Models for short-term economic forecasting during the recent crises

Short-term business cycle analysis at the Bundesbank is designed to obtain a robust assessment of the economic situation and the immediate outlook. The focus is on the quarterly growth rate of seasonally and calendar-adjusted gross domestic product (GDP). A key role is played here by econometric forecasting models, which are augmented by the economic forecasters' expert knowledge. This combination yields the Bundesbank's final assessment of the economic situation.

The COVID-19 pandemic and the Russian war of aggression against Ukraine have presented considerable challenges for business cycle analysis and forecasting. The repeated containment measures during the pandemic and their subsequent easing led to massive swings in economic activity and high uncertainty about the economic situation and outlook. This uncertainty was heightened by the Russian war of aggression against Ukraine. Both events entailed economic burdens that were not adequately reflected by the conventional models in the Bundesbank's and other forecasters' toolboxes. The timely provision of robust model-based forecasts was thus not possible. This gave the expertise of business cycle experts a position of prominence.

Against this background, the toolbox for short-term forecasting has been modified and augmented. In addition, new methods and models that model economic activity at a higher frequency than quarterly have been introduced. Examples include the estimation of monthly GDP, a weekly activity index and the development of a weekly GDP indicator.

On average, the accuracy of the revised and new GDP forecasting models for the current quarter and the quarter just ended is higher than that of a simple comparison model in which the GDP rate is extrapolated using the historical average. The bridge equation model, which has the highest overall accuracy, also achieves this for forecasts one quarter ahead. The model forecast accuracy, which deteriorated massively following the outbreak of the pandemic, has improved again considerably since the end of 2020. However, it has not yet returned to its pre-pandemic level. Therefore, the knowledge and judgement of business cycle experts is likely to remain of prominent importance for the foreseeable future.

Challenges in post-pandemic economic forecasting for models and experts

Business cycle analysis important for monetary policy decisions

A timely and accurate assessment of the current economic situation and outlook plays an important role for monetary policy decisions. The Bundesbank's short-term business cycle analysis is intended to reliably assess macroeconomic activity and its determinants. It is centred on the growth rate of real GDP in the current quarter and one to two quarters ahead.[1] The Bundesbank regularly communicates its qualitative assessment of the German economy to the public in its Monthly Reports. The short-term forecast is also included as a quantitative benchmark in the semi-annual macroeconomic projections for the German economy.[2]

Using expert knowledge to augment econometric methods

Ongoing business cycle analysis at the Bundesbank is based on combining quantitative methods with qualitative approaches. This means that econometric models form the basis for short-term economic forecasting, which is then rounded off with the expertise and experience of economic experts. In this manner, the various model results are classified and merged, and information that cannot be fully captured by the pure model forecasts can be incorporated into the business cycle assessment.

Three forecasting models prior to the COVID-19 pandemic

Before the COVID-19 pandemic, there were three established forecasting models in the Bundesbank's business cycle analysis and forecast: a bridge equation model, a dynamic factor model and a vector autoregressive (VAR) model. While these models follow different approaches, what they have in common is that they contain different economic indicators in order to cover as many areas of economic activity as possible. In addition, they can process data that are available at different frequencies and for which observations are missing at the current end due to publication delays.[3]

Major challenges for forecasting models and business cycle analysis due to the COVID-19 pandemic and the Ukraine war

The crises of the past three years have posed considerable challenges to forecasting models and business cycle analysis. The COVID-19 pandemic and the measures taken to contain it led to historically unprecedented interventions in economic processes. From March 2020 onwards, they caused sudden and very strong fluctuations in economic activity. In Germany, GDP fluctuations of this magnitude were previously unknown.[4] In addition, economic uncertainty increased considerably. As pandemic-related uncertainties were gradually subsiding in early 2022, the Russian war of aggression against Ukraine and its impact on the economy introduced a new set of substantial imponderables. For instance, the energy markets were, at times, in danger of sliding into considerable turmoil. Traditional models were not prepared for these circumstances, and there were considerable doubts about the reliability of their results. One outcome was that economic experts' know-how took on a stronger role in applied business cycle analysis. Another was that the abrupt changes in the economic framework required rapid and significant modifications to the forecasting models and to the entire business cycle analysis toolbox.[5]

The difficulties of the models were, amongst other things, due to the delay in the publication of most monthly economic indicators. As a result, information on the possible effects on the economy could be incorporated into the models only with a time lag. Some effects,

1 Until the Federal Statistical Office publishes GDP and the detailed results of the national accounts for the past quarter, the ongoing business cycle analysis also includes this quarter.
2 The projection horizon is roughly three years. They are prepared every six months as part of the Eurosystem staff projections and enter into the euro area projections; see Deutsche Bundesbank (2023a).
3 For more information on these aspects and for detailed information on the short-term forecasting models used at the Bundesbank, see Deutsche Bundesbank (2018a).
4 The decline in GDP in the second quarter of 2020 was approximately eleven times the average fluctuations in GDP, measured by the standard deviation between 1991 and 2019. No such movements had hitherto been seen either in Germany since 1991, or in the available quarterly GDP rates for West Germany between 1970 and 1990.
5 The toolbox for short-term economic forecasts is generally continuously evolving. Therefore, the models used are reviewed at regular intervals. The last scheduled update took place in 2018; see Deutsche Bundesbank (2018a). The modifications since then have focused on the consequences of the crises.

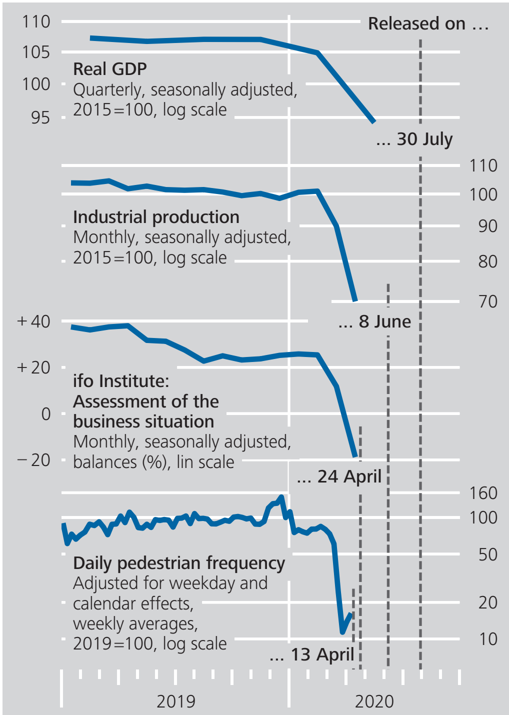
Fluctuations in activity sometimes captured by models only with a significant time lag, and sometimes not at all; forecasts also complicated by high volatility in the data

such as the mandatory business closures to avoid contact and contagion, were also virtually impossible to model. Traditional data did not reflect those effects at all, or not in full, or not in a timely manner.[6] In addition, the fluctuations in activity increased the uncertainty of the model estimates and thus diminished the robustness of the forecasts. Moreover, the usual forecasting models were not suited to adequately take into account the measures to contain the pandemic and the massive disruptions in the energy markets resulting from the Russian war of aggression against Ukraine. All of this increased forecast uncertainty and thus weakened the reliability of the model results.

Stochastic volatility and high-frequency economic indicators are particularly promising solution approaches in the literature

Uncertainty and how to deal with it, as well as major swings in economic activity, are not fundamentally new to forecasters. There are various approaches to dealing with such challenges. With regard to the econometric model estimation, for example, one possible approach lies in removing from the estimation the pandemic-induced outliers in the data.[7] Although that would make it possible to avoid the undesirable impact of large fluctuations in the data on the model estimation, this approach would not be able to adequately capture the unusually sharp increase in uncertainty about economic developments as a result of the pandemic and the historically unprecedented intervention measures. Another proposal is therefore to model time-varying residual volatility adapted to the data outliers (stochastic volatility).[8] This can improve the model estimation and the forecast. In addition, the uncertainty surrounding economic forecasts can also be taken into account. Lastly, in order to receive timely economic signals in times of very rapid economic fluctuations, collective high-frequency economic indicators were also developed in the early phase of the COVID-19 pandemic based, amongst other things, on daily or weekly indicators that are available in a timely manner.[9]

Time lags of data releases, using Q2 2020 as an example



Sources: Federal Statistical Office, ifo Institute and Hystreet.
Deutsche Bundesbank

Modifications to the model toolbox

Modifications to the Bundesbank's short-term forecasting models

The short-term forecasting models at the Bundesbank have been revised in line with the foregoing proposals from the academic literature. The main focus was on making the forecasting models more robust to large fluctuations in data and an economic environment with a high degree of uncertainty. This was intended to enable them to provide robust forecasts in times of economic tranquillity and turbulence alike. The revisions to the Bundes-

6 Some containment measures, for example, hit the parts of the services sector with frequent interpersonal contact, such as the hairdressing industry or the event sector, particularly massively. In Germany, the usual economic indicators capture such services neither in a timely manner nor completely.
7 See, inter alia, Schorfheide and Song (2021).
8 See, inter alia, Carriero et al. (2022) and Lenza and Primiceri (2022).
9 See, inter alia, Lewis et al. (2020) and Woloszko (2020).

bank's established forecasting models will be presented below.

Pandemic necessitated modifications to bridge equation model

The Bundesbank's bridge equation model consists of a system of individual forecast equations. This system is based on the structure of the national accounts. The GDP aggregate can thus be forecast directly. In addition, a GDP forecast can also be calculated by aggregating the forecasts of the production-side and demand-side components developed on the basis of monthly economic indicators.[10] Despite their sophisticated structure, the bridge equations were unable to adequately capture the impact on economic activity of the pandemic and the measures taken to contain it. The relatively rapid and strong fluctuations in economic activity caused forecasts to overshoot in both directions after the pandemic situation had already reversed itself. To make the model more robust to such strong fluctuations in activity, various modifications were examined to see whether they improve forecast quality during the pandemic without significantly worsening it in the pre-pandemic period.[11]

Lagged endogenous variables omitted from the model equations …

Reducing the use of lagged variables in the model equations has proved useful. In normal times, to be sure, lagged variables improve the adaptation of the estimation equations to the data and thus, on average, also the forecast quality. However, in times of high and unsystematic volatility, they often lead to false signals. Therefore, lagged endogenous and exogenous variables have been omitted from the quarterly bridge equations. Lagged endogenous variables are no longer used in the upstream equations for extrapolating monthly-frequency indicators, either.[12]

… and naive forecast modified for some GDP components

A further modification relates to the GDP components that were – in the absence of suitable leading indicators – previously extrapolated using naive forecasts.[13,14] These components are now extrapolated at the same growth rate as the superordinated areas for which reliable indicators are generally available. The modification rests on the assumption that similar sectors of the economy are driven by similar determinants.[15]

VAR model also facing particular challenges following onset of pandemic

The VAR model is designed as a Bayesian, mixed-frequency model, with a quarterly variable – GDP – and a dataset of monthly indicators.[16] These include hard indicators such as industrial production, production in the main construction sector and real retail sales, as well as soft survey-based indicators such as the ifo business climate index.[17] The sharp fluctuations in the data at the start of the pandemic distorted parameter estimation. These distortions were then extrapolated via the extensive feedback effects; this had an adverse impact on forecast quality.

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10 For both the production and demand sides, a direct GDP forecast and two forecasts using variants disaggregated to different depths are prepared. The forecasts on both sides are averaged. The two (production and demand-side) forecasts calculated in this way are then weighted and merged to form a final GDP forecast. For a detailed description of the bridge equation model used at the Bundesbank, see Pinkwart (2018) and Deutsche Bundesbank (2018a).

11 Further changes have been made compared to the bridge equation model described in Deutsche Bundesbank (2018a). For example, the underlying dataset was expanded by 100 time series, which mainly contain additional details from the ifo Institute's and S&P Global's business surveys, to a total of 233 monthly indicators. Specifications of the forecast of individual GDP components were also modified and the error correction mechanisms used in some equations were deactivated. Although, in some cases, the error correction mechanism makes theoretical sense, empirical evidence has shown that it does not contribute to an improvement in the forecast quality.

12 However, lagged exogenous variables are still included owing to the leading properties of the leading indicators used.

13 Naive forecasts are those according to historical averages or on the basis of autoregressive processes.

14 See Deutsche Bundesbank (2018a), p. 22.

15 For example, mean forecasting was previously used for the following areas of gross value added in the services sector: transportation, finance and insurance services, public services, education and healthcare, and other services. Assume now that these sectors follow the same dynamics as services excluding these sectors. The components of government demand (consumption and investment) are excluded from this modification and continue to be extrapolated using mean forecasting. Procyclical behaviour would not be economically plausible here – especially in times of economic crises.

16 See Deutsche Bundesbank (2018a), p. 22 and Götz and Hauzenberger (2021).

17 The monthly set of indicators is augmented by the number of persons in employment, new orders in industry and real exports and imports.

Time-varying residual variance stabilises the VAR model in times of high volatility

In the version of the VAR model used in short-term forecasting practice prior to the outbreak of the pandemic, all model parameters were considered to be time-invariant.[18] The revision allowed for time variation in volatility. It can help to incorporate large fluctuations in the data and thus mitigate distortion in the parameter estimation.[19] This makes forecasts more robust in the event of large fluctuations, without sacrificing forecast quality in normal times.

Data-based determination of the dynamics of time-varying volatility significantly improves the forecast quality of the VAR model

A further improvement in the VAR model was achieved in the area of Bayesian model estimation. In VAR models with time-varying volatility, parameters that determine the dynamics of time-varying volatility are often given values derived from the literature.[20] Under the modified variant of the model, these parameters are determined based on data instead.[21] This allows the parameters to be estimated more precisely and the forecast quality to be significantly improved.[22]

Factor model redesigned and, in particular, extended to include stochastic volatility

The factor model was replaced with a revamped model of the same category.[23] This is a dynamic factor model that is capable of processing indicators with different publication frequencies and lags. It also takes into account stochastic volatility in the residuals. This allows large fluctuations in the data to be captured in the time-varying residuals in part and a potential distortion of the parameter estimation to be mitigated.

Numerous model specifications produce empirical forecast distribution

The new factor model estimates a large number of model specifications[24] which result from all possible combinations of GDP and a set of monthly indicators.[25] GDP growth shows up as the target in each specification of the factor model. The number of factors is re-estimated for each model specification before each model run.[26] For each model run, the 32,767 point forecasts of GDP growth (one per model specification) form an empirical forecast distribution. This distribution is then used to generate two combined point forecasts for GDP growth: an unweighted median forecast and a forecast weighted by past quality.[27]

New methods and models in the toolbox

Transition from conventional models to innovative methods …

Although the Bundesbank's traditional short-term forecasting models are also based on modelling quarterly GDP, estimation methods with conventional monthly economic indicators and survey-based sentiment indicators are applied for the most part. While the latter are at least available at the end of the reporting month, the economic indicators in the official statistics are released with a lag of one to two

18 This version of the VAR model essentially borrows from the model of Schorfheide and Song (2015); see Deutsche Bundesbank (2018a).
19 For methodological details, see Götz and Hauzenberger (2021).
20 See, in particular, Schorfheide and Song (2015) as well as Götz and Hauzenberger (2021).
21 See Chan (2023).
22 In addition, the monthly set of indicators is augmented by a "weather variable": the ifo indicator of weather-related constraints to construction. In the VAR model, this indicator is entered into the equation of production in the main construction sector – exogenously with a current and a lagged value. The weather channel then unfolds across all other variables via interdependencies with the main construction sector. For exogenous indicators, the extrapolation is carried out outside the model. The long-term averages of the individual months are used for the weather-related constraints to construction. This extension reflects the growing importance of weather-related fluctuations in activity as a result of climate change.
23 For a comprehensive overview of the model, the estimation procedure and the technical details, see Eraslan and Schröder (2023).
24 The model estimation is based on a new and fast algorithm that is based on the algorithm of Koop and Korobilis (2014), extended for a mixed-frequency model. The estimation method makes it possible to estimate a large number of model specifications more quickly than with Bayesian or frequency estimation methods.
25 In addition to quarterly GDP, the dataset contains 15 monthly indicators: industrial production, new orders received by industry, production in the main construction sector, exports and imports of goods, number of persons in employment, sales in industry, hotels and restaurants and in the retail trade, consumer price index, HWWI commodity price index, DAX, three-month EURIBOR rate and ifo business situation and expectations in manufacturing. The indicators are adjusted for calendar, seasonal and price variations, where appropriate. This results in 2^{15} -1 = 32,767 different model specifications with 2 to 16 indicators.
26 The number of factors for each model specification is estimated using the statistical criterion of Bai and Ng (2002).
27 The weighted point forecast is calculated using dynamic model averaging; see Raftery et al. (2010). In this method, the model specifications, which have led to smaller forecast errors in the recent past, are given a higher weight. These weights are updated after each new GDP release. The weighted forecasts are the focus of applied business cycle analysis and this article.

months. During the pandemic, however, there were some phases where economic activity changed significantly within a quarter or even within a month. Quarterly and even monthly indicators only capture these fluctuations inadequately or with a time lag. Following the outbreak of the COVID-19 pandemic, the Bundesbank therefore used a number of methods which were unconventional at the time, modelling economic activity at a higher frequency than quarterly. To a degree, these approaches also take into account innovative indicators that are recorded on a weekly or daily basis and are therefore available more quickly.

… such as the estimate of monthly GDP

In one such approach, monthly GDP is estimated using a regression-based interpolation.[28] Five monthly economic indicators are included in the estimate: industrial production, real retail sales, real exports of goods, production in the main construction sector and real turnover in the hotel and restaurant industry.[29] For the estimate, an unobservable monthly GDP series is regressed on monthly indicator variables, ensuring that the quarterly average of the estimated monthly GDP corresponds to the published quarterly GDP.

Monthly GDP is extrapolated beyond the current end for the short-term forecast

For the short-term forecast, quarterly GDP is interpolated using the method described above and extrapolated beyond the current end. In a first step, indicators for the months with data that have not yet been published are extrapolated. The respective forecasts from the bridge equation model are used for this purpose. In a second step, a calculation is then made of monthly GDP – including the forecast for quarterly GDP. This approach, referred to hereinafter as the MGDP model, thus paints a picture of changes in economic activity within a quarter. This is particularly advantageous if the activity is clearly moving in one direction and thus creates a positive or negative carry-over effect for the following quarter. The MGDP model also provided a useful tool for economic experts to harness non-model-based information on the pandemic in a transparent and model-based way for their expert assessment. For instance, it allowed markdowns to the model-based extrapolations of turnover in the hotel and restaurant sector or in retail to be made based on expert knowledge, for instance, when measures to contain the COVID-19 pandemic were tightened. The auxiliary forecasts produced in this manner were thus improved considerably in these phases, as such abrupt adjustments are not captured promptly in the pure model forecasts.

Weekly activity index

The Bundesbank's weekly activity index (WAI) was developed in the early phase of the COVID-19 pandemic.[30] In addition to GDP and industrial production, it is composed of indicators that are recorded weekly or even daily and are available in a very timely manner. These indicators, which were unconventional back then, were selected according to two criteria: they should, first, cover different sectors of the economy and, second, contain relevant information for real economic activity. This includes, for example, pedestrian frequency figures in inner-city shopping streets and credit card payments, which partly capture consumer behaviour, or indicators based on Google search queries for unemployment and short-time work, which relate to the labour market.[31]

28 The interpolation method is based on an approach by Chow and Lin (1971). For application of the procedure to Germany, see Deutsche Bundesbank (2021); for application of the procedure to the euro area, see Mönch and Uhlig (2005) and Deutsche Bundesbank (2020a).

29 When selecting monthly indicators, the explanatory power with regard to the estimation of monthly GDP as well as the sign and stability of the estimated parameters was investigated for various model constellations. As in Mönch and Uhlig (2005), the ratio of the variance of the change in estimated monthly GDP to the sum of the variance of the change in estimated monthly GDP and the variance of the residual is used as a measure for the explanatory power.

30 See Deutsche Bundesbank (2020b) and Eraslan and Götz (2021). Since June 2020, weekly WAI updates are published on the www.bundesbank.en/wai website. The WAI is similar to the weekly economic index (WEI) for the US economy published by the Federal Reserve Bank of New York, see Lewis et al. (2020).

31 Source of unadjusted figures for the Google search queries: Google Trends; for the pedestrian frequency indicator: Hystreet sourced from the Federal Statistical Office; for the credit card payments indicator: Fable Data. For the current indicators in the WAI and their sources, see methodology at www.bundesbank.en/wai

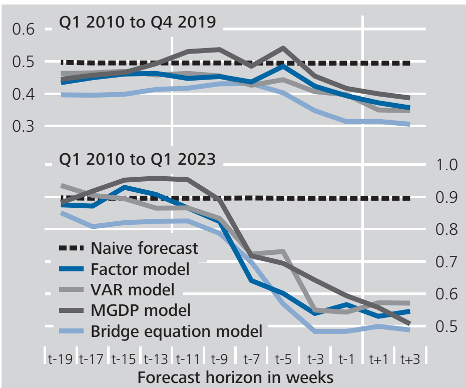
Evaluation of forecast quality: cross-comparison between models and comparison over time

This box uses historical forecast quality to evaluate the short-term forecasting models for gross domestic product (GDP) used in business cycle analysis.[1] To this end, the models' past forecast errors are calculated. The target against which forecasts are evaluated is the quarterly growth rate of seasonally and calendar-adjusted real GDP. Forecast quality is measured based on the mean absolute error (MAE). For each forecast horizon, the MAE is calculated as the arithmetic average of the difference in size between the forecast and the realised figures.[2]

The evaluation period runs from the first quarter of 2010 to the first quarter of 2023. Forecast quality based on the MAE is illustrated for two periods. The first period from the first quarter of 2010 to the fourth quarter of 2019 includes the relatively calm periods for the German economy following the financial crisis and before the COVID-19 pandemic. The second period covers the entire evaluation period. It thus also includes the exceptionally strong fluctuations in activity and the heightened uncertainty in the period following the onset of the COVID-19 pandemic and the start of Russia's war of aggression against Ukraine. In both periods, the MAE of the short-term forecasting models is compared with the MAE of a simple ("naive") comparison model. In the comparison model, the GDP growth rate is extrapolated using its historical mean. Over time, short-term forecasting models can take more and more information into account. Their forecast errors can therefore be expected to decrease as the forecast horizon shrinks.[3]

Mean absolute forecast errors*

Percentage points



* Depending on the forecast horizon, estimated based on quarterly GDP growth rates.

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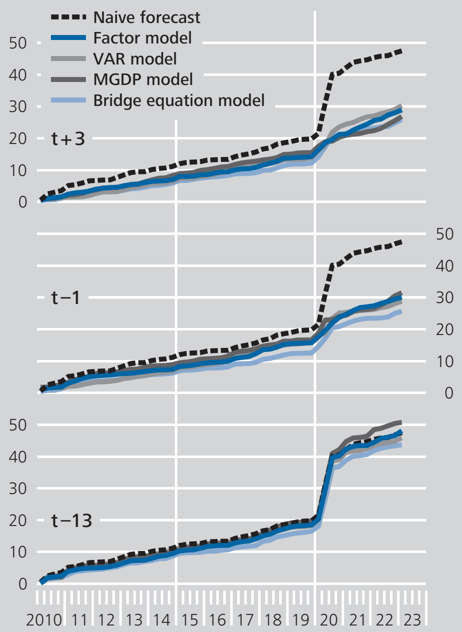
1 The forecast evaluation is based on data as at 25 May 2023. Since the historical forecasts are calculated on the basis of final data, this exercise takes place in "pseudo real time". Although this replicated the respective data availability, it was not possible to take into account historical data revisions. Two forecasts per month are calculated for each target quarter. The first forecast for a target quarter is calculated approximately one week after the release of the flash estimate for the quarter two quarters earlier, i.e. 19 weeks before the end of the forecast quarter. Forecasts for the target quarter are then calculated every two weeks until the target figure is published. Accordingly, the forecast horizon is given in weeks relative to the forecast quarter and ranges from $t{-}19$ to $t{+}3$, where t denotes the end of the quarter. For example, the horizons from $t{-}19$ to $t{-}13$ indicate the forecasts one quarter ahead, and the horizons $t{-}11$ to $t{-}1$ cover the forecasts for the current quarter. Since GDP is not published until around four weeks after the end of the reference quarter, forecasts for the previous quarter are also prepared up to this point in time ($t{+}1$ and $t{+}3$).
2 For example, an MAE of 0.2 means that the forecast fluctuates 0.2 percentage point around the actual values on average.
3 The factor model calculates weighted forecasts for GDP growth based on past forecast quality. In business cycle analysis as practised by the Bundesbank, this weighting takes forecast quality into account using real-time data. However, complete real-time data records are not available for all models under consideration. For this reason, weighting for the factor model was also calculated using the final data in this evaluation. This ensures better comparability with the other models.

Cumulative absolute forecast errors*

Percentage points



* Estimated based on quarterly GDP growth rates, for three forecast horizons: the last forecast for the past quarter in t+3, the last forecast for the current quarter in t−1, and the last forecast for one quarter ahead in t−13.

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In the evaluation period ending in 2019, the short-term forecasting models produce better predictions than the naive forecast over almost the entire forecast horizon. The MGDP model is an exception in some instances. The models' accuracy tends to increase as the publication date approaches, as more information is available. A cross-comparison of the models shows that the bridge equation model has the highest accuracy on average over almost all forecast horizons. The VAR and factor models perform somewhat worse. The MGDP model has the lowest accuracy.

Looking at the entire evaluation period up to the beginning of 2023, the average forecast errors are significantly higher for all models. This reflects the deterioration in forecasting capacity in the period from 2020 onwards, which is now also considered, as a result of the impact of the pandemic and the Ukraine war.[4] For the longer forecast horizons, the models are now not always superior to a naive forecast. This does not apply to the bridge equation model, which at the same time also proves more accurate in a cross-comparison with the other models across almost all forecast horizons.

In addition, the cumulative absolute error (CAE) is calculated. This metric sums together the absolute forecast errors over time for a given forecast horizon. It thus summarises developments in forecast errors over the evaluation period. This has the advantage of making it easy to spot periods with particularly high forecast errors. They are characterised by a steeper slope or a sharp rise in the CAE. By way of example, three specific horizons are considered: the last forecast for the previous quarter produced shortly before publication of the flash estimate ($t+3$), the last forecast for the current quarter ($t-1$), and the last forecast calculated one quarter ahead ($t-13$).

According to the CAE, as for the MAE, the short-term forecasting models perform better than the comparison model for the shorter forecast periods $t+3$ and $t-1$. The differences in the accuracy between the models is also similar: the bridge equation model cumulates the smallest errors, the factor and VAR models somewhat more and close to one other, and the MGDP model somewhat higher still.

The exceptionally large forecast errors for the first three quarters of 2020 due to the COVID-19 pandemic are clearly reflected in the CAEs: they spike higher for all models.

4 As the forecasting models used here derive their forecast quality from identifying historical relationships between variables, and the fluctuations during the COVID-19 pandemic, in particular, were historically unique, the deterioration in accuracy comes as no great surprise.

For the horizons $t+3$ and $t–1$, it is evident that the errors of the forecasting models increase significantly less than those of the comparison model. The forecasting models therefore performed better than the comparison forecast during this period. Errors increase least in the MGDP model; it was thus best able to anticipate the strong fluctuations in activity at that time. For $t–13$, however, the forecasting models show no advantage over the comparison model during the same period. For all models, CAEs rise by a similar magnitude. In general, the accuracy of the forecasts is lower on average for longer horizons. However, this shows, above all, that the forecasting models were simply unable to identify the COVID-19 pandemic and its effects so far in advance.

From the fourth quarter of 2020 onwards, the forecast quality for all three horizons improved considerably again as compared with the beginning of 2020 but it is still noticeably impaired.[5] The accuracy of the short-term forecasting models is not yet back to where it was before the COVID-19 pandemic. However, this is not surprising given the volatile economic environment of the past three years.

5 This is reflected in the somewhat steeper slope of the CAE compared with the slope before 2020.

High correlation with GDP growth, but no model-based forecasts; hence …

The WAI[32] is calculated as the common factor driving the underlying indicators.[33] It provides a timely assessment of current real economic activity and also exhibits a high correlation with quarterly GDP growth. However, the WAI data are not easy to interpret as the indicator looks at moving 13-week periods within a quarter. Moreover, the WAI does not provide forecasts for quarterly GDP growth rates either.

… a weekly GDP indicator has been developed

Given the limitations of the WAI, a dynamic factor model has been developed to estimate a weekly GDP indicator (WGDP indicator).[34] The WGDP indicator is calculated as a common factor driving the indicators available at different frequencies[35]. The model is based on weekly growth rates and can approximate latent weekly GDP growth rates. In addition, observed data from monthly and quarterly indicators are taken into account. In terms of both growth rates and its level, the WGDP indicator roughly adds up to the observed quarterly GDP.

Weekly forecasts for GDP growth

The WGDP indicator has some advantages over the WAI when it comes to the ongoing observation of the business cycle. Above all, a clear interpretation can be made within one quarter. A calculation can be made every week of the quarter-on-quarter (rate of) change in GDP, for example. In addition, the model can generate purely data-based forecasts for quarterly GDP growth (and the level of GDP) on a weekly basis.

32 The WAI is based on 13-week moving averages of the indicators and their 13-week growth rates. It fluctuates around its mean, which is zero by construction, and therefore provides the trend-adjusted growth rate of real economic activity. For the methodology and the technical details of the WAI, see Eraslan and Götz (2021).
33 Indicators that are originally available on a daily basis feed into the calculation as weekly averages. The indicators are adjusted for calendar, seasonal and price variations, where appropriate. See Ollech (2023) for details on the seasonal adjustment of high-frequency indicators.
34 See Eraslan and Reif (2023).
35 Similar to the WAI, the WGDP indicator is based on a dataset consisting of weekly, monthly and quarterly indicators with different release patterns. However, in order to improve the explanatory power of the WGDP indicator in relation to quarterly GDP, the dataset has been expanded compared with the WAI to include other conventional economic indicators.

The short-term economic forecast for GDP growth from 2018 to 2023 in practice

Short-term forecasts and expert assessments in real time

The use of forecasting models and expert assessments in the practice of economic analysis is investigated using the example of the short-term forecasts for German GDP that were issued twice a month between the first quarter of 2018 and the second quarter of 2023. The second quarter of 2023, for which the GDP growth rate was recently published, is discussed in greater detail in the box on pp. 72 ff. These illustrations offer a glimpse behind the scenes of the Bundesbank's applied business cycle analysis and forecasting. They highlight, in particular, the problems faced by business cycle analysis during the COVID-19 pandemic. The forecasts are presented in the same way as they were actually produced, amidst a continuous influx of new information – i.e. in real time. Forecasts by economic experts are also shown alongside the model-based forecasts.[36] The former notably incorporate expert knowledge gained through experience, and also information on special factors that models do not capture sufficiently, or at all. This allows us to illustrate the composition of model-based forecasts and expert assessments under different economic conditions.

Cyclical slowdown in 2018-19 flagged by models and correctly assessed by experts

After the German economy boomed with strong growth rates in 2017, GDP growth slowed significantly in 2018 and 2019. This weakening of growth was generally well predicted by the models. However, special factors caused some fluctuations, creating difficulties for both model-based forecasting and the experts' business cycle analysis. These notably included the difficulties faced by the German automotive industry with the changeover to a new EU-wide standard for measuring exhaust emissions in the summer of 2018.[37] Over the course of 2019, however, the models then overstated the slowdown, producing significantly negative growth rates pointing to economic warning signs. Although the economic experts considered a technical recession, meaning two consecutive quarters with negative GDP growth rates, to be possible in the course of the economic slowdown, they did not expect a recession in the sense of a significant, broad-based and persistent decline in economic output with underutilised aggregate capacity.[38] On the whole, the experts' assessments of economic developments in the years 2018-19 were good, albeit a little too optimistic at times.

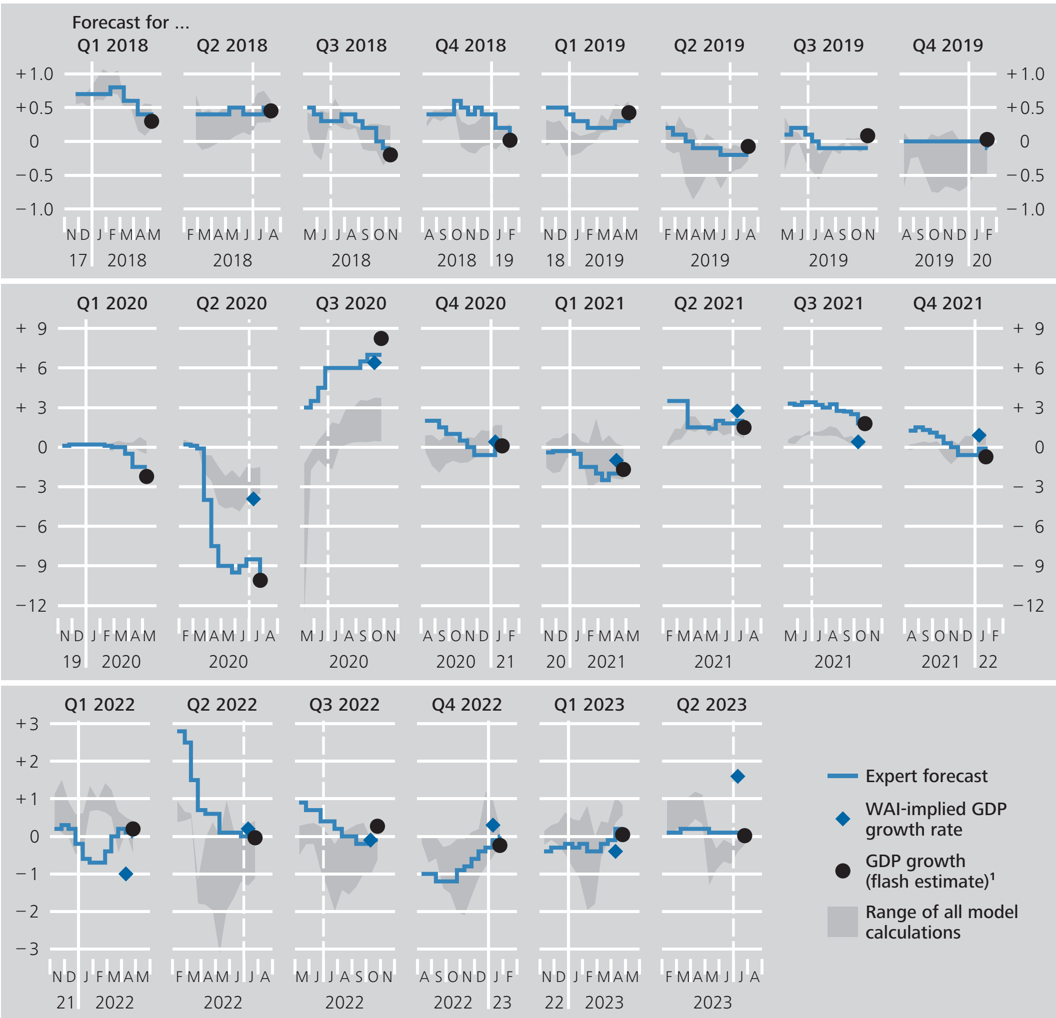
Economic experts were significantly better than models at predicting the huge economic slump after the outbreak of the pandemic …

When the COVID-19 pandemic reached Germany in March 2020, it caused massive difficulties for the forecasting models. The models only identified the very sharp drop in economic output with a significant lag, and even then they fell far short of capturing the actual magnitude of the decline in GDP. In this situation, economists' expert knowledge gained substantially in importance. The experts responded more quickly to the possible economic impact of the COVID-19 pandemic, performing a swift and substantial downward revision to their forecast for the first two quarters of 2020. Ultimately, they were remarkably successful at predicting the reported declines in GDP given their size and the high uncertainty. Information that was not included sufficiently, or at all, in classic forecasting models played an essential part in these assessments. This was particularly true of the pandemic situation and evaluations of the economic impact of containment measures. Here, estimates using heavily disaggre-

36 Both the revised models and the new methods were integrated into applied business cycle analysis at varying points in time. For example, the WAI was developed shortly after the outbreak of the COVID-19 pandemic and was already put into operation in the second quarter of 2020. Between the third quarter of 2020 and the first quarter of 2022, the bridge equation model was revised successively and integrated into day-to-day operations. The MGDP model has been in use since the beginning of 2022, while the revised VAR model has been in operation since the third quarter of 2022. The new factor model did not replace its predecessor in day-to-day business until the first quarter of 2023. For this reason, the model-based forecasts are derived partly from model variants that pre-date the changes and partly from those after them, i.e. each forecast is as it was actually calculated at the time.
37 See Deutsche Bundesbank (2018b).
38 See Deutsche Bundesbank (2019).

Short-term forecasts of GDP growth in real time

Percentage quarter-on-quarter change



Sources: Federal Statistical Office and Bundesbank calculations. **1** Since July 2020, the GDP flash estimate has been based on information available around 30 days after the end of the target quarter. Until then, GDP estimates became available for the first time around 45 days after quarter-end.
Deutsche Bundesbank

gated sectoral analyses of the relevant sectors became important, for example. Amongst other things, real-time high-frequency data, such as the truck toll index, were used for this purpose.[39] The WAI also provided timely, fairly accurate signals about the current economic situation.[40] Finally, the Bundesbank's macroeconometric model[41] was used to create alternative macroeconomic scenarios regarding the pandemic, which also included an estimation of their GDP effects via the expenditure components.[42]

… but underestimated the impact of supply bottlenecks in 2021

After the pandemic containment measures were eased, there were signs of a strong countermovement in the third quarter of 2020. Here, too, the models identified the recovery only slowly and on a smaller scale. By contrast, at an early stage, the experts already foresaw a sharp rise in GDP, aided, in particular, by the relevant signal from the WAI. As the pandemic continued, GDP growth no longer fluctuated quite so strongly. In the winter of 2020-21, the model forecasts diverged greatly. On the whole, however, their forecasts were much closer to

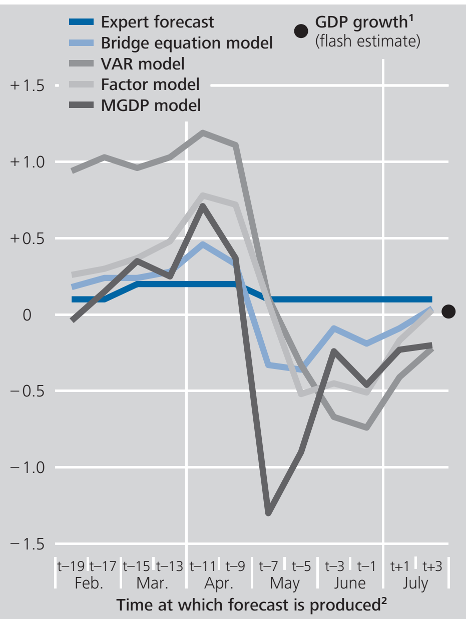
39 See Deutsche Bundesbank (2020c).
40 See Deutsche Bundesbank (2020d).
41 See Haertel et al. (2022) for an overview of the Bundesbank's macroeconometric model.
42 See Deutsche Bundesbank (2020e) and Work stream on Eurosystem modelling (2021).

Business cycle analysis: an illustration based on the second quarter of 2023

In practice, the Bundesbank's business cycle analysis for Germany is guided by the publication calendar for key indicators of economic activity and sentiment. While hard economic indicators in the form of official statistics (mainly industrial data) are usually released in the second week of each month, soft indicators such as the ifo business climate index are generally published in the fourth week of every month. Accordingly, model forecasts and experts' economic assessments are updated twice a month.[1] This box gives a detailed explanation of applied business cycle analysis based on the real-time forecasts produced by the revised short-term forecasting models and the expert assessment for the second quarter of 2023.[2]

Short-term forecasts for Q2 2023

Quarter-on-quarter percentage change, data as at reference date



Source of GDP flash estimate: Federal Statistical Office. **1** Price, seasonally and calendar adjusted. **2** t refers to the end of the forecast quarter. The first forecast is produced 19 weeks before the end of the quarter, i.e. t − 19.

Deutsche Bundesbank

At the beginning of February 2023, the underlying dynamics of the German economy were more robust than had been anticipated in the Bundesbank's December 2022 projection.[3] As a result, the Bundesbank's economic experts initially forecasted a slightly positive growth rate (0.1%), positioning themselves still at the lower end of the spectrum in terms of the model forecasts. Two weeks later, with the publication of the national accounts details for the fourth quarter of 2022 by the Federal Statistical Office, the corresponding GDP rate was also revised – to a more pronounced than previously reported decline, which almost matched the figure from the December projection.[4] On the other hand, surveys conducted by the ifo Institute showed a further improvement in enterprises' business expectations. Moreover, uncertainty about the energy supply declined steadily, and energy prices fell significantly.

In addition, at the beginning of March it became apparent that there had been a strong countermovement in the manufacturing sector in January following the setback seen

1 In addition, the weekly activity index for the German economy (WAI) is updated weekly on the Bundesbank's website.
2 Following publication of the flash estimate for the fourth quarter of 2022 at the beginning of February 2023, the short-term forecast horizon was extended to include the second quarter of 2023. Until the publication of the corresponding GDP flash estimate at the end of July, forecasts for the second quarter were thereafter prepared on a twice-monthly basis.
3 In the projection, a slight decline had been expected for the second quarter of 2023; see Deutsche Bundesbank (2022d).
4 However, this decline was driven by a broad-based, strong setback in many economic indicators in December. This was due not only to cyclical effects but also to temporary effects such as an exceptionally high level of sickness and unseasonably cold weather in the two weeks leading up to Christmas 2022.

in December.[5] This suggested that the German economy might be recovering somewhat faster than previously expected. In this environment, the model forecasts for the second quarter increased. In line with this, the expert assessment was also revised up somewhat (to 0.2%).[6]

In April, it even looked as though German economic activity had not contracted again at the start of 2023, as previously expected, but could actually have grown somewhat. Industrial production, in particular, continued to rise steeply in February, and the decline in demand appeared to have been overcome as new orders rose strongly. Against the backdrop of well-filled order books and easing supply bottlenecks, a temporary boost for industry was even conceivable. At the time, however, the Bank's economic experts did not yet react by revising up their forecast for the second quarter.[7]

The Federal Statistical Office's flash estimate for GDP growth in the first quarter of 2023, which was published at the end of April, showed stagnating GDP and consequently fell slightly short of experts' expectations. However, the exceptionally weak industrial data for March, which were published shortly afterwards, were much more surprising. In particular, the sharp decline in new orders cast doubt on whether industrial demand had, in fact, already bottomed out.[8] In addition, ifo surveys showed a deterioration in the business climate. These new data caused a downright collapse in some model forecasts. By contrast, the WAI, which continued to indicate an expansion during this period, sent the opposite signal.

The expert assessment was also downgraded at the beginning of May, but the forecast was lowered only slightly to 0.1%. One factor was that it was thought that the high order backlog and the easing of supply bottlenecks would further cushion the effects of weak demand on production.[9] Moreover, it still appeared likely that private consumption had bottomed out, as real disposable incomes were probably no longer declining thanks to easing inflation and markedly rising wages. This appears also to have buoyed the services sector, for which survey results among businesses and purchasing managers tended to be positive at the end of May. The fact that indicators relating to the services sector tend to be underrepresented in the short-term forecasting models was another reason why a more positive view than that taken by the models seemed appropriate.[10] The Bundesbank's new macroeconomic projections, which

5 The temporary factors that were likewise responsible for the setback in December evidently carried greater weight than initially thought. It is possible that firms in the manufacturing sector halted their production sooner or for longer than usual in response to the high levels of sickness and high energy prices as well as the way the calendar fell with an unusually large number of working days around the holidays. In addition, the weather in January proved unusually mild, after much of December had been characterised by exceptionally unfavourable weather conditions. As a consequence, construction could have experienced catch-up effects as activity recovered and made up for lost time.
6 Given weak demand from abroad, ongoing high inflation and further monetary policy tightening, a significant improvement was not yet in sight, however. See Deutsche Bundesbank (2023b).
7 One reason for the experts' cautious attitude was that the ifo business climate index improved only slightly as the assessment of the current situation had deteriorated somewhat.
8 As a result, GDP growth for the first quarter of 2023 was revised down noticeably (to -0.3%) with the publication of the national accounts details on 24 May.
9 According to data published at the beginning of June, industrial production in April remained almost unchanged from its March level, which had been revised up, but was still depressed. In addition, industrial new orders continued to decline slightly. However, according to non-official data from the German Association of the Automotive Industry, car production rose sharply in May.
10 The same applies to government consumption, which is barely captured in short-term forecasting models. Following the decline in the first quarter, which was unexpectedly strong based on the data available at the time, a certain countermovement was expected in the second quarter.

were finalised on 31 May, were also based on slight GDP growth for the second quarter of 2023.[11]

Nor did this assessment for the second quarter change when a significantly gloomier business climate indicator was published at the end of June, as this was driven first and foremost by business expectations relating mainly to the third quarter. Surveys also signalled a further easing of supply bottlenecks both in industry and construction. Following the publication of the hard data at the beginning of July, most model forecasts improved somewhat. Industrial new orders rose sharply again, although the underlying trend was still downward-directed. Moreover, the labour market remained stable. Therefore, the assessment that real GDP was likely to have risen slightly in the second quarter remained unchanged, with growth still at 0.1%. It was thus still somewhat above the range of the model forecasts.

At the end of July, the Federal Statistical Office reported in its flash estimate that GDP had stagnated in the second quarter of 2023. This was slightly less than had previously been expected by economic experts. For the period from the beginning of February to the end of July as a whole, their assessment was fairly stable, but somewhat too optimistic. By contrast, the models were initially significantly too optimistic and then much too pessimistic for a long time. These fluctuations were least pronounced in the bridge equation model.

11 See Deutsche Bundesbank (2023a).

the realised GDP growth rates than at the start of the pandemic. The expert forecast was again quite accurate in that same period. In the spring of 2021, however, the economic experts somewhat overestimated the strength of the recovery after containment measures were eased, while the models tended to underestimate it. One factor in the experts' overestimation was that they underestimated the sharp increase in supply bottlenecks for intermediate goods in many sectors at the time. At the end of 2021, by contrast, models and experts correctly gauged the impact of the renewed intensification of the pandemic on the economy. In the first quarter of 2022, however, the experts remained overly pessimistic for a long time in view of ongoing restrictions, while the models overestimated the strength of the recovery.

Strongly elevated forecast uncertainty with the outbreak of Russia's war of aggression against Ukraine

The outbreak of Russia's war of aggression against Ukraine in February 2022 led to a very high degree of uncertainty about economic developments. The range of the model forecasts increased again sharply. Owing to the substantial deterioration in business expectations, some models predicted a sharp economic downturn. Behind this lay concerns that, in particular, a halt in Russian gas supplies to Germany could trigger massive disruptions in the energy markets, and possibly even mandated rationing. The Bundesbank initially took these risks into account by simulating adverse risk scenarios.[43] At the same time, the experts' baseline scenario remained fairly optimistic regarding the 2022 summer half-year, thus predicting the relatively robust development of the German economy rather well.

However, when it became apparent in the summer that Germany would need to get through the coming winter largely without Russian gas supplies, the outlook for the 2022-2023 winter half-year deteriorated. The

43 See Deutsche Bundesbank (2022a, 2022b).

Following the halt in Russian gas deliveries to Germany, models and experts predicted a gloomier outlook for 2022-2023 winter half-year

models showed a considerable decline in economic output, and the experts performed a large downward revision on their assessment. In the September Monthly Report, the experts warned of a heightened risk of recession.[44] In the following months, however, it became increasingly clear that the German economy would be better able to cope with the changed underlying conditions than initially feared. Nevertheless, the energy crisis constituted a substantial burden. The December projection therefore predicted a 0.6% decline in GDP in the fourth quarter of 2022. A further decline (of 0.3%) was expected for the first quarter of 2023.[45] In fact, the German economy performed somewhat better in the winter than was assumed in December.[46] The industrial sector withstood the energy crisis and the weakening of demand thanks to diminishing supply bottlenecks and well-filled order books. Gas shortages became increasingly unlikely because of partly weather-related energy savings that were partly due to mild weather conditions, and increased (liquefied) gas deliveries. According to survey indicators, there was a widespread decline in corporate pessimism about the future.

Conclusion: Forecasting models remain the most important tool for business cycle analysis

Accuracy of the model forecasts deteriorated massively with the onset of the pandemic and is still not as good as beforehand

An evaluation of the short-term forecasting models based on their forecast quality shows that, on average, the adjusted models provide informative forecasts of economic growth for the current quarter and, as the case may be, the quarter just ended (see the box on pp. 67 ff.). This applies both in the period from 2010 to 2019 and in the period from 2010 to the first quarter of 2023. The adapted bridge equation model, which has the highest overall accuracy, also manages to achieve this for forecasts one quarter ahead. Moreover, having deteriorated massively with the onset of the pandemic, the accuracy of the model forecasts has improved again considerably since the end of 2020. The evaluation results thus underline the key role of the forecasting models as a valuable tool for applied business cycle analysis. At the same time, however, their accuracy has not yet returned to its pre-pandemic level. Consequently, the expertise of the economists will probably continue to play a vital role for the foreseeable future.

Regular reviews of models still necessary

As soon as the German economy enters a lasting calmer phase, the accuracy of the forecasting models is likely to improve further. At the same time, the latest revisions do not mark the end of work on the short-term forecasting toolbox. Regular reviews and adjustments of the models are necessary in order to maintain their ability to perform under changing economic conditions.

Inclusion of new data and methods in economic forecasting

Technological progress also permits new data and methods to be utilised. For example, in the future, computer-based text analysis could make it possible to use media information to generate high-frequency economic indicators, which enable timely model-based recording of cyclical fluctuations.[47] Newly available methods, e.g. in the field of machine learning and artificial intelligence, can also be incorporated into business cycle analysis and forecasting.[48] Reviewing the suitability of these and other new data and methods for forecasting Germany's GDP will remain an ongoing task.

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44 See Deutsche Bundesbank (2022c).
45 The direct effects of the energy crisis played a key role in the expectation of weakening economic activity, particularly the loss of household purchasing power due to high inflation and the burden placed by high energy prices on the industrial sector. However, additional factors included braking effects from weak foreign demand for the export sector, dampened investment due to high uncertainty and increased financing costs, and a decline in government consumption as pandemic-related expenditure came to an end. See Deutsche Bundesbank (2022d).
46 The Federal Statistical Office initially reported a 0.2% decline in GDP for the fourth quarter of 2022 and stagnation for the first quarter of 2023. The figures for both quarters were later revised markedly; recent data show a fall in GDP for both quarters. The decline is still milder than was expected in the December projection, however.
47 See, inter alia, Thorsrud (2020) and Barbaglia et al. (2023).
48 See, inter alia, Babii et al. (2022) and Coulombe et al. (2022).

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