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Panel Nowcasting for Countries Whose Quarterly GDPs are Unavailable

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ABSTRACT: Quarterly GDP statistics facilitate timely economic assessment, but the availability of such data are limited for more than 60 developing economies, including about 20 countries in sub-Saharan Africa as well as more than two-thirds of fragile and conflict-affected states. To address this limited data availablity, this paper proposes a panel approach that utilizes a statistical relationship estimated from countries where data are available, to estimate quarterly GDP statistics for countries that do not publish such statistics by leveraging the indicators readily available for many countries. This framework demonstrates potential, especially when applied for similar country groups, and could provide valuable real-time insights into economic conditions supported by empirical evidence .

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WORKING PAPERS

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Contents

Glossary

CPI	Consumption price index
EMDE	Emerging market and developing economies
FCS	Fragile and conflict-affected states
GDP	Gross domestic product
LGB	Light gradient boosting regression
LIDC	Low-income developing country
NO2	Nitrogen dioxide
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PPP	Purchasing power parity
RMSE	Root mean square error
SSA	Sub-Saharan Africa

1. Introduction

A notable hurdle in monitoring economic activities of developing economies is the limited availability of quarterly GDP statistics. A recent stocktaking of national account statistics by Silungwe, Bear, and Guerreiro (2022) indicates that more than 60 countries do not publish official quarterly GDP statistics. Those include about 20 countries in sub-Saharan Africa (SSA), more than half of low-income developing countries (LIDCs), and more than two-thirds of fragile and conflict-affected states (FCS).[1] Even in cases where quarterly GDP data are available, there is often a delay in its release. In fact, for about 20 countries, this time lag exceeds one quarter. This limited availability of timely quarterly GDP statistics poses a significant challenge for policymakers, particularly when responding swiftly to sudden shifts in economic conditions as in the case of recent multiple global shocks.

To address this challenge, this paper proposes a panel approach to nowcast quarterly GDPs, particularly targeting countries that do not publish quarterly GDP statistics.[2] This panel approach assumes a common statistical structure across countries, acknowledging that pooling together countries with different characteristics may introduce specification errors. However, it leverages insights from countries with available data into economic activity of countries with limited data availability. In particular, the approach features the use of nontraditional data sources which are relatively more available across many countries. Given a panel dataset of countries, an estimation method (e.g., ordinary least squares, OLS) can generate a nowcast as a fitted value of quarterly GDP, using input variables for a given country. To mitigate an obstacle that there are still missing values for input variables in some countries, particularly for more recent periods, this paper proposes to use an ensemble of nowcasts.

The proposed approach complements existing efforts to enhance timely economic assessments for countries with data gaps, such as a workstream in the IMF's African Department (Barhoumi and others 2022). Constructing a high-frequency indicator of economic activity has been also an area that the IMF's Statistics Department has been focusing on, including in its capacity development agenda. This study is also related to the growing literature on the use of nontraditional data sources for economic analysis, including remote sensing data such as nighttime lights (e.g., Debbich 2019; Hu and Yao 2022; Beyer, Hu, and Yao 2022), Google trends (Narita and Yin 2018), and Google Places API (Austin and others, 2021).[3]

The rest of the paper is organized as follows. Section 2 provides an overview of the proposed panel nowcasting framework, while details are presented in Annex I. Section 3 evaluates the performance of panel nowcasts. Section 4 demonstrates results for selected countries in SSA. Section 5 concludes with key caveats and room for improvement.

[1] This is based on the FCS classification by the World Bank as of March 2023, following the IMF's FCS Strategy (IMF 2022a).

[2] Nowcasting is an estimation of present or recent past values of unobserved variables using observed high frequency indicators. It is part of a more general approach to produce a composite indicator that correlates with the level of economic activities, by combining data available at a high frequency.

[3] Google Trends data have been widely used for nowcasting and forecasting purposes. See, for example, papers cited in Narita and Yin (2018). More recently, Woloszko (2020) sets up a GDP growth nowcast framework named OECD Weekly Tracker for 46 OECD and G20 countries using Google Trends search data with a neural network model (ensembled multi-layer perceptron regressions). Cevik (2022) uses travel-related online search queries to forecast tourist arrivals from the U.S to The Bahamas.

2. Panel Nowcasting of Quarterly GDP Growth

The proposed framework assumes a common statistical relationship across all economies in the sample. Let y_{it} denote quarterly GDP growth, calculated by log difference, from the same quarter a year ago (i.e., year-on-year growth) for economy i and time t. Similarly, all other input variables, denoted by X_{it}, are transformed into quarterly growth from the same quarter a year ago. Conceptually, our objective is to construct a nowcast of y_{it} by estimating conditional expectation $\mathrm{E}[y_{it}|X_{it}]$, which is an arbitrary function of X_{it}, which may in general depends on country i and period t. Our panel approach relies on a strong assumption that this function is common across countries and periods, denoted by $f(X_{it})$, without index i or period t, such that:

$$y_{it} = f(X_{it}) + \varepsilon_{it}, \qquad \hat{y}_{it} \stackrel{\text{def}}{=} f(X_{it}),$$

where ε_{it} is a nowcast error and $\hat{y}_{it}$ is a nowcast of quarterly real GDP growth from the same quarter a year ago[4]. Since y_{it} is not observable for the countries that do not publish quarterly GDP data, the functional relation, $f(.)$, is estimated using the panel-country group with available data. To estimate function $f(X_{it})$, we use a machine learning technique called "light gradient boosting regression" (LGB[5]) as well as OLS. For the LGB, we use the default hyperparameters. See Annex I.B for details and see Annex I.C for how we construct a nowcast of annual growth based on a nowcast of quarterly growth.

A key challenge of panel estimation is to collect a set of input data series X_{it} that are commonly available for the set of countries in the sample. We collect 117 quarterly indicators that are related to economic activity, among which 76 indicators are from nontraditional data sources, for as many as 200 economies since 2008Q1 (see Annex I.A for details)[6]. Even after leveraging nontraditional data sources, it is still challenging to cover all country-period pairs of interest, especially for recent periods. In our dataset, the variables that are available for all economies for all sample periods are six global commodity prices, two global financial indexes (U.S. 2-year bond yields, U.S. stock market volatility index), and 14 world-wide search volume indexes (out of 28 in our sample). Strictly speaking, we can use these 22 variables only (together with quarter and country group dummies), but these may be too few to capture growth dynamics.

To reflect the information from all available input variables as much as possible, we consider an ensemble of nowcasts by taking the average over all specifications based on data available for each country in each period. This average ensemble ensures that nowcasts are generated for all countries and periods, at least using the minimum set of the 22 input variables as mentioned above. Then, if more variables are observed for a country in a period, the nowcast reflects more information. For comparison, we also consider the most 'general' specification (i.e., the specification whose number of input variables is the largest, depending on a country-period pair) and the least one (i.e., the specification whose number of input variables is the smallest—a model with the 22 variables mentioned above). Correspondingly, three ensemble nowcasts are generated, named "average," "maximum," and "minimum" models, with the "average" ensemble being the baseline (Figure 1). See Annex I.D for more discussions in handling missing observations.

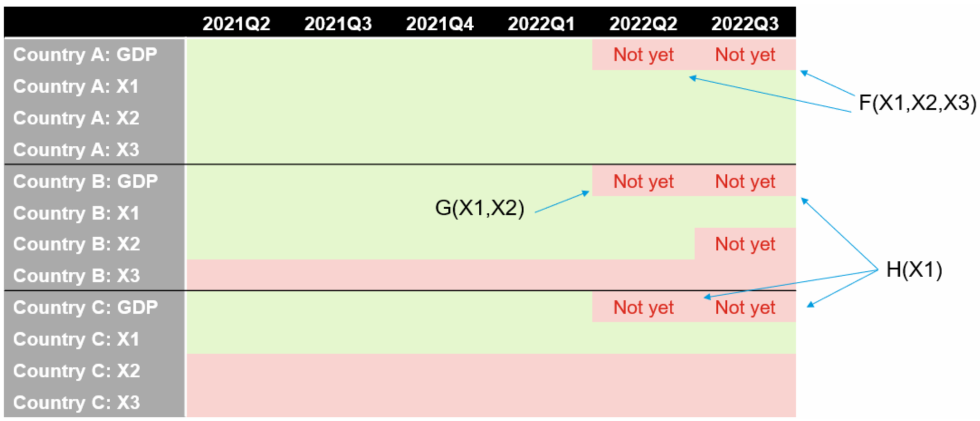
[4] Many countries implement chain link volume measures whereby the headline GDP growth rate might differ from the one derived from the aggregation of components. This paper does not impose any structural aggregation from GDP components to headline GDP growth, instead aims to utilize information gathered from granular data into a single headline growth.

[5] Light gradient boosting is a decision tree-based learning algorithm. Its efficiency, low memory use, and capacity of handling large-scale data make it an advantageous machine-learning algorithm for this toolkit.

[6] A future work considered for this study is to extend the data coverage with IMF High Frequency Data Hub.

We also consider different estimation subsamples to leverage similarity within country groups. To mitigate a caveat of assuming a common statistical structure across countries of different natures, nowcasts are also estimated by subsamples, based on regions (e.g., SSA) and export types (e.g., fuel exporters). Subsample nowcasts are generated for those economies within the subsample. To maximize the coverage, our baseline remains to use the full sample (labeled “Global”), although subsampling economies with similar natures may improve nowcast performance.

Figure 1. Ensemble nowcasts depending on data availability



Source. Authors.

Notes. This is a conceptual diagram to explain how ensemble nowcasts are constructed, based on data availability. Cells in green indicate the country-period pairs where data are available, and cells are in red otherwise. For country A for 2022Q2 and 2022Q3, all input data X1, X2, and X3 are available, and therefore, all models F, G, and H can be used to generate nowcasts. In such a case, the “average” model is constructed by taking the average of three nowcasts from the three models. The “maximum” model in this case is model F, which has the maximum number of input variables in each period for country pairs, i.e., not maximum number of variables covering all periods for a single country. For country B for 2022Q2, models G and H can be used, and the “average” model is the average of two nowcasts from models G and H. The “maximum” model in this case is model G. Model H only uses input variable X1 and can be used all cases so that the “minimum” model is model H for all country-period pairs. For country B for 2022Q3 and country C for 2022Q2 and 2022Q3, only model H can be used so that the “minimum,” “average,” and “maximum” models are all the same, i.e., model H.

To provide more insights, contributions of input variables to a nowcast are also estimated. In the case of LGB, we use an approach named “SHAP” (SHapley Additive exPlanations) by Lundberg and Lee (2017). The SHAP values $\{\hat{s}_{kit}\}$ of input variables $\{x_{kit}\}$ are locally additive so that the sum of the contributions from all inputs (as well as the constant term) is equal to the nowcast $\hat{y}_{it}$ for each pair of country i and period t as follows[7]:

$$\hat{y}_{it} = \widehat{\mathrm{E}}(y_{it}) + \sum_{k} \hat{s}_{kit},$$

where $\widehat{\mathrm{E}}(y_{it})$ denotes the sample mean. In the case of OLS, the SHAP value is simply coefficient $\hat{\beta}_k$ times the value of the input variable x_{kit} (i.e., $\hat{s}_{kit} = \hat{\beta}_k x_{kit}$).

To understand what had contributed to growth in the quarter of interest since a quarter before, we also calculate the differences in SHAP values over time. This approach necessarily includes the residual in the

[7] Note that the SHAP contributions are described as causal effects from the factors to overall growth since there is also the reverse causality. Section 4 provides a more detailed discussion.

previous quarter (i.e., $\hat{\varepsilon}_{i,t-1} \stackrel{\text{def}}{=} y_{i,t-1} - \hat{y}_{i,t-1}$) as one of the factors contributing to nowcast $\hat{y}_{it}$ in the quarter of interest as follows:

$$\hat{y}_{it} - y_{i,t-1} = y_{it} - \hat{y}_{i,t-1} + \hat{y}_{i,t-1} - y_{i,t-1} = \sum_k (\hat{s}_{kit} - \hat{s}_{k,i,t-1}) + (-\hat{\varepsilon}_{i,t-1}),$$

assuming that there is no change in the set of input variables $\{x_{kit}\}$ between period $t-1$ and t. The SHAP values for ensemble nowcasts need another residual term due to changes in specifications over time (see Annex I.E for details).

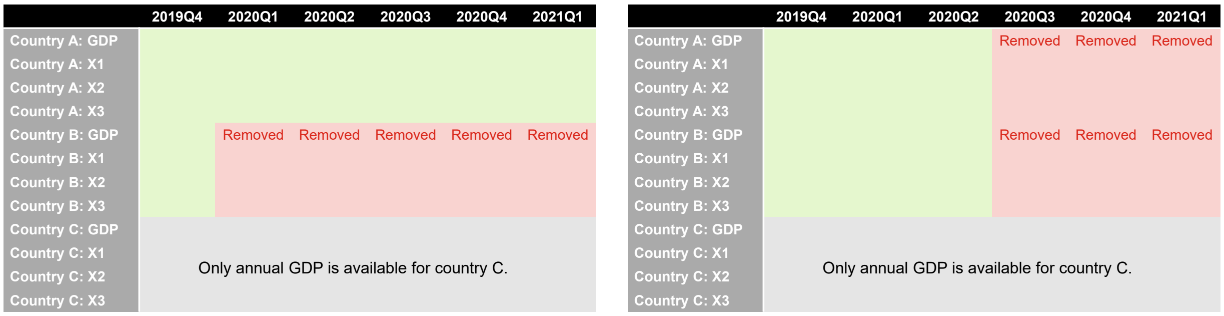
3. Evaluation of Panel Nowcast Performance

In theory, panel nowcasts may lead to lower in-sample fit than country-specific nowcasts but may potentially lead to better out-of-sample fit by suffering less from overfitting issues. Keeping the same complexity of nowcast models, in-sample fit may be better if the model is estimated specific to a country of interest than if it is estimated in a panel setup. But out-of-sample fit of panel nowcasts may be potentially good because the strong assumption of a common structure over many different countries prevents the nowcasts from being overfitted to observed data points. The overfitting issue is a key concern particularly when using a machine learning technique with a high model complexity (see, e.g., Barhoumi and others 2022, Figure A1).

Out-of-sample fit, where quarterly growth data are available, is evaluated in two directions: country-wise and period-wise (Figure 2). Country-wise evaluation is based on an estimation sample excluding a country whose observations will be used only to calculate root mean squared errors (RMSEs). This pseudo out-of-sample performance indirectly assesses how nowcasts could perform for countries without quarterly growth data. It also evaluates how data in other countries can help nowcast growth in another country of interest. On the other hand, period-wise evaluation is based on an estimation sample without recent periods (e.g., up to 2021Q3. This direction of pseudo out-of-sample performance assesses how historical statistical relationships can help estimate nowcasts. Although period-wise out-of-sample assessments are more common, country-wise assessments fit better to our purpose to provide insights to countries with limited data availability. Neither of these country-wise and period-wise evaluations, however, can be used to directly evaluate the performance of panel nowcasts for countries without quarterly growth data because nowcast errors cannot be calculated without observed quarterly growth data.

Figure 2. Two directions of out-of-sample evaluation

Panel A: Country-wise **Panel B: Period-wise**



Source. Authors.

Notes. This is a conceptual diagram to explain how out-of-sample performance of panel nowcasts is evaluated, where quarterly real GDP growth data are available. “Removed” indicates data points that are excluded from nowcast estimation and then used only to calculate out-of-sample RMSEs. In this example, country-wise out-of-sample RMSEs are evaluated for country B from 2020Q1 to 2021Q1. Period-wise out-of-sample RMSEs are evaluated for countries A and B from 2020Q3 to 2021Q1. Quarterly growth data are not available for country C, for which these two evaluations cannot be conducted directly.

Results show that out-of-sample fit is generally well when evaluated country-wise although it is poor period-wise. Evaluated for 15 selected countries in SSA, country-wise out-of-sample fit of our baseline panel nowcast (which is the “average” ensemble nowcast based on the LGB estimated using the full “global” sample) is relatively well compared to a naïve random walk nowcast (which is just a one-quarter lag of quarterly real GDP growth). The Theil U index[8]—the ratio of RMSEs over the RMSEs of the random walk nowcast—is less than 75 percent for 9 out of 15 countries (Table 1, Panel A). It is less than 50 percent for five countries, implying a reduction of nowcast errors by more than a half. The Theil U index is very off exceeding 500 percent for Tanzania, but it is because the random walk nowcast rather performs very well in this case, and the panel nowcast’s out-of-sample RMSEs is 5.27 percent, which is weak but not so much as implied by the very large Theil U index. In contrast, period-wise out-of-sample RMSEs indicate poor performance, showing larger RMSEs than the random walk nowcast (Table 1, Panel B). This poor performance partly stems from the difficulty to capture the very volatile growth path since the onset of the pandemic but also suggests that it may not be easy to learn about the present from the past. Still, relatively good country-wise performance implies that panel nowcasts may be helpful to learn from data on other countries to provide insights into economic situations in countries where data availability is limited.

Evaluation of out-of-sample fit for subsamples indicates the potential to improve the fit by tailoring estimation samples to country characteristics. If the LGB model is estimated only for 25 SSA countries for which quarterly growth data are available in our sample, then period-wise out-of-sample performance to show the Theil U index of less than one, and country-wise performance also tend to improve to some extent (Table 2). Such improvements are not so obvious for other subsample estimations (Annex Tables 3, 4, 5, 6), but it may be worth exploring a way to identify a subsample that leads to better out-of-sample fit, as suggested by Bolhuis and Rayner (2020).

There is still large room for improvement. Even when the Theil U index is small, our panel nowcasts tend to produce larger out-of-sample RMSEs than those of country-specific nowcasts (e.g., Barhoumi and others 2022, showing about 2 percent of RMSEs for the selected best models). Out-of-sample bias is also large. Our panel nowcasts tend to be correct in their directions (i.e., they indicate a positive rate of growth when actual growth is

[8] The Theil U index version used in this paper is also referred as Theil U2 index.

positive, and vice versa) with probability of more than 70 percent for 9 out of 15 cases, but in some cases, the directional predictions are correct just with probability ½ (Ghana, Mauritius). LGB-based nowcasts tend to perform better than OLS-based nowcasts (Annex Tables 7, 8), implying that there is room to explore a better estimation method and a better calibration of hyperparameters.

Table 1. Performance of panel nowcasts: LGB, global sample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-0.04	0.29	1.96	0.79	0.86	0.71	2.18	0.70	3.44	1.20
Botswana (15)	-0.04	-0.17	-1.12	0.79	0.79	0.57	2.18	3.06	8.95	0.58
Cabo Verde (15)	-0.04	-0.43	-1.03	0.79	0.71	0.71	2.18	3.17	8.82	0.49
Cameroon (15)	-0.04	0.20	1.04	0.79	0.77	0.62	2.18	0.97	2.90	0.81
Côte d'Ivoire (15)	-0.04	-0.47	-1.87	0.79	0.93	0.93	2.18	1.09	3.81	0.73
Ghana (15)	-0.04	-0.29	-1.05	0.79	0.79	0.43	2.18	0.82	2.97	0.70
Kenya (15)	-0.04	-0.44	-1.50	0.79	1.00	0.86	2.18	0.66	2.03	0.57
Lesotho (15)	-0.04	1.21	3.04	0.79	0.86	0.57	2.18	2.05	5.36	0.46
Mauritius (15)	-0.04	0.17	0.80	0.79	0.86	0.57	2.18	1.76	4.97	0.42
Namibia (15)	-0.04	0.44	2.72	0.79	0.93	0.64	2.18	0.95	4.13	0.86
Nigeria (15)	-0.04	-0.06	-0.41	0.79	0.87	0.73	2.18	0.49	2.22	0.80
Seychelles (15)	-0.04	-0.18	-0.86	0.79	1.00	0.79	2.18	3.45	11.29	0.87
South Africa (15)	-0.04	0.32	1.17	0.79	0.80	0.73	2.18	0.93	3.33	0.38
Tanzania (15)	-0.04	-1.21	-2.49	0.79	0.71	0.57	2.18	2.04	5.27	5.31
Uganda (15)	-0.04	-0.35	-0.57	0.79	0.86	0.71	2.18	1.13	1.80	0.37

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (2200)	-0.04	0.07	1.83	0.79	0.87	0.69	2.18	2.90	9.76	1.07
2020Q4-2022Q3 (1600)	-0.04	-0.04	-4.19	0.79	0.84	0.62	2.18	2.31	8.49	1.04
2021Q3-2022Q3 (1000)	-0.04	0.00	4.07	0.79	0.81	0.55	2.18	2.33	7.34	1.30

Sources: Authors estimations (see Annex Table 2 for data sources).
Notes: The estimation sample includes 6,507 observations for 127 economies from 2009Q1 to 2022Q3 (see Annex I for details). The term “bias “is the average deviation from actual observation in the panel set, and the term “direction” is share of capturing increases, decreases, and no changes in overall panel set. The in-sample bias, in-sample direction, and in-sample RMSE values are calculated for country groups as panel and equal across countries withing the grouping.

Table 2. Performance of panel nowcasts: LGB, SSA subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	0.01	0.02	1.47	0.90	1.00	0.79	1.66	0.31	2.52	0.88
Botswana (15)	0.01	-0.04	-0.41	0.90	0.86	0.57	1.66	4.95	9.53	0.62
Cabo Verde (15)	0.01	0.75	0.18	0.90	0.86	0.50	1.66	4.86	11.43	0.64
Cameroon (15)	0.01	0.33	1.98	0.90	0.85	0.77	1.66	0.60	2.66	0.74
Côte d'Ivoire (15)	0.01	-0.17	-1.75	0.90	0.93	0.71	1.66	0.60	3.40	0.65
Ghana (15)	0.01	-0.01	-0.60	0.90	0.93	0.36	1.66	0.33	2.39	0.56
Kenya (15)	0.01	-0.22	-1.91	0.90	1.00	0.79	1.66	0.51	2.56	0.72
Lesotho (15)	0.01	0.60	4.01	0.90	0.93	0.50	1.66	1.24	6.75	0.58
Mauritius (15)	0.01	0.56	1.67	0.90	1.00	0.64	1.66	2.61	6.05	0.51
Namibia (15)	0.01	0.29	2.49	0.90	0.93	0.64	1.66	0.55	4.13	0.86
Nigeria (15)	0.01	-0.21	-0.99	0.90	0.93	0.87	1.66	0.36	1.25	0.45
Seychelles (15)	0.01	-0.35	-0.85	0.90	0.93	0.79	1.66	1.66	5.02	0.39
South Africa (15)	0.01	0.08	0.83	0.90	1.00	0.60	1.66	1.97	5.21	0.59
Tanzania (15)	0.01	-0.59	-2.68	0.90	0.86	0.57	1.66	1.29	4.58	4.62
Uganda (15)	0.01	-0.10	-0.29	0.90	1.00	0.71	1.66	0.34	2.04	0.42

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (495)	0.01	0.03	2.02	0.90	0.89	0.59	1.66	1.97	7.52	0.89
2020Q4-2022Q3 (360)	0.01	-0.10	-2.83	0.90	0.87	0.57	1.66	1.39	5.64	0.79
2021Q3-2022Q3 (225)	0.01	0.02	-0.02	0.90	0.86	0.51	1.66	0.62	3.23	0.65

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 1,134 observations for 25 SSA countries from 2009Q1 to 2022Q3 (see Annex I for details). LGB=light gradient boosting regression; SSA=sub-Saharan Africa.

To directly evaluate nowcast performance for countries without quarterly growth data, annual growth nowcasts, derived from quarterly growth nowcasts, are used to compute RMSEs. Since no data from these countries are used to estimate nowcasts, the performance evaluated this way is considered out-of-sample. Annual growth nowcasts are approximately derived as growth of the four-quarter sum of the implied levels of quarterly real GDP by parsimoniously assuming no seasonality in the levels of real GDP across quarters in the initial year (i.e., in the year 2008 in our sample). This cumulative formulation is intended to account for a sharp reduction in real GDP followed by a sharp recovery, such as in the case of the onset of the COVID-19 pandemic in 2020Q2 and its recovery in 2021Q2. For the latest estimation year (e.g., 2022, at the time of writing) when nowcasts still do not cover some quarters (e.g., 4th quarter), annual growth nowcast is calculated as year-on-year growth of the average of quarterly nowcasts available to date (e.g., first three quarters). See Annex I.C for details.

Results show a reduction in RMSEs from the naïve random walk nowcast, although the size of RMSE is large. The Theil U index shows about 30 percent of reduction in RMSE across specifications, and the reduction is more for tourism-oriented country groups, The out-of-sample RMSEs exceeds 6 percent for all but one case (Table 3). In-sample RMSE (i.e., evaluated on the sample where quarterly growth data are available) is 1.71 percent for the baseline model, while it ranges from 0.90-1.91 percent for other LGB-based average-ensemble models on subsamples. The same pattern broadly holds for OLS-based panel nowcasts (Annex Table 9). There is also a uniform positive out-of-sample bias of above 1 percent across specifications (including those based on the OLS), although in-sample bias is -0.03 for the baseline model, and it ranges from -0.04-0.10 percent for other LGB-based average-ensemble subsample models. This out-of-sample positive bias may potentially reflect sampling bias regarding the availability of quarterly growth data.

Table 3. Performance of panel nowcasts for countries without quarterly growth data: LGB

Model 2010-2022 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
LGB, Global, average (1,017)	-	-	1.06	-	-	0.63	-	-	6.64	0.67
LGB, EMDEs, average (926)	-	-	1.07	-	-	0.63	-	-	6.75	0.68
LGB, SSA, average (293)	-	-	1.08	-	-	0.60	-	-	6.10	0.75
LGB, Comm. exp., average (480)	-	-	1.78	-	-	0.62	-	-	8.56	0.70
LGB, Fuel exp., average (164)	-	-	2.60	-	-	0.66	-	-	11.72	0.67
LGB, Tourism, average (207)	-	-	1.22	-	-	0.70	-	-	4.37	0.52

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample period is from 2009Q1 to 2022Q3 (see Annex I for details). Comm. exp.=commodity exporting economies; Fuel exp.=fuel exporting economies; EMDEs=emerging market and developing economies; LGB=light gradient boosting regression; SSA=sub-Saharan Africa; Tourism=tourism-oriented economies.

4. Quarterly GDP Nowcasts for SSA Countries

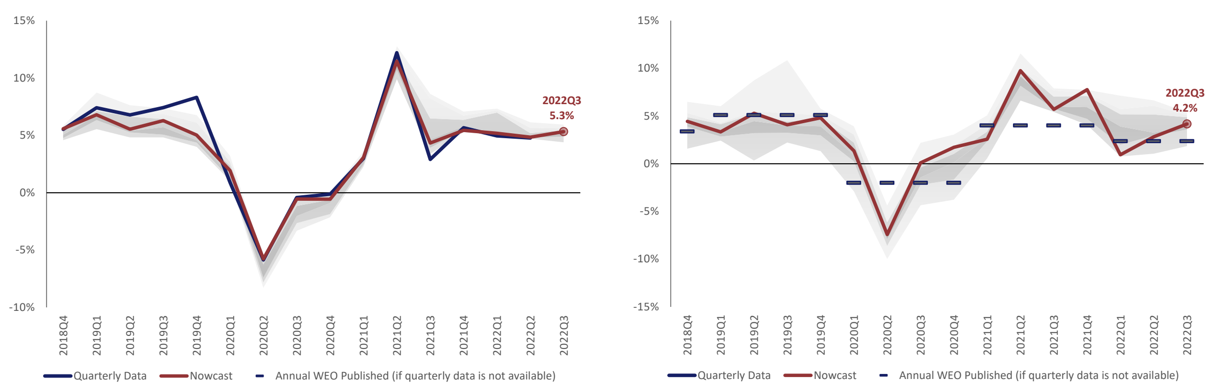
To demonstrate the proposed framework, we present selected results for countries in SSA. Out of the 45 countries in SSA, there are 20 countries that do not publish quarterly GDP, but our panel nowcasts are available for these countries. We start with an example of countries that publish quarterly GDP statistics, which is Uganda, and then move on to an example of those that do not, which is Sierra Leone. Both Uganda and Sierra Leone are grouped under Emerging Market and Developing Economies, and they are not considered as tourism oriented or fuel exporter economies.

In the case of Uganda, nowcasts largely follow actual quarterly real GDP growth (Figure 3, Panel A). The nowcast shown in this chart (red line) is the baseline nowcast (i.e., LGB-based average-ensemble nowcast estimated using the full global sample). The shaded areas show the variations in panel nowcasts from different specifications (e.g., across estimation subsamples) to indicate the degree of estimation uncertainty. Although the chart shows in-sample fitted values, where a good fit is relatively guaranteed, it is encouraging to see that the baseline nowcast does capture the bottom and the peak of growth path along the COVID-19 pandemic. In most periods, actual quarterly growth locates within the shaded areas, except for a few periods (e.g., 2019Q4, 2021Q3).

In the case of Sierra Leone, nowcasts also broadly follow actual annual real GDP growth and provide quarterly dynamics (Figure 3, Panel B). Since quarterly growth data are not available, the chart shows annual growth data, by repeating it four times for all four quarters. The baseline nowcasts broadly fits with actual annual growth, covering it within the shaded areas in most periods. The quarterly nowcasts also seemingly depict a reasonable within-year dynamic along with a recession at the onset of the pandemic and the following recovery, as well as another shock in 2022Q1 related to spillovers from the war in Ukraine.

Figure 3. Quarterly growth nowcasts and actual growth: Uganda and Sierra Leone

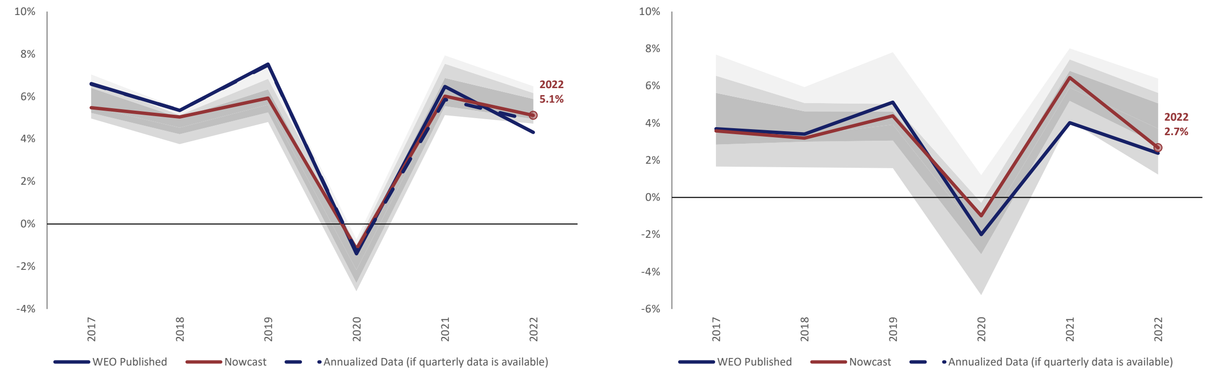
Panel A: Uganda **Panel B: Sierra Leone**



Sources. Authors estimations (see Annex Table 2 for data sources).
Notes. The blue line visualizes quarterly year-on-year real GDP growth data if available, and if not, the blue dashed line shows annual real GDP growth rate, taken from the published WEO database (IMF 2022c). The shaded area represents the nowcast variation of different specifications across estimation methodologies (LGB, OLS), available country group specifications (Global, EMDE, SSA, commodity exporters, fuel exporters, tourism-oriented economies), and nowcast ensemble options (minimum, average, maximum; see Annex I.E for details), where each 1/8th percentile is illustrated with a different gray shade. The red line represents the baseline quarterly GDP nowcast, averaged over available specifications estimated by the LGB using the full global sample.

Figure 4. Annual growth nowcasts and actual growth: Uganda and Sierra Leone

Panel A: Uganda **Panel B: Sierra Leone**



Sources. Authors estimations (see Annex Table 2 for data sources).

Notes. The blue solid line visualizes annual real GDP growth data. The red line shows the annualized growth rates, approximately derived from the baseline quarterly real GDP growth nowcast (see Annex I.C for details). The blue dashed line shows the annualized growth rates, derived from quarterly real GDP growth data if available, using the same formula. See Annex I.C for details. The shaded area represents the nowcast variation of different specifications across estimation methodologies (LGB, OLS), available country group specifications (Global, EMDE, SSA, commodity exporters, fuel exporters, tourism-oriented economies), and nowcast ensemble options (minimum, average, maximum; see Annex I.E for details), where each 1/8th percentile is illustrated with a different gray shade.

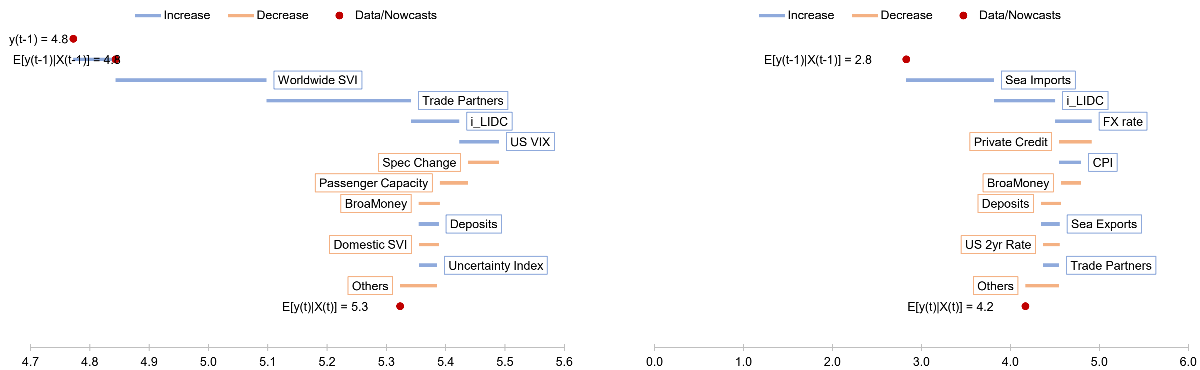
Looking at annual growth nowcasts approximately derived from quarterly growth nowcasts is helpful especially for countries without quarterly growth data (Figure 4). In both cases of Uganda and Sierra Leone, the derived annual growth nowcasts tend to follow the actual growth path. For 2022, the panel nowcasts indicate slightly higher growth than those in the October 2022 World Economic Outlook (WEO) vintage (IMF 2022c). The goodness of fit is not so strong for the case of Sierra Leone, with out-of-sample RMSE of 8.57 percent (compared with annual growth in-sample RMSE of 1.15 percent for Uganda), which will be discussed further below. Nonetheless, the panel nowcasts could helpfully provide a starting point of discussion on growth dynamics in countries where quarterly GDP statistics are unavailable.

SHAP values help us better understand the underlying factors of the panel nowcasts. For Uganda, growth nowcast for 2022Q3 picks up from 4.8 percent to 5.3 percent, mostly reflecting better external conditions (trading partners' growth and worldwide attention to Uganda, measured by Google Trends indicators). In the case of Sierra Leone, growth nowcast for 2022Q3 also picks up from 2.8 percent to 4.2 percent, seemingly due to an easing on supply-side constraints, indicated by an increase in seaborne import estimates as well as price developments (both CPI and exchange rate), although domestic financial conditions show some downside effects (private credit, broad money, deposits). These narratives supported by underlying evidence can facilitate policy discussions and may help refine a baseline growth estimate for country work (e.g., recalibrating the macro framework).

An important reminder, though, is that the SHAP contributions should not be described as causal effects from these factors to overall growth, because there is also reverse causality from overall growth to individual factors. This is a classical warning but is important to be kept in mind. For example, on the one hand, private credit growth could lead to real growth by supporting aggregate demand, but on the other hand, real growth could increase national income, leading to an increase in credit supply. The two narratives are different. Also, a desired policy response depends on which one of the two causalities is dominating.

Figure 5. Decomposition of growth nowcasts for Uganda and Sierra Leone, 2022Q3

Panel A: Uganda **Panel B: Sierra Leone**



Sources. Authors estimations (see Annex Table 2 for data sources).
Notes. Each bar shows the change in the contribution of each factor to the quarterly growth nowcast from 2022Q2 to 2022Q3. Labels “y(t-1)” and “E[y(t-1)|X(t-1)]” represent the actual real GDP growth in the previous period (2022Q2) and its corresponding nowcast conditional on the information available up to then. Similarly, “E[y(t)|X(t)]” represents the growth nowcast for 2022Q3. The top 10 factors in the absolute value of their contributions are shown, while the contributions of the rest of factors are consolidated in the bar labeled “Others”. The contributions of factors are estimated by python package shap (Lundberg and Lee 2017, Lundberg and others 2020).

The weak fit for Sierra Leone largely reflects country idiosyncrasies. The large out-of-sample RMSE for Sierra Leone reflects large deviations from actual annual growth when it was so strong in years 2012 and 2013 (14 percent and 19 percent, respectively) and when it was largely negative in 2015 (-23 percent). The strong growth reflected the start of new iron ore production (IMF 2014) and the sharp contraction reflected twin shocks from the 2014 Ebola outbreak and a collapse in iron ore prices since mid-2014 (IMF 2016). The baseline nowcast indicates 3-4 percent of growth in these years, failing to capture the country-specific developments in these years. Although international commodity prices and country-specific commodity terms of trade (Gruss and Kebhaj 2019) are included in the nowcast model, development of mining production capacity does not exactly follow the commodity prices, or likely follow with a time lag. The same also applies for a halt of mining production. On the Ebola outbreak, SHAP values indicate that some impacts may have been captured by Google Trends data (e.g., search category of health; Narita and Yin 2018), as in the case of Liberia, although it is not clear in the case of Guinea. It is worth noting that the large deviations between nowcasts and observed growth due to country specific circumstances are the natural outcome of the panel nowcasting strategy followed in this study. However, this property of the panel approach introduces an operational advantage where the country teams might establish whether the economy is in a relatively normal situation, for which panel nowcasting could be usefully applied, or if there are exceptional circumstances that warrant an application of judgement.

5. Conclusion

This paper proposes a panel framework to produce nowcasts of quarterly GDPs particularly for countries that do not publish quarterly GDP statistics. A common estimation structure imposed to different countries in a panel data setup enables to produce an estimate for any country, based on an estimated statistical relationship using observed quarterly GDP growth in other countries. The main strategy is to use panel nowcasts to learn from data from other countries to provide insights into economic activity in countries where the quarterly GDP data is not available. Nowcasts can helpfully allow us to draw a summary implication from various underlying high-frequency indicators that may show different patterns that prevent a conclusive assessment. In addition, decomposing nowcasts into the contributions from underlying indicators provides insights that help form a narrative backed by evidence.

A limitation of this panel nowcasting framework is the presence of large country idiosyncrasies which could result in relatively weak nowcast performance. For example, the panel framework could miss important country-specific factors (as in the case of Sierra Leone). However, the framework has a scope to improve in several directions. One direction is choosing a pool of countries in the panel optimally depending on out-of-sample fits (Bolhuis and Rayner 2020). Another direction is having a more structured pre-estimation data preparation. If there are substantial country-specific developments, an indicator for such developments could be combined with the panel nowcast produced by this framework in a parsimonious way (e.g., by running an additional regression of observed GDP growth on country-specific indicators and panel nowcasts). Finally, annual growth estimates could be directly produced in a mixed-frequency setup (by mixing annual and quarterly frequencies). For example, Eichenauer and others (2022) propose a procedure to address inconsistency across different frequencies and substantial sampling noise in raw data extracted from Google Trends. Exploring the potential of these options is left for future research.

Annex I. Details of data collection and estimation

I.A. Data collection

The most challenging part of this panel nowcast framework is data collection. Compiling a panel dataset for many countries at the quarterly frequency is already challenging, but in addition, our objective is to include those where data availability is limited. In this regard, the use of unconventional data sources is very helpful to cover many countries including those with a data gap, most likely at the expense of increased measurement error. See Annex Table 1 for the list of all 200 economies in the sample, covering all IMF members. See also Annex Table 2 for a full list of collected indicators and statistics.

Data collection from conventional data sources substantially benefits from a new tool named IMF Datatools (IMF internal only).[9] This tool enables us to build a code to automatically download data from the International Financial Statistics (IMF 2022b), the World Economic Outlook (IMF 2022c), Haver Analytics (Haver 2022), the data.IMF.org website, and so on. A key set of conventional data for panel nowcasts are global variables (e.g., commodity prices) because they are available to all economies and are especially influential to many countries of our focus. Other country-specific variables include commodity terms of trade (Gruss and Kebhaj 2019); CPI and its 12 components; nominal and real exchange rates; monetary aggregates; and data on balance of payments. Gathering fiscal data across countries is challenging and left for future work.

Unconventional data sources are very important to capture country-specific economic developments in this panel setup. Many of helpful conventional data are not available for countries of our focus. If we build a nowcast model mostly relying on global variables, then such a model produces nowcasts mostly similar to all countries, just reflecting global economic situations, without accounting for country-specific conditions. Unconventional data help provide country-specific information, even for countries with constrained statistical capacity. For example, indicators from Google Trends can be compiled to capture people's attention to a country from all over the world (Narita and Yin 2018). Remote sensing data such as nighttime lights can also provide insights to local conditions (Debbich 2019; Hu and Yao 2022; Beyer, Hu, and Yao 2022). Maritime data can also provide nowcasts on seaborne trade (Cerdeiro and others 2020), which is related to economic activity more generally. Passenger capacity index compiled by IMF's STA using data from FlightRadar24 (O'Hanlon and Sozzi, forthcoming) helps capture COVID-19 related travel restrictions. World Uncertainty Index (Ahir, Bloom, and Furceri 2022) leverages a text-mining approach to provide a dataset with wide coverage at the quarterly frequency regarding economic and political uncertainty.

All variables are transformed into quarterly growth from a year ago, with some exceptions. Most of data, especially those from unconventional sources, are not seasonally adjusted, although they may exhibit strong seasonality, in general (e.g., internet searches about tourism destinations). Seasonality is mitigated by taking growth from a year ago. For some variables that include many missing observations or zero values that complicate the growth rate calculation (e.g., passenger capacity index, world uncertainty index), we include both its level and its four-quarter lag level, in place of the growth rate from a year ago. For the passenger capacity index, it is available only since 2019, but given its importance in capturing COVID-19 related travel restrictions, we included it with zero padding for the period before 2019.

[9] We are very grateful to the kind and strong support from Kei Moriya, Li Tang, and other colleagues on the IMF Datatool team.

The sample period is set from 2008Q1 to the latest available (e.g., 2022Q3 at the time of writing), because Google Trends data are not so stable in initial periods but still the sample could cover the global financial crisis. Google Trends data are key in this framework, covering all 200 economies in the sample since 2004 up to the latest previous month (except for several search categories), but the data are noisy in the initial years. The data are getting more stable over time after 2010. At the same time, to capture potentially large fluctuations in economic growth, including the observations during the global financial crisis could be helpful. On balance, we set the start quarter of this dataset to 2008Q1, with 2009Q1 being the first period for nowcasts of quarterly growth since a year ago to be available.

I.B. Estimation

Two estimation methods are used: LGB and OLS. For LGB, we use a decision-tree based model named the Light GBM (Ke and others 2017, Python package lightgbm) with default hyperparameters. We use the Python package scikit-learn (Pedregosa and others 2011) for the OLS and other estimation functionalities. We use Stata 17 in managing datasets and run the Python packages on Stata 17.

I.C. How to construct annual nowcasts from quarterly nowcasts

Annual nowcasts are derived from quarterly nowcasts as follows. Definitional equations are as below:

$$y_{\tau,q} \overset{\text{def}}{=} \ln\left(Y_{\tau,q}\right) - \ln\left(Y_{\tau-1,q}\right), \qquad Y_\tau \overset{\text{def}}{=} \sum_{q=1}^{4} Y_{\tau,q} = \sum_{q=1}^{4} \exp\left(\ln\left(Y_{\tau,q}\right)\right), \qquad y_\tau \overset{\text{def}}{=} \ln(Y_\tau) - \ln(Y_{\tau-1}),$$

where $\ln\left(Y_{\tau,q}\right)$ can be cumulatively calculated, applying the first equation above repeatedly as follows:

$$\ln\left(Y_{\tau,q}\right) = \ln\left(Y_{\tau-1,q}\right) + y_{\tau,q} = \ln\left(Y_{\tau-2,q}\right) + y_{\tau-1,q} + y_{\tau,q} = \cdots = \ln\left(Y_{2008,q}\right) + \sum_{u=2008}^{\tau} y_{u,q}.$$

Considering limited data availability, we parsimoniously assume that $Y_{2008,q} = 1$ for all $q = 1,2,3,4$ (i.e., $\ln\left(Y_{2008,q}\right) = 0$), which implies that any quarterly seasonality on the level of real GDP is not reflected.[10] Still, the annual nowcasts derived in this way reflect cumulative effects of fluctuations in quarterly growth over time. This is particularly important to account for a sharp reduction in real GDP followed by a sharp recovery, such as in the case of the pandemic impact in 2020Q2 and its recovery in 2021Q2. For comparison, we also calculate the simple average of quarterly nowcasts for each year, which does not reflect cumulative effects of fluctuations over time.

For the current year, annual nowcast is the average of quarterly nowcasts available to date, reflecting cumulative effects. For example, when nowcasts are available only for the first three quarters, then annual nowcast $\tilde{y}_\tau$ is produced as:

[10] While this assumption ignores the sensitivity of initial settings for countries with strong quarterly seasonality, it also allows to calculate quarterly annualized growth rates without quarterly GDP using a consistent definition that can be beneficial for cross comparison in future work.

$$\tilde{y}_\tau \stackrel{\text{def}}{=} \ln(\tilde{Y}_\tau) - \ln(\tilde{Y}_{\tau-1}), \qquad \tilde{Y}_\tau \stackrel{\text{def}}{=} \sum_{q=1}^{3} Y_{\tau,q} = \sum_{q=1}^{3} \exp(\ln(Y_{\tau,q})).$$

This annual nowcast may overemphasize growth in the first three quarters, especially when there was a strong recovery (e.g., as in 2021Q2). For comparison, we also calculate a conservative annual nowcast $\tilde{y}_\tau^c$ for which we assume zero growth in the rest of the year:

$$\tilde{y}_\tau^c \stackrel{\text{def}}{=} \ln(\tilde{Y}_\tau^c) - \ln(\tilde{Y}_{\tau-1}^c), \qquad \tilde{Y}_\tau^c \stackrel{\text{def}}{=} \sum_{q=1}^{3} Y_{\tau,q} + Y_{\tau,3} = \sum_{q=1}^{3} \exp(\ln(Y_{\tau,q})) + \exp(\ln(Y_{\tau,3})).$$

More comprehensive alternatives are (1) directly estimating annual nowcasts in a mixed frequency model; (2) supplementing quarterly nowcasts with quarterly forecasts for the rest of the year; and (3) annualizing input variables to estimate a model at the annual frequency.

I.D. Handling missing observations—alternatives and discussions

To mitigate the issue of missing values in input variables, a simple ensemble of predicted values is considered. For each specification m (based on which input variables are used), let $\hat{y}_{mit}$ denote the predicted value for economy i in period t. Then, the average ensemble, denoted by $\hat{y}_{it}^{\text{avg}}$, takes average of all predicted values $\hat{y}_{mit}$ for all specifications available for economy i in period t, denoted by M_{it}, the number of whose elements is denoted by n_{it}, as follows:

$$\hat{y}_{it}^{\text{avg}} \stackrel{\text{def}}{=} \frac{1}{n_{it}} \sum_{m \in M_{it}} \hat{y}_{mit}.$$

For comparison purposes, “minimum” specification $\hat{y}_{it}^{\min}$ and “maximum” specification $\hat{y}_{it}^{\max}$ are also computed. The minimum specification $\hat{y}_{it}^{\min}$ uses specification $m = 0$, which we define as the model that is available for every economy i in every period t. The maximum specification $\hat{y}_{it}^{\max}$ uses specification $\bar{m}_{it}$, which includes the maximum number of input variables among all specifications available for economy i in period t. When there is more than one specification that uses the same maximum number of input variables, we choose one in an ad hoc deterministic way. In equation, we have:

$$\hat{y}_{it}^{\min} \stackrel{\text{def}}{=} \hat{y}_{0,i,t}, \qquad \hat{y}_{it}^{\max} \stackrel{\text{def}}{=} \hat{y}_{\bar{m}_{it},i,t}.$$

We also considered two alternative approaches to handling missing observations as follows.

The first is to use the standard functionality of gradient boosting tree models to allow for missing observations. In each node, missing observations are classified to one or the other leaf to maximize the gain to the objective function. This would work best in the case where missing observations occur not purely randomly and the fact that the variable is missing implies either its value is too large or too small. This may be the case of labor earnings (where unemployed people’s earnings are missing) or logged bilateral trade flows (where zero trade flows become missing if the logarithm is taken). This strategy has a huge benefit in computation time by estimating only one, most general specification, compared to our baseline approach where we must estimate so many different specifications as 78 in the current setup. But this strategy may not work well if missingness occurs at random or for different reasons depending on countries and periods (e.g., too early to observe, missing seaborne trade flows for in-land countries). Our trials so far in this alternative approach indeed indicates weak out-of-sample performance.

The second alternative approach is to impute all input variables. This is too time-consuming because the number of estimations to conduct increases, at least, by the number of input variables. When we tried this approach, we used a python package named missingpy, which sequentially imputes all variables repeatedly until some convergence is achieved, making the computation time even longer than a factor of the number of input variables. In theory, this approach can be seen as an expectation-maximization (EM) approach. Our trials so far in this alternative approach indicates weak out-of-sample performance, potentially due to misspecification error because the relationship between observed variables may be largely different from the relationship between observed and imputed variables.

Imputing missing values also needs caution because of a bias-variance trade-off. An increase in the number of observations will help reduce the variance of the estimates but will also add attenuation bias from measurement error. Although we did not fully examine this trade-off, our trials indicate that the cost of adding noise in estimation may outweigh the benefit of reducing the variance of the estimates. Considering this trade-off, we remove observations that are only partially observed at monthly frequency. For example, if nighttime lights are observed only for April and May, but not for June, then we treat the corresponding 2nd quarter data point as missing.

I.E. Estimated contributions of input variables

We use a python package named shap, which estimates locally additive contributions of input variables to the nowcast. Lundberg and Lee (2017) propose a unified approach, named “SHAP” (SHapley Additive exPlanations) to interpret predictions produced by machine learning methods, conceptually based on the Shapley value (Shapley 1953). Within this approach, Lundberg and others (2020) discusses the one specific to tree models (“TreeExplainer”).

For each specification m (based on which input variables are used) for economy i in period t, the SHAP values $\{s_{mkit}\}$ are calculated for each input x_k among the set K_m of input variables included in specification m, such that SHAP values $\{s_{mkit}\}$ add up to predicted value $\hat{y}_{mit}$ as follows:

$$\hat{y}_{mit} = \sum_{k \in K_m} s_{mkit}.$$

To draw insights over time, we also calculate the differences in SHAP values, but we need a different formula for each of the three ensemble predicted values because of potential changes in specifications over time. For the minimum specification, it is simply calculated as a difference over time as follows:

$$\hat{y}_{it}^{\min} - \hat{y}_{i,t-1}^{\min} = \hat{y}_{0,i,t} - \hat{y}_{0,i,t-1} = \sum_{k \in K_0} s_{0,k,i,t} - \sum_{k \in K_0} s_{0,k,i,t-1} = \sum_{k \in K_0} \left(s_{0,k,i,t} - s_{0,k,i,t-1}\right).$$

For the maximum specification, however, the formula needs to reflect the change in specifications over time from $\overline{m}_{i,t-1}$ to $\overline{m}_{it}$ as follows:

$$\hat{y}_{it}^{\max} - \hat{y}_{i,t-1}^{\max} = \hat{y}_{\overline{m}_{it},i,t} - \hat{y}_{\overline{m}_{i,t-1},i,t-1} = \sum_{k \in K_{\overline{m}_{it}}} s_{\overline{m}_{it},k,i,t} - \sum_{k' \in K_{\overline{m}_{i,t-1}}} s_{\overline{m}_{i,t-1},k',i,t-1}$$

$$= \sum_{k_1 \in \tilde{K}_1} \left(s_{\bar{m}_{it},k_1,i,t} - s_{\bar{m}_{i,t-1},k_1,i,t} \right) + \sum_{k_2 \in \tilde{K}_2} s_{\bar{m}_{it},k_2,i,t} - \sum_{k_3 \in \tilde{K}_3} s_{\bar{m}_{it},k_3,i,t-1},$$

where, with a simplified notation, input variable index sets are defined as follows:

$$\tilde{K}_1 \stackrel{\text{def}}{=} \left(K_{\bar{m}_{it}} \cap K_{\bar{m}_{i,t-1}} \right), \qquad \tilde{K}_2 \stackrel{\text{def}}{=} K_{\bar{m}_{it}} \setminus \tilde{K}_1, \qquad \tilde{K}_3 \stackrel{\text{def}}{=} K_{\bar{m}_{i,t-1}} \setminus \tilde{K}_1.$$

For interpretability, we combine the last two summations into one term denoted by $\tilde{S}_{it}^{\max}$, which represents the residual contribution of the change in specifications over time from $\bar{m}_{i,t-1}$ to $\bar{m}_{it}$. Therefore, we have:

$$\tilde{S}_{it}^{\max} \stackrel{\text{def}}{=} \sum_{k_2 \in \tilde{K}_2} s_{\bar{m}_{it},k_2,i,t} - \sum_{k_3 \in \tilde{K}_3} s_{\bar{m}_{it},k_3,i,t-1} \;\; \Rightarrow \;\; \hat{y}_{it}^{\max} - \hat{y}_{i,t-1}^{\max} = \sum_{k_1 \in \tilde{K}_1} \left(s_{\bar{m}_{it},k_1,i,t} - s_{\bar{m}_{i,t-1},k_1,i,t} \right) + \tilde{S}_{it}^{\max}.$$

For the average specification, the formula additionally needs to reflect the change in the numbers of input variables from $n_{i,t-1}$ to n_{it}, used as the denominators when taking the averages. First, we let $s_{k'it}^{\text{avg}}$ denote the adjusted SHAP value for the average specification, defined in the following way:

$$\hat{y}_{it}^{\text{avg}} = \frac{1}{n_{it}} \sum_{m \in M_{it}} \hat{y}_{mit} = \frac{1}{n_{it}} \sum_{m \in M_{it}} \left\{ \sum_{k \in K_m} s_{mkit} \right\} = \frac{1}{n_{it}} \sum_{m \in M_{it}} \left\{ \sum_{k' \in \tilde{K}_{it}} s_{mk'it} \right\} = \sum_{k' \in \tilde{K}_{it}} \left\{ \frac{\sum_{m \in M_{it}} s_{mk'it}}{n_{it}} \right\} \stackrel{\text{def}}{=} \sum_{k' \in \tilde{K}_{it}} s_{k'it}^{\text{avg}},$$

where we set $s_{mk'it} = 0$ for $k' \notin K_m$ to ensure that the third equality holds and let $\tilde{K}_{it}$ denote the index set of input variables included in any of $m \in M_{it}$, that is, we have:

$$\tilde{K}_{it} \stackrel{\text{def}}{=} \bigcup_{m \in M_{it}} K_m.$$

With this notation, we can follow the formulation that we use for the maximum specification to obtain:

$$\hat{y}_{it}^{\text{avg}} - \hat{y}_{i,t-1}^{\text{avg}} = \sum_{k \in \tilde{K}_{it}} s_{kit}^{\text{avg}} - \sum_{k' \in \tilde{K}_{i,t-1}} s_{k',i,t-1}^{\text{avg}} = \sum_{k_4 \in \tilde{K}_4} \left(s_{k_4,i,t}^{\text{avg}} - s_{k_4,i,t-1}^{\text{avg}} \right) + \sum_{k_5 \in \tilde{K}_5} s_{k_5,i,t}^{\text{avg}} - \sum_{k_6 \in \tilde{K}_6} s_{k_6,i,t-1}^{\text{avg}},$$

where, again with a simplified notation, input variable index sets are defined as follows:

$$\tilde{K}_4 \stackrel{\text{def}}{=} \left(\tilde{K}_{it} \cap \tilde{K}_{i,t-1} \right), \qquad \tilde{K}_5 \stackrel{\text{def}}{=} \tilde{K}_{it} \setminus \tilde{K}_4, \qquad \tilde{K}_6 \stackrel{\text{def}}{=} \tilde{K}_{i,t-1} \setminus \tilde{K}_4,$$

Together with the residual contribution $\tilde{S}_{it}^{\text{avg}}$ of the change in specifications over time, we have:

$$\tilde{S}_{it}^{\text{avg}} \stackrel{\text{def}}{=} \sum_{k_5 \in \tilde{K}_5} s_{k_5,i,t}^{\text{avg}} - \sum_{k_6 \in \tilde{K}_6} s_{k_6,i,t-1}^{\text{avg}} \;\; \Rightarrow \;\; \hat{y}_{it}^{\text{avg}} - \hat{y}_{i,t-1}^{\text{avg}} = \sum_{k_4 \in \tilde{K}_4} \left(s_{k_4,i,t}^{\text{avg}} - s_{k_4,i,t-1}^{\text{avg}} \right) + \tilde{S}_{it}^{\text{avg}}.$$

In implementation, $\tilde{S}_{it}^{\max}$ and $\tilde{S}_{it}^{\text{avg}}$ are computed as residuals as follows:

$$\tilde{S}_{it}^{\max} = \hat{y}_{it}^{\max} - \hat{y}_{i,t-1}^{\max} - \sum_{k_1 \in \tilde{K}_1} \left(s_{\bar{m}_{it},k_1,i,t} - s_{\bar{m}_{i,t-1},k_1,i,t} \right), \qquad \tilde{S}_{it}^{\text{avg}} = \hat{y}_{it}^{\text{avg}} - \hat{y}_{i,t-1}^{\text{avg}} - \sum_{k_4 \in \tilde{K}_4} \left(s_{k_4,i,t}^{\text{avg}} - s_{k_4,i,t-1}^{\text{avg}} \right).$$

Annex Table 1. Country coverage

Panel A. List of 200 economies in the sample by availability of quarterly real GDP growth data

Quarterly growth data are included in the sample (127)	Quarterly growth data are not included in the sample (73)
Low-income developing countries (LIDCs; 59)	
Benin, Burkina Faso, Cameroon, Côte d'Ivoire, Ghana, Guinea-Bissau, Honduras, Kenya, Kyrgyz Republic, Lesotho, Mali, Moldova, Mozambique, Nicaragua, Niger, Nigeria, Rwanda, Senegal, Tanzania, Togo, Uganda, Vietnam, Zambia (23)	Afghanistan, Bangladesh, Bhutan, Burundi, Cambodia, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of the Congo, Djibouti, Eritrea, Ethiopia, The Gambia, Guinea, Haiti, Kiribati, Lao P.D.R., Liberia, Madagascar, Malawi, Mauritania, Myanmar, Nepal, Papua New Guinea, São Tomé and Príncipe, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Tajikistan, Timor-Leste, Uzbekistan, Yemen, Zimbabwe (36)
Emerging market and middle-income economies (97)	
Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bahrain, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Cabo Verde, Chile, China, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Guatemala, Hungary, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kosovo, Kuwait, Lebanon, Malaysia, Maldives, Mauritius, Mexico, Mongolia, Montenegro, Morocco, Namibia, North Macedonia, Panama, Paraguay, Peru, Philippines, Poland, Qatar, Romania, Russia, Samoa, Saudi Arabia, Serbia, Seychelles, South Africa, Sri Lanka, Thailand, Trinidad and Tobago, Tunisia, Türkiye, Ukraine, United Arab Emirates, Uruguay, West Bank and Gaza (67)	Antigua and Barbuda, Aruba, The Bahamas, Barbados, Bolivia, Dominica, Equatorial Guinea, Eswatini, Fiji, Gabon, Grenada, Guyana, Iraq, Libya, Marshall Islands, Micronesia, Nauru, Oman, Pakistan, Palau, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Syria, Tonga, Turkmenistan, Tuvalu, Vanuatu, Venezuela (30)
Advanced economies (40)	
Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong S.A.R. of China, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Macao S.A.R. of China, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China, United Kingdom, United States (37)	Andorra, Puerto Rico, San Marino (3)
Other economies (4)	
N/A (0)	Anguilla, Curaçao, Montserrat, Sint Maarten (4)

Panel B. List of economies in the selected subsamples by availability of quarterly real GDP growth data

Sub-Saharan African countries (45)	
Quarterly growth data are included in the sample (25)	**Quarterly growth data are not included in the sample (20)**
Angola, Benin, Botswana, Burkina Faso, Cabo Verde, Cameroon, Côte d'Ivoire, Ghana, Guinea-Bissau, Kenya, Lesotho, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, South Africa, Tanzania, Togo, Uganda, Zambia (25)	Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of the Congo, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, The Gambia, Guinea, Liberia, Madagascar, Malawi, Mauritania, São Tomé and Príncipe, Sierra Leone, South Sudan, Zimbabwe (20)
Tourism-oriented economies (29)	
Quarterly growth data are included in the sample (14)	**Quarterly growth data are not included in the sample (15)**
Belize, Cabo Verde, Dominican Republic, Greece, Honduras, Jamaica, Maldives, Mauritius, Panama, Portugal, Samoa, Seychelles, Singapore, Spain (14)	Antigua and Barbuda, Aruba, The Bahamas, Barbados, Comoros, Dominica, Fiji, The Gambia, Grenada, Palau, Puerto Rico, São Tomé and Príncipe, Solomon Islands, St. Lucia, Vanuatu (15)

Sources: World Economic Outlook (IMF, 2022c) and authors. Note: The terms "country" and "economy" are used interchangeably, which do not in all cases refer to a territorial entity that is a state as understood by international law and practice.

Annex Table 2. Full variable list with data sources

Variable	Series code	Database
Agriculture Material Prices, Index (GAS)	PAGRIW	WEO (GAS)
Broad Money, Domestic Currency	FMB_XDC	IFS
Consumer Prices	PCPI_IX	IFS
Consumer Prices, Alcoholic Beverages, Tobacco, and Narcotics	PCPIFBT_IX	IFS
Consumer Prices, Clothing and Footwear	PCPIA_IX	IFS
Consumer Prices, Communication	PCPIEC_IX	IFS
Consumer Prices, Education	PCPIED_IX	IFS
Consumer Prices, Food and Non-alcoholic Beverages	PCPIF_IX	IFS
Consumer Prices, Furnishings, Household Equipment and Routine Household Maintenance	PCPIHO_IX	IFS
Consumer Prices, Health	PCPIM_IX	IFS
Consumer Prices, Housing, Water, Electricity, Gas and Other Fuels	PCPIH_IX	IFS
Consumer Prices, Recreation and Culture	PCPIR_IX	IFS
Consumer Prices, Restaurants and Hotels	PCPIRE_IX	IFS
Consumer Prices, Transport	PCPIT_IX	IFS
Climate Data: Precipitation	PRE	Authors
Climate Data: Temperature	TEMP	Authors
CPI-Based Real Effect Exchange Rate	EREER_IX	IFS
Domestic Google Trends: All	DSVI_ALL	Narita and Yin (2018) and Google Trends
Domestic Google Trends: Arts and Entertainment	DSVI_ENT	
Domestic Google Trends: Autos and Vehicles	DSVI_VEH	
Domestic Google Trends: Beauty and Fitness	DSVI_FIT	
Domestic Google Trends: Books and Literature	DSVI_LIT	
Domestic Google Trends: Business	DSVI_BUS	
Domestic Google Trends: Computers and Electronics	DSVI_CMP	
Domestic Google Trends: Finance	DSVI_FIN	
Domestic Google Trends: Food and Drink	DSVI_FOD	
Domestic Google Trends: Games	DSVI_GAM	
Domestic Google Trends: Health	DSVI_HTH	
Domestic Google Trends: Hobbies and Leisure	DSVI_LEI	
Domestic Google Trends: Home and Garden	DSVI_HOM	
Domestic Google Trends: Internet and Telecom	DSVI_TEL	
Domestic Google Trends: Jobs	DSVI_JOB	
Domestic Google Trends: Jobs and Education	DSVI_JED	
Domestic Google Trends: Law and Government	DSVI_LAW	
Domestic Google Trends: Military	DSVI_ARM	
Domestic Google Trends: News	DSVI_NEW	
Domestic Google Trends: Online Communities	DSVI_OCM	
Domestic Google Trends: Pets and Animals	DSVI_PET	
Domestic Google Trends: Real Estate	DSVI_RES	
Domestic Google Trends: Reference	DSVI_REF	
Domestic Google Trends: Science	DSVI_SCI	
Domestic Google Trends: Shopping	DSVI_SHP	
Domestic Google Trends: Sports	DSVI_SPT	
Domestic Google Trends: Travel	DSVI_TVL	
Domestic Google Trends: Weather	DSVI_WTH	
Export Commodity Prices	X_GDP	Gruss and Kebhaj (2019)
Export of Goods and Services, USD	BXGS_BP6_USD	IFS
Export of Goods, USD	BXG_BP6_USD	IFS
Export of Services, USD	BXS_BP6_USD	IFS

Export Prices (export-value weighted average of real GDP growth in export destination countries)	TM_D_WX001	WEO (GEE)
Food Prices, Index (GAS)	PFOODW	WEO (GAS)
Fuel Prices, Index (GAS)	PNRGW	WEO (GAS)
Import Commodity Prices	M_GDP	Gruss and Kebhaj (2019)
Import of Goods and Services, USD	BMGS_BP6_USD	IFS
Import of Goods, USD	BMGS_BP6_USD	IFS
Import of Services, USD	BMGS_BP6_USD	IFS
Import Prices (export-value weighted average of real GDP growth in export destination countries)	TX_D_WX001	WEO (GEE)
Metal Prices, Index (GAS)	PMETAW	WEO (GAS)
Nighttime lights	NL	Authors
NO2 Emissions	NO2_MEAN	Authors
Non-fuel Prices, Index (GAS)	PNFUELW	WEO (GAS)
Oil Prices, U.S. Dollar (GAS)	POILAPSP	WEO (GAS)
Other Depository Corporations Survey: All Deposits Included in Broad Money, Domestic Currency	FOS_XDC	IFS
Other Depository Corporations Survey: Claims on Private Sector, Domestic Currency	FOSAOP_XDC	IFS
Passenger Flight Capacity	PASSENGERCAPACITY	IMF STA Estimates
Primary Income: Credit, USD	BXIP_BP6_USD	IFS
Primary Income: Debit, USD	BMIP_BP6_USD	IFS
Real GDP, level	NGDP_R	WEO
Seaborne Export Volumes: Bulk	EXP_BULK	Cerdeiro and others (2020)
Seaborne Export Volumes: Container	EXP_CONTAINER	
Seaborne Export Volumes: Foodstuff	EXP_FOODSTUFF	
Seaborne Export Volumes: LPG/LNG	EXP_LPG_LNG	
Seaborne Export Volumes: Oil and Chemicals	EXP_ OIL_CHEMICALS	
Seaborne Export Volumes: Vehicles	EXP_VEHICLES	
Seaborne Export Volumes: Total	EXP_TOTAL	
Seaborne Import Volumes: Bulk	IMP_BULK	
Seaborne Import Volumes: Container	IMP_CONTAINER	
Seaborne Import Volumes: Foodstuff	IMP_ FOODSTUFF	
Seaborne Import Volumes: LPG/LNG	IMP_ LPG_LNG	
Seaborne Import Volumes: Oil and Chemicals	IMP_ OIL_CHEMICALS	
Seaborne Import Volumes: Vehicles	IMP_ VEHICLES	
Seaborne Import Volumes: Total	IMP_ TOTAL	
Secondary Income: Credit, USD	BXISXF_BP6_USD	IFS
Secondary Income: Debit, USD	BMIS_BP6_USD	IFS
Trading Partners' Real GDP Growth (export-value weighted average of real GDP growth in export destination countries)	NGDP_R_WX001	WEO (GEE)
Total Reserves minus Gold	RAXG_USD	IFS
ULC-Based Real Effect Exchange Rate	EREER_ULC_IX	IFS
U.S. Treasury Y2 Yield, p.a., NSA	FTA2YK	HAVER
USD Rate, Period Average	ENDA_XDC_USD_RATE	IFS
U.S. VIX, p.a., NSA	SPVIX	HAVER
World Uncertainty Index	WUI	Ahir, Bloom, and Furceri (2022)
Worldwide Google Trends: All	WSVI_ALL	Narita and Yin (2018) and Google Trends
Worldwide Google Trends: Arts and Entertainment	WSVI_ENT	
Worldwide Google Trends: Autos and Vehicles	WSVI_VEH	
Worldwide Google Trends: Beauty and Fitness	WSVI_FIT	
Worldwide Google Trends: Books and Literature	WSVI_LIT	

Worldwide Google Trends: Business	WSVI_BUS	
Worldwide Google Trends: Computers and Electronics	WSVI_CMP	
Worldwide Google Trends: Finance	WSVI_FIN	
Worldwide Google Trends: Food and Drink	WSVI_FOD	
Worldwide Google Trends: Games	WSVI_GAM	
Worldwide Google Trends: Health	WSVI_HTH	
Worldwide Google Trends: Hobbies and Leisure	WSVI_LEI	
Worldwide Google Trends: Home and Garden	WSVI_HOM	
Worldwide Google Trends: Internet and Telecom	WSVI_TEL	
Worldwide Google Trends: Jobs	WSVI_JOB	
Worldwide Google Trends: Jobs and Education	WSVI_JED	
Worldwide Google Trends: Law and Government	WSVI_LAW	
Worldwide Google Trends: Military	WSVI_ARM	
Worldwide Google Trends: News	WSVI_NEW	
Worldwide Google Trends: Online Communities	WSVI_OCM	
Worldwide Google Trends: Pets and Animals	WSVI_PET	
Worldwide Google Trends: Real Estate	WSVI_RES	
Worldwide Google Trends: Reference	WSVI_REF	
Worldwide Google Trends: Science	WSVI_SCI	
Worldwide Google Trends: Shopping	WSVI_SHP	
Worldwide Google Trends: Sports	WSVI_SPT	
Worldwide Google Trends: Travel	WSVI_TVL	
Worldwide Google Trends: Weather	WSVI_WTH	

Sources: Ahir, Bloom, and Furceri (2022); Cerdeiro and others (2020); Google Trends; Gruss and Kebhaj (2019); Haver Analytics (2022); International Financial Statistics (IFS, IMF, 2022b); Narita and Yin (2018); World Economic Outlook (WEO, IMF, 2022c); and authors.
Notes: The data on nighttime lights are sourced from Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) data produced by the Earth Observation Group, NOAA/NCEI.

Annex II. Additional results

Annex Table 3. Performance of panel nowcasts: LGB, EMDE subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-0.05	0.28	1.47	0.83	0.93	0.71	1.92	0.70	2.87	1.00
Botswana (15)	-0.05	-0.09	-1.06	0.83	0.71	0.50	1.92	3.04	9.12	0.59
Cabo Verde (15)	-0.05	-0.46	-1.63	0.83	0.71	0.71	1.92	3.23	9.14	0.51
Cameroon (15)	-0.05	0.40	1.16	0.83	0.69	0.69	1.92	1.05	2.99	0.83
Côte d'Ivoire (15)	-0.05	-0.35	-1.60	0.83	1.00	0.86	1.92	0.92	3.59	0.69
Ghana (15)	-0.05	-0.19	-1.19	0.83	0.86	0.43	1.92	0.63	2.93	0.69
Kenya (15)	-0.05	-0.32	-1.60	0.83	1.00	0.86	1.92	0.54	2.19	0.61
Lesotho (15)	-0.05	1.20	3.38	0.83	0.79	0.57	1.92	1.97	5.65	0.49
Mauritius (15)	-0.05	0.10	0.55	0.83	0.86	0.64	1.92	1.72	5.13	0.43
Namibia (15)	-0.05	0.42	2.81	0.83	0.93	0.64	1.92	0.87	4.20	0.88
Nigeria (15)	-0.05	-0.04	-0.42	0.83	0.87	0.73	1.92	0.49	2.21	0.80
Seychelles (15)	-0.05	-0.03	-0.20	0.83	1.00	0.86	1.92	3.13	9.38	0.73
South Africa (15)	-0.05	0.25	1.29	0.83	0.93	0.80	1.92	0.83	3.37	0.38
Tanzania (15)	-0.05	-1.16	-2.87	0.83	0.86	0.57	1.92	1.91	5.63	5.68
Uganda (15)	-0.05	-0.32	-0.79	0.83	0.93	0.86	1.92	1.06	1.98	0.41

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (1716)	-0.05	0.05	1.92	0.83	0.89	0.67	1.92	2.52	9.28	1.01
2020Q4-2022Q3 (1248)	-0.05	-0.06	-4.80	0.83	0.87	0.59	1.92	2.23	8.83	1.10
2021Q3-2022Q3 (780)	-0.05	-0.05	3.48	0.83	0.84	0.55	1.92	2.25	6.97	1.26

Sources: Authors estimations (see Annex Table 2 for data sources).
Notes: The estimation sample includes 4,475 observations for 90 EMDEs from 2009Q1 to 2022Q3 (see Annex I for details).
EMDE=Emerging market and developing economies; LGB=light gradient boosting regression.

Annex Table 4. Performance of panel nowcasts: LGB, commodity exporter subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	0.01	0.11	1.24	0.90	0.93	0.57	1.52	0.36	2.44	0.85
Botswana (15)	0.01	0.15	-0.38	0.90	0.79	0.64	1.52	4.50	9.24	0.60
Cabo Verde (0)	-	-	-	-	-	-	-	-	-	-
Cameroon (0)	-	-	-	-	-	-	-	-	-	-
Côte d'Ivoire (15)	0.01	-0.13	-1.19	0.90	1.00	0.57	1.52	0.46	2.84	0.55
Ghana (15)	0.01	-0.13	-1.43	0.90	0.86	0.50	1.52	0.74	3.25	0.77
Kenya (0)	-	-	-	-	-	-	-	-	-	-
Lesotho (0)	-	-	-	-	-	-	-	-	-	-
Mauritius (0)	-	-	-	-	-	-	-	-	-	-
Namibia (0)	-	-	-	-	-	-	-	-	-	-
Nigeria (15)	0.01	-0.11	-0.70	0.90	0.87	0.67	1.52	0.38	1.95	0.71
Seychelles (0)	-	-	-	-	-	-	-	-	-	-
South Africa (15)	0.01	0.15	1.00	0.90	1.00	0.80	1.52	1.26	3.64	0.41
Tanzania (0)	-	-	-	-	-	-	-	-	-	-
Uganda (0)	-	-	-	-	-	-	-	-	-	-

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (693)	0.01	0.01	2.08	0.90	0.93	0.57	1.52	1.80	7.32	1.04
2020Q4-2022Q3 (504)	0.01	-0.08	-4.06	0.90	0.94	0.66	1.52	1.44	6.96	1.17
2021Q3-2022Q3 (315)	0.01	0.03	-1.01	0.90	0.95	0.61	1.52	0.59	3.88	0.86

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 1,335 observations for 28 commodity exporting economies from 2009Q1 to 2022Q3 (see Annex I for details). LGB=light gradient boosting regression.

Annex Table 5. Performance of panel nowcasts: LGB, fuel exporter subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-0.01	0.09	1.15	0.93	0.93	0.71	0.64	0.45	2.12	0.74
Botswana (0)	-	-	-	-	-	-	-	-	-	-
Cabo Verde (0)	-	-	-	-	-	-	-	-	-	-
Cameroon (0)	-	-	-	-	-	-	-	-	-	-
Côte d'Ivoire (0)	-	-	-	-	-	-	-	-	-	-
Ghana (0)	-	-	-	-	-	-	-	-	-	-
Kenya (0)	-	-	-	-	-	-	-	-	-	-
Lesotho (0)	-	-	-	-	-	-	-	-	-	-
Mauritius (0)	-	-	-	-	-	-	-	-	-	-
Namibia (0)	-	-	-	-	-	-	-	-	-	-
Nigeria (15)	-0.01	-0.16	-1.18	0.93	0.93	0.80	0.64	0.44	2.12	0.77
Seychelles (0)	-	-	-	-	-	-	-	-	-	-
South Africa (0)	-	-	-	-	-	-	-	-	-	-
Tanzania (0)	-	-	-	-	-	-	-	-	-	-
Uganda (0)	-	-	-	-	-	-	-	-	-	-

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (286)	-0.01	0.02	2.39	0.93	0.96	0.54	0.64	0.83	5.99	1.41
2020Q4-2022Q3 (208)	-0.01	-0.04	-1.99	0.93	0.98	0.63	0.64	0.70	4.32	1.17
2021Q3-2022Q3 (130)	-0.01	-0.01	-1.62	0.93	0.98	0.61	0.64	0.58	4.15	1.49

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 673 observations for 14 fuel exporting economies from 2009Q1 to 2022Q3 (see Annex I for details). LGB=light gradient boosting regression.

Annex Table 6. Performance of panel nowcasts: LGB, tourism-oriented country subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-	-	-	-	-	-	-	-	-	-
Botswana (15)	-	-	-	-	-	-	-	-	-	-
Cabo Verde (15)	-0.01	0.57	-0.42	0.88	0.79	0.57	2.56	3.69	7.34	0.41
Cameroon (15)	-	-	-	-	-	-	-	-	-	-
Côte d'Ivoire (15)	-	-	-	-	-	-	-	-	-	-
Ghana (15)	-	-	-	-	-	-	-	-	-	-
Kenya (15)	-	-	-	-	-	-	-	-	-	-
Lesotho (15)	-	-	-	-	-	-	-	-	-	-
Mauritius (15)	-0.01	0.24	1.40	0.88	0.93	0.79	2.56	1.97	5.66	0.47
Namibia (15)	-	-	-	-	-	-	-	-	-	-
Nigeria (15)	-	-	-	-	-	-	-	-	-	-
Seychelles (15)	-0.01	0.12	0.47	0.88	0.93	0.71	2.56	3.33	9.50	0.73
South Africa (15)	-	-	-	-	-	-	-	-	-	-
Tanzania (15)	-	-	-	-	-	-	-	-	-	-
Uganda (15)	-	-	-	-	-	-	-	-	-	-

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (319)	-0.01	0.29	2.62	0.88	0.92	0.62	2.56	5.70	17.76	1.11
2020Q4-2022Q3 (232)	-0.01	-0.66	-8.86	0.88	0.90	0.55	2.56	4.38	15.11	1.09
2021Q3-2022Q3 (145)	-0.01	-0.37	-3.62	0.88	0.88	0.60	2.56	4.24	11.99	1.58

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 704 observations for 14 tourism-oriented economies from 2009Q1 to 2022Q3 (see Annex I for details). LGB=light gradient boosting regression.

Annex Table 7. Performance of panel nowcasts: OLS, global sample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-0.07	1.44	1.65	0.59	0.57	0.50	4.54	2.42	2.74	0.96
Botswana (15)	-0.07	-0.92	-0.97	0.59	0.64	0.57	4.54	7.53	8.70	0.56
Cabo Verde (15)	-0.07	-0.44	-0.21	0.59	0.50	0.50	4.54	8.30	9.47	0.53
Cameroon (15)	-0.07	1.59	1.75	0.59	0.62	0.62	4.54	2.86	3.03	0.84
Côte d'Ivoire (15)	-0.07	-0.52	-0.59	0.59	0.71	0.71	4.54	2.87	3.20	0.61
Ghana (15)	-0.07	-0.93	-1.07	0.59	0.57	0.57	4.54	3.28	3.57	0.84
Kenya (15)	-0.07	-1.07	-1.18	0.59	1.00	1.00	4.54	1.76	1.87	0.53
Lesotho (15)	-0.07	3.40	3.58	0.59	0.50	0.50	4.54	6.26	6.49	0.56
Mauritius (15)	-0.07	0.86	1.00	0.59	0.64	0.64	4.54	5.39	5.71	0.48
Namibia (15)	-0.07	2.28	2.70	0.59	0.71	0.64	4.54	3.92	4.47	0.94
Nigeria (15)	-0.07	-0.57	-0.92	0.59	0.73	0.73	4.54	2.41	2.84	1.03
Seychelles (15)	-0.07	0.85	0.85	0.59	0.71	0.71	4.54	5.71	6.04	0.47
South Africa (15)	-0.07	0.84	0.98	0.59	0.87	0.80	4.54	2.93	3.24	0.37
Tanzania (15)	-0.07	-2.01	-2.10	0.59	0.64	0.64	4.54	4.82	5.04	5.08
Uganda (15)	-0.07	-0.09	-0.09	0.59	0.71	0.71	4.54	2.36	2.42	0.50

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (495)	-0.07	0.04	4.55	0.59	0.79	0.59	4.54	7.07	11.47	1.25
2020Q4-2022Q3 (360)	-0.07	-0.23	-2.21	0.59	0.74	0.67	4.54	5.86	7.16	0.88
2021Q3-2022Q3 (225)	-0.07	0.33	7.14	0.59	0.68	0.57	4.54	5.21	9.16	1.62

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 1,134 observations for 25 SSA countries from 2009Q1 to 2022Q3 (see Annex I for details). OLS=ordinary least squares; SSA=sub-Saharan Africa.

Annex Table 8. Performance of panel nowcasts: OLS, SSA subsample, average

Panel A. Country-wise evaluation

Country 2019Q1-2022Q3 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
Angola (15)	-0.03	0.04	-0.10	0.62	0.64	0.57	3.76	1.66	2.51	0.87
Botswana (15)	-0.03	-1.55	-1.92	0.62	0.64	0.71	3.76	6.24	8.91	0.58
Cabo Verde (15)	-0.03	-0.35	0.01	0.62	0.57	0.57	3.76	6.10	9.52	0.53
Cameroon (15)	-0.03	0.98	1.32	0.62	0.69	0.69	3.76	2.11	2.69	0.75
Côte d'Ivoire (15)	-0.03	-0.59	-1.15	0.62	0.79	0.71	3.76	2.11	3.40	0.65
Ghana (15)	-0.03	0.06	0.78	0.62	0.57	0.57	3.76	2.33	3.34	0.79
Kenya (15)	-0.03	-1.12	-1.55	0.62	0.93	0.86	3.76	1.71	2.16	0.61
Lesotho (15)	-0.03	2.91	3.43	0.62	0.64	0.64	3.76	5.24	6.06	0.52
Mauritius (15)	-0.03	0.97	1.83	0.62	0.64	0.64	3.76	4.20	5.40	0.45
Namibia (15)	-0.03	-0.03	0.11	0.62	0.71	0.43	3.76	2.15	3.53	0.74
Nigeria (15)	-0.03	-0.26	-1.12	0.62	0.93	0.87	3.76	1.32	2.47	0.90
Seychelles (15)	-0.03	0.82	1.00	0.62	1.00	0.86	3.76	4.24	5.09	0.39
South Africa (15)	-0.03	0.17	0.98	0.62	0.87	0.80	3.76	2.47	4.82	0.55
Tanzania (15)	-0.03	-2.31	-2.63	0.62	0.71	0.64	3.76	4.10	4.72	4.76
Uganda (15)	-0.03	-0.30	-0.32	0.62	0.79	0.71	3.76	2.04	2.16	0.45

Panel B. Period-wise evaluation

Test sample period (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
2020Q1-2022Q3 (495)	-0.03	-0.00	6.62	0.62	0.75	0.51	3.76	3.48	17.52	2.08
2020Q4-2022Q3 (360)	-0.03	-0.01	-4.12	0.62	0.69	0.65	3.76	3.17	7.58	1.06
2021Q3-2022Q3 (225)	-0.03	0.39	3.03	0.62	0.61	0.57	3.76	2.32	4.28	0.87

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample includes 1,134 observations for 25 SSA countries from 2009Q1 to 2022Q3 (see Annex I for details). OLS=ordinary least squares; SSA=sub-Saharan Africa.

Annex Table 9. Performance of panel nowcasts for countries without quarterly growth data: OLS

Model 2010-2022 (sample size)	In-sample bias	In-sample bias on test sample	Out-of-sample bias	In-sample direction	In-sample direction on test sample	Out-of-sample direction	In-sample RMSE	In-sample RMSE on test sample	Out-of-sample RMSE	Theil U
OLS, Global, average (1,017)	-	-	1.27	-	-	0.62	-	-	6.90	0.69
OLS, EMDEs, average (926)	-	-	1.26	-	-	0.63	-	-	6.99	0.70
OLS, SSA, average (293)	-	-	1.62	-	-	0.64	-	-	6.09	0.75
OLS, Comm. exp., average (480)	-	-	2.10	-	-	0.62	-	-	8.55	0.70
OLS, Fuel exp., average (164)	-	-	2.81	-	-	0.65	-	-	12.08	0.69
OLS, Tourism, average (207)	-	-	1.01	-	-	0.66	-	-	4.75	0.56

Sources: Authors estimations (see Annex Table 2 for data sources).

Notes: The estimation sample period is from 2009Q1 to 2022Q3 (see Annex I for details). Comm. exp.=commodity exporting economies; Fuel exp.=fuel exporting economies; EMDEs=emerging market and developing economies; OLS=ordinary least squares; SSA=sub-Saharan Africa; Tourism=tourism-oriented economies.

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