BANK OF ENGLAND

Quarterly Bulletin

2018 Q3

Topical article

Gauging the globe: the Bank's approach to nowcasting world GDP

ISSN 2399-4568

Gauging the globe: the Bank's approach to nowcasting world GDP

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- Global activity is a key driver of UK GDP and a bellwether of prospects. Nowcasting global GDP growth, or predicting outturns ahead of their release, is therefore a key input into the Monetary Policy Committee's assessment of the UK economic outlook.
- The Bank uses a suite of models to assess the momentum in the world economy in real time. A wide range of financial market, survey-based and high-frequency output indicators are used to inform the suite.
- The statistical suite of global nowcasting models tends to provide an accurate assessment of global activity growth, and significantly outperformed a simple model that did not benefit from the use of high-frequency data during the financial crisis.

Overview

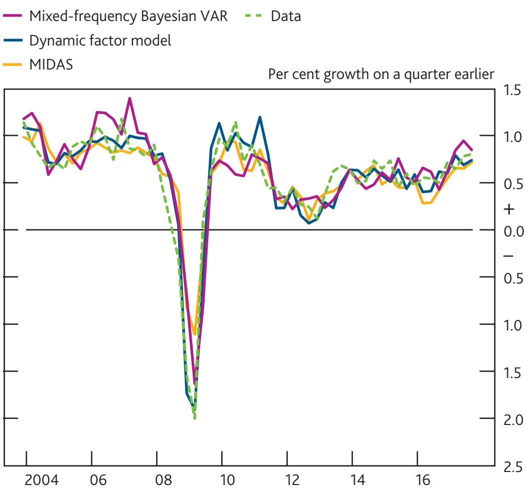
Developments in world activity can spill over to UK gross domestic product (GDP) growth both through trade and non-trade linkages. World GDP growth is therefore a key input into the Monetary Policy Committee's forecast. Official GDP releases, particularly in sufficient number to construct a global aggregate, only appear with a significant lag. However, there are many sources of economic activity and financial market data that can provide more timely insights into the path of world activity.

The Bank focuses on two key measures of global activity: UK export-weighted world GDP, and purchasing power parity-weighted world GDP. The first provides a picture of demand conditions with a larger weighting towards the UK's main trading partners. The second provides a more general picture of global activity growth, weighting together economies by their respective output.

Statistically tracking the growth of world GDP can potentially benefit from the use of a huge range of high-frequency indicators. However, that poses a challenge where indicators provide conflicting signals. To process those data efficiently, the international nowcasting suite contains three core models, some of which are similar to those used to nowcast UK GDP (Anesti *et al* (2017)).

The nowcasting suite has performed well historically, producing a sound model-based anchor for the first quarter of the Bank's quarterly global forecast that feeds into the *Inflation Report* (see **summary chart**). The use of high-frequency data has added the most value to predicting world GDP growth during the financial crisis. And models using high-frequency data are particularly valuable during turning points for global growth — therefore they will be a useful tool in monitoring the sustainability of the recent upturn in global growth. That said, a simpler benchmark model has been difficult to outperform in the post-crisis period given the low volatility of world GDP growth.

Summary chart World GDP (UK export-weighted) and real-time nowcasts from a suite of models



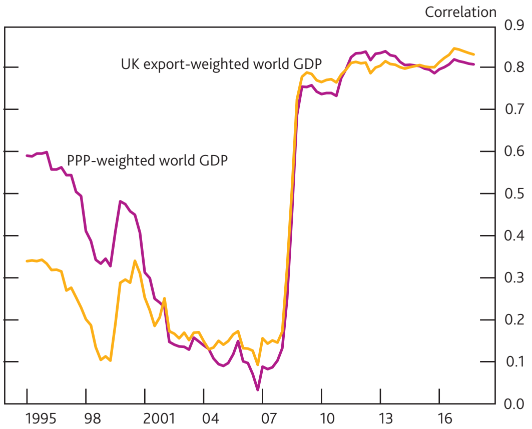
Source: Bank calculations.

(1) The authors would like to thank Emil Iordanov and Alexander Naumov for their help in producing this article.

Introduction

Understanding the current strength and direction of travel for world GDP growth are key considerations for the Monetary Policy Committee's (MPC's) assessment of the UK outlook. In addition to direct links through trade channels, the strength of global activity growth can also be informative of the impact of other factors, such as global changes in confidence and financial conditions. The importance of these factors can be seen in the high degree of synchronisation of GDP across countries, which has increased significantly following the financial crisis (**Chart 1**).

Chart 1 The synchronisation of world and UK GDP growth has increased since the crisis[(a)]



Sources: IMF *World Economic Outlook (WEO)*, Thomson Reuters Datastream and Bank calculations.

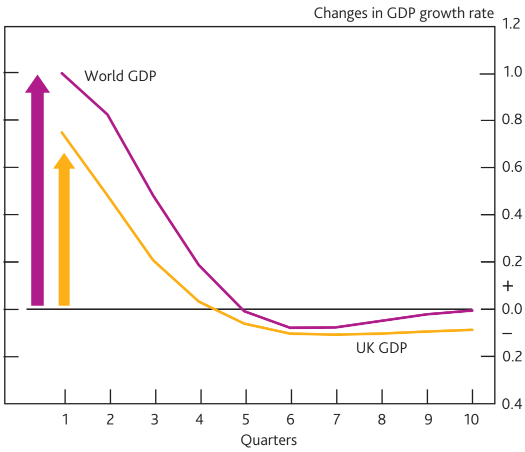
(a) Rolling 10-year correlation.

A UK export-weighted aggregate of world GDP growth, showing the strength of activity in major trading partners, is a useful proxy of external demand for UK products. This measure feeds directly into the Bank of England's UK forecasting model, COMPASS.[(2)] But a measure aggregated using purchasing power parity (PPP)-adjusted GDP weights provides a useful cross-check on global activity that is more robust to idiosyncratic developments in the UK's major trading partners.

This second measure weights together economies by their total output, after adjusting for price differentials in each country for comparability, and may provide a greater insight into non-trade factors that affect global and UK growth, such as common financial market developments or shocks affecting consumer and business confidence around the world. The synchronisation of UK GDP with both measures is broadly consistent, suggesting that non-trade factors are also important for the UK economy.

A simple model shows that global demand shocks can have a substantial impact on UK GDP growth. While the model is silent on the channels of transmission, it can quantify the size of spillovers from abroad.[(3)] A surprise 1 percentage point increase in global demand growth would normally be associated with a 0.7 percentage point increase in UK GDP growth, gradually fading over time (**Chart 2**).

Chart 2 A surprise increase in global growth is associated with a substantial pickup in UK GDP growth[(a)]



Source: Bank calculations.

(a) Lines show impulse responses from a VAR containing UK-weighted world GDP growth and export price inflation, the VIX index, UK GDP, UK CPI and Bank Rate. Recursive identification (Cholesky) in the order listed above is used to calculate impulse response functions.

Given the importance of global developments for UK prospects, it is important to understand the strength and direction of travel of world GDP on a timely basis. GDP growth estimates for major economies are generally released with a lag of approximately one month following the end of each quarter. Some economies, particularly emerging markets, may release their estimates of quarterly GDP growth with a lag of up to three months following the end of a quarter. Therefore, a methodology for assessing the current level of world activity ('nowcasting' in economic jargon) at an earlier stage is useful for quantifying global influences on the UK economy.

Fortunately, there are many sources of economic activity and financial market data that can provide more timely insights into the path of world activity. Statistical agencies in many economies release several data series on a monthly basis that help predict GDP, a host of financial market data are available almost instantaneously, and leading indicators of global activity are also available. Thus, the problem is not data availability, but how to efficiently exploit all of the available information. To solve this problem, the Bank uses three statistical models: a mixed-data sampling approach (MIDAS), a dynamic factor model (DFM), and a mixed-frequency Bayesian VAR (MF-BVAR).

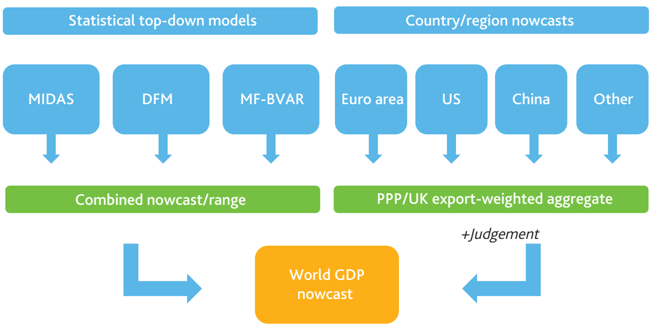
(2) See Burgess *et al* (2013).
(3) See Chowla, Quaglietti and Rachel (2014) for a more detailed discussion of this and similar models of spillovers to the UK.

This article begins by describing the Bank's broader approach to nowcasting world GDP, including the data used to inform our assessment. It then introduces each of the statistical models used to assess global activity in real time, exploring their main features and historical performance.

The Bank's approach to assessing near-term momentum in the world economy

The Bank takes several approaches to assessing the strength of world activity ahead of the release of official GDP statistics. First, a bottom-up approach is used to build up a picture of the strength of world GDP from individual countries. Bank staff employ statistical models and judgement to nowcast GDP growth in major economies and regions. These are then aggregated to form a nowcast of global GDP growth. Second, top-down statistical models of global growth are used as a cross-check on the bottom-up assessment of growth. In addition, staff or MPC judgement may be imposed to reconcile these two separate views of global growth (**Figure 1**).

Figure 1 Country-level and global top-down nowcasts inform the Bank's near-term outlook for world activity



Both approaches have their own merits and limitations. The top-down approach captures a broader range of economies, which is important as the Bank does not directly nowcast many emerging market or smaller advanced economies. Instead, the Bank relies on calendar-year forecasts produced by the International Monetary Fund (IMF), augmented by staff judgement and a more limited selection of high-frequency data. In addition, erratic factors in some regions which are difficult to nowcast may average out across countries, making the top-down approach more accurate overall. At the same time, these idiosyncratic factors can sometimes be an important influence on global growth, particularly in UK export-weighted space, which for example assigns a high weight to the US and euro area.

Taking these factors into account, MPC and staff judgement is used to reconcile these sources of information and assess the near-term strength of global activity. In this article, we focus on the top-down approach of statistically modelling world GDP, rather than on nowcasting individual economies around the world. The latter approach follows a similar process to that used for nowcasting the UK, described in Anesti *et al* (2017).

High-frequency indicators of world activity

Before turning to the models employed to nowcast world GDP, we briefly review the available data that can provide information on the strength of the world economy. Our current database includes around 90 indicators available at least at monthly frequency. We weigh up the relative merits of different types of data in terms of timeliness and information content.

Soft data

Surveys of current economic conditions, such as purchasing managers' indices (PMIs), are often one of the most informative indicators of the strength of activity. In addition, these indicators are released monthly, providing continued updates throughout the quarter in question. Other survey-based measures, such as consumer and business confidence, are also important indicators of present and future activity prospects.

We use a range of PMIs to inform the global nowcast, including global aggregates of surveys, as well as PMIs from individual regions. Some PMI measures cover the whole economy, but we also include PMIs for specific sectors, such as manufacturing or services. PMIs can also be divided into measures of current output, and more forward-looking measures, such as new orders.

As in Stratford (2013), we find that Global PMIs tend to have the highest correlation with world GDP growth relative to other indicators (**Chart 3**). However, PMIs from individual economies are released earlier than the aggregate measure and still have a high information content about world activity.

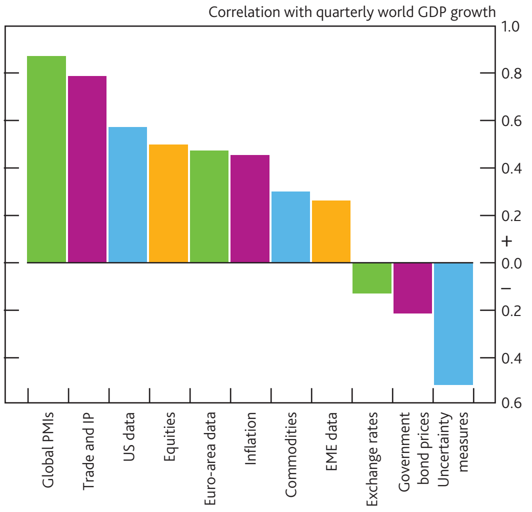
Hard data

In many economies, data on trade, retail sales and industrial production (IP) can provide an insight into overall activity. These indicators are produced on a monthly basis by national statistical authorities and ultimately feed into the production of GDP statistics. Global measures of trade and industrial production are available from the Netherlands Bureau for Economic Policy Analysis (CPB). The global measures have a very high correlation with world GDP growth. However, they are released with more of a lag than the survey indicators, given the delay associated with all country releases being made available.

Market data

In addition, market data such as equities, interest rates, exchange rates and commodity prices may provide important information on confidence and economic sentiment. One of

Chart 3 Different categories of data contain varying degrees of information about the state of the world economy(a)



Sources: Thomson Reuters Datastream and Bank calculations.

(a) Average correlation with quarterly UK-weighted world GDP growth of each data type (78 series total). US and euro-area data refer to releases of IP, PMIs, trade and other indicators specific to those regions. Uncertainty measures include both financial market data (VIX) and Bloom measures of uncertainty.

the advantages of market data is their timeliness. A downside is that not all factors that affect asset and commodity prices are related to activity levels, making them noisier than other types of data. Some market data are inversely correlated with world GDP (**Chart 3**). This relationship may still contain useful predictive properties for nowcasting world GDP. For example, a rise in bond prices and measures of uncertainty such as the VIX index (implied future equity market volatility), is often associated with a slowing pace of global activity growth.

Data availability

While the number of data series available for global nowcasting is large, the estimation period for our models is restricted by the limited time for which some indicators have been produced. For example, the Global PMI variables and PMIs for some major regions have only been produced since the late 1990s, and few high-frequency emerging market indicators are available before the turn of the century. For these reasons, estimation of most of the models described in this article only use data from 1998 onwards, and few emerging market series are used in order to maintain a consistent data set over time.

The models and their features

Exploiting this large amount of data presents challenges. First of all, GDP is a quarterly variable, whereas most indicators we use are monthly (and some could potentially even be weekly or daily). Therefore, our models need to be able to deal with mixed-frequency data.

A second issue is that different indicators can provide a contrasting steer on the strength of world activity in different circumstances, so the information provided by different indicators needs to be weighted appropriately. Furthermore, the number of available series, together with the relatively short time span over which they are available, pose technical challenges for estimation. And finally, monthly data are not all released on the same date. Therefore, the models need to be able to deal with 'ragged edge' data, ie a situation where some data are available for a particular time period, but others are not.

The models in the nowcasting suite adopt different strategies for dealing with these challenges. The MIDAS approach selects an optimal combination of indicators from a pool of candidates to use at a particular point in time. The DFM compresses the information contained in the available indicators to extract the overarching trends within a broad selection of series (for example a 'financial' and a 'real' factor). And the MF-BVAR combines the data with prior information to pin down a very large number of model parameters.

Mixed-data sampling (MIDAS)

The MIDAS approach (Ghysels, Santa-Clara and Valkanov (2004)) is a standard regression-based approach for predicting lower-frequency outcomes, such as quarterly GDP growth, with higher-frequency predictors, such as PMIs.

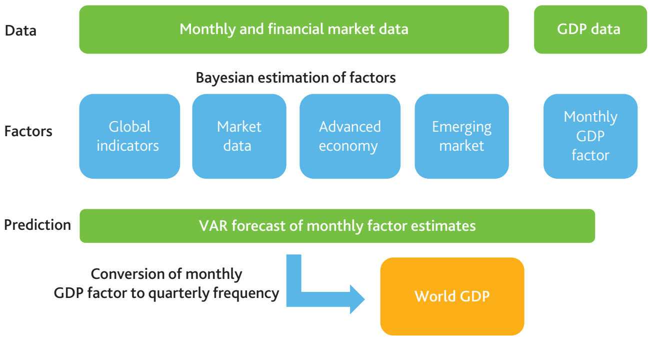
GDP is regressed on lags of the indicators, with the specification for each indicator optimised for forecast performance. In addition, the combination of indicators that best predicts GDP growth at each stage of the data cycle is chosen. For example, the global export orders PMI may be the best predictor of GDP growth after one month, but after two months, a measure of global industrial production may be superior. The predictions from each model are combined using weights derived from their historic forecast performance.

To limit the complexity of this model, only monthly global indicators are used. This MIDAS approach is similar to the one used in the UK nowcast suite (Anesti *et al* (2017)).

Dynamic factor model (DFM)

Unlike the MIDAS approach, the DFM uses all available monthly and daily data series available in our data set of around 90 indicators in order to predict GDP growth. To make this feasible, a common signal is extracted from groups of data, which can be used to predict GDP growth (Banbura *et al* (2013) and Giannone, Reichlin and Small (2008)). This model creates four factors from the data set: a factor representing global monthly data aggregates (PMIs, IP and trade), one representing market data (bonds, equities and commodities), one summarising advanced-economy monthly data from individual economies (PMIs, IP, trade, retail sales, job creation) and one for emerging-market monthly data from individual economies (PMIs, trade and IP). These factors are used in turn to predict GDP using a VAR. **Figure 2** shows this process diagrammatically.

Figure 2 Dynamic factor model construction



The factors can be updated with each new data release, allowing 'ragged edge' data to be used to update the nowcast. In addition to estimating factors summarising the high-frequency data, the model produces a monthly world GDP series, whose values are pinned down by combining observable quarterly GDP data with information from the monthly factors. This monthly GDP series can be forecast within the model up to the end of the quarter or into the next quarter, generating a nowcast and nearcast for world GDP growth. Furthermore, it provides an indication of activity growth in each individual month, which can sometimes be interesting in its own right.

Mixed-frequency Bayesian VAR (MF-BVAR)

Instead of selecting a subset of indicators at a particular juncture, or compressing the information contained in the high-frequency indicators into factors, the mixed-frequency Bayesian VAR (MF-BVAR, see Schorfheide and Song (2015); Brave, Butters and Justiniano (2016); Giannone, Monti and Sokol (2018)) explicitly models the relationship between quarterly world GDP and the monthly indicators. Moreover, the model also includes quarterly GDP of the main economies and regions that constitute world GDP, and is therefore able to also provide nowcasts and forecasts for all of them simultaneously.

This set-up has several advantages. Indicators of activity and official data for individual countries or regions might contain useful information for nowcasting activity in other countries/regions or the world, and *vice versa*. And the use of global indicators might lead to better projections for individual countries/regions.

Furthermore, because world GDP and GDP in major regions are modelled jointly, it is possible to provide a coherent account of how any piece of data news leads to revisions of the nowcasts for regions and for world GDP, providing a model-based answer to the tension between 'top-down' and 'bottom-up' approaches to nowcasting world GDP.

The key challenges to overcome are the estimation of a very large number of parameters with relatively few available data points[4] and the fact that the data are available at different frequencies. The annex provides a sketch of how these issues are addressed.

Model performance

This section evaluates the forecast performance of the three models, assessing their respective forecast errors over different time periods. In addition, we provide a simple model against which to compare the performance of our suite. To that end, we use an autoregressive AR(1) model, which uses the previous period's GDP outturn as a predictor for GDP in the current quarter. Despite its simplicity, this model is often found to be hard to beat in many empirical applications.[5] In addition, we provide results for a 'combined' nowcast, showing the average nowcast across the three models.

To compare forecast performance, a metric called root mean squared error (RMSE)[6] provides a measure of the 'typical' error made by each model. The RMSE penalises larger errors compared to other common metrics such as the average absolute error.

Nowcast performance across time periods

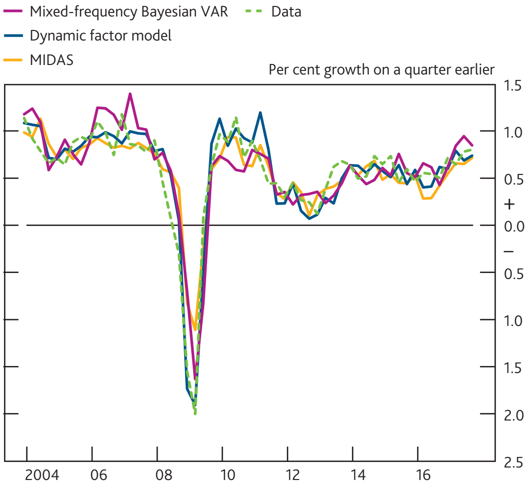
Our evaluation begins in 2004. This provides at least five years of data for Global PMIs, which as outlined earlier are the indicators most highly correlated with global GDP. As discussed below, forecast performance shows marked changes over time, highlighting the need for continuous monitoring of forecast errors.

Each model provides a close fit to GDP outturns in out-of-sample forecast evaluations (**Chart 4**). In this type of evaluation, models are gradually estimated up until the quarter being evaluated, so that they cannot observe a longer time series than would have been available at the time. However, it is noticeable that it is difficult to outperform a simple AR(1) model in some periods (**Chart 5**). That result is likely to be related to the relatively low volatility of world GDP compared to country-level GDP. In normal times, aggregating GDP across countries essentially cancels out idiosyncratic shocks, making world GDP a rather persistent and stable process, which can be forecasted well even using an AR(1) model.

One significant exception to this was during the 2008–09 period, when the volatility of world GDP increased dramatically. Here, the performance of the MIDAS, DFM, MF-BVAR and combined nowcast significantly outperforms the nowcasts from the naïve model. So during large turning points, the modelling toolkit provides significant advantages,

(4) This is sometimes referred to as the 'curse of dimensionality'.
(5) See Hamilton (1994) and Marcellino (2007).
(6) RMSE is the square root of the average squared error.

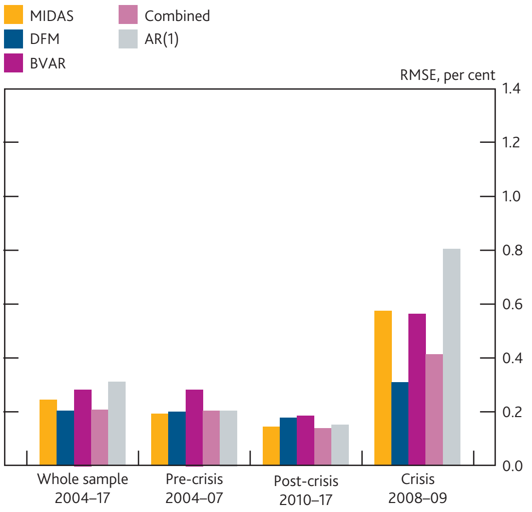
Chart 4 The suite of models provides a relatively tight range of estimates of current-quarter GDP growth(a)



Source: Bank calculations.

(a) Nowcasts shown are based on data available in the second month of each quarter. The nowcasts are based on the latest vintage of data rather than real-time data availability.

Chart 5 Nowcast errors vary across time periods (UK export-weighted world GDP)(a)



Source: Bank calculations.

(a) Nowcasts errors are shown for UK export-weighted world GDP based on the data available in the second month of each quarter. 'Combined' model shows the errors from a nowcast based on the average of each of the suite models.

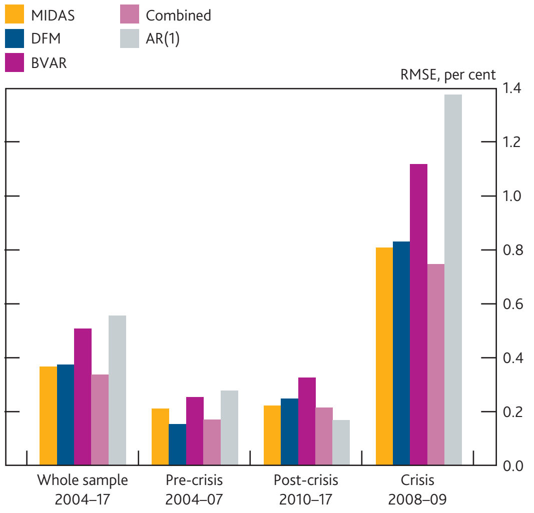
while retaining a comparable performance during normal times.

Each model is also capable of 'nearcasting', or forecasting the next quarter ahead. The results are similar to the current-quarter case in terms of relative performance of the models in each time period (**Chart 6**). However, the errors are much larger during the crisis, suggesting that the high-frequency indicators add much less information during volatile periods when forecasting the subsequent quarter.

Nowcast performance throughout the quarter

Chart 7 shows the evolution of forecast performance over the data cycle across models. In each case, the RMSE falls the

Chart 6 Performance deteriorates when predicting world GDP growth in the next quarter ahead (UK export-weighted world GDP)(a)



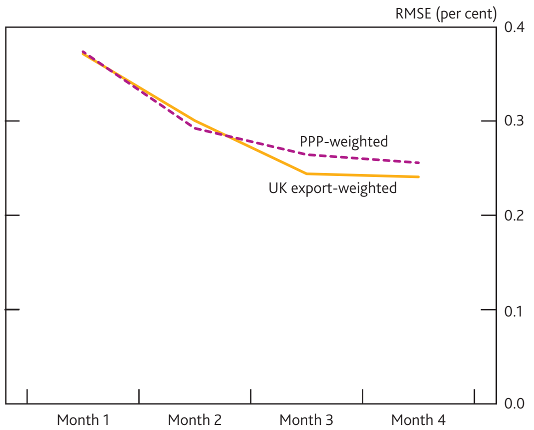
Source: Bank calculations.

(a) Nowcast errors are shown for UK export-weighted world GDP based on the data available in the second month of each quarter. 'Combined' model shows the errors from a nowcast based on the average of each of the suite models.

most between months 1 and 2, before declining more modestly, as more data become available. On average, RMSEs fall significantly between month 1 and the end of the quarter.

In addition, **Chart 7** shows the relative performance of nowcasts of PPP and UK export-weighted GDP growth. The RMSE of UK-weighted forecasts tend to be a bit lower, but relative performance between the models is generally preserved when nowcasting both types of global aggregate.

Chart 7 Forecast performance improves over the quarter as more data are made available(a)



Source: Bank calculations.

(a) X-axis refers to the month of the quarter being nowcast. For example, in month 1, data from the final month of the previous quarter will be available. In month 4, the majority of monthly data for the final month of the nowcast quarter will be available. The RMSE in month 4 does not take into account the limited GDP data releases available towards the end of the month.

Conclusion

The importance of the world economy as a driver of UK GDP growth means that effective monitoring of the strength of world activity can provide an important input into the MPC’s assessment of UK prospects.

The three models in the Bank’s global nowcasting statistical suite can provide an edge in understanding global prospects. Each model has its own advantages and disadvantages in handling the large quantity of data available to assess world GDP, but exhibits a similar forecast performance.

The outputs of this suite of models, in combination with country-level analysis, as well as with staff’s and the MPC’s judgement, provides an important input into assessing the UK economy’s prospects.

Annex

MIDAS

An individual MIDAS model to estimate quarterly GDP using monthly data at a particular point of the data cycle can be written down as follows:

$$\hat{y}_{Q1} = \hat{\beta}_0 + \hat{\beta}_1 x_{Jan} + \hat{\beta}_2 x_{Dec} + \hat{\beta}_3 x_{Nov} + u_t$$

Many such equations can be estimated within a quarterly data cycle, and their outputs combined using various model averaging techniques, from simple averages to assigning weights based on past forecasting performance.

The advantages of the MIDAS approach lie in its transparency and relative simplicity of implementation. The disadvantages include requiring different equations for each point in the data cycle and only a small number of indicators on the right-hand side due to degrees of freedom constraints, as the estimation is done using simple OLS.

Dynamic factor model

The dynamic factor model consists of two sets of equations: a VAR model of (unobserved) monthly factors, and an observation equation consisting of monthly and quarterly observed macroeconomic and financial variables. The observed data are related to the factors by an estimated set of factor loadings in the observation equation.

Monthly factor VAR (transition equation):

$$f_t = \begin{bmatrix} f_{tGDP} \\ f_{tmonthly\ indicators} \\ f_{t-1GDP} \\ f_{t-1monthly\ indicators} \end{bmatrix}, \; f_t = \beta f_{t-1} + u_t$$

where f is a vector of estimated factors, including an estimate of monthly world GDP growth, and factors summarising the information contained within the monthly indicators.

Observation equation:

$$Y_t = \begin{bmatrix} Y_{tQuarterlyGDP} \\ Y_{tmonthly\ indicators} \end{bmatrix}, \; Y_t = \Lambda f_{t-1} + v_t$$

A Bayesian estimation approach pins down the parameter values of β and Λ, as well as the variance of u and v. In the observation equation, quarterly GDP growth is observed in month 3 of each quarter, with missing data in the remaining two months of the quarter. The observation equation for GDP is set such that quarterly GDP is the average of the current and previous two months of the GDP monthly factor (plus an error term). This gives the monthly GDP factor growth rate the interpretation of a growth rate relative to the equivalent month of the preceding quarter, so that the average of the growth rates in a quarter is (approximately) equal to quarterly growth.

Mixed-frequency Bayesian VAR

The VAR jointly models global, US, eurozone, UK (in the PPP version), China and Emerging Asia (ex-China) GDP with both global and country-specific monthly indicators, using a novel technique for estimating potentially large mixed-frequency VARs.(7) The procedure works by first turning all monthly variables into quarterly averages and then estimating a quarterly VAR using standard Bayesian techniques (in particular, prior tightness is chosen optimally following Giannone, Lenza and Primiceri (2015)):

$$\begin{bmatrix} GDPQ_t \\ IndicatorsQ_t \end{bmatrix} = A_0 + A_1(L) \begin{bmatrix} GDPQ_{t-1} \\ IndicatorsQ_{t-1} \end{bmatrix} + u_t$$

The estimated quarterly model is then turned into a monthly model exploiting certain restrictions imposed on the monthly model (intuitively, the monthly model is required to match the estimated quarterly model at the end of each quarter, when the quarterly variables are observed):

$$\begin{bmatrix} GDPM_t \\ IndicatorsM_t \end{bmatrix} = B_0 + B_1(L) \begin{bmatrix} GDPM_{t-1} \\ IndicatorsM_{t-1} \end{bmatrix} + w_t$$

Finally, missing data points (the unobserved monthly counterparts to the quarterly variables in months 1 and 2 and the 'ragged edge') are filled out by running a standard Kalman filter on the monthly model. The monthly model can then be used for forecasting, data news accounting, scenario simulation etc.

(7) The procedure follows work in progress by Giannone, Monti and Sokol (2018), and is based on techniques adapted from Giannone, Monti and Reichlin (2016).

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