Nowcasting Made Easier: A Toolbox for Economists
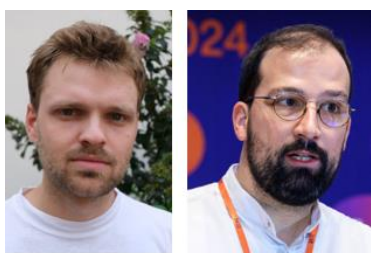
Jan Linzenich | Humboldt University of Berlin
Baptiste Meunier | European Central Bank

Abstract

This policy brief showcases a versatile toolbox that facilitates creation, evaluation, and deployment of nowcasting models. The toolbox supports three model classes (dynamic factor models, Bayesian VAR, bridge equations) and offers to manage data selection and adjusting for Covid-19 observations. The toolbox is organized along a structured three-step approach to building a nowcasting model. Non-specialists can easily follow these steps to develop high-performing models, while experts can leverage the automated tests and analyses. The toolbox produces a large range of outputs for regular policy analysis, aimed at opening the "black box" associated with nowcasts. We showcase the toolbox by creating and assessing a nowcasting model for global real GDP growth. Code and templates are available on GitHub: https://github.com/baptiste-meunier/Nowcasting_toolbox.

A Holistic Solution for Applied Economists

Nowcasting has emerged as an indispensable tool for policy institutions in need of early estimates of economic indicators, especially during episodes of crisis. However, creating a nowcasting model is often an arduous task. Moreover, as the economy evolves and new data sources becomes available, nowcasting models require periodic revisions to maintain accuracy. Finally, as any other tool used for policy purposes, nowcasting models should go beyond providing numbers and give an idea of the underlying forces driving model predictions.

Unfortunately, existing nowcasting tools do not offer a comprehensive toolkit that combines these functions in a unified infrastructure. We aim at addressing this limitation by designing a user-friendly and adaptable toolbox for building, refining, and deploying nowcasting models for policy analysis. The tool can be adapted to any mixed-frequency model with a quarterly target variable and a set of (many) potential regressors at monthly and quarterly frequencies. This work builds on a long-standing effort in the External Developments division of the ECB to design an adaptable and easy to use environment for model-based predictions, involving the work of many ECB colleagues. Compared with other codes available in the literature, this toolbox combines two main nowcasting duties under a single roof: building new nowcasting models from scratch and enhancing policy analysis through detailed insights into model-based predictions (Figure 1).

Figure 1. Schematic overview of main purposes of the nowcasting toolbox
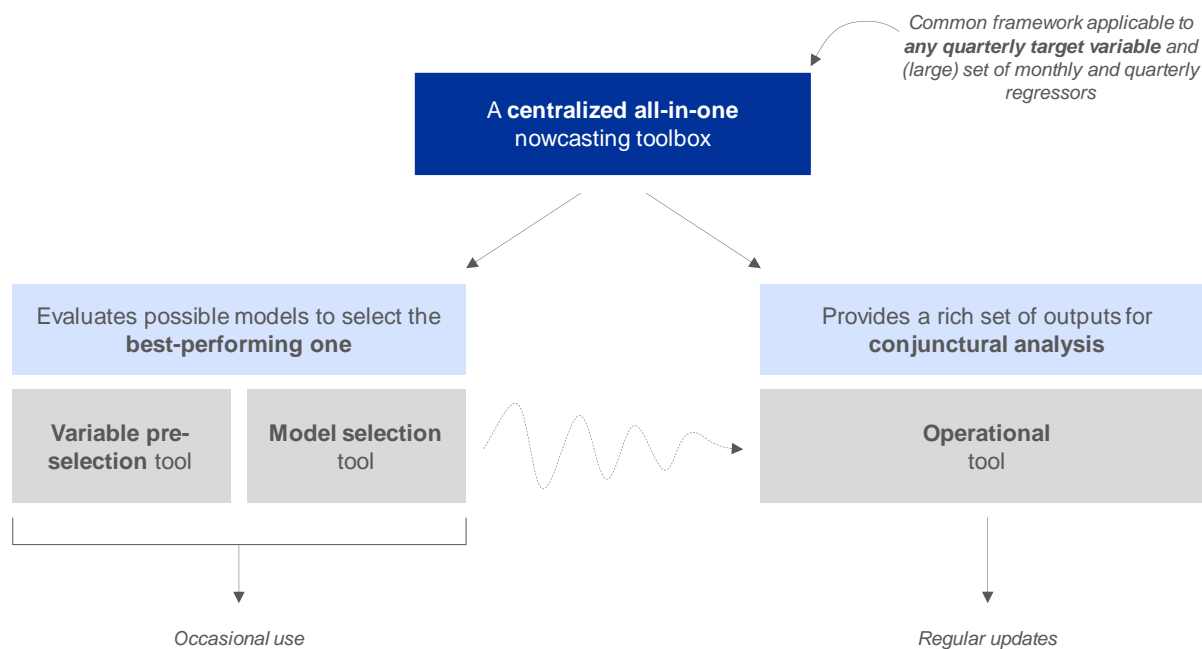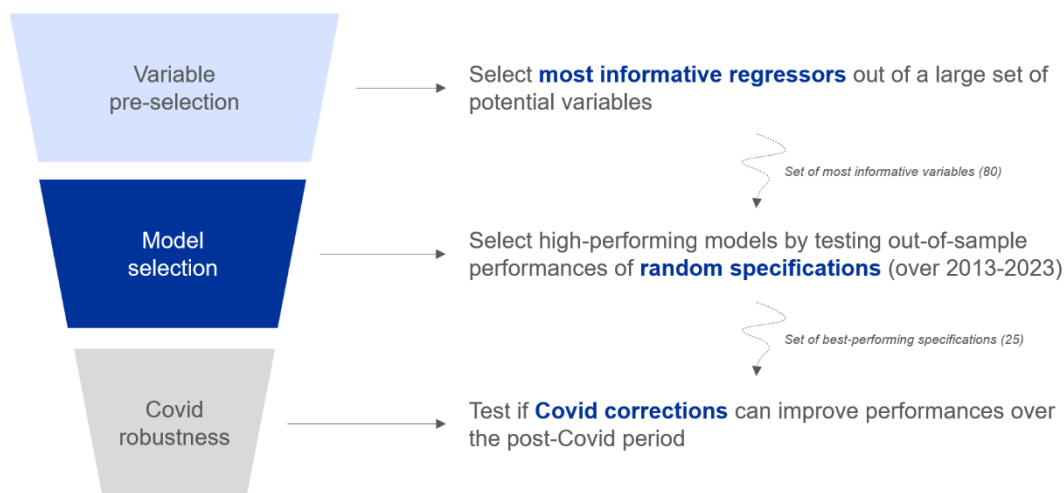

Sources: authors

The toolbox integrates various model classes and methods to manage data selection or adjust for Covid-19 observations. It supports three popular model classes: dynamic factor model (Bánbura and Modugno, 2014; Delle Chiaie et al., 2022), large Bayesian vector auto-regression (Cimadomo et al., 2022) and a combination of bridge equations à la Bánbura et al. (2023). The toolbox standardizes inputs and outputs for each model, allowing the user to switch easily across them. The toolbox also incorporates three pre-selection techniques (Efron et al., 2004; Bair et al., 2006; Fan and Lv, 2008) and three options for correcting for the Covid period (outlier correction, dummy variables, and deleting Covid-related observations). These various tools make the toolbox easily adaptable to various frameworks: it can notably accommodate for big data as it offers methods to pre-select the most informative regressors and model classes that work with many input variables.

A Structured Three-Step Approach to Model Creation

While the nowcasting literature generally offers only limited intuition into how to build a model from scratch, one key contribution of the toolbox is to organize model creation along a structured three-step approach of variable pre-selection, model selection, and Covid robustness (Figure 2). This approach, which formalizes the steps generally followed by forecasters, offers a practical start-to-finish and step-by-step guide for non-specialists to create a tailored high-performing model. Specialists can still benefit from the automation and the flexibility of the toolbox.

Figure 2. The proposed three-step approach for building nowcasting models

Sources: authors

We showcase the three-step approach by creating a model for quarterly global GDP growth and comparing it with an existing model, which was built on a more ad hoc procedure. Using the three-step procedure, we narrow down a large set of potential regressors to a set of most relevant predictors. The toolbox then handles the automatic testing of a large number of model specifications across the three model classes (DFM, BVAR, BEQ), randomizing over model parameters. Out-of-sample evaluation (on the 2013-2013 period) is handled by a pseudo real-time exercise, where the toolbox automatically reconstructs the "ragged edge" pattern of the data that a forecaster would have faced in real-time. Accuracy measures — specifically the Root Mean Squared Error (RMSE) and the Forecast Directional Accuracy (FDA) — are calculated based on these out-of-sample predictions. In our example, DFMs produced the best performing models. We therefore focus the rest of our exercise on DFMs and extracted the 25 best performing models. We then let the toolbox handle the final step – automatically testing whether corrections for the Covid period could further increase performances. Our final model utilizes outlier correction to adjust for the Covid period.

Overall, we were able to achieve a significant increase in prediction accuracy. Figure 3 (panel a) compares the point accuracy of the new model (from the toolbox) with the previous ad hoc model. Across all horizons, we achieve a significant reduction in out-of-sample RMSE over 2013-2023. Figure 3 (panel b) compares nowcasts over the post-Covid period with the actual outcome. The new model tracks the movements of global GDP growth much more accurately than the previous model and the naïve AR benchmark.

Figure 3. Accuracy of the best-performing model

a) Accuracy over full period
(out-of-sample RMSE over 2013-2023)

b) Predictions on post-Covid period
(quarterly percentage changes)
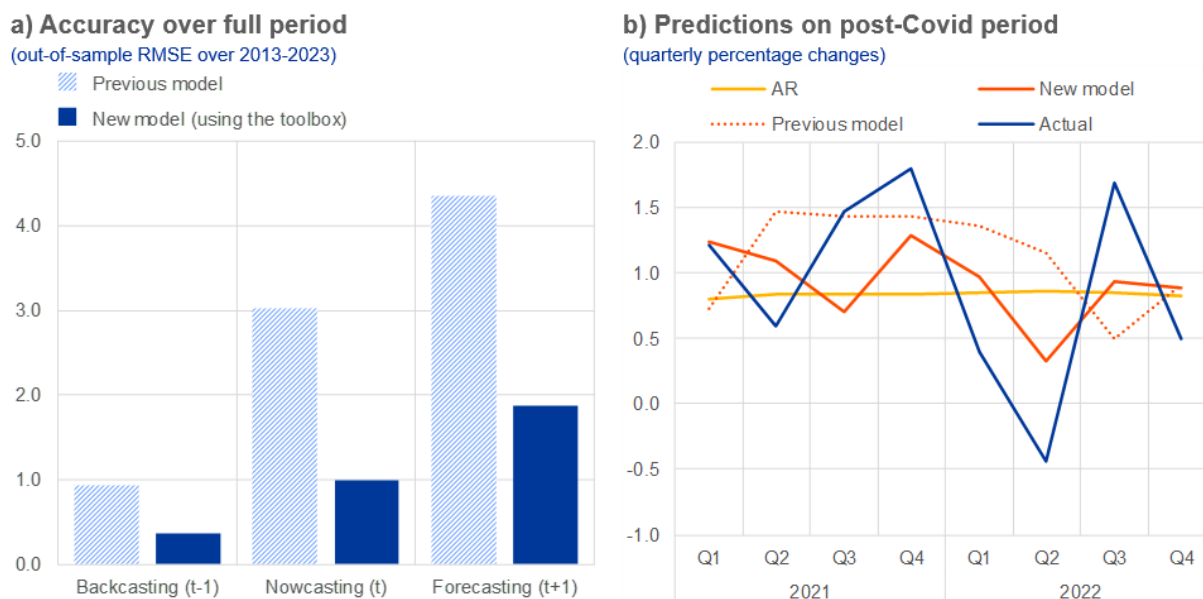
Sources: Bloomberg, Haver, S&P Global, and authors' calculation.

Notes: Out-of-sample predictions are done recursively in a pseudo real-time set-up. In panel a) the new model is without Covid-19 correction until Dec. 2020 and with correction afterwards. In panel b) predictions are done in the data at the 3rd month of the quarter.

Opening the "Black Box" – Outputs for Policy Analysis

After having built a nowcasting model, the toolbox can be put to work for regular policy analysis of the economic conjuncture. The toolbox not only generates model predictions but also, for the purpose of facilitating policy analysis, offers insights on what's happening "beneath the surface" of the model. Its outputs can be grouped in two broad categories serving different goals: 1) providing the narrative underlying model predictions, and 2) assessing the reliability of predictions.

The outputs aimed at providing the narrative underlying model predictions include:
- **News decomposition** (Figure 4, panel a) which quantifies the impact of each recent data release on model predictions, following the seminal work of Bańbura and Modugno (2014).
- **Contributions**, which are approximated by computing the impact of all data releases over recent months.
- **Heatmap of input variables**, which provides a bird's-eye view at how input variables deviate from the long-term mean. This can be especially useful when model predictions seem off as it provides a look at the "raw source" (i.e., the input variables).

On the other hand, the outputs aimed at gauging the reliability of model predictions include:
- **Confidence intervals** associated with the point forecast based on the mean absolute error of past forecasts over the last ten years, in line with Reifschneider and Tulip (2019) and corrected for outliers as in ECB (2009). The bands are dynamically reassessed as new data becomes available.
- **Share of available data**, to gauge whether a prediction is based on actual data or on data that are extrapolated by the model.
- **Range of alternative models**, which are automatically calculated by disconnecting one or two group(s) of variables from the information set (Figure 4, panel b). The interest of those alternative forecasts is to assess what would be the prediction if some variables are excluded.

Figure 4. Examples of policy outputs

a) News decomposition
(quarterly percentage changes, percentage points)

- Industrial Production
- Retail sales
- Trade
- Labour market
- Surveys
- Other
- Revisions (data and model)
- Current nowcast
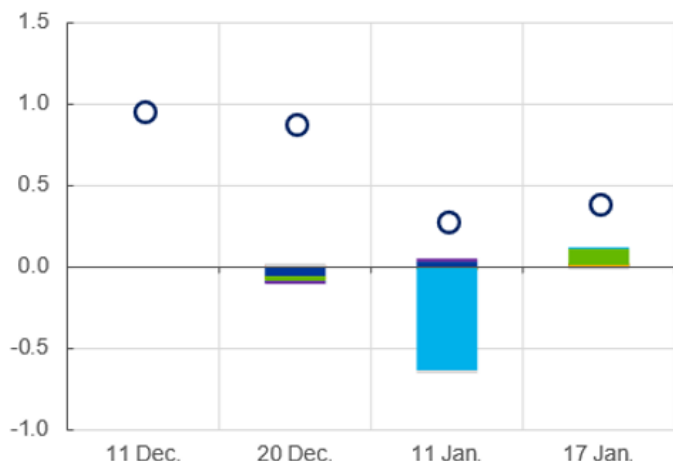
b) Alternative short-term predictions
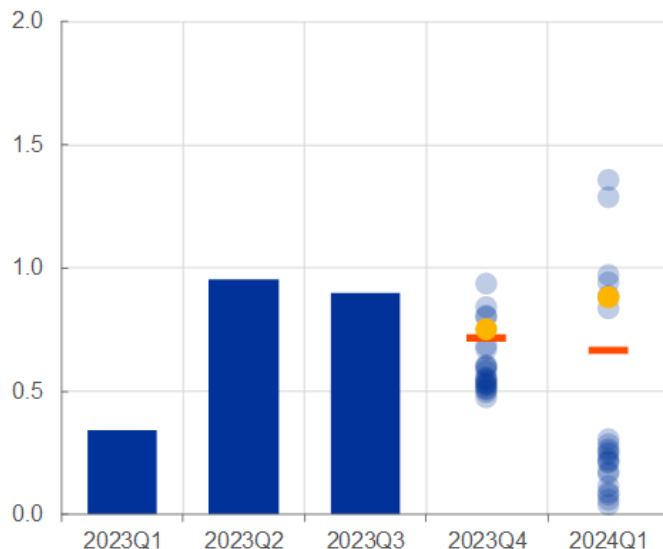(quarterly percentage changes)

- Outcome
- Dec. 2023 BMPE
- DFM (20 Dec.)

Sources: Bloomberg, Haver, S&P Global, and authors' calculation.
Notes: In panel a), dots represent the evolution of short-term estimates. Bars are contributions from news to revisions between two consecutive rounds. In panel b), light blue dots represent predictions by alternative models obtained by removing one or two groups of variables from inputs.

Besides opening the "black box", another goal of offering many outputs is to maintain the policy relevance of the nowcasting toolbox, regardless of how reliable model predictions may be. Even a model that displays good nowcasting performances on average can be off at times due to the complexity of economic systems and unforeseeable events (Engle and Brown, 1986; Makridakis et al., 2009). In these un-avoidable cases when model predictions are off, some of the many outputs could still prove useful – notably the heatmap of input variables which provide a view of the raw input data (Figure 5).

Figure 5. Heatmap of input variables

	Q2 2023			Q3 2023			Q4 2023		
	Aug. 23	Sep. 23	Oct. 23	Nov. 23	Dec. 23	Jan. 24	Feb. 24	Mar. 24	Apr. 24
Industrial Production — World[ex US]:Industrial Production(NSA, 2005=100) - Seasonal Adjustment, All									
World excl Euro Area: IP ex Construction [Production-Wghtd] (SWDA, 2010=100)									
World: Industrial Production ex Construction [Import-Weighted](SWDA, 2010=100)									
U.S.: Industrial Production ex Construction (SA, 2015=100)									
Brazil: Industrial Production ex Construction (SA, 2015=100)									
Czech Republic: Industrial Production (SWDA,2021=100)									
U.S.: Car Production (SA, Units)									
Canada: Shipments: All Manufacturing Industries (SA, Thous.C$)									
U.S.: New Orders: Manufacturing (SA, Mil.$)									
Czech Republic: Industrial Sales (NSA, 2021=100) - Seasonal Adjustment, All									
Czech Republic: Industrial New Orders (NSA, 2021=100) - Seasonal Adjustment, All									
Hungary: Volume of New Orders (NSA, 2021=100) - Seasonal Adjustment, All									
Mfrs' New Orders: Nondefense Capital Goods ex Aircraft (SA, Mil.$)									
Retail sales — U.S.: Wholesale Sales (SA, Mil.$)									
Canada: Wholesale Trade (SA, Thous.C$)									
Trade — Emerging Markets: Merchandise Exports (NSA, 2005=100) - Seasonal Adjustment, All									
U.S.: Imports of Goods, Customs Value (SA, Mil.$)									
World excl Euro Area: Import Volume (SA, 2010=100)									
Exports, FAS Value (SA, Mil.Chn.2017$)									
Labour market — Unemployment Insurance: Initial Claims, State Programs (SA, Thous)									
Insured Unemployment, State Programs (SA, Thous)									
Civilian Unemployment Rate: 16 yr + (SA, %)									
Surveys — Global excl Euro Area PMI: Manufacturing New Export Orders (SA, 50+=Expansion)									
Global excl Euro Area PMI: Manufacturing (SA, 50+=Expansion)									
Global excl Euro Area PMI: Manufacturing Quantity of Purchases(SA,50+=Expansion)									
Global excl Euro Area PMI: Manufacturing New Orders (SA, 50+=Expansion)									
Japan: Total Leading Indicator (SA, Amplitude Adjusted)									
Poland: Manufacturing Index of Overall Economic Climate (SA, % Bal)									
Other — FTSE All-World Automobiles & Parts Stock Price Index Total Return(Index)									
U.S.: Housing Units Authorized by Building Permit (SA, Thous.Units)									
World (excl. EA) real imports									

Sources: Bloomberg, Haver, S&P Global, and authors' calculation.

Note: The heatmap is based on z-scores, computed by subtracting the mean and dividing by the standard deviation.

Conclusion: A New Tool for Economists

Our toolbox combines two main workstreams: First, building new models and evaluating existing ones on a periodical basis. Second, providing regular conjunctural policy analysis. In our example, we apply the toolbox to the revision of a model for quarterly global GDP growth, showcasing increases in model performance. The model outputs provided by our toolbox are designed to open the "black box" of nowcasting. As such, all toolbox features as well as the structured approach to building a model are designed to be valuable to users specialized and non-specialized in nowcasting applications. However, while we aim to provide a high level of automation and ease-of-use, careful user judgement is still required at every step when building, evaluating, and using models for policy analysis. The automated nature of the toolbox only aims to assist economists in arriving at an accurate, and most importantly, useful nowcasting model.

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About the author(s)

Jan Linzenich is a PhD student in Economics at Humboldt University of Berlin and the Berlin School of Economics. Previously, he was a trainee in the External Developments Division at the ECB's Directorate General International and European Relations. His research interests include Applied Econometrics, Economic History, International Trade and Macroeconomics.

Baptiste Meunier is a trade economist in the External Developments Division of the European Central Bank (on leave from Banque de France). He graduated from Ecole Polytechnique in 2013 and obtained a PhD at the Aix-Marseille School of Economics in 2024. His research covers trade as well as the use of data science and alternative data in economics.