Box 1: Real-Time Forecast of Quarterly GDP Growth Using Nowcasting Techniques

The continuous monitoring of advanced economies is necessary for the International Investments Department (DII for the acronym in Spanish), as their developments affect financial markets and, consequently, the returns of the foreign reserve portfolio. This monitoring requires tools capable of synthesizing movements in aggregate variables to reduce uncertainty in environments where frequent statistical revisions and delays in official publications makes it difficult to assess the macroeconomic situation. Timely assessment of economic conditions requires up-to-date information; however, key variables, such as gross domestic product (GDP), are often published with significant lags. For example, U.S. GDP data are released thirty days after the end of the quarter, whereas the lag in the Euro zone can be even longer. This delay limits the ability to conduct timely analysis, catalyzing methodological advancements to estimate current economic growth using high-frequency data. In this regard, DII decided to implement an approach that allows the real-time integration of key indicators to support decision-making in foreign reserves management.

A widely adopted solution is nowcasting, a technique that combines advanced statistical models with available information to forecast variables prior to their official publication. Unlike traditional forecasting techniques, which estimate values for future periods (such as the next quarter or year) using historical data, nowcasting predicts current data using partial figures. Its advantage lies in its ability to update estimates as new monthly or weekly indicators are released, such as industrial production, retail sales, or confidence surveys. However, the main challenge of this methodology is to synthesize information from numerous indicators without overfitting the model. To this end, Giannone et al. (2008), who coined the term "nowcasting", proposed a two-stage estimator to identify macroeconomic shocks by combining dynamic factor analysis using a Kalman filter. The core idea of this methodology is to leverage the existing collinearity among the series, summarizing as much information as possible into a few factors. We define the information set as follows:

$$\Omega_{v_j} = \left\{X_{it|v_j}; t = 1,\ldots,T_{iv_j}; i = 1,\ldots,n\right\}$$

This set of information consists of n variables, $X_{it|v_j}$, where i identifies each series, t denotes time in months from the first to the last observation, and v is an index associated with the information release date, which has a higher frequency greater than t. T_{iv_j} indicates the most recent period for which series i in block v_j has an observed value. For example, the retail sales report is released in month v, but the information is only available for the previous period, $T_{iv_j} = v - 1$. By contrast, manufacturing surveys are released for the current month, in which case $T_{iv_j} = v$.

As GDP is a quarterly series, while the information used for nowcasting is monthly, an additional notation is introduced to handle time conventions. Each month or quarter has a fixed number of days, and there are k periods. However, variables are not necessarily collected at that interval and may be reported at a different frequency. For example, if industrial production data is released monthly, then in a monthly model $k = 1$, whereas in a weekly model $k = 4$. Accordingly, GDP in a monthly model, where $k = 3$ and t is a multiple of k, which is described by the following equation:

$$\begin{aligned} y_t^k &= Y_t^k - Y_{t-3}^k \approx \left(Y_t^M + Y_{t-2}^M\right) - \left(Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M\right) \\ &= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4}, \qquad t = 3,6,9,\ldots \end{aligned}$$

The key feature of this type of approach is that a joint model is specified for Y_t^k and it has a state-space representation, where the measurement equation links observed variables to unobserved ones. The state-space model is governed by measurement equations, which relate the data to the unobserved states, and by the transition equations, which describe the dynamics of the system:

$$Y_t^k = \mu + \beta X_t + G_t$$

$$X_t = X_{t-1} + H_t,\ \ H_t \sim i.i.d\ \ N\left(0, \sigma^2_{H_t}\right)$$

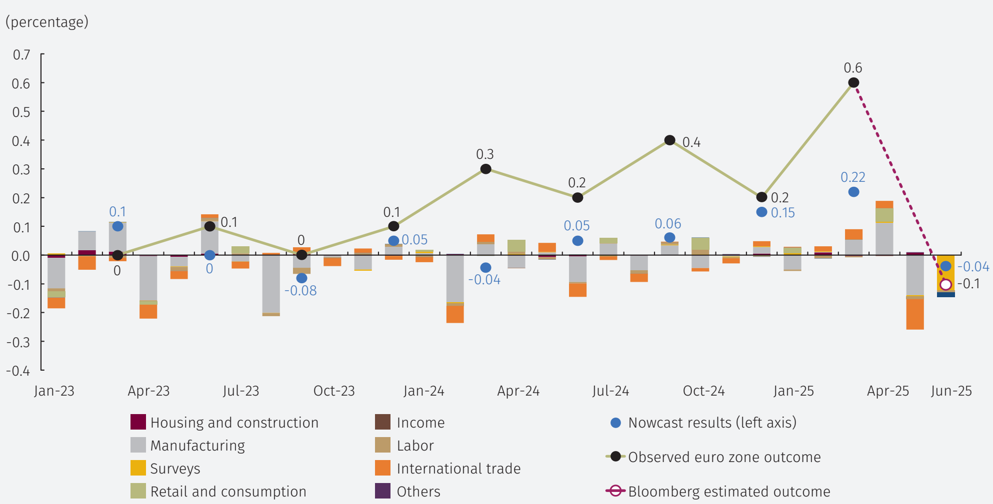
The parameters used in this state-space representation are estimated through principal component analysis applied to a balanced panel of Y_t for the estimated factors, which is obtained by considering only the sample for which all observations are available. The factors are then re-estimated using the Kalman filter and the EM algorithm. These two steps are repeated until the maximum likelihood estimates are obtained.

It is worth noting that the Kalman filter can efficiently handle any missing observations in Y_t^k and provide the conditional expectation for them. Consequently, immediate forecasts for the target variable and predictors can be easily obtained, allowing new data to be incorporated and predictions to be updated using innovative components known as news and revisions. In this regard, published data are rigorously weighted, and it is possible to assess how different data categories (surveys, construction, labor market, among others) contribute to signaling changes in economic activity. As a result of this exercise, the model produces a monthly GDP forecast broken down by components for the economies to which it was applied, including the United States, Canada, the Euro zone, the United Kingdom, Australia, and New Zealand.

To assess the practical usefulness of the nowcasting approach, its ability to estimate GDP for one of the most relevant economies within the foreign reserve portfolio was compared: the Euro zone (Graph B1.1). To conduct this comparison, a traditional vector autoregressive (VAR) forecasting model was estimated as a benchmark. Accordingly, the developed nowcasting model shows a significant improvement in accuracy, with a 47.1% reduction in error compared to the traditional VAR model in the preliminary GDP estimate released by the statistics office, and a 51.8% reduction compared to the final data for this indicator between the first quarter of 2023 and the second quarter of 2025. These results demonstrate significant progress in anticipating the economic performance of a complex economy.

Additionally, the implementation of the nowcasting forecasting model offers several practical advantages, ranging from the automatic integration of tens of macroeconomic variables via filtering algorithms to the ability to handle missing data in historical series without compromising the robustness of the estimates, unlike many traditional forecasting models. Moreover, this model enables the processing of information on economic activity as it is received by market agents (in real time), since data releases are monitored, expectations are formed, and projections are subsequently reviewed in response to significant updates in the figures. In this regard, the result becomes more accurate as the quarter progresses, facilitating the assessment of growth direction prior to the official dissemination of results by the statistics office. Finally, the forecast broken down by sectors enables assessment of each one's contribution to the aggregate output and the identification of vulnerable segments, thereby supporting a more informed investment decision-making process.

Graph B1.1
Euro Zone



Source: Calculations by *Banco de la República.*