Global Linkages and Global Nowcasting*

Preliminary and Incomplete; Please do not circulate.

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Abstract

Timely assessment of economic activity is crucial for effective policymaking at the national, regional, and global levels. However, many countries still do not publish GDP data on a quarterly basis, creating persistent information gaps. In 2025, 34% of countries publish only annual GDP statistics. This lack of data frequency is particularly limiting for emerging and developing economies, where economic volatility and spillover risks are often highest. The problem is more severe when historical data is considered, because only 42% of countries can provide historical quarterly estimates for a period longer than 20 years. To address these gaps, this paper develops a model that estimates missing quarterly GDP series by leveraging global and regional economic interconnections. The method transforms sparse annual data into quarterly estimates by exploiting higher-frequency information from the rest of the world, enabling real-time policymaking in both data-scarce economies and in global-level discussions. This method allows for internally consistent aggregates of regional and global economic activities that can support two-way scenario analyses.

JEL Classification: F62, C53, E32, E37, F02.
Keywords: Globalization, International Integration. Business Cycles, Factor Models, Nowcasting

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1 Introduction

Timely monitoring of economic activity is essential for policymakers, analysts, and private sector participants. Yet, many countries do not report GDP at a quarterly frequency, hindering both immediate decision-making and long-term analysis.

Data availability varies considerably across countries and over time. Figure 1 illustrates the percentage of quarters covered in historical datasets, with darker shades indicating more complete coverage. Advanced economies provide complete quarterly GDP data, but for many emerging markets and almost all low-income countries, such data are either partial or entirely unavailable.

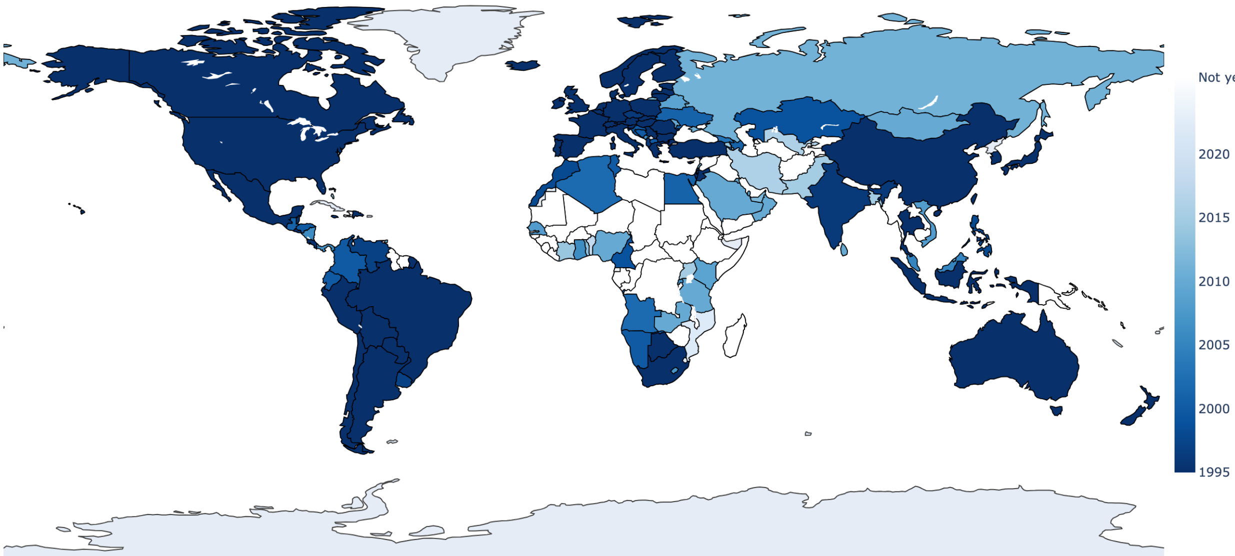


Figure 1: Availability of quarterly GDP data

Note: The heatmap shows the first availability of quarterly GDP data between 1995-2025. White regions indicate countries that do not have any quarterly data. Source: Haver Analytics.

As of 2025, 34% of countries continue to report GDP only on an annual basis (Figure 2). The coverage issue deepens when considering historical data, since only 42% of countries provide quarterly GDP series extending over more than two decades. This creates blind spots in understanding global economic dynamics, particularly in emerging markets and developing economies where growth volatility and spillover risks are highest. The consequences are twofold. First, real-time debates and policy actions—especially in fast-changing environments—become less effective, ignoring a huge share of countries. Second, sustainable growth research and macroeconomic modeling are limited by sparse long-run data. These issues affect not just analysts in data-scarce countries, but also limit the understanding of aggregate trends in the global economy. As a result, almost a quarter of the global population, representing roughly 10% of nominal global GDP over the past twenty years, is effectively in the dark for both real-time analysis and historical research.

To address these gaps, we build on the multicountry dynamic factor model (DFM) literature (Marcellino et al. 2003, Negro & Otrok 2008, Breitung & Eickmeier 2016, Cascaldi-

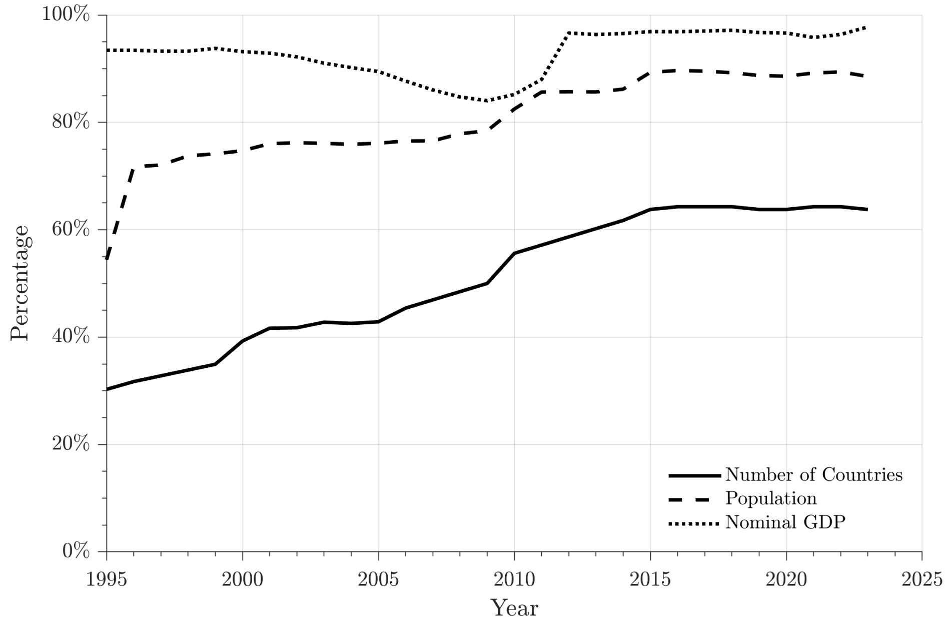


Figure 2: Global ratios of quarterly GDP data availability

Source: Haver Analytics.

Garcia, Ferreira, Giannone & Modugno 2024), adapting it to handle mixed-frequency and ragged-edge data on a global scale. In our context, we account for mixed frequencies with both annual and quarterly data, jagged edges arising from asynchronous data releases, and ensure that the model is scalable to large country panels. The model also allows country-specific idiosyncratic fluctuations with dedicated autoregressive structure to capture heterogeneity.

The modeling choices benefit from the increasing economic integration between countries with limited GDP data and those with high-frequency statistics. For example, in 2024, over 96% of exports from countries lacking quarterly GDP series are directed to trading partners with more frequent data releases. Import patterns indicate even deeper integration[1]. This interconnectedness reinforces the suitability of the multicountry DFM approach.

An alternative to the DFM framework is the multicountry vector autoregression (VAR); Pesaran et al. 2009, Del Negro et al. 2019). To handle large datasets and prevent overfitting, these models use homogeneity restrictions or shrinkage priors (Giannone & Reichlin 2009, Banbura et al. 2010, 2015), and typically recover similar common factors. Both VAR and DFM frameworks can be specified in state-space form, handling mixed frequencies and jagged edge characteristics through Kalman filtering (Cimadomo et al. 2022).

This paper contributes to the global, regional and country level economic activity estimation literature with a consistent setup. It provides both a real-time economic activity measure[2], and historical estimates for further analysis. The methodology proposes an intu-

[1]See Appendix 5 for detailed trade shares across country groups.

[2]Cascaldi-Garcia, Luciani & Modugno (2024) and Bańbura et al. (2013) summarize this literature, highlighting recent methodological progress and country coverage that mainly focuses on advanced economies and frontier emerging market countries. While countries covered by nowcasting studies published in refereed

itive design, which also allows consistent bidirectional scenario analysis from country-level data to higher aggregates such as regional or global scenarios, and vice versa.

The remainder of the paper is organized as follows: Section 2 outlines the model, data, and methodology, including our approach to frequency conversion. Section 3 presents estimation results and case studies. Section 4 benchmarks performance using out-of-sample projections. Concluding remarks are in Section 5

2 Model and Methodology

This section introduces the model structure for producing quarterly GDP estimates in a heterogeneous, data-sparse environment. The setup is motivated by the data limitations outlined in Section 1 and aims to address mixed-frequency, ragged-edge data and country heterogeneity.

We define two sets of countries according to data availability. Let Ω^Q be the set of N countries with quarterly GDP series and Ω^A be the set of M countries with annual GDP data, with $\Omega^Q \subset \Omega^A$. At each period t, denote the observed data by $Y_t = [Y_t^Q, Y_t^A]$, a vector of length $N + M$, where Y_t^Q are quarterly year-over-year growth rates, and Y_t^A are annual growth rates, reported only for the last quarter of each year in annual-data-only countries.

Building on a multi-country DFM that introduces a factor structure to measure global and regional cyclical components, we adopt an extended dynamic factor model following Stock & Watson (2010), and Giannone et al. (2008). Each country's GDP growth is expressed as a function of several latent factors reflecting global, regional, income, and sectoral influences:

- F_t^G: global economic factor
- F_t^R: vector of regional factors[3]
- F_t^I: income-group factors (advanced, emerging-market, low-income)
- F_t^{EA}: economic activity or sectoral factors[4]

Collect all factors in $F_t = [F_t^G, F_t^R, F_t^I, F_t^{EA}]'$.

The model is as follows:

$$\begin{aligned} Y_t &= CF_t + e_t \\ F_t &= AF_{t-1} + v_t \\ e_t &= \delta_1 e_{t-1} + \cdots + \delta_p e_{t-p} + \varepsilon_t \\ \varepsilon_t &\sim \mathcal{N}(0, R), \quad v_t \sim \mathcal{N}(0, Q) \end{aligned} \tag{1}$$

journals account for more than 3/4 of global GDP, they comprise mostly advanced economies and frontier emerging markets. Studies on nowcasting economic activity in low-income and developing economies are much less common due to data limitations and technical capacity constraints. See Akbal et al. (2023) for the low-income country aspect.

[3]The regions are Asia, CIS, Europe, Latin America and the Caribbean, Middle East and North Africa, Sub-Saharan Africa, and North America, and follow IMF/WB classifications. See Appendix A for the country region match table.

[4]The economic activity component covers tourism, fuel-exporter, manufacturing, primary non-fuel exporter, services, and other economic activities.

where C and A are parameter matrices, e_t captures country-specific idiosyncratic dynamics, and innovations v_t and ε_t are assumed independent and normally distributed. The structure allows modeling heterogeneity and persistence in both shared components and idiosyncratic terms.

2.1 Quarterly to annual frequency aggregation

To integrate countries with both quarterly and annual GDP data, the model relates annual and quarterly growth rates over a structural relationship. Let v_t^Q represent the quarterly and v_t^A the annual year-on-year (yoy) GDP growth rate at time t. For countries with only annual data, the model links the two frequencies by treating the annual growth rate as the average of the previous four quarterly rates:

$$v_t^A \approx \frac{1}{4}\left(v_t^Q + v_{t-1}^Q + v_{t-2}^Q + v_{t-3}^Q\right) \tag{2}$$

Under the assumption, for a country with only annual data, the model uses the annual observation as an average of the previous four latent v^Qs, restricting the sum of coefficients accordingly. This guarantees internal consistency in estimation and enables the extraction of quarterly series even in the absence of underlying quarterly observations.

Following this approximation, the measurement equation in (2) is modified with the appropriate restrictions[5].

3 Estimation Results and Discussion

This section evaluates the model's ability to capture the structure of economic comovement, reconstruct missing quarterly GDP series, and deliver informative decompositions across global, regional, sectoral, and country-specific factors. Results are presented both at the country and aggregate, i.e. regional and global, level.

Persistent factors indicate lasting impact of co-movement or shocks, while less persistent factors reflect more transient, local disturbances. Table 1 presents the estimates of persistence for the four factors. As expected, persistence is more evident in regional and economic activity factors. These factors correspond to higher-momentum cyclical activities that are difficult to change in the short run. In line with that, global comovement series has the least persistence across all.

Table 1. Persistence of the Factors

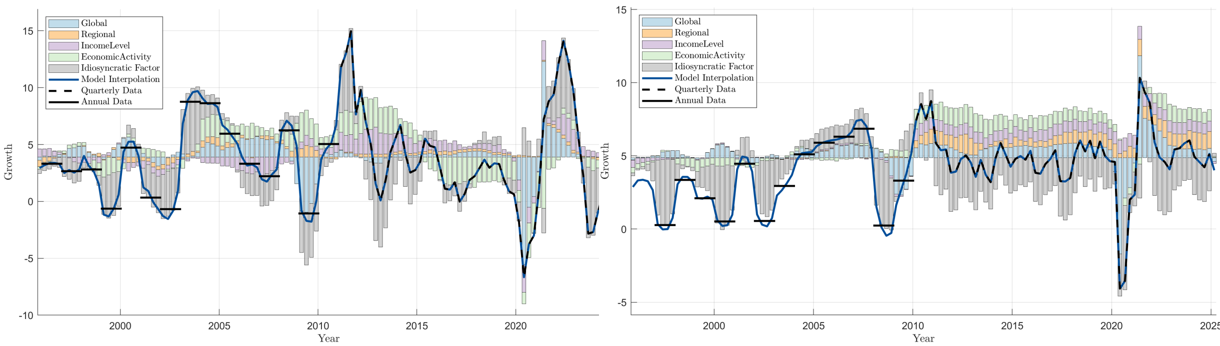
	Global	Regional	Income Level	Economic Activity
Persistence	0.58	0.82	0.81	0.89

Note: The persistence levels for the regional, income level, and economic activity factors are the simple average of the individual factors within group. See Appendix 5 for a more detailed table.

[5] See Appendix 5 for technical assumptions, relaxation of equal-weight averaging, and further details.

3.1 Country Level Estimation Results

To illustrate model features at the country level, we focus on Saudi Arabia and Kenya, which transitioned from annual-only to quarterly reporting in 2010. Figure 5 compares actual and model-based quarterly growth rates, decomposing the estimates into its factor contributions.



(a) Saudi Arabia (b) Kenya

Figure 3: Actual vs Estimated GDP with Factor Contributions

Note: The solid line is model-estimated; the dashed and horizontal lines are observed. Bar segments indicate the relative factor contributions at each period.

The model closely follows the actual quarterly data where available and reconstructs plausible quarterly patterns for periods when only annual data are available.. Both countries show a major influence of the global factor in episodes of recession and recovery, i.e., the Great Financial Crisis (GFC) and the COVID-19 pandemic. Specific economic activities, such as oil exports in this example, are particularly ant for Saudi Arabia. Idiosyncratic country components remain critical, illustrating persistent divergence among global and regional trends.

To test robustness, the estimation is repeated under the assumption that both countries continued to report annual data after 2010. The strong correlation across two series suggests strong robust behavior of the methodology[6].

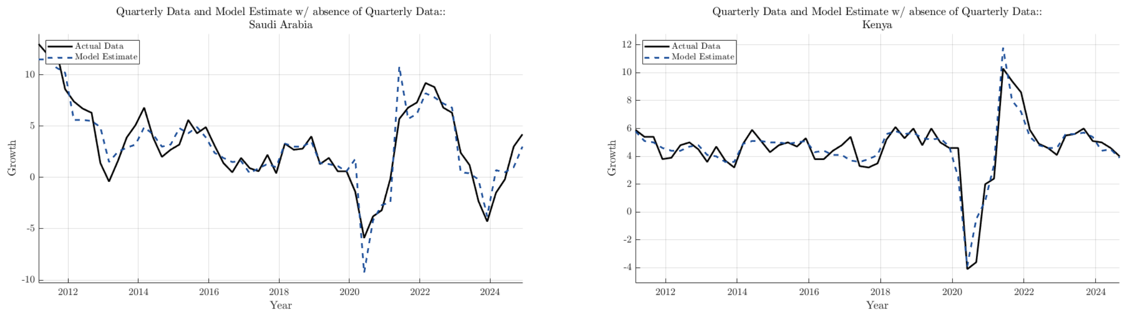
3.2 Aggregate Estimation Results

Aggregating estimated quarterly growth across countries yields global series:

$$y^{Q}_{Global,t} = \sum_{j} \omega_{j,t} y^{Q}_{j,t} \tag{3}$$

where $\omega_{j,t}$ are nominal GDP share weights. This approach facilitates the decomposition of global growth into contributions from each factor and can be similarly applied at the regional level.

[6]Although this is not the case here, discrepancies between actual data and robust model estimates could also reflect challenges related to data publication capacity. We are grateful to the RES-DM seminar participants for bringing this perspective to our attention.



(a) Saudi Arabia (b) Kenya

Figure 5: Quarterly GDP Estimates with Absence of Actual Data

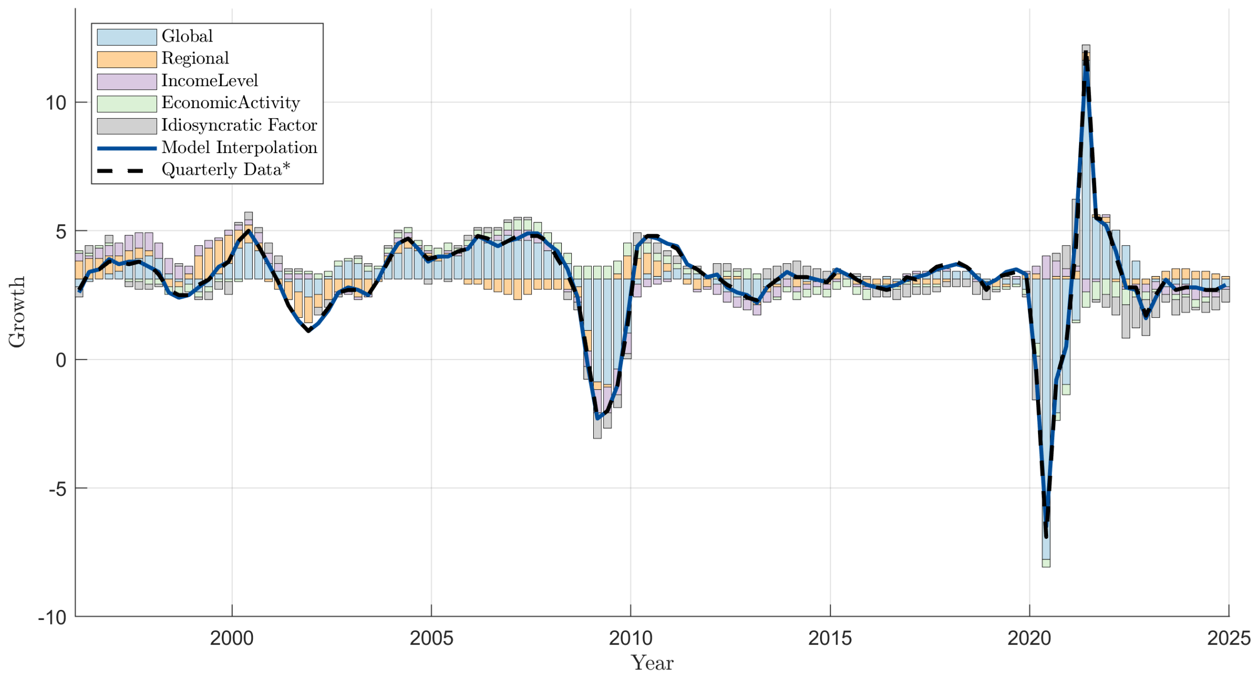


Figure 6: Global GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

Figure 6 shows the model estimate and individual factor contributions for the global GDP growth[7]. Visually being more clear around 2008 great financial crisis, COVID-19 and its aftermath, the global factor is the dominating force explaining global GDP variation. The factor explains 54% of the overall variation. Its impact is dominant especially during major global recession periods, such as the great financial crisis and the Covid-19. Regional factors contribute to the overall variation in 11% and all four factors together explain 72% of the global cyclical activities.

While the impact of income level and specific economic activities seems secondary to that

[7] Appendix 5 shows the GDP growth and individual factor contributions in regional level.

of global and regional comovement, this does not hold for all regions globally. Table 2 shows the explained variance score for global and regional aggregation.

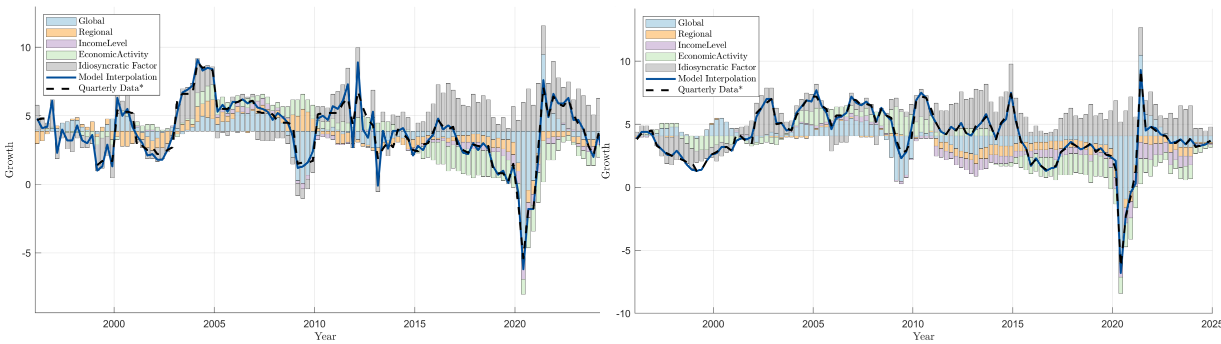
Table 2. Explained Variance by Factors

	F_t^G	F_t^R	F_t^I	F_t^{EA}	$[F_t^G, F_t^R]$	$[F_t^G, F_t^R, F_t^I, F_t^{EA}]$
World	0.54	0.11	0.04	0.06	0.65	0.72
Asia	0.31	0.10	0.04	0.09	0.40	0.49
The Caucasus	0.25	0.34	0.17	0.07	0.60	0.82
Europe	0.69	0.04	0.04	0.04	0.74	0.79
Latin America and Caribbeans	0.50	0.09	0.02	0.17	0.59	0.78
Middle East and North Africa	0.24	0.05	0.08	0.12	0.27	0.34
North America	0.69	0.22	0.05	0.00	0.92	0.98
Sub-Saharan Africa	0.40	0.14	0.13	0.20	0.46	0.39

Note: The table shows the proportion of explained variance attributed to each factor and their combinations.

In the global aggregation, global and regional factors together correspond to 65% of the overall variation, and including income level and economic activity specific factors, this share increases to approximately 70%. This phenomenon is strongly observed in Europe and especially in North America. This is due to two way causality of the factors, i.e. global factors are mainly driven by the advanced economies listed in two regions. However, impact of global and regional factors is not similarly powerful in the regions with a higher share of low-income and non-frontier emerging market countries. For instance, the share of variation covered by the regional and global factors only explains 27% and 46% in Middle East and Sub-Saharan Africa regions respectively. Figures 7a and 7b show that the main driving force in two regions are the idiosyncratic terms, i.e., country-unique movements, whereas global factors are still highly impactful.

Finally, the Asia region also shows a unique behavior where the global and regional factors are effective over the last two decades, hence their total share is around 40% in the entire period. Figure 9 shows that, prior to 2000s, the overall variation is majorly affected by regional factors, and the global movements became significant during the GFC and COVID-19 pandemic period. The region differs from others in the COVID aftermath, where the global recovery has not been felt with the same strength. In addition, economic activity-specific factors, such as heavy manufacturing and commodity activities, have been highly impactful since the early 2000s.



(a) Middle East and North Africa (b) Sub-Saharan Africa

Figure 7: Regional GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

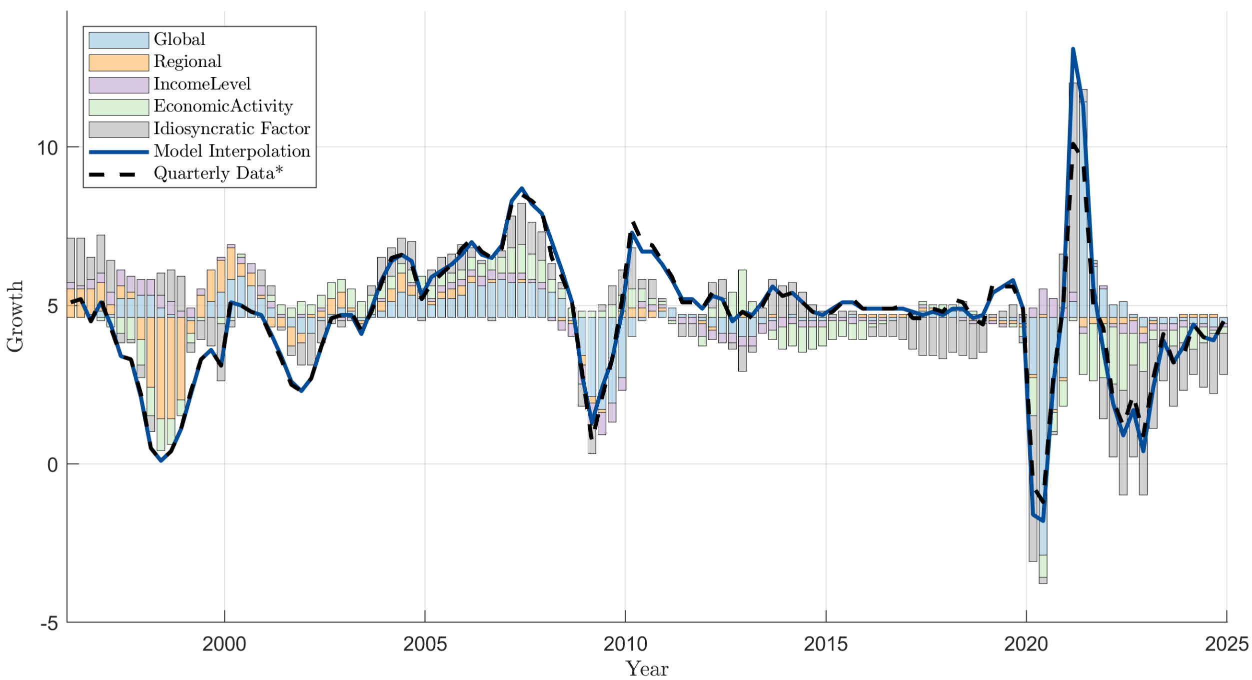


Figure 9: Asia GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

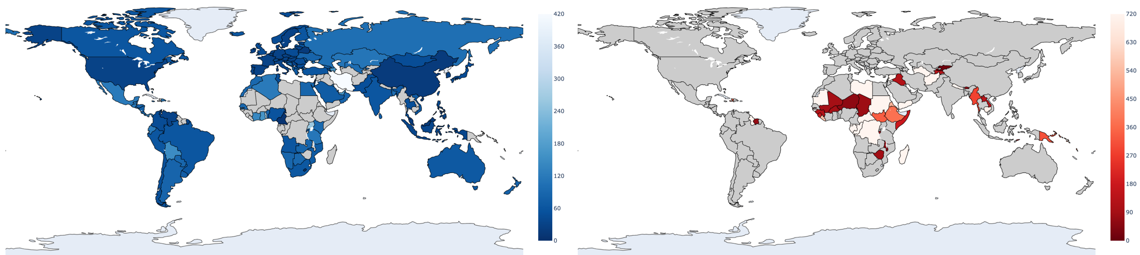
4 Data Release Lag and Out of Sample Performance

In addition to the heterogeneity across data frequency in national statistics, countries differ in the timeliness of their statistical capacity to publish the latest growth figures. To assess how much the variation in data release lag schedule affect the performance of the methodology, we propose and implement a systematic test.

In terms of coverage and consistency, the most relevant point of comparison for real-time country-level growth projections is the IMF's World Economic Outlook (WEO), which publishes biannual short-term forecasts in April and October. WEO projections are typically annual, providing a single estimate for year-end GDP growth.

To benchmark the methodology against WEO forecasts, a two-step evaluation is implemented. First, each country's specific data release lag is mapped to construct synthetic (”pseudo-vintage”) datasets reflecting the actual information set available in October and April of each year over the past decade. Second, using these vintages, the model estimates end-of-year GDP growth for each country, which is then compared with the corresponding WEO projections.

Release lags for countries reporting quarterly GDP are generally shorter than those for countries reporting only annual data. Figure **??** illustrates the cross-country distribution. For quarterly-reporting countries, median release lags are roughly 90 days. For annual-reporting countries, the distribution is bi-modal, with peaks at six months and one year. A complete visualization of release lags by country is provided in Figure 17 in Appendix D.



(a) Countries with quarterly statistics

(b) Countries with annual statistics

Figure 10: Release lag of national statistics by country

Note: Color shading indicates the number of days by which data releases are delayed in each country. Figure 10a displays release lags for countries reporting data quarterly, while Figure 10b presents lags for countries publishing data only annually. Countries that publishes the national statistics in quarterly frequency is excluded from Figure 10b since partial information is available over the year.

Let $y_{i,t}^{Oct}$ denote the model's October estimate of country i's growth in year t, and $y_{i,t}^{Apr}$ the estimate available in the following April after more complete data has been released. The WEO projections for those vintages are $y_{i,t}^{WEO,Oct}$ and $y_{i,t}^{WEO,Apr}$, respectively. Realized growth outcomes are denoted as $y_{i,t}$. For each vintage, the relative root mean square error (RMSE) is calculated as follows:

$$RMSE_{i,t} = \frac{\|y_{i,t}^{WEO,j} - y_{i,t}\|}{\|y_{i,t}^{j} - y_{i,t}\|}, \quad j \in [Apr, Oct]. \tag{4}$$

Table 3 summarizes the median RMSE ratio for April and October releases across countries.

For the April vintage—when more complete statistics are available—the model's forecasts outperform WEO projections in very short run in most cases, as evidenced by median RMSE ratios above unity. This suggests the methodology successfully leverages updated data to

Table 3. Median Absolute Relative RMSE Ratio per Release

Release	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
April	2.77	2.84	3.49	2.72	1.93	1.93	0.68	2.41	1.49	0.35
October	0.94	0.98	1.19	0.91	0.95	0.98	0.70	0.70	0.87	0.69

provide more accurate short-term projections than the benchmark forecasts. For the October vintage, when real-time data remain sparse, model performance is generally comparable to WEO projections. This demonstrates the model's robustness even with limited information.

We see that model performance weakened during the post-COVID-19 recovery period, reflecting the wider difficulty all forecasting tools faced in predicting the scale and pace of the rebound. Finally, preliminary results for 2024 indicate the model's projections underperformed compared to WEO forecasts; however, this is based only on countries that have so far released their actual 2024 growth outcomes. Final assessments may change as additional national data become available.

5 Conclusion

This paper tackles the significant challenge of incomplete and infrequent economic data reporting at the global level, with an emphasis on the persistent gaps in quarterly GDP series for many emerging and developing economies. By leveraging a global dynamic factor model that accommodates both mixed-frequency and ragged-edge data structures, the approach enables the estimation of missing quarterly GDP figures through the exploitation of economic interconnections across countries and regions.

Empirical results demonstrate that the methodology can reliably reconstruct plausible quarterly series for countries with missing data, while preserving internal consistency and capturing the dominant drivers of economic cycles at multiple aggregation levels. Out-of-sample benchmarking further underscores the practical utility of this framework for real-time policy analysis, particularly when additional data becomes available.

A further virtue of the proposed approach is its ability to support scenario-based analysis. Given the model's reliance on observed covariation and shared dynamics, analysts can design country-specific scenarios—such as a simulated domestic shock or data revision for one or several countries—and directly observe the resulting spillover effects on regional aggregates and the global economy. This scenario system allows researchers and policymakers to consistently quantify both the direct and indirect consequences of shocks in near real-time. Moreover, the model's structure makes it possible to conduct two-way analyses: both assessing how local changes ripple outward, and how external/global shocks impact individual countries.

This work thus provides a practical and scalable framework for improving global economic surveillance, reducing information blind spots, and informing policymaking in an increasingly interconnected world.

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Appendix

A. Frequency Aggregation

Suppose V_t^M represents the monthly unobservable constant price GDP volume at time t. The year-over-year (y-o-y) growth rates of the GDP volume stocks, for monthly and quarterly periods, are expressed by the following equations:

$$v_t^M = \frac{V_t^M}{V_{t-12}^M} - 1 \tag{5}$$

$$v_t^Q = \frac{\sum_{j=0}^{2} V_{t-j}^M}{\sum_{j=0}^{2} V_{t-12-j}^M} - 1 \tag{6}$$

By substituting (5) into (6), we obtain:

$$\begin{aligned} v_t^Q &= \frac{(1+v_t^M)V_{t-12}^M + (1+v_{t-1}^M)V_{t-13}^M + (1+v_{t-2}^M)V_{t-14}^M}{V_{t-12}^M + V_{t-13}^M + V_{t-14}^M} - 1 && (7)\\ &= \frac{(v_t^M)V_{t-12}^M + (v_{t-1}^M)V_{t-13}^M + (v_{t-2}^M)V_{t-14}^M}{V_{t-12}^M + V_{t-13}^M + V_{t-14}^M} && (8) \end{aligned}$$

Basic Model: Assuming that the initial GDP volume stocks are approximately equal for the preceding periods, i.e., $V_{t-12}^M \approx V_{t-13}^M \approx V_{t-14}^M$:

$$v_t^Q \approx \frac{1}{3}(v_t^M + v_{t-1}^M + v_{t-2}^M) \tag{9}$$

Similarly, the annual growth can be approximated as:

$$v_t^A \approx \frac{1}{12}\left(\sum_{j=0}^{11} v_{t-j}^M\right) \tag{10}$$

Let $Y_t^M = [Y_{1,t}^M, Y_{2,t}^M, Y_{3,t}^M, ...Y_{N,t}^M]$ denote the set of monthly observables $Y_{i,t}^M$, where the y-o-y growth rate of each variable is defined as $y_{i,t}^M = \frac{Y_{i,t}^M}{Y_{i,t-12}^M} - 1$. The growth rates can be modeled as a factor structure with idiosyncratic component ε_t:

$$\begin{bmatrix} y_t^M \\ v_t^Q \\ v_t^A \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Lambda} \\ \frac{1}{3}\mathbb{1}_{3x1} \quad \emptyset_{9x1} \\ \frac{1}{12}\mathbb{1}_{\boldsymbol{12x1}} \end{bmatrix} \begin{bmatrix} \boldsymbol{f_t} \\ \vdots \\ \boldsymbol{f_{t-11}} \end{bmatrix} + \varepsilon_t \tag{11}$$

where the unobservable factor f_t follows an autoregressive process of order p.

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + e_t, \quad e_t \overset{\text{iid}}{\sim} N(0, R) \tag{12}$$

Alternative Model: While the above assumption, that previous period GDP volumes are sufficiently close to allow the approximation from (7) to (9), is intuitive, it may not hold for every consecutive year. To address this, we relax the assumptions regarding the initial GDP volume stocks being approximately equal.

To illustrate the idea, first, write the one-year and two-year ahead growth rates of GDP volume stocks as in their first order approximations:

$$v_{13}^M \approx \frac{V_{13}^M}{V_1^M} - 1 \tag{13}$$

$$v_{13}^M + v_{25}^M \approx \frac{V_{25}^M}{V_1^M} - 1 \tag{14}$$

$$\tag{15}$$

Then one-year and two-year ahead quarterly growth rates can be expressed as

$$\begin{aligned}
v_{15}^Q &\approx \frac{(1+v_{15}^M)V_3^M + (1+v_{14}^M)V_2^M + (1+v_{13}^M)V_1^M}{V_3^M + V_2^M + V_1^M} - 1 \\
&\approx \frac{(v_{15}^M)V_3^M + (v_{14}^M)V_2^M + (v_{13}^M)V_1^M}{V_3^M + V_2^M + V_1^M} \\
&\approx \frac{V_3^M}{V_3^M + V_2^M + V_1^M} \times v_{15}^M + \frac{V_2^M}{V_3^M + V_2^M + V_1^M} \times v_{14}^M + \frac{V_1^M}{V_3^M + V_2^M + V_1^M} \times v_{13}^M
\end{aligned}$$

Define $\alpha^i = \frac{V_i^M}{V_3^M + V_2^M + V_1^M} \quad \forall i \in 1, 2, 3$. Then,

$$v_{15}^Q \approx \alpha_3 \times v_{15}^M + \alpha_2 \times v_{14}^M + \alpha_1 \times v_{13}^M \tag{16}$$

Similarly, we have:

$$\begin{aligned}
v_{15}^Q + v_{27}^Q &\approx \frac{V_{27}^M + V_{26}^M + V_{25}^M}{V_3^M + V_2^M + V_1^M} - 1 \\
&\approx \frac{(v_{15}^M + v_{27}^M)V_3^M + (v_{14}^M + v_{26}^M)V_2^M + (v_{13}^M + v_{25}^M)V_1^M}{V_3^M + V_2^M + V_1^M} \\
&\approx \alpha_3 \times (v_{15}^M + v_{27}^M) + \alpha_2 \times (v_{14}^M + v_{26}^M) + \alpha_1 \times (v_{13}^M + v_{25}^M)
\end{aligned}$$

By subtracting (16), we find:

$$v_{27}^Q \approx \alpha_3 \times v_{27}^M + \alpha_2 \times v_{26}^M + \alpha_1 \times v_{25}^M$$

This expression can be iterated for subsequent quarters to obtain:

$$v_t^Q \approx \alpha_3 \times v_t^M + \alpha_2 \times v_{t-1}^M + \alpha_1 \times v_{t-2}^M \tag{17}$$

The annual growth rates can be approximated as shown in equations (13) to (17):

$$v_t^A \approx \beta^{12} \times v_t^M + \beta^{11} \times v_{t-1}^M + \ldots + \beta^1 \times v_{t-11}^M‘ \tag{18}$$

Then the growth rates has a factor structure with idiosyncratic component ε_t as:

$$\begin{bmatrix} y_t^M \\ v_t^Q \\ v_t^A \end{bmatrix} = \begin{bmatrix} \multicolumn{2}{c}{\mathbf{\Lambda}} \\ \alpha_{3x1}^i & \emptyset_{9x1} \\ \multicolumn{2}{c}{\beta_{12x1}^i} \end{bmatrix} \begin{bmatrix} \boldsymbol{f_t} \\ \vdots \\ \boldsymbol{f_{t-11}} \end{bmatrix} + \varepsilon_t \tag{19}$$

where

$$\sum_{1}^{3} \alpha^i = 1, \quad 0 < \alpha^i < 1 \quad \forall i \in 1,2,3 \tag{20}$$

$$\sum_{1}^{12} \beta^i = 1, \quad 0 < \beta^i < 1 \quad \forall i \in 1,2,\ldots,12 \tag{21}$$

and the unobservable factor f_t follows an autoregressive process of order p.

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + e_t, \quad e_t \overset{\text{iid}}{\sim} N(0,R) \tag{22}$$

This model estimates and additional set of constrained parameters α^i's and β^i's to relax the assumption of the basic model.

Following this approximation, the measurement equation in (2) is modified with the following restrictions. For any country j belonging to the annual-only set Ω^A, the contemporaneous and lagged coefficients of each unobservable variable are assumed equal. For the countries with quarterly data $[i \in \Omega^Q]$, the coefficients on the contemporaneous unobservable are four times the annual observation, which guarantees that the estimated factors F_t explain both quarterly and annual data with the maximum likelihood. Finally, using this structure, the model allows us to estimate the quarterly production for any country $[j \notin \Omega^Q \wedge j \in \Omega^A]$ benefiting from the estimated factors, model parameters, and country-specific idiosyncratic term.

$$\begin{bmatrix} \vdots \\ y^Q_{t,i} \\ y^A_{t,i} \\ \vdots \\ y^A_{t,j} \\ \vdots \end{bmatrix} = \begin{bmatrix} & & & & \vdots & & & & & \\ \beta^G_i & 0 & 0 & 0 & \beta^R_i & 0 & 0 & 0 & \cdots & \cdots \\ \frac{\beta^G_i}{4} & \frac{\beta^G_i}{4} & \frac{\beta^G_i}{4} & \frac{\beta^G_i}{4} & \frac{\beta^R_i}{4} & \frac{\beta^R_i}{4} & \frac{\beta^R_i}{4} & \frac{\beta^R_i}{4} & \cdots & \cdots \\ & & & & \vdots & & & & & \\ \frac{\beta^G_j}{4} & \frac{\beta^G_j}{4} & \frac{\beta^G_j}{4} & \frac{\beta^G_j}{4} & \frac{\beta^R_j}{4} & \frac{\beta^R_j}{4} & \frac{\beta^R_j}{4} & \frac{\beta^R_j}{4} & \cdots & \cdots \\ & & & & \vdots & & & & & \end{bmatrix} \cdot \begin{bmatrix} F^G_t \\ F^G_{t-1} \\ F^G_{t-2} \\ F^G_{t-3} \\ F^R_t \\ F^R_{t-1} \\ F^R_{t-2} \\ F^R_{t-3} \\ \vdots \\ \vdots \end{bmatrix}$$

B. Regional Model Estimates and Factor Contributions

C. Persistence of Factors

D. Data Release Lags by Country

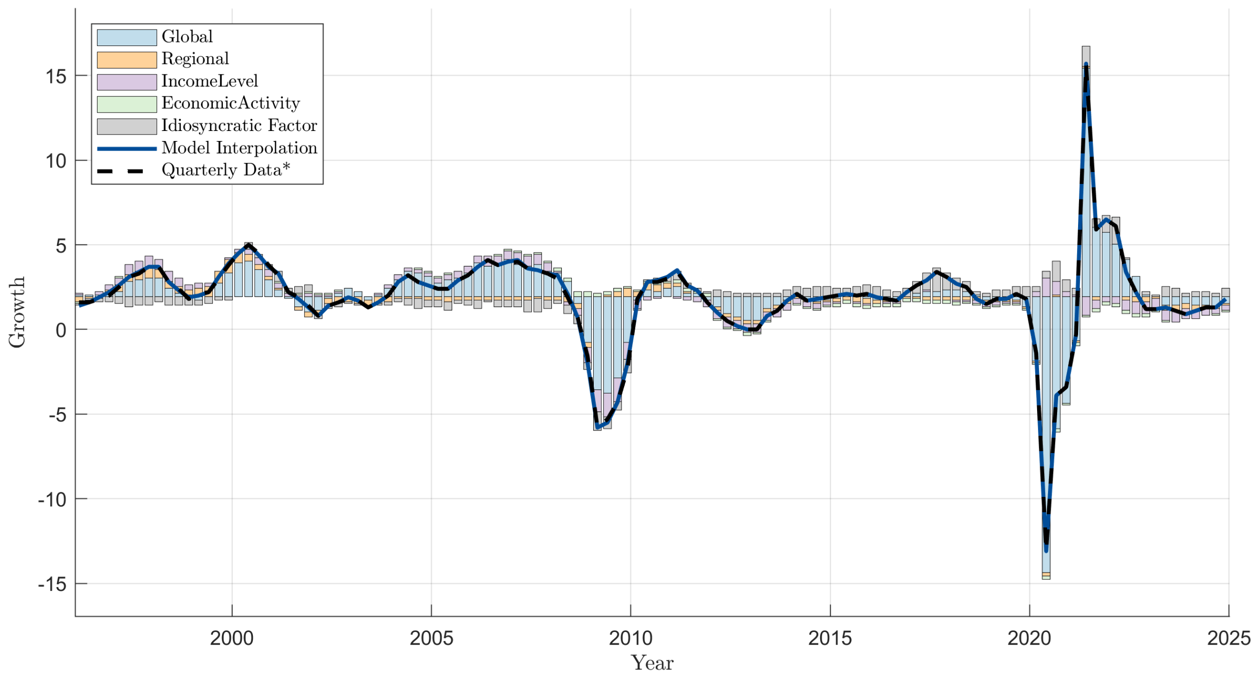

Figure 12: Europe GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

E. Trade Shares of Countries with Quarterly Data

Consider a universe of countries partitioned into two sets:

- Ω^{NQ}: countries whose GDP statistics are not published on a quarterly frequency.
- Ω^{Q}: countries whose GDP statistics are published quarterly.

Let $i \in \Omega^{NQ}$, $j \in \Omega^{Q} \cup \Omega^{NQ}$, and let $X^t_{i\to j}$ and M^t_{ij} denote the export and import value from i to j (or from j to i), respectively, in year t.

The total exports of non-quarterly countries in year t is:

$$EX^{NQ}_t = \sum_{i\in\Omega^{NQ}} \sum_j X^t_{i\to j}$$

The share of non-quarterly country exports to a specified group S (e.g., US, China, G7, G20, Rest of World) in year t is:

$$SHARE^{NQ\to S}_t = \frac{\sum_{i\in\Omega^{NQ}} \sum_{k\in S} X^t_{i\to k}}{EX^{NQ}_t}$$

Here, the numerator is the sum of exports from non-quarterly countries to all destinations in group S, and the denominator is total exports from non-quarterly countries to all partners.

Analogous definitions hold for imports (IM^{NQ}_t) and shares of imports received from specific groups. Table 6 calculates the rates over last three decades using the Gurevich (2018) dataset.

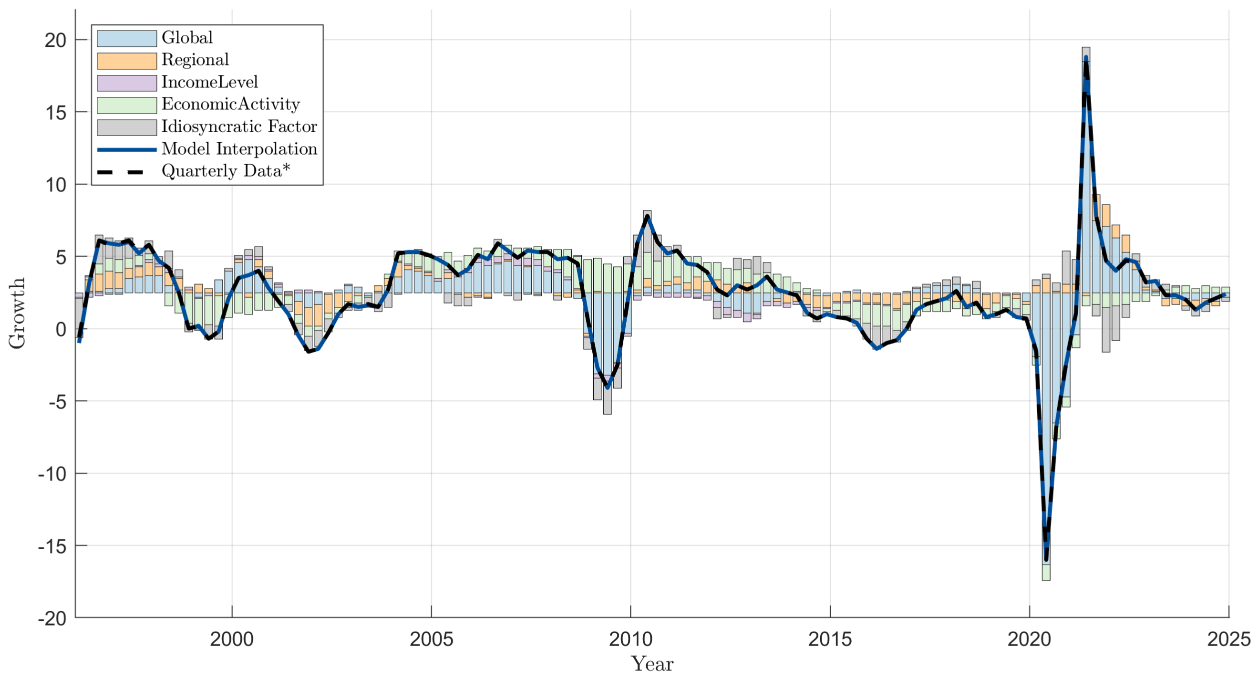

Figure 13: Latin America and Caribbeans GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

Table 4. Persistence by Region, Income Level, and Economic Activity

Region:	Latin America and Caribbean	Sub-Saharan Africa	North America	Europe	Asia	MENA	CIS
	0.86	0.84	0.80	0.92	0.80	0.76	0.77
Income Level:	**Low-Income Developing Economies**	**Emerging Markets**	**Advanced Economies**				
	0.73	0.85	0.86				
Economic Activity:	**Primary Non-fuel Exporter**	**Fuel Exporter**	**Manufacturing**	**Tourism**	**Services**	**Other**	
	0.93	0.88	0.85	0.91	0.86	0.93	

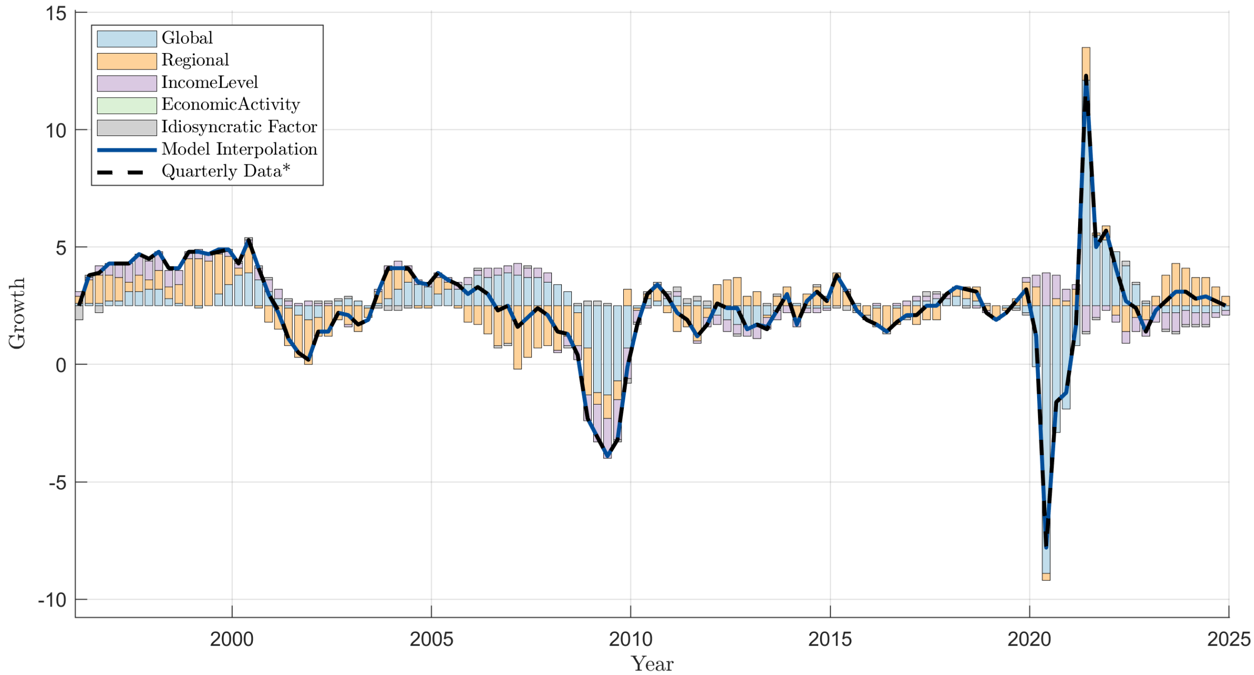

Figure 14: North America GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

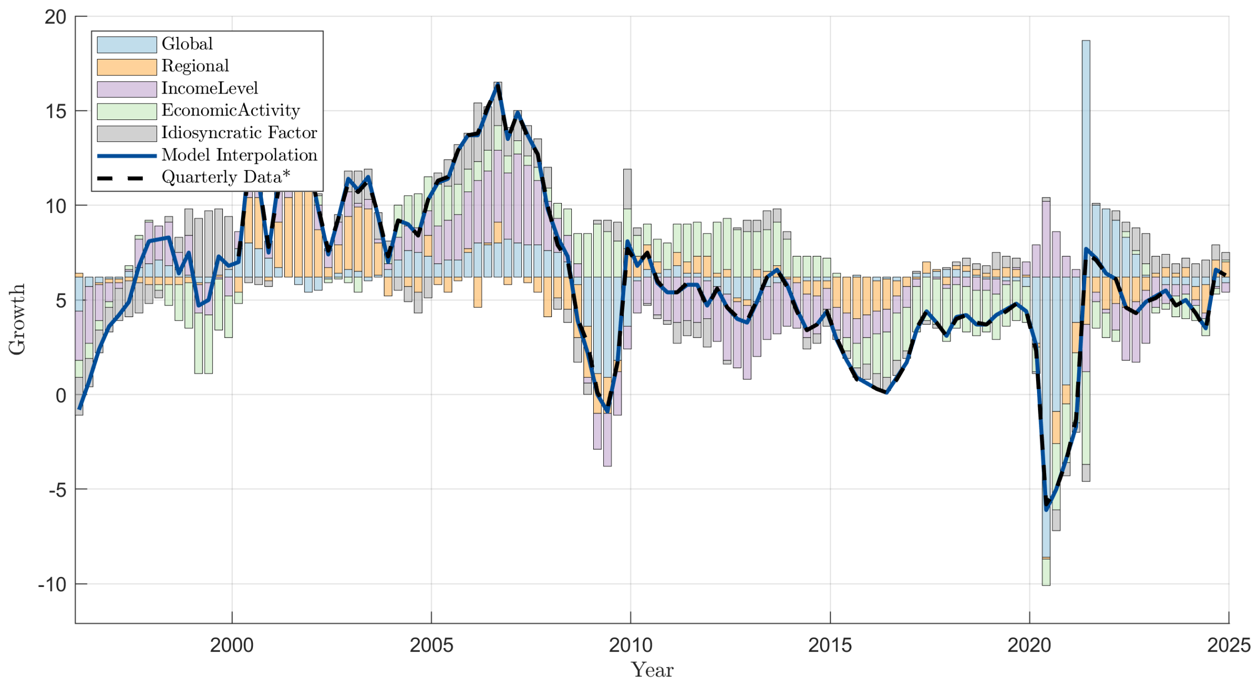

Figure 15: The Caucasus GDP Data, Model Estimate and Factor Contributions

Note: The solid line represents model-estimated values. The dashed line indicates quarterly aggregated growth calculated under the assumption that, for countries with only annual data, the quarterly growth rate is set to the end-of-year value for all quarters. This assumption is employed solely for comparison and visualization purposes. Bar segments indicate the relative factor contributions at each period.

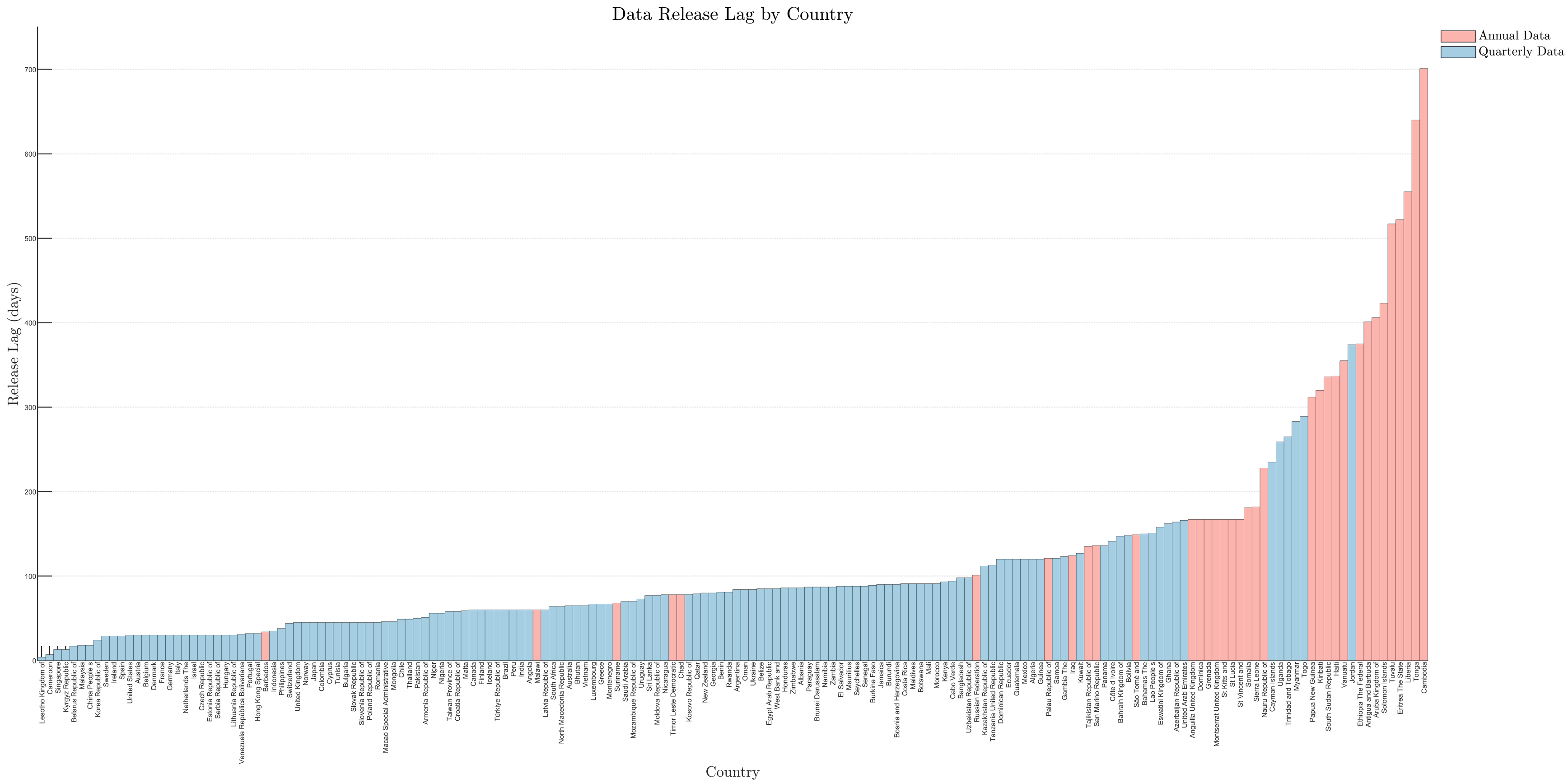

Figure 16: Data Release Lags by Country

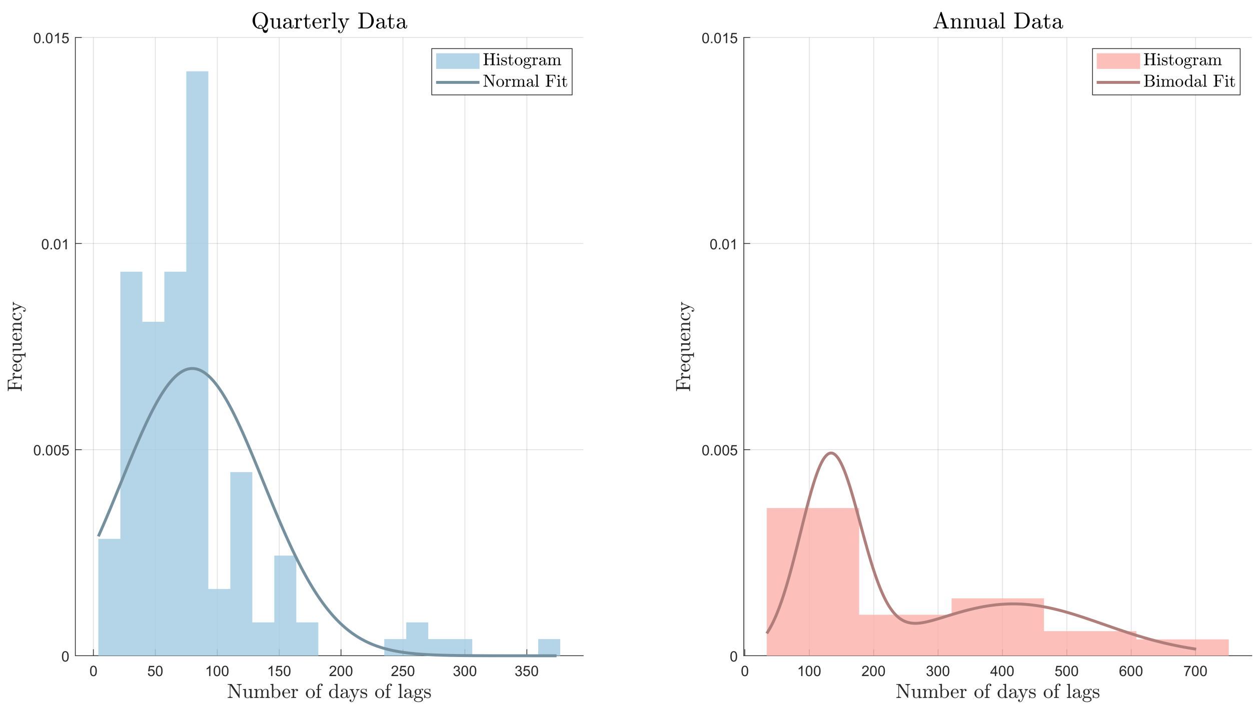

Figure 17: Distribution of Data Lags for Quarterly and Annual Data Countries

Table 5. Data Release Lags

Country	Frequency	Release Lag	Country	Frequency	Release Lag
United States	Q	30	Macao Special Administrative Region	Q	46
United Kingdom	Q	45	Malaysia	Q	18
Austria	Q	30	Maldives	Q	91
Belgium	Q	30	Pakistan	Q	50
Denmark	Q	30	Palau, Republic of	A	121
France	Q	30	Philippines	Q	38
Germany	Q	30	Singapore	Q	13
San Marino, Republic of	A	136	Thailand	Q	49
Italy	Q	30	Vietnam	Q	65
Luxembourg	Q	67	Algeria	Q	120
Netherlands, The	Q	30	Angola	Q	60
Norway	Q	45	Botswana	Q	91
Sweden	Q	29	Burundi	A	90
Switzerland	Q	44	Cameroon	Q	7
Canada	Q	60	Cabo Verde	A	94
Japan	Q	45	Chad	A	78
Finland	Q	60	Benin	Q	81
Greece	Q	67	Eritrea, The State of	A	522
Iceland	Q	60	Ethiopia	A	375
Ireland	Q	29	Gambia, The	A	123
Malta	Q	59	Ghana	Q	162
Portugal	Q	32	Guinea	A	120
Spain	Q	29	Côte d'Ivoire	Q	141
Turkey, Republic of	Q	60	Kenya	Q	93
Australia	Q	65	Lesotho, Kingdom of	Q	4
New Zealand	Q	80	Liberia	A	555
South Africa	Q	64	Malawi	A	60
Argentina	Q	84	Mali	A	91
Bolivia	Q	148	Mauritius	Q	88
Brazil	Q	60	Morocco	Q	91
Chile	Q	49	Mozambique, Republic of	Q	70
Colombia	Q	45	Niger	A	56
Costa Rica	Q	91	Nigeria	Q	56
Dominican Republic	Q	120	Zimbabwe	A	86
Ecuador	Q	120	Rwanda	Q	81
El Salvador	Q	88	São Tomé and Príncipe	A	149
Guatemala	Q	120	Seychelles	Q	88
Haiti	A	337	Senegal	Q	88
Honduras	Q	86	Sierra Leone	A	182
Mexico	Q	120	Somalia	A	181
Nicaragua	Q	78	Namibia	Q	87
Panama	Q	136	South Sudan, Republic of	A	336
Paraguay	Q	87	Eswatini, Kingdom of	A	158
Peru	Q	60	Tanzania, United Republic of	Q	113
Uruguay	Q	73	Togo	Q	289
Venezuela	Q	31	Tunisia	Q	45
Antigua and Barbuda	A	401	Uganda	Q	259
Anguilla	A	167	Burkina Faso	A	89
Bahamas, The	Q	150	Zambia	Q	87
Aruba	A	406	Solomon Islands	A	423
Barbados	A	34	Kiribati	A	320
Dominica	A	167	Nauru, Republic of	A	228
Grenada	A	167	Vanuatu	A	355
Belize	Q	85	Papua New Guinea	A	312
Jamaica	Q	90	Samoa	Q	121
Montserrat	A	167	Tonga	A	640
St. Kitts and Nevis	A	167	Tuvalu	A	517
St. Lucia	A	167	Armenia, Republic of	Q	51
St. Vincent and the Grenadines	A	167	Azerbaijan, Republic of	Q	164
Suriname	A	68	Belarus, Republic of	Q	17
Trinidad and Tobago	Q	265	Albania	Q	86
Cayman Islands	A	235	Georgia	Q	80
Bahrain, Kingdom of	Q	147	Kazakhstan, Republic of	Q	112
Cyprus	Q	45	Kyrgyz Republic	A	13
Iraq	A	124	Bulgaria	Q	45
Israel	Q	30	Moldova, Republic of	Q	77
Jordan	Q	374	Russian Federation	Q	101
Kuwait	Q	127	Tajikistan, Republic of	A	135
Oman	Q	84	China, People's Republic of	Q	18
Qatar	Q	79	Ukraine	Q	84
Saudi Arabia	Q	70	Uzbekistan, Republic of	Q	98
United Arab Emirates	Q	166	Czech Republic	Q	30
Egypt, Arab Republic of	Q	85	Slovak Republic	Q	45
West Bank and Gaza	Q	85	Estonia, Republic of	Q	30
Bangladesh	Q	98	Latvia, Republic of	Q	60
Bhutan	A	65	Serbia, Republic of	Q	30
Brunei Darussalam	Q	87	Montenegro	Q	67
Myanmar	A	283	Hungary	Q	30
Cambodia	A	701	Lithuania, Republic of	Q	30
Sri Lanka	Q	77	Mongolia	Q	46
Taiwan Province of China	Q	58	Croatia, Republic of	Q	58
Hong Kong Special Administrative Region	Q	32	Slovenia, Republic of	Q	45
India	Q	60	North Macedonia, Republic of	Q	64
Indonesia	Q	35	Bosnia and Herzegovina	Q	90
Timor-Leste, Democratic Republic of	A	78	Poland, Republic of	Q	45
Korea, Republic of	Q	24	Kosovo, Republic of	Q	78
Lao People's Democratic Republic	A	151	Romania	Q	45

Table 6. Trade share of countries without quarterly GDP over country groups.

	1990	1995	2000	2005	2010	2015	2020	2024
Export								
US	25.53	22.33	26.25	28.66	19.75	11.50	8.53	9.91
US+China	25.99	24.83	33.20	38.41	31.11	31.71	29.22	30.64
G7	61.34	51.19	50.72	49.99	38.28	26.89	23.62	25.52
G20	82.11	75.62	77.20	79.28	73.08	76.75	72.65	76.57
RoW	98.24	96.08	97.24	97.55	94.31	95.01	95.12	96.22
Import								
US	9.49	3.77	2.51	2.95	4.04	3.99	1.56	1.29
US+China	11.57	4.98	4.70	6.61	11.87	24.05	25.23	26.07
G7	30.56	16.55	8.89	8.85	13.74	10.28	7.24	6.42
G20	82.32	73.80	65.92	71.91	70.40	66.90	73.61	66.97
RoW	99.45	99.36	99.49	99.17	99.37	99.52	99.57	99.68