lag. More sophisticated modelling can also take account of deviations in production volume from order volume through an error correction mechanism. In a further step, deviations from equilibrium for the stock of orders which cannot be directly observed are factored into the calculation.

Because the forecasts to be derived from orders only extend about three months into the future, it is also important to update new orders as accurately as possible; indicators from the Ifo business survey and financial market variables, amongst other things, can be used for this purpose. In addition, holiday and bridging day effects are taken into account above and beyond calendar and seasonal adjustment. Unlike with GDP forecasts, monthly forecasts are issued in the case of industrial production; the quarterly forecasts are then calculated from the monthly figures already published plus the forecast monthly figures. Overall, somewhat more than 3,400 model variants are calculated for industrial production. These extend from simple autoregressive specifications to complex, theory-based models which reflect the interplay between production, order volumes and order books through a multi-co-integration approach.

Forecast uncertainty

Estimating forecast uncertainty

Assessments of the short-term performance of the economy are incomplete if they fail to incorporate a gauge of the uncertainty associated with the usual point forecasts. For reasons of simplicity, when assessing the uncertainty attached to a given forecast, analysts frequently place their trust in a measure derived from past forecast errors. This implicitly takes account of all potential sources of uncertainty that have contributed to the deviation of realised values from forecast values. Paramount among these are random disturbances such as a sudden bout of winter weather in March or parameter uncertainty when estimating the models. Uncertainty as to whether a model adequately captures correlations that are of forecasting significance is also indirectly reflected in past experience with forecast errors. Commonly used measures of uncertainty include the mean absolute error of previous forecasts or the square root of the mean squared error.[14] As a general rule, uncertainty margins narrow as more and more information becomes available.

A reliable assessment of current forecast uncertainty based on past experience can best be achieved if the degree of uncertainty does not vary too greatly over time. This poses the question of how to deal with the exceptionally severe recession of 2008-09 and the recovery that followed, neither of which are reasonably well forecast, even in readjusted calculations. Such unusually large forecast errors are often factored out when calculating the level of uncertainty. In the section below, however, these

13 See Deutsche Bundesbank, Reliability and revision profile of selected German economic indicators, Monthly Report, July 2011, pp 49-62.
14 To translate an uncertainty margin into an explicit statement on the probability of a predicted development occurring in reality, a distribution pattern has to be assumed for the forecast errors. For example, in the case of normally distributed forecast errors, a corridor of plus/minus one mean absolute error around the point forecast covers a probability of 57.5%. For more detailed information, in particular with additional regard to how uncertainty margins are calculated, see Deutsche Bundesbank, Uncertainty of macroeconomic forecasts, Monthly Report, June 2010, pp 29-46.

errors are deliberately retained in the calculations. As a result, the uncertainty of forecasts for time periods in which standard-scale business cycle fluctuations can be expected is likely to be overstated rather than understated.

Inconsistencies between forecasts act as a warning

An alternative way of depicting forecasting uncertainty derives from the degree of homogeneity exhibited by different forecasts. As already mentioned, forecast results are averaged within model classes, but not beyond these classes. Sizeable differences between the averaged forecasts of the various model classes throw up questions. The same is true for a strongly pronounced dispersion of forecasts within a model class – if, for example, industrial production and new order data fail to provide a coherent picture.

Time-lapse business cycle analysis for the first half of 2013

Short-term forecasts in challenging conditions

The following aims to explain the way in which forecast models are used, taking the first two quarters of 2013 as an example. During the first half of 2013, short-term forecasts faced particular challenges. First, the winter weather persisted into March, leading to a marked contraction in construction output and a shift of value added from the first into the second quarter. Second, it later transpired that industrial production, which is probably Germany's most important monthly economic indicator and is normally quite reliable, had increasingly been distorted upwards owing to misreported data. It was not until the July output figures were published at the beginning of September that the data for the first six months of the year underwent a comprehensive revision. In the following, developments in this six-month period are therefore first of all conveyed as they actually occurred (ie in real time). This is followed by a simulation that uses the adjusted industrial production data as a basis in otherwise unchanged conditions.

Forecast cycle up to GDP flash estimate

Publication of the GDP outcome for the third quarter of 2012, in the middle of November that year, included the first quarter of 2013 in its short-term forecast. At this point in time, hard economic data like industrial orders and production up to September and soft sentiment indicators up to October were available. Given that production contracts provide upfront economic signals for a three-month period on average (ie until December) and expectations for output and exports look no farther than three months ahead (ie up to January), the initial forecasts were largely produced using updated indicator variables. As a result of the constant influx of economic indicators, the information for making forecasts gradually expanded. As can be discerned from the continuous narrowing of the uncertainty margins in the chart above, this typically improves the quality of forecasts.

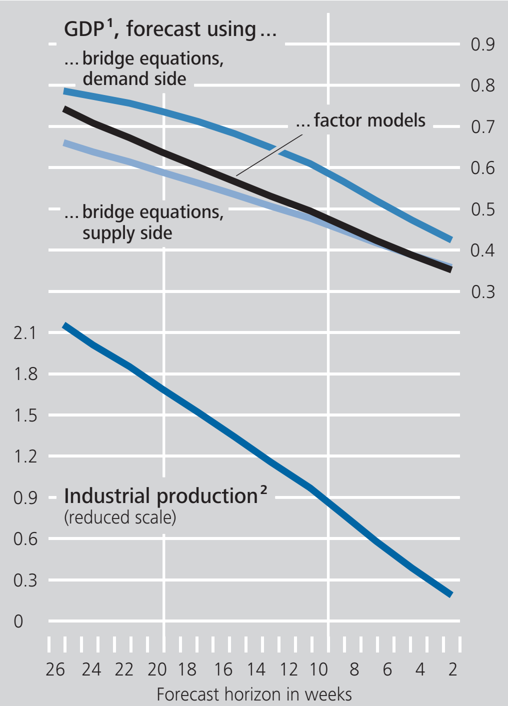
Towards the end of each month, when new survey data become available, and just after the beginning of each month when hard indicators like new orders, production and foreign trade figures are published, forecasts are recalculated. Hence, between the end of November and the beginning of May, twelve separate GDP forecasts were drawn up for the first quarter of 2013. In mid-February, following the compilation of the sixth forecast, the GDP flash estimate for the fourth quarter of 2012 was published, and factored into future forecasts. Then, at the end of February, work began on drawing up the forecasts for the second quarter of 2013. As regards industrial production, the relevant forecast cycle precedes that for GDP by about two weeks as the relevant figures are published at the start of each month.

Model characteristics and aggregation of individual forecasts to deliver an overall business cycle analysis

In the task of bringing together the four groups of model forecasts – factor models, bridge equations for the supply and demand side of GDP and models for industrial production – to produce a business cycle analysis, some broad characterisation is useful. The forecasts delivered by the factor models are heavily smoothed on account of the compression of a

Forecast uncertainty margins*

Percentage points



***** Mean absolute forecast errors (over the last seven years) in relation to forecast horizon, estimated from quarter-on-quarter changes. **1** Adjusted for price, seasonal and calendar effects. **2** Adjusted for seasonal and calendar effects.

huge volume of data. As a rule, exceptional developments relating to individual indicators only affect the overall outcome to a small extent, with the result that relatively sharp GDP movements are understated. By contrast, bridge equations react more quickly and sharply to exceptional developments. This applies particularly to the supply side of the calculation. The industrial production model is effective at capturing calendar-related phenomena such as bridging days. All models have difficulty dealing with weather effects, which can have a marked impact on the short-term GDP profile – a circumstance which was to be of considerable importance during the first half of 2013.

Time-lapse forecast flow in 2013: from the first quarter ...

The chart on page 78 shows the path followed by short-term forecasts during the first six months of 2013 in time lapse. It shows point forecasts as well as uncertainty margins generated by double the mean absolute forecast error over the past seven years.[15] Here, it is notable that the initial forecasts arising from the factor models and the supply-side bridge equations not only came close to the subsequent GDP flash estimate for each of the two quarters but also gauged developments more accurately than the final forecasts. The initially subdued assessment of Germany's economic prospects for the first quarter played a role in this regard, not least in terms of the outlook for industry. As detailed in January's brief commentary on economic conditions in Germany, the Ifo business survey data published at the end of December then pointed to the possibility of an economic recovery from as early as the first quarter of 2013 onward.[16] This impression was later substantiated by newly available data. For a time, a GDP growth rate of 0.5% seemed possible, based *inter alia* on a clear countermovement on the part of the industrial sector in response to adjustments made to production at the end of 2012.

There are two reasons why this did not actually materialise. First, industrial production fell short of the expectations that had initially been fuelled by, amongst other things, the relatively high January figure originally reported in March. Second, February and particularly March saw exceptionally cold winter weather, causing the main construction industry to be impaired to a much greater extent than is usual for this time of year. This was only captured by the models at a later date and only partially. The very high estimates generated initially by the bridge equations on the demand side were produced by an accumulation of errors in important demand components and in imports. Nevertheless, the results unanimously indicated that in the first quarter of 2013 the German economy lagged behind macroeconomic trends shown by the models, as described in the short commentary published in April and

15 In concrete terms, the prototypical forecast cycle described was simulated for the past seven years using data available at the end of July 2013. Data revisions are not taken into account in this kind of simulation.
16 The short commentaries and quarterly economic reports on the current economic situation cited here and below are contained in the Deutsche Bundesbank monthly reports between December 2012 and August 2013.

the more comprehensive quarterly report on the economic situation that appeared in May.

… to the second quarter of 2013

When interpreting the history of forecasts for the second quarter of 2013, it is significant that an adequate discount had already been applied to the GDP flash estimate in order to accommodate the consequences of erroneous reports relating to industrial production, whilst this important indicator was being incorporated into the forecast models in increasingly distorted form. These distorted industry-related figures affected the forecast outcomes of the three model classes in different ways. The temporary error had less impact on factor models with their more marked smoothing effect and reduced reaction to special developments. In this context, the inadequate attention paid to after-effects and catch-up effects in the construction sector also had a moderately countervailing impact. With respect to the bridge equations, the distortion entailed was correspondingly greater and the assessments came closer to a "notional" GDP result with no discount.

Both model classes displayed a significant strengthening in the upturn from the first to the second quarter, which was duly communicated in the relevant economic reports. Overall, the factor models and the bridge equations proved relatively robust, even with a key indicator distorted. This is also evident from the fact that the GDP flash estimate fell within the uncertainty margins for the forecasts. Conversely, all the second-quarter forecasts generated by the industrial production model fell substantially short of the initial unadjusted quarterly result for industry, although the inflated monthly data were gradually fed into the calculations. In particular, the smaller volume of new orders, and therefore the comparatively large realisations of the error correction term, served to dampen industrial production forecasts, thus drawing attention to the tension vis-à-vis new orders.

Following publication of the index level of industrial production for July, the entire series for the period since the beginning of the year was also revised in September. This resulted in downward revisions throughout the series, involving large-scale changes to the second-quarter figures. The revised index level for June stood 2.1% below the initially published figure while the quarter-on-quarter rate of change for the second quarter narrowed from 2.6% to 1.0%. To gauge how the short-term forecast models would have performed if industrial production had been reported without any errors, the adjusted time series is incorporated into the otherwise unchanged data records and the forecasts are gradually followed through (see chart on page 79).

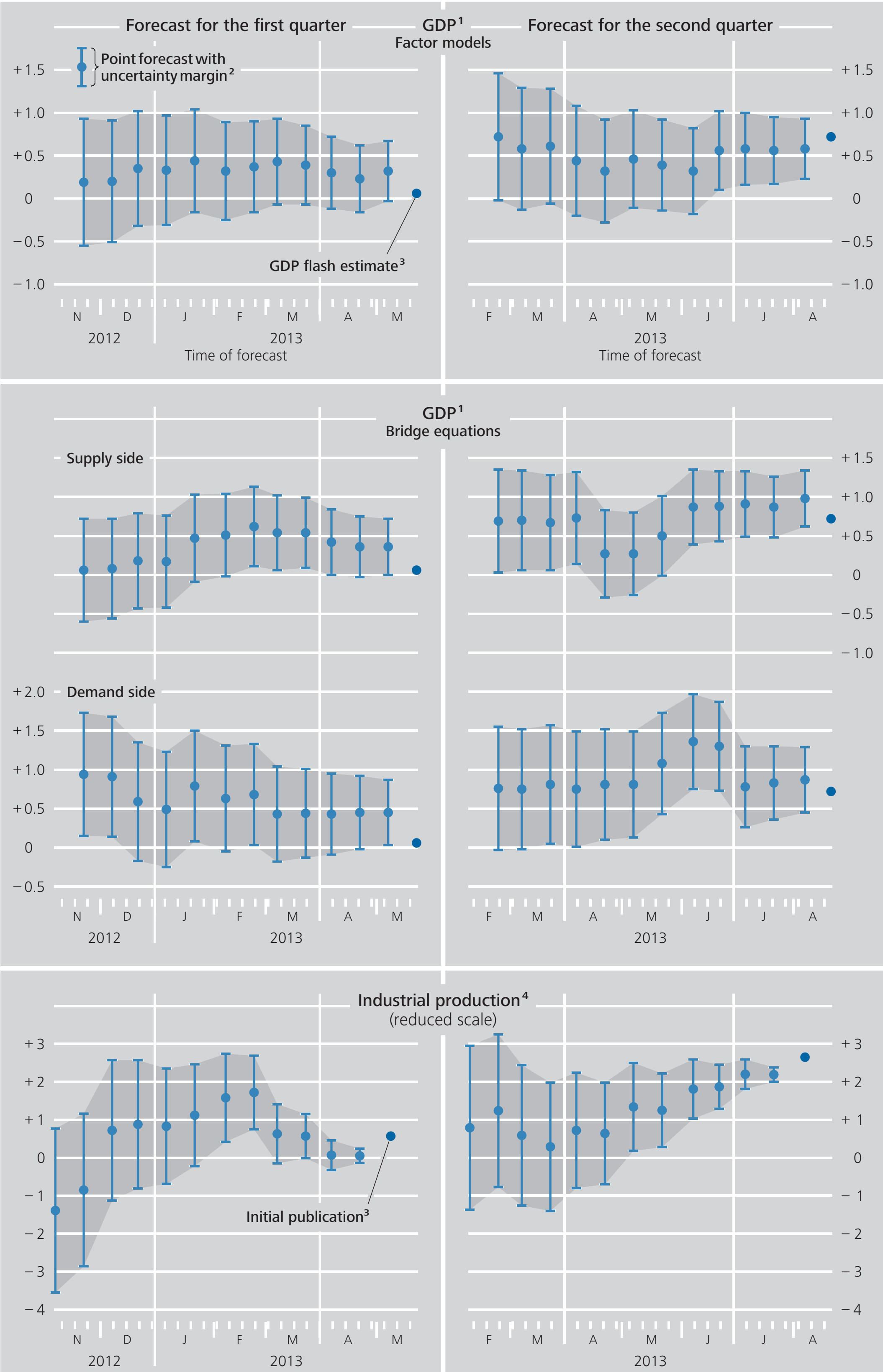
Alternative calculations using revised industrial production data

Such alternative calculations clearly illustrate the different properties of the three model classes. Inasmuch as they use information from a wide range of economic indicators, and owing to the comparatively pronounced degree of smoothing, factor models only entail small-scale changes to the GDP forecasts. These small changes even have the effect of widening the gap against the second-quarter GDP flash estimate as the factor models ascribe too little importance to catch-up effects, particularly in the construction sector. By contrast, the supply-side GDP estimate from the bridge equations leads to a relatively significant downward adjustment of around 0.3 percentage point. This adjustment could more or less put an exact figure on the anticipated GDP discount. Since, on the demand side, industrial production is merely used as an indicator in the equations for gross investment and investment in machinery and equipment for the GDP calculation, this results only in a minor downward adjustment which, however, also brings the estimated figure closer to the GDP flash estimate.

By contrast, in the models for industrial production, the revised figures provide a totally new picture to an extent. The last two first-quarter estimates released in April proved remarkably adept at identifying the size of industrial production. However, the difference between the forecasts produced in February and March

Short-term forecasts for 2013 in real time

Change against previous period in %, end-of-period values



1 Adjusted for price, seasonal and calendar effects. **2** Width of uncertainty margin corresponds to twice the mean absolute forecast error (over the last seven years). **3** Source: Federal Statistical Office. **4** Adjusted for seasonal and calendar effects.

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Short-term forecasts for 2013 with revised industrial production*

Change against previous period in %, end-of-period values

* Data vintage for industrial production: 6 September 2013. Comprehensive revisions from January 2013 owing to rectification of incorrect statistical reporting. **1** Adjusted for price, seasonal and calendar effects. **2** Width of uncertainty margin corresponds to twice the mean absolute forecast error (over the last seven years). **3** Source: Federal Statistical Office. **4** Adjusted for seasonal and calendar effects.

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widens. In this context, it should be noted that the alternative calculation makes use of data that already include a downward revision to the January production figures originally published in March, which was actually effected in April. As regards the second quarter, the quarterly forecasts now track the new order figures much more closely, whereas previously the order forecasts implied by the model had been pushed up by the invalid output data. The fact that each of the models ultimately failed to predict the adjusted outcome accurately is likely to be largely due to the exceptional cluster of springtime bridging days in May. For while the industrial production model encompassed bridging day effects, it did so on the basis of a long-term mean, which may well explain the understated catch-up effect for June.

Outlook

Interplay between model results and economic expertise

The forecast models presented here have been shown to provide reasonable assessments for a time horizon of two quarters. The quality of the forecasts typically improves as additional information becomes available. One important implication in this regard is that publishing the GDP flash estimate at an earlier date would potentially entail risks to its accuracy because of the larger proportion of estimation involved. In addition, the analyses point to the frequent discrepancies that arise between the various forecast models. This is especially true of supply-side and demand-side equations but also of factor models on account of their more pronounced smoothing. These differences are therefore partially caused by the specific design of the models, although they can just as well arise from the data. They can provide pointers for an overall evaluation by business cycle experts whose workload is significantly lightened by the use of short-term models but is by no means rendered unnecessary.

Constant modification and enhancement of the models

The econometric short-term forecast models currently in use at the Bundesbank have evolved from a process in which research findings have been tested in terms of their practical applicability and rendered useful. This process is still ongoing. Indeed, modifications and enhancements are constantly being tried out by, for example, examining how forecasts would have performed in the past had they made use of a different dataset or modified methods. A number of promising ideas that have proven useful when applied to other countries' data have been rejected. But such input is nonetheless useful inasmuch as it improves analysts' understanding of Germany's short-term business cycle dynamics.

Addition of daily data obtained from the financial markets

This applies, for instance, to the inclusion of financial market data on a daily basis. To cite an example, equity indices should be well suited for forecasting GDP owing to their forward-looking nature, in which case it would also make sense not to wait until a full month's worth of information becomes available but instead to feed readily available daily data into the forecasts. However, the lengthy computation required to interlink data with an appreciable frequency difference results in a certain loss of information. Studies for the United States indicate that macroeconomic short-term forecasts can be improved by including daily data obtained from the financial markets.[17] Whether this positive finding could also apply to Germany remains to be seen. This might be attributable, not least, to the looser interlinking of the real economy and the financial markets in Germany.

Inclusion of international indicators

Including international indicators would seem to be a more promising approach. To date, global developments have in most cases been factored into the Bundesbank's forecast models in an indirect manner, for instance through new export orders or enterprises' export expectations. Only commodity prices and exchange rates are fed directly into the factor models. However, survey indicators from other

17 For analyses on the United States, see E Andreou, E Ghysels and A Kourtellos (2013), Should Macroeconomic Forecasters Use Daily Financial Data and How?, Journal of Business & Economic Statistics 31, pp 240-251.

countries, for instance, could also be incorporated. Such indicators would improve the forecast, if they bring additional information. This seems to be the case for somewhat longer forecast horizons,[18] although the relevant surveys have been limited to quarterly data up to now. The difficulties associated with changing over to mixed frequencies stem from the large volume of data which has to be processed. Even factor models reach their limits when having to deal with several hundred indicators, thus making it necessary to pre-select the variables used. To this end, a range of options are available which, however, react very sensitively to modified specifications in terms of the resulting forecast quality.[19]

Derived forecasts of imports in bridge equations

An approach that is closer to being realised relates to an enhancement in the demand-side system in the bridge equations. As described earlier, the disaggregated approach takes no account of possible interdependencies between the individual components. Because imports, in particular, are very much influenced by other variables in the national accounts, this implicit assumption often leads to distortions in the form of conflicting errors in individual forecasts. Modelling imports in line with other demand-side components (derived forecast) can prevent such an accumulation of errors in disaggregated GDP forecasts.[20]

18 See C Schumacher (2010), Factor Forecasting Using International Targeted Predictors: The Case of German GDP, Economics Letters 107, pp 95-98.
19 See, for example, S Eickmeier and T Ng (2011), Forecasting National Activity Using Lots of International Predictors: An Application to New Zealand, International Journal of Forecasting 27, pp 496-511.
20 See P S Esteves (2013), Direct vs Bottom-up Approach when Forecasting GDP: Reconciling Literature Results with Institutional Practice, Economic Modelling 33, pp 416-420.

Annex

Factor models

Factor models are based on the fundamental consideration that many economic variables show similar development over the business cycle. Information from N individual indicators is consolidated into r factors F_{tm} in such a way that the dataset X_{tm} is represented as accurately as possible.

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

Here, the factor loadings Λ, together with F_{tm}, describe the components exhibiting similar developments in X_{tm}, ie that part of the dataset explained by the factors. The variable ζ_{tm}, by contrast, denotes the idiosyncratic component that is interpreted as the variable-specific part of X_{tm}. The time index t_m denotes monthly observations. The consolidation of information in factor models is evident from the fact that the large number of individual indicators is explained by a small number of factors. The literature has shown that a large part of the variation in datasets consisting of several hundred time series can be captured by a few factors.[21] There are procedures for estimating the factors that also take into account peculiarities in the data, notably missing observations at the current end.[22]

Various methods can be used to forecast GDP with estimated factors. One approach is to treat the estimated factors in a GDP equation as observable indicators. The discrepancy between monthly and quarterly frequencies in the GDP equation is bridged, in most cases, using exponential Almon lag functions, which require only limited parameterisation.[23] As an alternative to this two-part procedure, the forecast can also be prepared within a closed model framework. For this purpose, a state space model is esti-

21 See J Bai and S Ng (2007), Determining the Number of Primitive Shocks in Factor Models, Journal of Business & Economic Statistics 25, pp 52-60.
22 For a comparison of various factor models for short-term forecasting, see M Marcellino and C Schumacher (2010), Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP, Oxford Bulletin of Economics and Statistics, Vol 72, pp 518-550.
23 See G Ghysels, A Sinko and R Valkanov (2007), MIDAS Regressions: Further Results and New Directions, Econometric Reviews, Vol 26, pp 53-90.

mated, in which GDP is simultaneously explained and interpolated using monthly indicators.

The estimation techniques of the factor models allow a large number of indicators to be taken into account. Depending on the number of time series included, some limitations may arise when estimating the factors themselves and making the necessary connection between the selected variables and the target variable. Econometricians must also decide on the specifics of the forecast model, such as the number of factors to be estimated, but, in principle, these could be error-prone. This problem is, however, alleviated as all plausible specifics are included in the model pool, whereby, for example, the number of factors gradually increases to a specified maximum. Furthermore, the model variants are enhanced through various methods for filling gaps in the data at the current end and various functions for dovetailing monthly and quarterly data.

Bridge equations

Bridge equations describe the correlation between quarterly variables, such as GDP (or its components in the case of a disaggregated approach), and certain monthly economic indicators.[24] A forecast can be prepared using a bridge equation as follows. The quarter-on-quarter rate of change in GDP is defined as $y_{q,tq}$, with observations available for the quarters $t_q = 1, \ldots, T_q$. The forecast is described as $y_{q,Tq+hq|Tq}$ and is based on a forecast horizon of h_q quarters and on information up to and including quarter T_q. This information is taken from k monthly indicators $x_{m,j,tm}$ for $j = 1, \ldots, k$. Months are denoted by the time series index $t_m = 1, \ldots, T_m$.

The bridge equation is formulated on a quarterly basis and can be represented in simplified form as

$$y_{q,t_q} = \sum_{j=1}^{k} \delta_j(L) x_{q,j,t_q} + \varepsilon_{t_q}$$

in which the monthly indicators $x_{m,j,tm}$ have been transformed into quarterly frequencies. An indicator is aggregated over a time period according to whether it is a stock variable or a flow variable. The polynomial $\delta_j(L)$ in the lag operator L contains the coefficients of the lagged indicator.

To derive a GDP forecast $y_{q,Tq+hq|Tq}$ from the estimated bridge equation, forecasts for the time-aggregated indicators $x_{q,j,Tq+hq|Tq}$ for $j = 1, \ldots, k$ need to be calculated as a first step. For an indicator $x_{m,j,tm}$, this is done using a dynamic monthly model that produces the required quarterly forecast by aggregating data over time. In most cases, this first step involves simple autoregressive processes. However, other leading indicators, such as survey-based expectations, may be used as explanatory variables. The forecast horizon for the monthly forecast must be adjusted in line with the time lag in publishing the respective indicator, ie the longer the time lag is, the more values need to be estimated in advance.

In contrast to factor models, the model for bridge equations cannot incorporate all the available indicators. The relevant variables therefore need to be selected beforehand, a process, however, that may in turn be used for the combined forecast, as the model pool is expanded through variations in the variables selected. Furthermore, the number of models increases further depending on variations in the level of disaggregation in GDP.

Industrial production

The models for industrial production range from traditional autoregressive (AR) and vector autoregressive (VAR) processes to models that take into account error correction mechanisms and multi-cointegration between the two core variables – industrial production and new orders. In other model variants, the core variables are also complemented by various economic indicators and financial market variables.

Multi-cointegration, which has been somewhat forgotten in the literature, is an innovative feature of the industrial production models in use at the Bundesbank. It assumes, in addition to the usual "simple" cointegration, a further cointegrating relationship between flow variables (ie production) and stock variables (ie backlog of orders). In the case of industrial production, such a long-term anchoring is feasible, as enterprises should ideally absorb fluctuations in demand through the orders on hand.

24 See, for example, A Baffigi, R Golinelli and G Parigi (2004), Bridge models to forecast the euro area GDP, International Journal of Forecasting, Vol 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.

Theoretically, this practice of enterprises can be derived in a model using a quadratic cost function,[25] whereby production x_t is the control variable, new orders y_t is the target variable, and the production surplus $z_t = x_t - y_t$ yields the control error. The cumulated control error $Q_t = \Sigma^t_{j=0} z_j$ also has a target variable, which is measured as a constant share κ of new orders. The control error for Q_t is thus the "stock surplus" $u_t = Q_t - \kappa y_t$. The enterprise incurs costs from both control errors, z_t und u_t, as well as through the adjustment of the control variable x_t. Given the target variable y_t, the enterprise sets x_t or Q_t in such a way that it minimises the expected value E_t of the discounted costs.

$$J_t = E_t \sum_{j=0}^{\infty} \delta^j \Big[(x_{t+j} - y_{t+j})^2 + \lambda_1 (Q_{t+j} - \kappa y_{t+j})^2 + \lambda_2 (x_{t+j} - x_{t+j-1})^2\Big],$$

whereby δ is the discount factor and both λ_1 and λ_2 denote non-negative parameters. The minimisation problem gives rise to the adjustment rule for Q_t:

$$\Delta Q_t = \alpha + \beta(Q_{t-1} - \kappa y_{t-1}) + \gamma(y_{t-1} - x_{t-1}) + \mu(y_t - y_{t-1}).$$

Here, β, γ and μ are functions of δ, λ_1 and λ_2. This equation formalises the optimal solution for an enterprise in terms of production planning.

For the actual forecast equation, the following empirical considerations can be derived from the theoretical model. If production x_t and new orders y_t I(1) are integrated, but the production surplus z_t is stationary, then x_t and y_t are cointegrated.[26] Furthermore, if the "stock surplus" u_t is also stationary, there is multi-cointegration between x_t and y_t. Theory and empirical data are therefore combined in a forecast equation within the framework of an error correction model (with only one lag for clearer illustration):

$$\begin{bmatrix} 1 & \theta \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta x_t \\ \Delta y_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_1 & \gamma_1 \\ \beta_2 & \gamma_2 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix} \begin{bmatrix} \Delta x_{t-1} \\ \Delta y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix},$$

whereby θ denotes the potential simultaneous effects of new orders on production. The above-mentioned adjustment rule for Q_t can be derived accordingly from this error correction model, using $\alpha = \alpha_1 - (1 - \theta)\alpha_2$, $\beta = \beta_1 - (1 - \theta)\beta_2$, $\gamma = \gamma_1 - (1 - \theta)\gamma_2 + 1$ and $\mu = \theta$.

The pool of models for the combined forecast is generated by varying the specifications and the estimation windows. This involves moving the estimation windows along the entire observation period up to the minimum number of observations required to still ensure a relatively accurate estimation. Varying the estimation windows provides a certain degree of protection against any structural changes, because models with shorter estimation windows often react too sharply to changes at the current end. The combination of longer estimation windows, in which the parameters barely react to new structural factors, thus provides the necessary counterweight for producing more accurate short-term forecasts.

25 See T-H Lee (1996), Stock Adjustment for Multicointegrated Series, Empirical Economics, Vol 21, pp 633-639.
26 In practice, the cointegrating relationship is not exact (1,–1). First, this is due to the fact that different weighting schemes are used for the aggregated indices of production and new orders. Second, the relationship is influenced by the fact that new orders are not adjusted for cancellations. See Deutsche Bundesbank, Industrial orders and production: how informative is the order capacity index?, Monthly Report, February 2007, pp 52-53.