Forecasting inflation at the Central Bank of Malta

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This Box describes the method adopted by the Bank to prepare its short-term forecasts of Harmonised Index of Consumer Price (HICP) inflation. These forecasts form part of the Bank's contribution to the Eurosystem's Narrow Inflation Projection Exercise (NIPE), which involves the preparation of projections of HICP inflation and key components at a monthly frequency spanning up to 15 months.

The forecasts are conditional as they are based on a set of common technical assumptions that all euro area national central banks (NCB) participating in the exercise have to apply in their projections. These assumptions cover future oil prices, exchange rates and international food prices. The NCBs price projections for their respective countries are then aggregated to obtain a forecast of inflation for the euro area as a whole. Given the openness of the Maltese economy, the technical assumptions applied in the exercise tend to have a very important bearing on changes to the outlook for inflation in Malta.[1]

The projections are prepared on a disaggregated basis, which means that forecasts are made for individual HICP components and then added up. Given the short-term nature of these forecasts, the core econometric tool used is an Auto-Regressive Integrated Moving Average (ARIMA) model, a statistical technique which links the expected behaviour of a variable to its history.[2]. This basic structure is augmented by projections for a number of macroeconomic variables which are, in theory, related to developments in inflation, such as the technical assumptions mentioned above, as well as growth in wages and unit labour costs.[3] In addition, the use of seasonal factors improves the model's ability to track pricing elements that have an impact in particular periods of the year, such as discounted sales.

However, some price indices are linked solely to macroeconomic variables. For example, changes to fuel prices are a function of changes in the international oil price, with a number of lags. In a limited number of other sub-indices, inflation is forecast using pricing rules; for instance, tobacco prices are most likely to change only at the time government budgetary measures are announced, while utility tariffs are assumed to change at most once a year. This approach works towards striking the right balance between simplicity, good forecasting performance[4] and consistency with some macroeconomic relationships.

*Disclaimer: The views expressed are the author's own and do not necessarily reflect those of the Central Bank of Malta.

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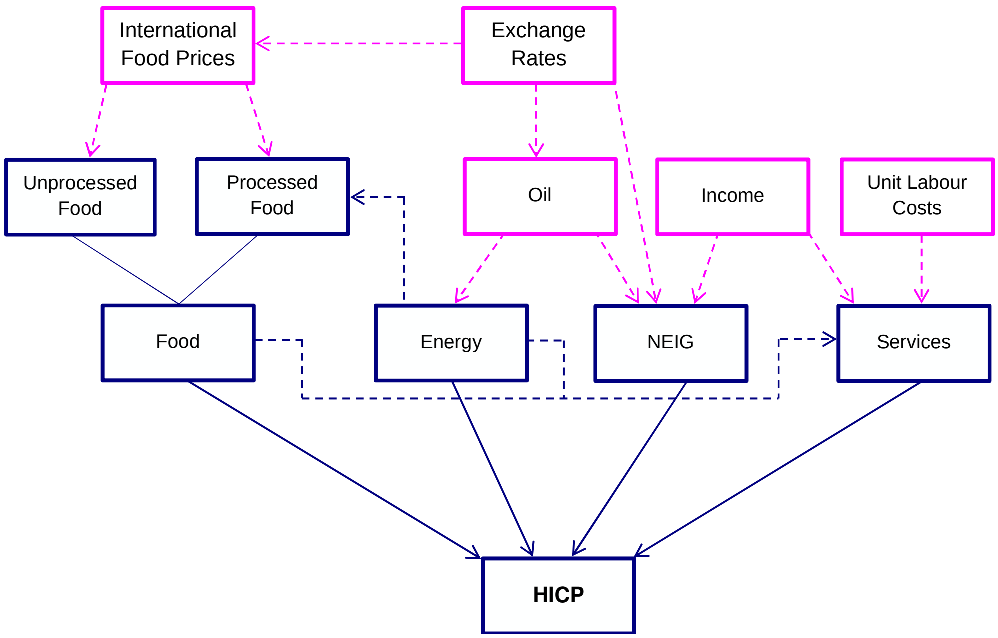
[1] The speed with which changes to these variables affect local price indices in the model varies according to the good or service in question.

[2] The traditional Box-Jenkins approach is used to determine the structure of the ARIMA model used, namely the (p, d, q) order. A key textbook on time series methods is Hamilton (1994). For a discussion on a similar approach to forecasting inflation see Meyler et al. (1998) The estimation sample used in the Bank's exercise uses monthly data and spans from 2004/5 till the latest observation.

[3] These are obtained from the Bank's macroeconomic projection exercises.

[4] Time series models tend to be superior to structural models in terms of short-term forecasting; see Litterman (1986) and Stockton and Glassman (1987).

Chart 1
A BIRD'S EYE VIEW OF THE FRAMEWORK

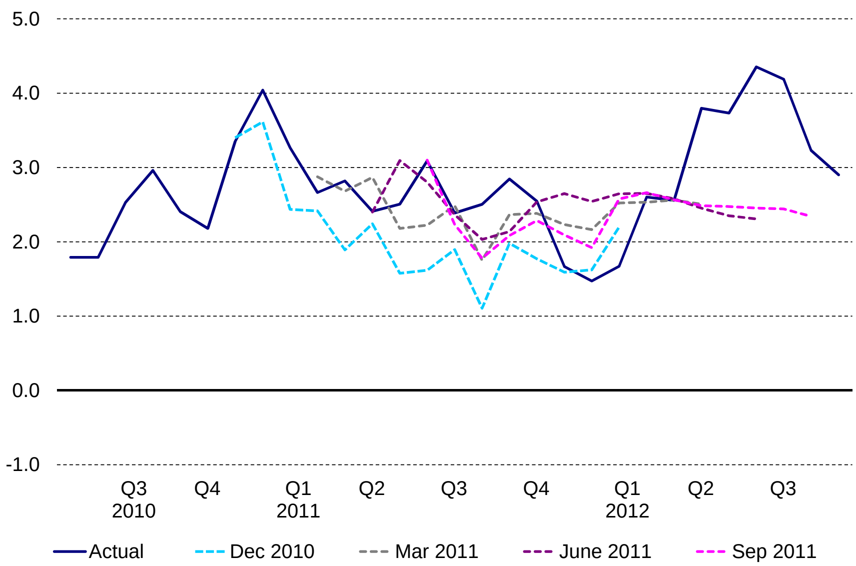


As stated above, and as Chart 1 illustrates, it is not simply overall HICP inflation that is forecast but price trends within the five main HICP components (namely unprocessed food, processed food, energy, non-energy industrial goods [NEIG] and services).[5] Furthermore, there is allowance for price developments in one sub-index to feed into another sub-index. For example, higher prices for fish in the food category lead to higher restaurant prices in the services category. These indices are then aggregated into the main subcomponents, and then into the overall HICP index, using the respective weights which are determined by the National Statistics Office (NSO). The in-depth analysis permitted by this approach further improves the forecasting performance of the model, as well as provides policy makers with a more solid understanding of the underlying dynamics of inflation.

To help evaluate this forecasting technique, Chart 2 compares the HICP inflation forecasts made by the Bank as part of four recent quarterly NIPEs with the actual outturns, which extend until the third quarter of 2012. The various forecast vintages are shown separately in the Chart. It is evident that forecast accuracy tends to be very high in the short term, with forecasts being broadly correct, especially for the first 12 months. However, one-off large events, such as the unexpected spike in accommodation prices during 2012, affect forecast accuracy considerably, particularly in the medium term.

[5] At present there are in total 28 equations for different sub-indices that are being used. Almost all of these are ARIMA equations.

Chart 2
HICP: FORECASTS AND OUTCOMES
(annual percentage changes)



Sources: NSO; Central Bank of Malta projections.

It should be noted that although econometric models in general can be very useful tools in forecasting, most are backward-looking and hence may not incorporate information which may be available during the exercise. In the case of time series approaches, these need to be supplemented with information on the structural relationships in the economy to provide more coherent projections in the medium term. Furthermore, model-generated projections are frequently augmented by additional information, be it about a specific event in the future, or more generally, the forecaster's judgement about the outlook for inflation. In this respect, forecast errors and historical events in the data which the model cannot explain also serve as useful inputs to the projections.[6]

The Central Bank of Malta continues to analyse the results of its inflation forecasting techniques with the aim of enhancing them. It is undertaking further research on inflation forecasting using alternative models.

References

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[6]An excellent discussion on the practical aspect of using models for forecasting and policy analysis can be found in Price (1996).