Lessons for macroeconomic forecasting in the aftermath of the pandemic and the energy shock

By Alfred Kammer[1]

Abstract

Three main lessons emerge from our recent experiences with macroeconomic forecasting at the IMF for European economies. The first is to strike the right balance between top-down and bottom-up approaches: top-down forecasting methods become more appropriate when common forces are dominant, but we always need to account for country-specific factors as well. The second is to be nimble; that is, to be ready to continuously develop and add new tools as needed. And the third one is to be modest—to focus on avoiding misses that would cause major policy mistakes rather than marginal variation around the modal forecasts.

1 Overview

Thank you very much, it's a pleasure to be here and discuss some of the common challenges we have faced in trying to make sense of developments and prepare macroeconomic projections over the past few years.

I will structure my remarks around three themes – first, the challenge of macroeconomic forecasting and how we approach it at the IMF. Then I'll explain how we adapted our forecasting methods during the uncertain and volatile periods of a pandemic and energy crisis. Finally, I will conclude with a few thoughts on what lessons we can take forward.

2 The Challenge of Macroeconomic Forecasting

Macroeconomic forecasting is difficult in the best of times. Economies are complex social systems as we all know. At the IMF we occasionally take stock of how well our forecasts perform and compare our performance with those of other major forecasters. We tend to find that at relatively short horizons (same year mainly) projections tend to do reasonably well. But moving out to even a 1.5 to two-year horizon the accuracy of both our and others' forecasts deteriorate very fast as Chart 1 shows (Celasun et al., 2021). The reason is that economies suffer constant

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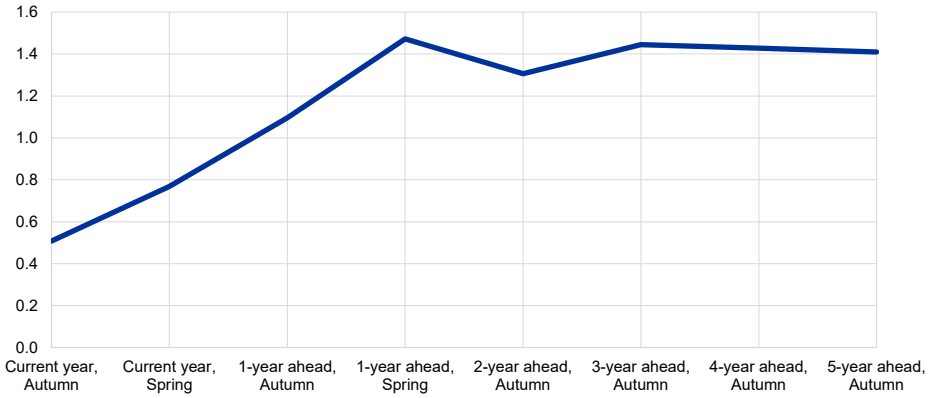
shocks. A related standard insight into growth forecast accuracy is that the higher the volatility of GDP in a country, the larger the forecast errors.

Chart 1

Forecast Accuracy: Median Root Mean Squared Errors of WEO Real GDP Forecasts, Advanced Economies

(Median root mean squared error)



Sources: Celasun et al. (2021).
Notes: Autumn and spring refer to projections as published in the autumn and spring World Economic Outlook, respectively. "Current year, Autumn" would thus refer to, for example, the 2015 GDP growth projection as published in the autumn 2015 World Economic Outlook. And "1-year ahead, Spring" would refer to the 2015 GDP growth projection as published in the Spring 2014 World Economic Outlook.

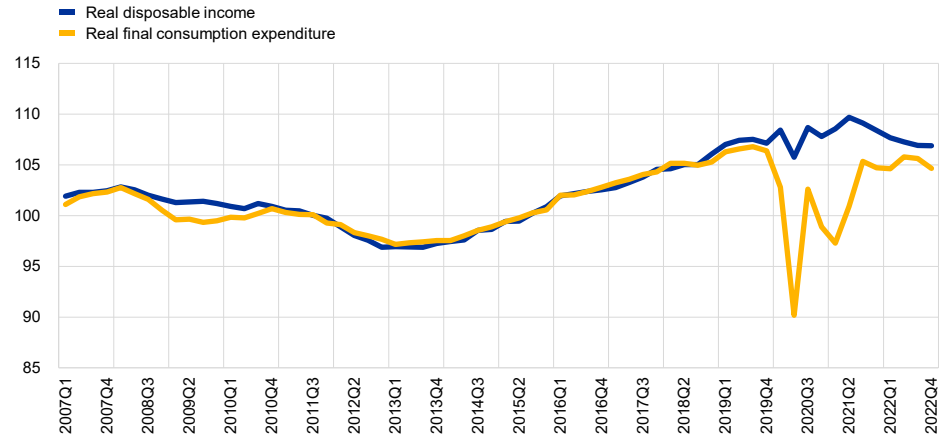
2.1 The Pandemic and Energy Shocks

The last few years have of course brought us big shocks, making forecasting particularly challenging. Lots of the standard macroeconomic relationships broke down following the pandemic. Think about Okun's law, the link between unemployment and output which weakened due to job retention schemes, and possibly an increased need or preference to work fewer hours per week. Or the "famous" excess savings of the past years. Essentially, they represent a breakdown of the historically tight relationship between household disposable income and consumption as Chart 2 shows. Another challenge over the past year has been the massive volatility in energy markets since the Russian invasion of Ukraine. Chart 3 shows the breakdown of another relationship – that between European oil and gas prices in 2022.

Chart 2

Relationship between real disposable income and real consumption expenditure

(Index, 2015=100)

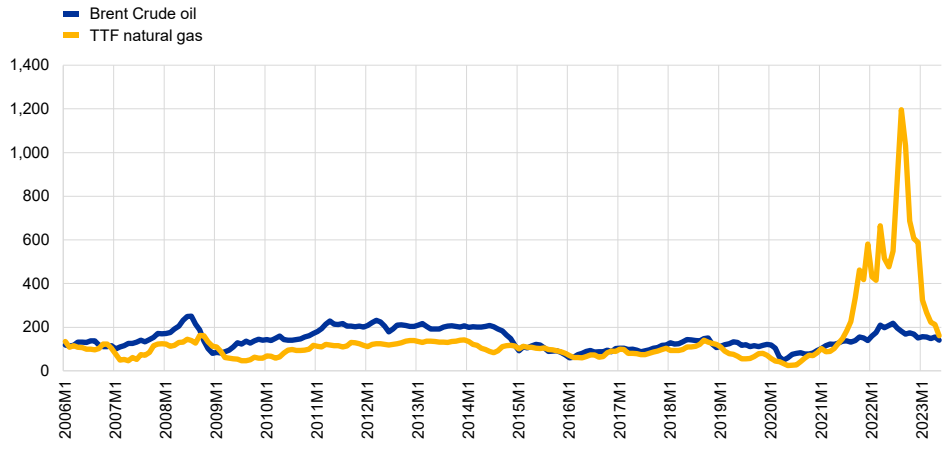


Sources: Eurostat; and IMF staff calculations.

Chart 3

Relationship between Brent Crude Oil and TTF Natural Gas Prices

(Index, 2015=100)



Sources: Bloomberg Finance L.P.; and IMF staff calculations

What does all this imply for forecasting? One initial question I will take up has to do with the trade-off between focusing on country specific factors versus common forces.

2.2 Bottom-Up versus Top-Down Forecasting at the IMF

What do bottom-up and top-down forecasting mean in the first place? Our main outlet for projections at the IMF is the World Economic Outlook (WEO), published quarterly. The WEO is a bottom-up exercise, aggregating forecasts for our member countries. 190 country teams prepare forecasts based on common assumptions for key global variables—such as commodity prices and benchmark interest rates—over the forecast horizon. As we go along the forecasting round, we perform many checks

to ensure cross-country consistency in how these assumptions are incorporated. Nonetheless, country teams have substantial discretion, including in terms of deciding how much their economy is affected by a common factor, embedding country specific information, and the tools and models they use. A top-down forecast uses the same global or regional model (with the same set of drivers) for all countries, with a more limited role for bringing in country-specific factors or judgment.

Giving country experts room to incorporate idiosyncratic factors is crucial, because domestic factors tend to be more important than foreign ones for the path of economic activity – on average. But it is also true that when we do ex-post evaluations, we find that common components are not sufficiently taken into account as they could be. For instance, Celasun et al. (2021) find that growth projections for the US, the euro area, or China, or countries own terms of trade forecasts, can all help predict growth forecast errors for a significant share of countries. If we used all available information efficiently, there would be no such correlation, and our forecasts errors would be smaller.

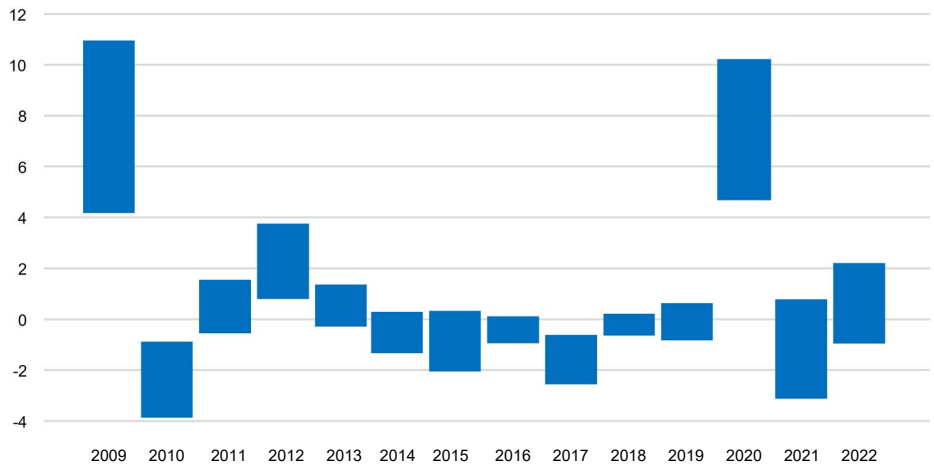
Especially during times of large global or regional shocks, the common factor can be dominant enough to justify a more top down approach to forecasting.

As Chart 4 shows, forecast errors for individual countries are usually broadly centred around 0 with both positive and negative surprises. But both during the GFC and pandemic, forecast errors were both very large and one-sided, highlighting the vast dominance of the common shock.

Chart 4

Distribution of One-Year Ahead GDP Forecast Error For Euro Area Countries and the UK by Year

(Index, 2015=100)



Sources: IMF World Economic Outlook Database.
Notes: Forecast errors are here defined simply as the annual GDP forecast made in autumn of year t-1 for year t, minus the actual GDP growth outturn in year t. The box shocks the 25th to 75th percentile of the country forecast error distribution.

3 Adapting Tools and Methods

3.1 Pandemic GDP Forecasts

These huge common shocks required us to adjust our approach. To give a concrete example, during the early months of the pandemic it became clear that the expected progression of infections, mobility restrictions, and the sensitivity of output to mobility would dominate the immediate outlook. Translating these qualitative factors into a quantitative forecast faced three challenges.

First, in March 2020, when our Spring WEO forecast was being finalized, reported infections were still clustered in just a few countries. The path of infections was uncertain, though we knew this was a highly contagious virus and likely to spread rapidly.

Second, it was unclear how severe the mobility restrictions would be in different countries.

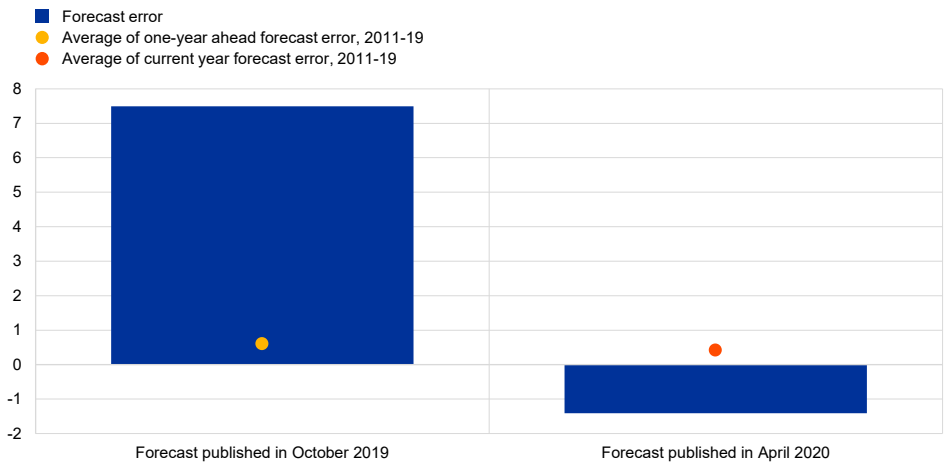
And third, there was little historical data to extrapolate how economic activity would respond to such restrictions.

We decided to take a centralized approach. Our Research Department engaged with epidemiologists and public health experts and then provided centralized guidance to teams on how many effective working days would be lost in the coming quarters. Depending on economic structures (for instance, the contact-intensive share of activity), country teams translated the lost days into GDP declines. Adding to these domestic disruptions, country teams factored in the impact of international demand and supply spillovers. Finally, based on available policy space, they factored in some offsetting policy support. Overall, this approach did quite well, with the “same year” forecast we made in the Spring of 2020 for the euro area being off only by about 1 percentage point (Chart 5). Not a large error given how massive the shock was.

Chart 5

Forecast Error for 2020 Euro Area GDP Growth

(in percentage points)



Sources: IMF World Economic Outlook Database.
Notes: The average forecast errors over 2011-19 show the average of the absolute value of the difference between forecast and actual turnout.

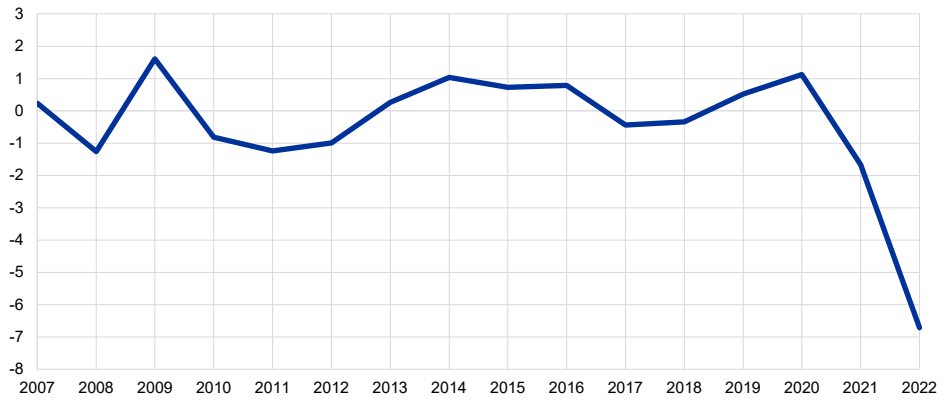
3.2 Inflation Forecasts after the Energy Shock

Let me briefly turn to the elephant in the room, the repeated underestimation of inflation over the past 1.5 years, which then points to the need to be nimble. Of course, the war and the pandemic supply shocks were unpredictable. But even after the shocks materialized, it was challenging to quantify their effects on inflation. Forecast errors were very large (Chart 6).

Chart 6

One-Year Ahead Inflation Forecast Error for the Euro Area

(in percentage points)



Sources: IMF World Economic Outlook Database.
Notes: Forecast errors are here defined simply as the annual inflation forecast made in autumn of year t-1 for year t, minus the actual inflation outturn in year t.

Let me highlight two specific shortcomings of our models and how we tried to improve them.

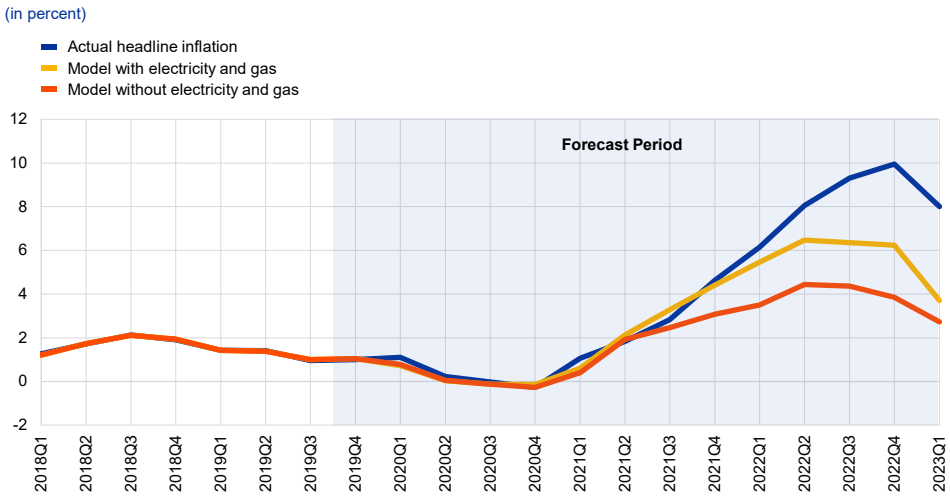
The first issue is about the right amount of granularity. Most of our forecasting was previously done using international oil prices as a proxy for overall energy prices. This worked very well in the past. But as I showed you earlier, gas prices decoupled significantly from oil prices when Russia cut gas flows to Europe.

Not allowing gas prices to enter inflation projections separately thus was a problem for projecting energy inflation and ultimately the passthrough from energy to core inflation. And this is just one example of models needing some amendment—quickly—to deal with a new situation.

In response, we now project inflation in a much more disaggregated way (see, for example, McGregor and Toscani (2022)). As the yellow line in the chart shows, adjusting the model structure of a Phillips curve based inflation projection framework and estimating it on data until 2019 produces significantly better out of sample forecasts than the previous model. But at the same time, that model still misses the most recent inflation surge by a meaningful margin (Chart 7). Note that what I am showing is quite a demanding exercise, being a pseudo out of sample forecast over a long period - from 2020q1 until 2023q1.

Chart 7

Actual HICP Inflation and Pseudo-Out-of-Sample forecasts



Sources: IMF Staff calculations
Notes: The red dashed line shows the pseudo out of sample projection over 2020Q1-2023Q1 of the model in McGregor and Toscani (2022) estimated on data until 2019Q4. The black line shows pseudo out of sample projections over the same horizon, removing wholesale electricity and gas from the inflation model (such that energy prices enter projections purely through Brent crude oil prices).

The second key shortcoming—much harder to correct—has to do with non-linearities. Whereas a firm might not react strongly to a 20 percent increase in the prices of one of its minor inputs, it does have to adjust its prices given a 500 percent increase. And models missed the mark because such movements were well out of the range of the data the model was trained on. We found out that it is challenging to gauge such nonlinearities in real time.

4 Some Thoughts on Lessons Learned and Challenges to Come

So forecasting is a humbling task. What lessons can we apply going forward?

First, after the experience of the past years, some enhanced role for top-down guidance will probably stay with us at the IMF relative to pre-pandemic times. That helps react in real time to important developments, which in a possibly more shock prone world could prove important. But we need to be balanced—idiosyncratic factors are also key.

Second, we will need to be nimble – it is clear that we need to continuously monitor and enhance our tools. Part of the way forward is also to exploit underused data sources and incorporating new data, including big data in a flexible way.

Finally, we should be modest about forecasting. It is worthwhile also reminding ourselves that macroeconomic data remains difficult to collect, and the key series we rely on—notably GDP—are prone to large revisions. De-emphasizing point estimates and focusing on forecast ranges thus seems important, especially when forecasting informs policy making. We should focus on avoiding forecast errors that would lead to gross policy mistakes rather than worrying excessively over marginal changes in the modal forecast. This also means scenario analysis has a clear role to play – allowing both to implement policies to avoid a downside scenario, and do contingency planning on how to react should it materialize.

To conclude, let me zoom back on today's forecasting challenge. A key question now that inflation has peaked, is whether we can trust the disinflation paths that come out of most model forecasts given the dissipation of supply shocks and tightening in monetary policy. We have high uncertainty on the level of slack in the economy, many of the standard relationships are not yet fully normalized, and wage and price inflation exceed the range on which we have estimated our models. We also know from past evaluations that we tend to overcompensate for large overpredictions of growth by then turning overly pessimistic. While our recent experiences make it right to question the smooth disinflation paths coming out of our models, we also need to avoid turning overly pessimistic.

So it is important to always be aware of the potential shortcomings of tools, and use several of them jointly, and cross check them. For instance, in addition to predicting inflation components in a disaggregated way, we now also look at prices from the "income" side, examining the wage growth, import prices, and profit share behaviour that is consistent with our projections (see Hansen et al., 2023).

I thus see an active role for us as forecasters, with a constant interaction between existing tools, new and refined tools and data sources and ultimately well-grounded judgment to bring in considerations not captured by the models.

References

Celasun, O., Lee, J., Mrkaic, M. and Timmermann, A. (2021), “An Evaluation of World Economic Outlook Growth Forecasts, 2004–17”, *IMF Working Paper 2021/216.*

McGregor, T. and Toscani, F. (2022), “A Bottom-Up Reduced Form Phillips Curve for the Euro Area”, *IMF Working Paper 2022/260.*

Hansen, N-J.., Toscani, F. and Zhou, J. (2023), “Euro Area Inflation after the Pandemic and Energy Shock: Import Prices, Profits and Wages”, IMF Working Paper 2023/131.