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Nowcasting Low-Income Countries Through Global Linkages

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ABSTRACT: Timely assessment of economic activity is crucial for effective policymaking at the national, regional, and global levels. However, many economies still do not publish GDP data at a quarterly basis, creating persistent information gaps. In 2025, 34% of economies publish only annual GDP statistics. This lack of higher-frequency and timely data is particularly restrictive for emerging market and developing economies, where economic volatility and spillover risks are often highest. The problem is more severe for historical data: only 42% of economies have quarterly GDP 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. Moreover, this method ensures internally consistent estimates of regional and global economic activity, allowing both top-down and bottom-up scenario analyses.

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WORKING PAPERS

Nowcasting Low-Income Countries Through Global Linkages

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1 Introduction

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

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

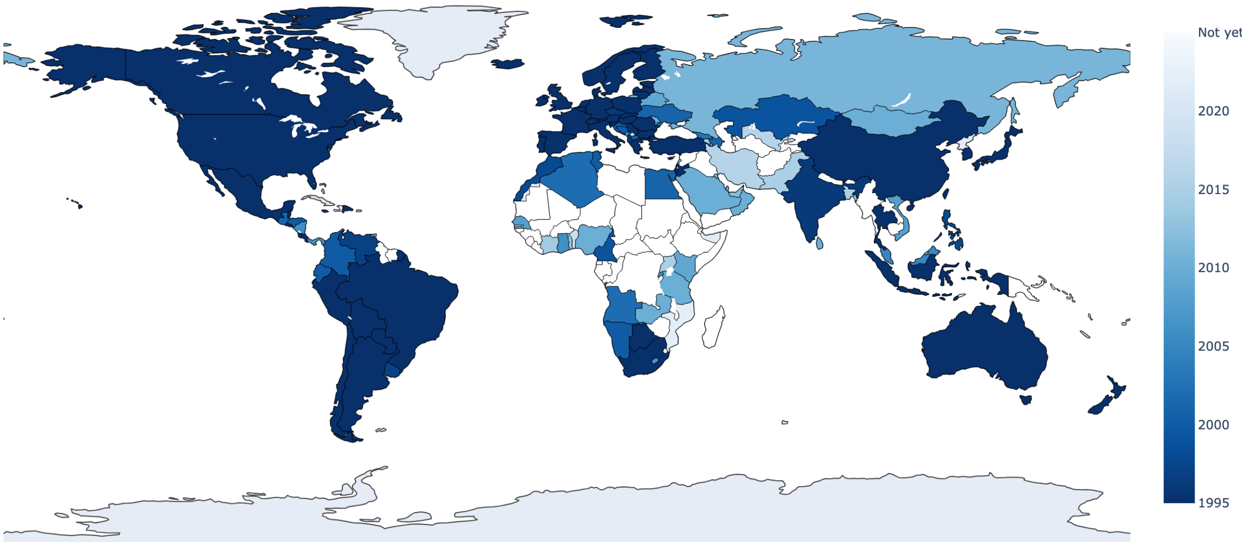


Figure 1: Availability of quarterly GDP data

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

As of 2025, 34% of economies continue to report GDP only through an annual national accounts release, with no official quarterly GDP series, and only 42% of economies provide quarterly GDP series extending over more than two decades [2]. This creates blind spots in understanding 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—may become less effective as they do not take into account the strength of economic activity in a large share of economies. Second, research and macroeconomic modeling are limited by

[1]Throughout the paper, 'quarterly GDP' refers to series published at a quarterly frequency, with growth measured in year-over-year terms. 'Annual GDP' refers to national accounts that are released only once per calendar year, without quarterly disaggregation; in these cases the reported value corresponds to the growth rate for the whole year in year-over-year terms.

[2]See Appendix 5 Figure 15 for also population and nominal GDP coverages.

sparse long-run data. These issues affect not only policymakers, analysts, and businesses in data-scarce economies, 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.

Even when quarterly GDP series are available, publication lags vary widely across economies, creating additional blind spots for real-time monitoring. In advanced economies such as the United States, the United Kingdom, and Japan, the first GDP estimate is typically released within about 30 to 45 days after the end of the quarter, whereas this lag extends to roughly three months in Kenya. In some emerging and developing economies, the delay can be much longer: for example, recent quarterly GDP releases in Togo, Uganda, and Jordan have appeared close to a year after the quarter ends [3]. For economies that publish only annual GDP, the delay is even more pronounced. By construction, the year must be completed before national accounts can be compiled, and in practice the typical delay ranges from about half a year to a median of one year after the end of the reference year. For instance, 2024 Somali GDP data are released in June 2025, while Eritrea's 2022 annual GDP growth statistics were published only in June 2024; the latest observed release lag for Eritrea is 522 days, implying that GDP growth for 2025 would only become available around mid-2027[4].

These blind spots are precisely where nowcasting can help, by exploiting information from economies with timely data to infer current conditions in those without. Nowcasting refers to the prediction of the present, the recent past, and the very near future of economic activity using timely information that arrives at higher frequencies than the target variable. Following Giannone et al. (2008), a large literature has developed factor-model-based approaches that process a flow of macroeconomic releases to update estimates of current and near-term GDP in real time.[5] In these frameworks, nowcasts are typically constructed for economies with rich monthly or quarterly indicators, such as industrial production, labour market statistics, survey data and financial variables.

The existing nowcasting literature is correspondingly concentrated on advanced economies and a subset of frontier emerging markets. Economies covered by published nowcasting models account for the majority of global GDP, but they comprise a narrow group of data-rich economies where both quarterly GDP and a wide range of high-frequency indicators are available and regularly updated. By contrast, there has been very limited systematic effort to nowcast economic activity in low-income and many developing economies. In these settings, data limitations are more pervasive: not only is quarterly GDP often unavailable, but other indicators are sparse, series are short and affected by breaks and rebasing, and survey infrastructure is limited. These constraints make it difficult to directly transplant standard within-country nowcasting frameworks, which rely on a dense flow of national data.

Traditional nowcasting models use high-frequency indicators within the same economy to track quarterly GDP in real time. For example, monthly business surveys, industrial production, labour market statistics and financial variables for the United States or the

[3]See Table 4 for the latest release lag timeline of quarterly GDP economies

[4]See Table 5 annual-only economies, and the supplementary material for the actual announcement sources as of July 2025

[5]Key surveys and applications include Banbura et al. (2011), Banbura et al. (2013), Bok et al. (2018), and Cascaldi-Garcia, Luciani & Modugno (2024), among many others.

euro area provide timely signals that can be summarised by dynamic factors and mapped into nowcasts of domestic GDP (Banbura et al. 2011, Bok et al. 2018). However, this approach is not feasible in many low-income economies, where timely indicators are scarce or missing, and GDP itself is published only once per year with long delays. At the same time, these economies are tightly integrated with countries that do publish frequent data: for instance, in 2024 more than 96% of exports from economies without quarterly GDP series are directed to trading partners with higher-frequency national accounts.[6] This observation suggests a different strategy: rather than relying on domestic indicators that scarcely exist, one can exploit the strong global and regional comovement in GDP across economies and use quarterly data from trading partners, neighbours, and global anchors as the primary real-time signal of current conditions in data-scarce economies. In this sense, a quarterly GDP release in a large partner such as the United States, the Euro Area, or China provides information not only about those economies themselves, but also about highly integrated low-income economies whose own GDP statistics are only reported annually.

To implement this idea, the paper develops a multi-country dynamic factor model that jointly tracks GDP for a large unbalanced panel of economies. The model is cast in state-space form and estimated with quasi maximum likelihood using Kalman filtering and smoothing techniques, following the approach of Doz et al. (2012), Bańbura & Modugno (2014), and Barigozzi & Luciani (2024). The framework is designed to handle a number of features that are central in this context: high-dimensional panels, mixed annual and quarterly frequencies, missing data and jagged edges arising from asynchronous data releases, and the presence of structural breaks and data revisions. A block structure is imposed on the factor space to capture global, regional, income-group and sectoral components, allowing the model to reflect cross-country heterogeneity in economic structures and degrees of integration[7].

This paper contributes to the nowcasting and global activity estimation literatures in several ways. First, it proposes a global nowcasting framework tailored to economies without quarterly GDP—particularly low-income and developing economies—by exploiting cross-country comovement in GDP from economies with timely quarterly releases. The model delivers real-time measures of economic activity for these economies despite the absence of domestic high-frequency indicators. Second, it provides internally consistent historical estimates of quarterly GDP for economies that only report annual national accounts, thereby filling long-standing data gaps and enabling structural and policy analysis at quarterly horizons. Third, by imposing a global–regional–income–sectoral block structure, the framework offers a unified tool to decompose fluctuations in GDP into common and idiosyncratic components at the economy, regional and global levels, and to conduct coherent top-down and bottom-up scenario analysis. Fourth, the paper demonstrates how far one can go with cross-country comovement alone—without any domestic high-frequency indicators—providing a judgment-free, transparent benchmark against which forecasts incorporating subjective assessments or

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

[7] An alternative to the DFM framework is the multicountry vector autoregression (VAR). To scale to large datasets, both approaches rely on homogeneity restrictions (Pesaran et al. 2009) or shrinkage priors (Giannone & Reichlin 2009, Del Negro et al. 2019). Interestingly, DFM and VAR typically produce similar predictions in economic data characterized by strong comovement (Banbura et al. 2010). Both VAR and DFM can be cast in state-space form, handling mixed frequencies and jagged edges through Kalman filtering (Banbura et al. 2015, Cimadomo et al. 2022).

additional information can be compared.

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 cross-economy heterogeneity.

We define two sets of economies according to data availability. Let Ω^Q be the set of N economies with national accounts published at a quarterly frequency, and Ω^A be the set of M economies for which at least an annual national accounts release is available, with $\Omega^Q \subset \Omega^A$. At each period t, denote by $Y_t = [Y_t^Q, Y_t^A]$ the stacked vector of observables, of length $N + M$, where Y_t^Q and Y_t^A collect, respectively, quarterly-frequency and annual-frequency GDP growth rates for all economies with available data. For an individual economy i, we denote its GDP growth rate at time t by $y_{i,t}$ when needed. The quarterly components Y_t^Q correspond to year-over-year (y-o-y) growth rates at a quarterly frequency, while the annual components Y_t^A are calendar-year GDP growth rates that are observed only once per year in economies without an official quarterly GDP series; for these economies, the annual observation is assigned to the last quarter of the year[8].

For the economies with quarterly national accounts, the model uses year-over-year (y-o-y) GDP growth rates observed at a quarterly frequency. For instance, in the case of the United States, we work with y-o-y rates constructed from the underlying chained volume indices.

Building on the multi-country dynamic factor model (DFM) literature (Marcellino et al. 2003, Negro & Otrok 2008, Breitung & Eickmeier 2016, Cascaldi-Garcia, Ferreira, Giannone & Modugno 2024), we develop 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. We adapt the multi-country DFM to handle mixed-frequency data combining both annual and quarterly data, to deal with jagged edges arising from asynchronous data releases, and to scale to large economy panels. The model also allows for economy-specific idiosyncratic fluctuations with dedicated autoregressive structure to capture heterogeneity.

Each economy'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[9]

[8]Since the annual GDP growth is also available for the economies with quarterly GDP, some economies contribute to both information vectors where both quarterly and annual data exist.

[9]The regions are Asia, CIS, Europe, Latin America and the Caribbean, Middle East and North Africa,

- F_t^I: income-group factors (advanced, emerging-market, low-income)
- F_t^{EA}: economic activity or sectoral factors[10]

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

The model is as follows:

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

where C and A are parameter matrices, and e_t captures economy-specific idiosyncratic dynamics in stacked form. The coefficients $\delta_1, \ldots, \delta_p$ govern the autoregressive dynamics of the idiosyncratic component e_t, allowing for persistent, economy-specific deviations from the common factors. Innovations v_t and ε_t are assumed to be independent and normally distributed. This structure allows us to model heterogeneity and persistence in both shared components and idiosyncratic terms.

2.1 Quarterly to annual frequency aggregation

To integrate economies with both quarterly-frequency and annual-frequency GDP data, the model links calendar-year and quarterly-frequency growth rates through a structural relationship. Let v_t^Q denote the quarterly-frequency y-o-y GDP growth rate, and let v_t^A denote the calendar-year GDP growth rate observed in countries that publish only an annual national accounts release. For annual-only countries, the model links the two frequencies by treating the calendar-year growth rate as the average of the four quarterly-frequency y-o-y growth rates within that year:

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

Under this assumption, for an economy with only annual data, the model treats the observed calendar-year growth rate as an average of the four latent quarterly-frequency y-o-y growth rates, restricting the sum of coefficients accordingly. This guarantees internal consistency between the annual national accounts release and the underlying unobserved quarterly path, and enables the extraction of quarterly GDP series even in the absence of officially published quarterly observations.

Following this approximation, the measurement equation in (2) is modified with the appropriate restrictions[11]. With the state-space representation and aggregation restrictions in place, the model can now be estimated on the global panel.

Sub-Saharan Africa, and North America, and follow IMF/WB classifications. See Appendix A for the list of economies included in each region.

[10] The economic activity component encompasses tourism, fuel exports, manufacturing, primary non-fuel exports, services, and other activities. Economies are categorized according to the IMF classification, allowing each economy to be flagged by multiple economic activity indicators.

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

The framework can be understood as a more efficient version of temporal disaggregation methods such as Chow & Lin (1971). In traditional approaches, one must select a set of quarterly indicator variables for each economy separately—a step that is difficult to scale to a large panel and may produce inconsistent estimates across economies. Our approach compresses the information from all quarterly-reporting economies into a small number of common factors—global, regional, income-group, and economic activity—and uses these as the high-frequency indicators for temporal disaggregation. The Kalman filter then performs the interpolation, signal extraction, and projection in a single pass, without requiring economy-by-economy variable selection.

3 Estimation Results and Discussion

The performance of the model is evaluated along several complementary dimensions. First, we assess in-sample fit and conduct variance decompositions to quantify the contribution of global, regional, income-group, and activity-specific factors to GDP fluctuations at different aggregation levels. Second, we implement pseudo-out-of-sample reconstructions of quarterly GDP for economies such as Saudi Arabia and Kenya that transitioned from annual-only to quarterly reporting, using pre-transition data to evaluate how well the model recovers the later-released quarterly series. Third, we benchmark the model's real-time forecasting performance against the IMF's World Economic Outlook (WEO) by constructing pseudo-vintages that respect economy-specific publication lags and comparing forecast errors. Results are presented at both the country and aggregate level.

The empirical analysis covers a large unbalanced panel of economies with varying degrees of data availability and frequency. The sample includes both advanced and emerging market and low-income economies, spanning the period from 1995 to 2025 at a quarterly frequency where available, and at an annual frequency otherwise. Quarterly and annual GDP statistics are taken from national sources.

Figure 2 and Table 1 summarize how much of the variance in GDP growth is explained by each group of common factors at the global level and across regions. Columns report the share of variance accounted for by the global factor F_t^G, regional factors F_t^R, income-group factors F_t^I, and economic-activity factors F_t^{EA}, as well as by selected combinations of these factors. At the global level, the combination of global and regional factors explains about two-thirds of the variance in GDP growth, rising to roughly 70 percent when income-group and activity-specific factors are added, while in regions with a larger share of low-income economies the explained share is notably lower and reflects a more important role for idiosyncratic and activity-specific components.

In the global aggregation, global and regional factors together explain 59% of the overall variation, and including income level and economic activity specific factors, this share increases to approximately 68%. This pattern is particularly pronounced in Europe and, most notably, in North America where the global factors are mainly driven by the advanced economies listed in two regions. However, the share of variance explained by the global and regional factors is not nearly as large in regions with more low-income and non-frontier emerging market countries. For instance, the share of variation covered by the regional and global factors is only 22% and 43% in Middle East and Sub-Saharan Africa regions

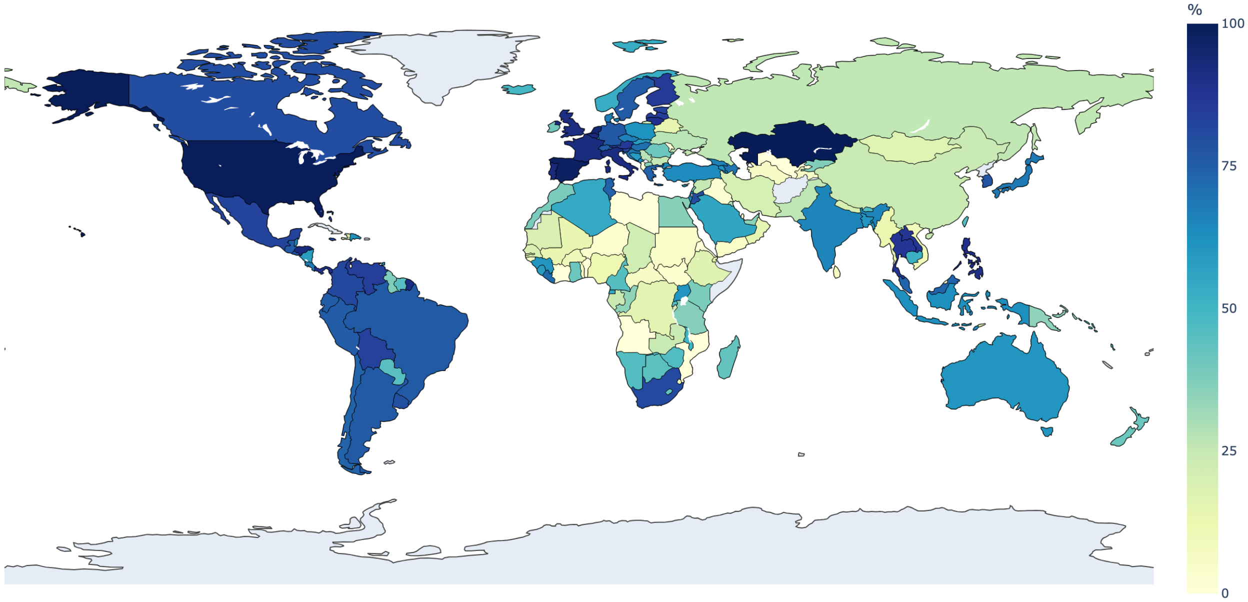


Figure 2: Explained Variance by Factors

Note: The figure visualizes the share of explained variance attributable to all combined factor groups across individual economies. Dark shades indicate higher explained variance.

Table 1. 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	0.49	0.11	0.04	0.07	0.59	0.68
Asia	0.24	0.07	0.04	0.11	0.30	0.43
The Caucasus	0.30	0.47	0.06	0.08	0.78	0.89
Europe	0.67	0.05	0.04	0.04	0.71	0.77
Latin America	0.54	0.07	0.02	0.15	0.61	0.78
Middle East and North Africa	0.18	0.07	0.06	0.12	0.22	0.29
North America	0.69	0.22	0.05	0.00	0.92	0.98
Sub-Saharan Africa	0.37	0.13	0.12	0.16	0.43	0.39

Note: The table reports the share of explained variance attributable to each factor group and to selected combinations of factors at the global level and across regions.

respectively. Figures 6a and 6b show that the main driving force in these regions are the idiosyncratic terms, i.e., country-unique movements, even if global factors are still highly impactful.

A similar pattern emerges when focusing explicitly on low-income developing economies (LIDCs), which are concentrated in regions such as Sub-Saharan Africa and parts of the Middle East and North Africa. Using the variance decompositions reported in Table 1 and the detailed breakdown in Appendix 5, global and regional factors account for a noticeably smaller share of GDP volatility in these economies than in advanced economies, while income-group and activity-specific factors—together with idiosyncratic components—play a comparatively larger role. This underscores the importance of allowing for rich heterogeneity in the model, rather than relying solely on a single global factor, utilizing more economy-specific and sector-driven dynamics precisely where quarterly data are scarcest.

Persistent factors indicate lasting impacts of co-movement or shocks, while less persistent factors reflect more transient, local disturbances. Persistence is summarized by the estimated autoregressive coefficient(s) governing each factor's dynamics; in Table 2, it is represented by the implied first-order autoregressive parameter for each factor group. 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, the global comovement series has the least persistence across all factors.

Table 2. Persistence by Global, Region, Income Level, and Economic Activity Factors

Global:	Global Factor						
	0.61						
Region:	Latin America and Caribbean	Sub-Saharan Africa	North America	Europe	Asia	MENA	CIS
	0.74	0.17	0.82	0.91	0.82	0.84	0.72
Income Level:	Low-Income Developing Economies	Emerging Markets	Advanced Economies				
	0.81	0.88	0.93				
Economic Activity:	Primary Non-fuel Exporter	Fuel Exporter	Manufacturing	Tourism	Services	Other	
	0.91	0.85	0.85	0.93	0.93	0.93	

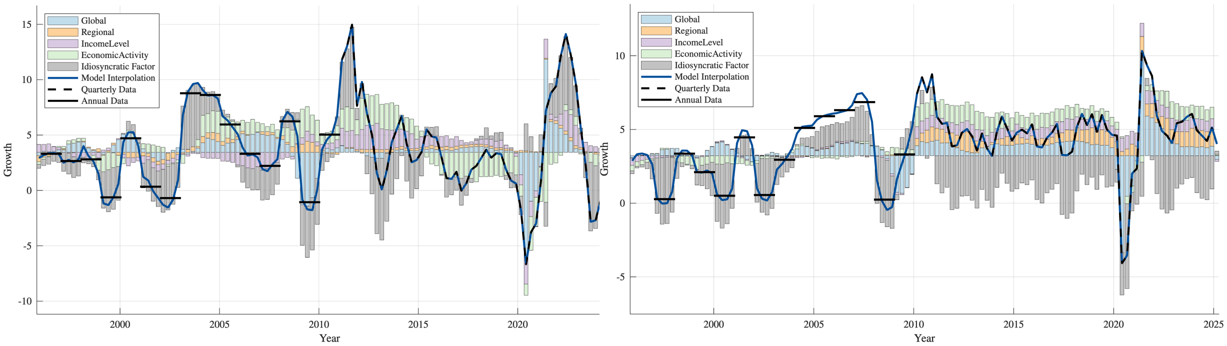
Note: Each entry reports the implied first-order autoregressive coefficient for the corresponding factor group; values closer to one indicate higher persistence.

3.1 Country Level Estimation Results

To illustrate the performance of the model at the country level, we focus on Saudi Arabia and Kenya, which transitioned from annual-only to quarterly reporting in 2010. Figure 3 compares actual and model-based quarterly growth rates, decomposing the estimates into factor contributions.

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 important 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 the actual quarterly series and the one obtained through our proposed methodology suggests strong robust

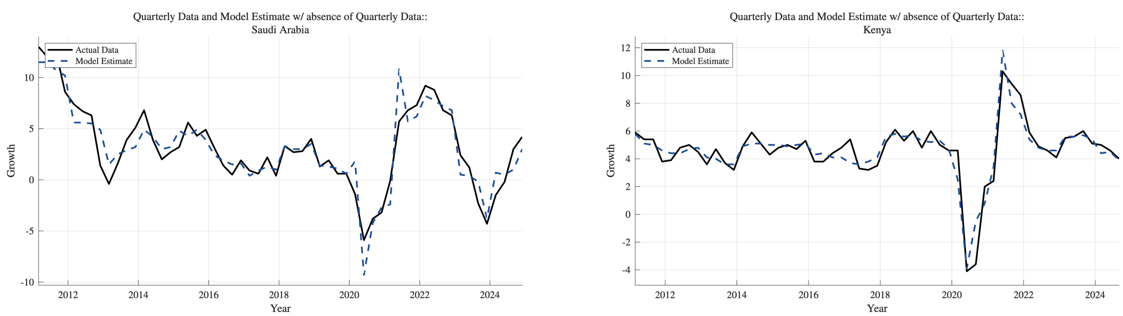


(a) Saudi Arabia (b) Kenya

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.

behavior of the methodology, as depicted in Figure 4 below[12].



(a) Saudi Arabia (b) Kenya

Figure 4: Quarterly GDP Estimates with Absence of Actual Data

3.2 Aggregate Estimation Results

Aggregating estimated quarterly growth across economies yields global growth series:

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

where $\omega_{j,t}$ denotes the weight for country j in year t, calculated annually as the ratio of nominal GDP in US dollars for country j to total global GDP. This approach facilitates the decomposition of global growth into contributions from each factor.

Figure 5 shows the model estimate and individual factor contributions for global GDP growth[13]. The global factor is the dominating force explaining global GDP variation especially around the great financial crisis of 2008, the COVID-19 pandemic and the subsequent

[12] Estimation results for all 196 economies, including counterfactual exercises, are available through an interactive dashboard at `https://sites.google.com/view/farukakbal/global-nowcasting`.

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

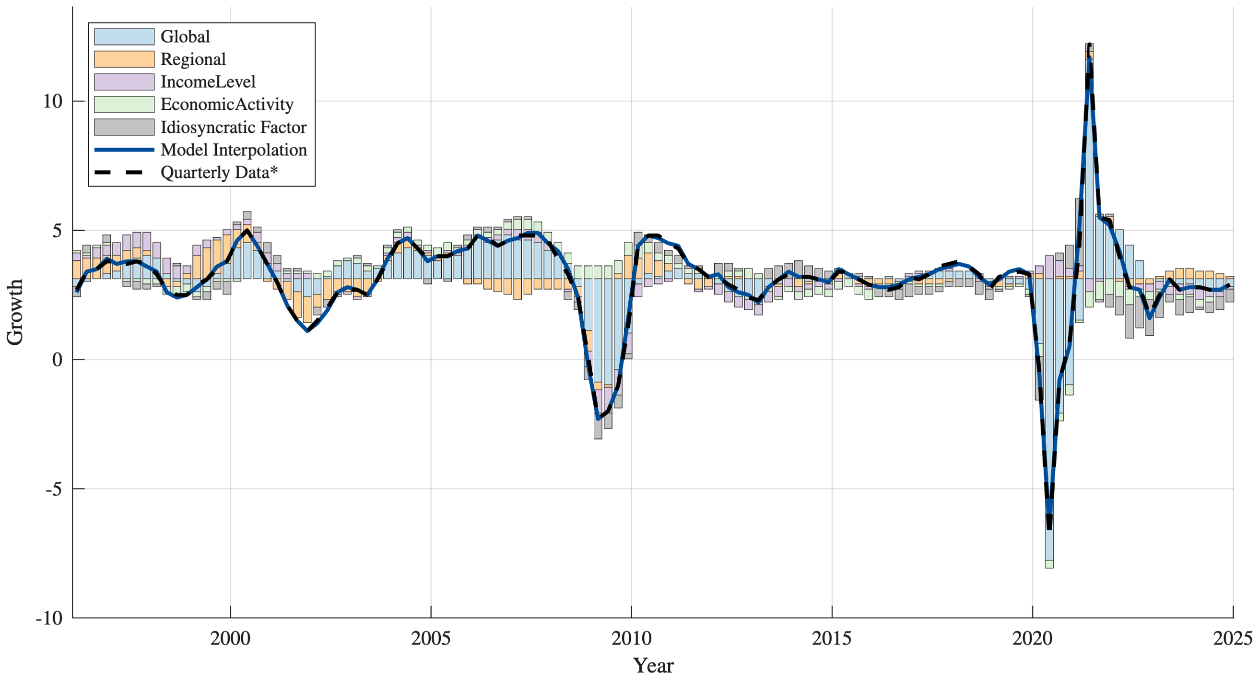


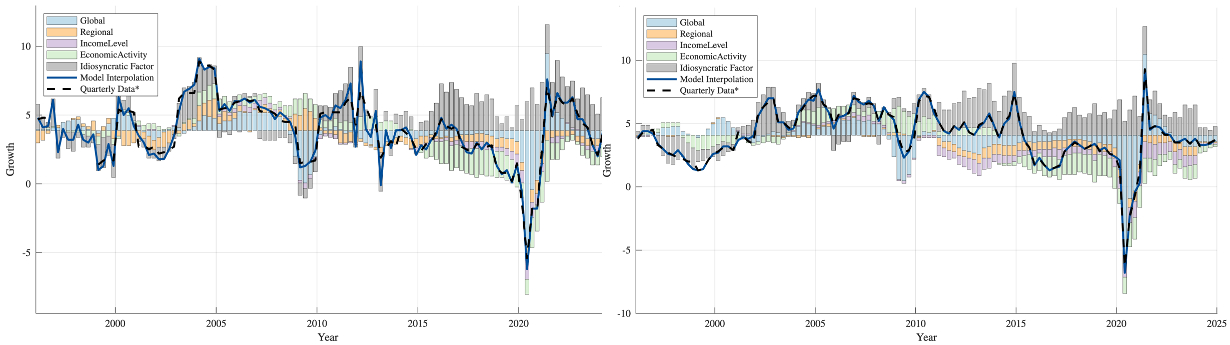
Figure 5: Global GDP Data, Model Estimate and Factor Contributions

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.

recovery. The global factor explains 54 percent of the overall variation. Regional factors contribute about 11 percent of the overall variation. All four factors account for close to three-quarters of global cyclical activities.

The model is estimated over a sample that spans several large global shocks and structural breaks, including the global financial crisis, the COVID-19 pandemic, and major data revisions or rebasing episodes in some economies. These events are primarily captured through movements in the global factor and, to a lesser extent, regional factors, which allows the framework to accommodate shifts in volatility and co-movement patterns, although sudden regime changes can still generate temporary discrepancies between model-implied and realized dynamics.

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 7 shows that, prior to 2000s, the overall variation is mostly driven by regional factors, while 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 6: 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.

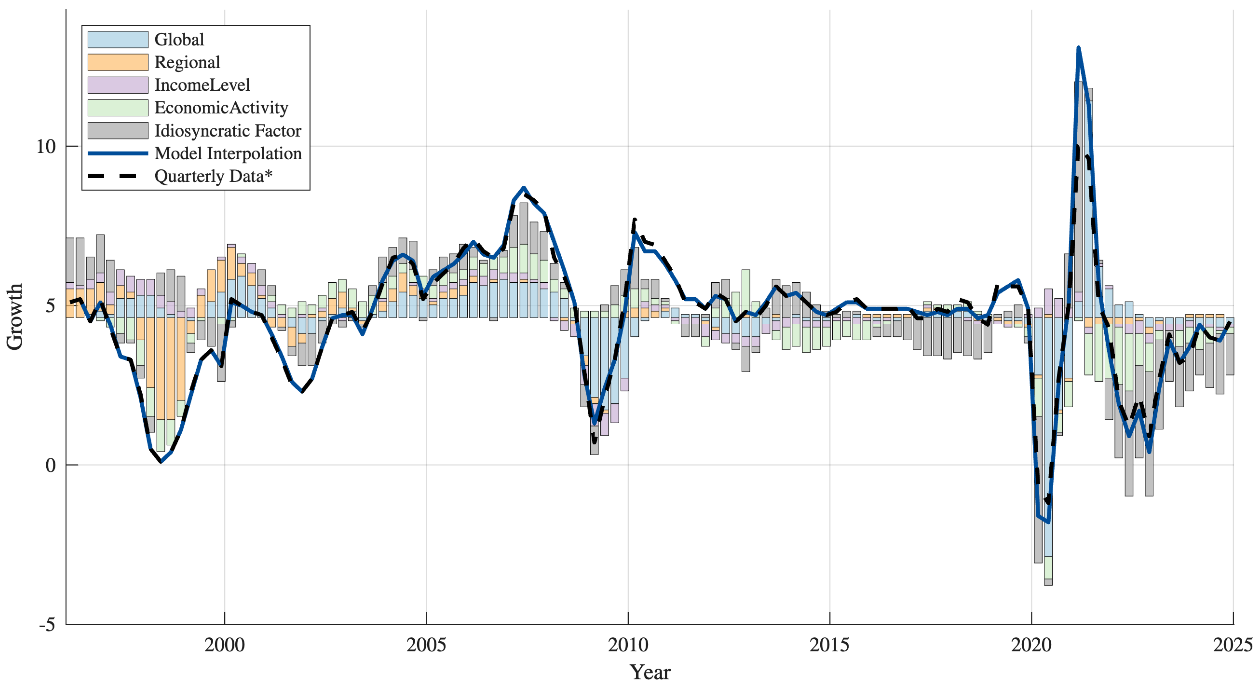


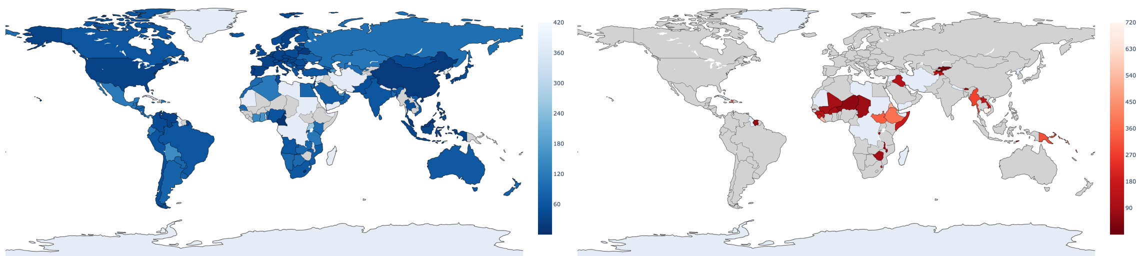
Figure 7: Asia GDP Data, Model Estimate and Factor Contributions

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 External Validation Exercise

In addition to the heterogeneity in data frequency across national statistical systems, countries also differ in the timeliness with which they publish the latest growth figures. To assess how much variation in data release lags affects the performance of the methodology, we propose and implement a systematic test.

Release lags for countries reporting quarterly GDP are generally shorter than those for countries reporting only annual data. Figure 8 illustrates the cross-country distribution. For countries reporting data at a quarterly frequency, median release lags are roughly 90 days. For countries reporting only annual data, 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 14 in Appendix C.



(a) Countries with quarterly statistics (b) Countries with annual statistics

Figure 8: 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 8a displays release lags for countries reporting data quarterly, while Figure 8b presents lags for countries publishing data only annually. Countries that publish the national statistics in quarterly frequency is excluded from Figure 8b since partial information is available over the year.

The IMF's World Economic Outlook (WEO) publishes annual GDP growth projections twice a year—in October and April—providing the most widely used benchmark for economy-level growth estimates. A notable feature of WEO projections is their high persistence: for emerging market and developing economies over 2018–2023, the correlation between the October and April projections for the same reference year averages 0.94, and the mean absolute revision is only 1.2 percentage points.[14] The corresponding figures for the model are a cross-vintage correlation of 0.61 and a mean absolute revision of 3.2 percentage points, reflecting the information-sensitive nature of the model as it incorporates new quarterly releases from across the global panel between meetings.

Among the 157 emerging market and low-income economies, 66 report GDP only at annual frequency—38 low-income developing economies and 28 emerging markets. Table 3 documents how much the data release lags constitute a problem in addition to the data frequency.

At the October meeting of year t, about 47% of the sample have second-quarter data as their most recent release. On the annual side, 24% of the sample have year $t-1$ data and 10% remain at year $t-2$. By April $t+1$, the quarterly side largely catches up—47% of the sample now have fourth-quarter data—but the annual side moves slowly: only 9% have published year t figures and 22% still have year $t-1$ as their latest. Even by October $t+1$, a quarter of annual-only economies have yet to publish year t data.

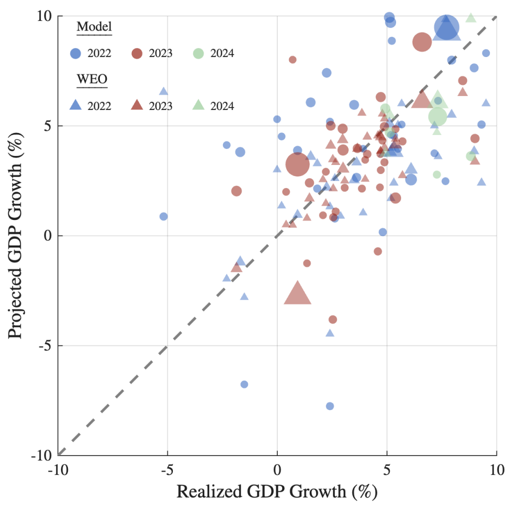
[14]Excluding the pandemic years 2020–2021, these figures are 0.92 and 0.8 percentage points, respectively.

Table 3. Data Availability at WEO Vintage Dates: Emerging Market and Developing Economies (%)

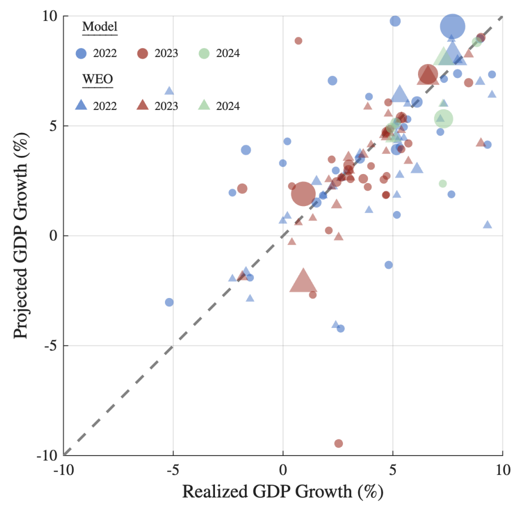
Vintage	Quarterly GDP $[t-1]_{\text{Q3}}$	$[t-1]_{\text{Q4}}$	t_{Q1}	t_{Q2}	t_{Q3}	t_{Q4}	Annual-Only GDP $t-2$	$t-1$	t
Oct t	1.5%	1.5%	14.8%	47.4%	0%	0%	9.6%	23.7%	0%
Apr $t+1$	0%	0.7%	1.5%	1.5%	15.6%	46.7%	3.7%	21.5%	8.9%
Oct $t+1$	0%	0%	0%	0.7%	1.5%	63.7%	1.5%	8.9%	23.7%

Note: For each economy, the observed release lag is subtracted from the vintage date; the most recent reference-period end date on or before that date determines the column. Each cell reports the share of the 135 tracked EMDEs (%). Year $t = 2025$. Of the 157 EMDEs in the model, 91 report quarterly GDP and 66 report only annual data (38 LIDCs and 28 EMs). 135 have release lag data; 22 are excluded.

To compare the model's performance against WEO projections for economies that report only annual GDP, Figure 9 pools three reference years—2022, 2023, and 2024—and plots both model estimates and WEO projections against realized growth for annual-only EMDEs at two set of vintage dates: October of the reference year and April of the following year.[15]



(a) October release



(b) April release

Figure 9: Realized vs. projected annual GDP growth: annual-only economies, 2022–2024

Note: Each panel pools 2022, 2023, and 2024 for annual-only emerging market and developing economies. Only economies with published realized GDP are included. Blue circles show model estimates; red circles show WEO projections. Bubble sizes are proportional to nominal GDP weight. Economies whose data had been released by the vintage date are excluded, resulting in fewer observations in panel (b).

At the October vintage, neither the model nor the WEO has access to the reference-year figure for any of these economies. Both sets of projections cluster around the 45-degree line with notable dispersion. By April, the information set has improved—quarterly releases from

[15]Only economies for which the realized annual GDP growth has been published in the national accounts are included. Economies whose data had been released by the vintage date are excluded from the corresponding panel based on observed release lags. As a result, 2024 contributes relatively few observations since most annual-only economies have not yet published 2024 GDP.

global and regional partners have accumulated—and projections tighten accordingly. That a purely statistical framework, without economy-specific input, achieves comparable accuracy to the WEO underscores the informational content of cross-country comovement for these data-scarce economies. This comparison is particularly noteworthy given that the WEO draws on a wide range of additional information sources—including trade flows, financial data, surveys, and the expertise of dedicated country desks—that are not available to the model. Incorporating such economy-specific information into the framework is a natural next step, and Danov et al. (2026) demonstrates how this can be done for the case of Kenya.

5 Conclusion

Timely monitoring of macroeconomic conditions in low-income countries is difficult when GDP is available only at an annual frequency: one must wait until after the year is over—and often much longer—to learn what happened. Even in low-income countries that do publish quarterly GDP, release lags are substantial. The situation is much less challenging in advanced and emerging market economies, where statistical offices produce quarterly figures and release them in a more timely manner. At the same time, low-income economies comove significantly with these data-rich economies. This paper takes advantage of that comovement, using the timely quarterly data from advanced and emerging market economies to obtain an early assessment of economic activity in low-income countries.

This paper shows that strong comovement in world business cycles makes it possible to obtain early estimates of economic activity for countries with significant delays in producing official statistics. This is particularly important for low-income countries that publish only annual GDP data. The strongly connected business cycles are also useful to cross-check the coherency of forecasts across countries and for scenario-based analysis, allowing analysts to check how trajectories for the world business cycle translate into expected trajectories for country or regional dynamics and vice versa.

The approach faces its most demanding test in Sub-Saharan Africa and the Middle East, where country-specific dynamics play a comparatively larger role. Yet even in these regions, the model's projections are competitive with the IMF's World Economic Outlook—a benchmark informed by country-level judgment and desk expertise. That a framework relying entirely on cross-country comovement performs well where the signal-to-noise ratio is lowest underscores the breadth of economic interconnections that the model captures. It also highlights a practical advantage: the model is fully transparent, judgment-free, and replicable, providing a robust benchmark against which any forecast incorporating subjective assessments can be compared.

A natural extension is to enrich the indicators for each country with timely within-country data—such as industrial production, trade flows, surveys, and financial variables—that are routinely used in single-country nowcasting models. Combining the cross-country comovement structure developed here with high-frequency domestic data would allow for more frequent updates and improved forecast accuracy, particularly as new monthly or weekly releases become available within a quarter. 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:

$$v_t^M = \frac{V_t^M}{V_{t-12}^M} - 1 \tag{4}$$

$$v_t^Q = \frac{\sum_{j=0}^{2} V_{t-j}^M}{\sum_{j=0}^{2} V_{t-12-j}^M} - 1 \tag{5}$$

By substituting (4) into (5), we obtain:

$$\begin{aligned} v_t^Q &= \frac{(1+v_t^M)V_{t-12}^M + (1+v_{t-1}^M)V_{t-13}^M + (1+v_{t-2}^M)V_{t-14}^M}{V_{t-12}^M + V_{t-13}^M + V_{t-14}^M} - 1 & (6)\\ &= \frac{(v_t^M)V_{t-12}^M + (v_{t-1}^M)V_{t-13}^M + (v_{t-2}^M)V_{t-14}^M}{V_{t-12}^M + V_{t-13}^M + V_{t-14}^M} & (7) \end{aligned}$$

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

$$v_t^Q \approx \frac{1}{3}(v_t^M + v_{t-1}^M + v_{t-2}^M) \tag{8}$$

Similarly, the annual growth can be approximated as:

$$v_t^A \approx \frac{1}{12}(\sum_{j=0}^{11} v_{t-j}^M) \tag{9}$$

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:

$$\begin{bmatrix} y_t^M \\ v_t^Q \\ v_t^A \end{bmatrix} = \begin{bmatrix} \multicolumn{2}{c}{\boldsymbol{\Lambda}} \\ \frac{1}{3}\mathbb{1}_{3x1} & \emptyset_{9x1} \\ \multicolumn{2}{c}{\frac{1}{12}\mathbb{1}_{\boldsymbol{12x1}}} \end{bmatrix} \begin{bmatrix} \boldsymbol{f_t} \\ \vdots \\ \boldsymbol{f_{t-11}} \end{bmatrix} + \varepsilon_t \tag{10}$$

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

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + e_t, \quad e_t \overset{\text{iid}}{\sim} N(0, R) \tag{11}$$

Alternative Model: While the above assumption, that previous period GDP volumes are sufficiently close to allow the approximation from (6) to (8), 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:

$$v_{13}^M \approx \frac{V_{13}^M}{V_1^M} - 1 \tag{12}$$

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

$$\tag{14}$$

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,

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

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 (15), 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:

$$v_t^Q \approx \alpha_3 \times v_t^M + \alpha_2 \times v_{t-1}^M + \alpha_1 \times v_{t-2}^M \tag{16}$$

The annual growth rates can be approximated as shown in equations (12) to (16):

$$v_t^A \approx \beta^{12} \times v_t^M + \beta^{11} \times v_{t-1}^M + \ldots + \beta^1 \times v_{t-11}^M \tag{17}$$

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

$$\begin{bmatrix} y_t^M \\ v_t^Q \\ v_t^A \end{bmatrix} = \begin{bmatrix} \multicolumn{2}{c}{\boldsymbol{\Lambda}} \\ \alpha_{3x1}^i & \emptyset_{9x1} \\ \multicolumn{2}{c}{\beta_{12x1}^i} \end{bmatrix} \begin{bmatrix} \boldsymbol{f_t} \\ \vdots \\ \boldsymbol{f_{t-11}} \end{bmatrix} + \varepsilon_t \tag{18}$$

where

$$\sum_{1}^{3} \alpha^i = 1, \quad 0 < \alpha^i < 1 \quad \forall i \in 1,2,3 \tag{19}$$

$$\sum_{1}^{12} \beta^i = 1, \quad 0 < \beta^i < 1 \quad \forall i \in 1,2,\ldots,12 \tag{20}$$

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

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + e_t, \quad e_t \overset{\text{iid}}{\sim} N(0,R) \tag{21}$$

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

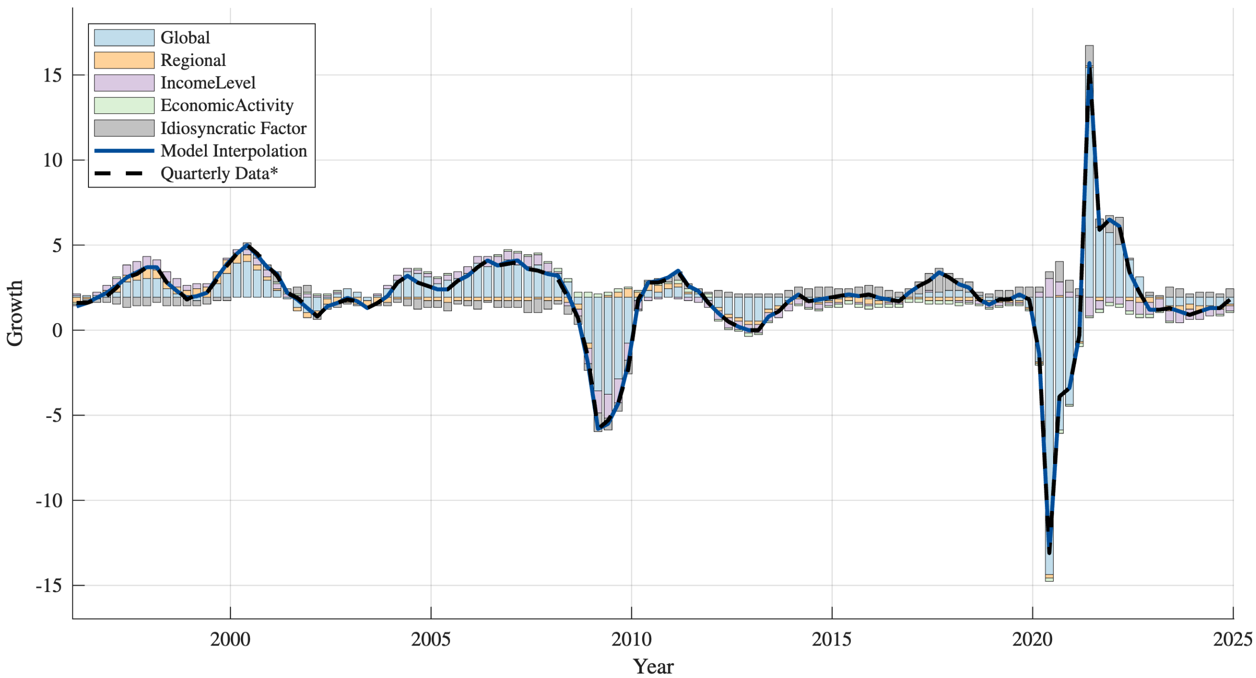

Figure 10: Europe GDP Data, Model Estimate and Factor Contributions

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.

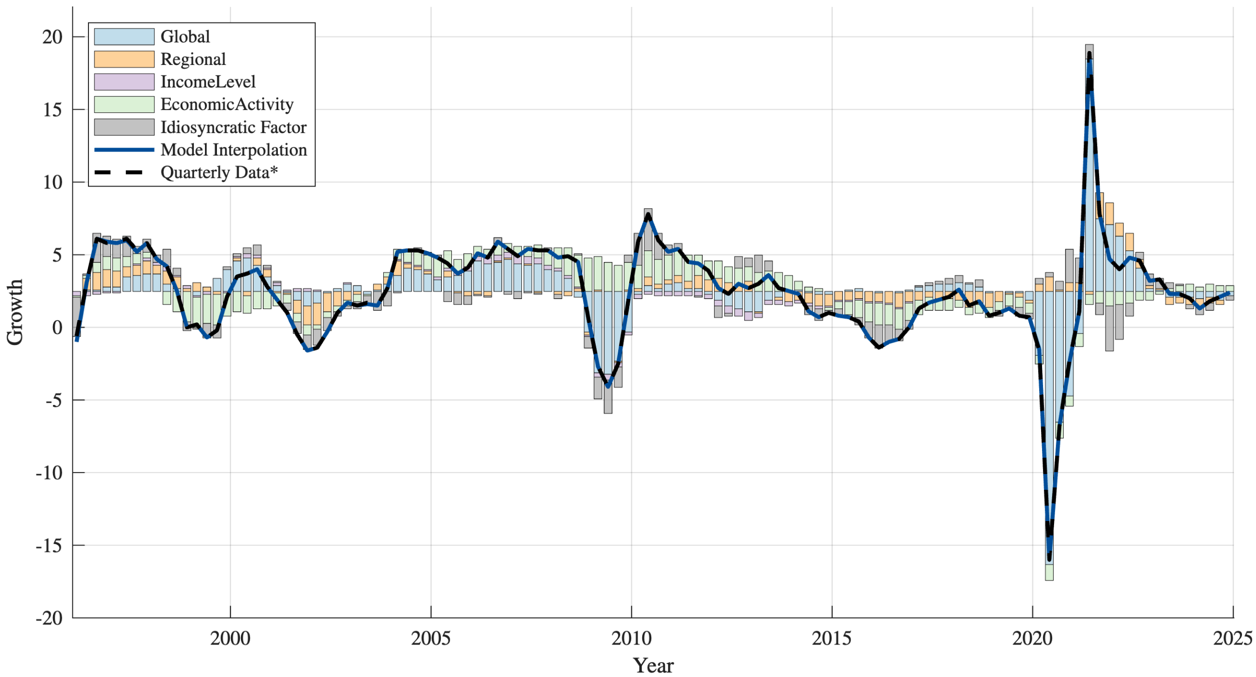

Figure 11: Latin America and Caribbeans GDP Data, Model Estimate and Factor Contributions

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.

C. Data Release Lags by Economy

Table 4. Release lags of national accounts statistics for quarterly GDP economies

Economy	Rel. Lag	Economy	Rel. Lag
United States	30	Hong Kong Special Administrative Region, People's Republic of China	32
United Kingdom	45	India	60
Austria	30	Indonesia	35
Belgium	30	Korea, Republic of	24
Denmark	30	Macao Special Administrative Region, People's Republic of China	46
France	30	Malaysia	18
Germany	30	Maldives	91
Italy	30	Pakistan	50
Luxembourg	67	Philippines	38
Netherlands, The	30	Singapore	13
Norway	45	Thailand	49
Sweden	29	Vietnam	65
Switzerland	44	Algeria	120
Canada	60	Angola	60
Japan	45	Botswana	91
Finland	60	Cameroon	7
Greece	67	Benin	81
Iceland	60	Ghana	162
Ireland	29	Côte d'Ivoire	141
Malta	59	Kenya	93
Portugal	32	Lesotho, Kingdom of	4
Spain	29	Mauritius	88
Turkey, Republic of	60	Morocco	91
Australia	65	Mozambique, Republic of	70
New Zealand	80	Nigeria	56
South Africa	64	Rwanda	81
Argentina	84	Seychelles	88
Bolivia	148	Senegal	88
Brazil	60	Namibia	87
Chile	49	Tanzania, United Republic of	113
Colombia	45	Togo	289
Costa Rica	91	Tunisia	45
Dominican Republic	120	Uganda	259
Ecuador	120	Zambia	87
El Salvador	88	Samoa	121
Guatemala	120	Armenia, Republic of	51
Honduras	86	Azerbaijan, Republic of	164
Mexico	120	Belarus, Republic of	17
Nicaragua	78	Albania	86
Panama	136	Georgia	80
Paraguay	87	Kazakhstan, Republic of	112
Peru	60	Bulgaria	45
Uruguay	73	Moldova, Republic of	77
Venezuela, República Bolivariana de	31	Russian Federation	101
Bahamas, The	150	China, People's Republic of	18
Belize	85	Ukraine	84
Jamaica	90	Uzbekistan, Republic of	98
Trinidad and Tobago	265	Czech Republic	30
Bahrain, Kingdom of	147	Slovak Republic	45
Cyprus	45	Estonia, Republic of	30
Israel	30	Latvia, Republic of	60
Jordan	374	Serbia, Republic of	30
Kuwait	127	Montenegro	67
Oman	84	Hungary	30
Qatar	79	Lithuania, Republic of	30
Saudi Arabia	70	Mongolia	46
United Arab Emirates	166	Croatia, Republic of	58
Egypt, Arab Republic of	85	Slovenia, Republic of	45
West Bank and Gaza	85	North Macedonia, Republic of	64
Bangladesh	98	Bosnia and Herzegovina	90
Brunei Darussalam	87	Poland, Republic of	45
Sri Lanka	77	Kosovo, Republic of	78
Taiwan Province of China	58	Romania	45

Note: Release lags are computed as the difference, in days, between the publication date and the end of the corresponding quarter.

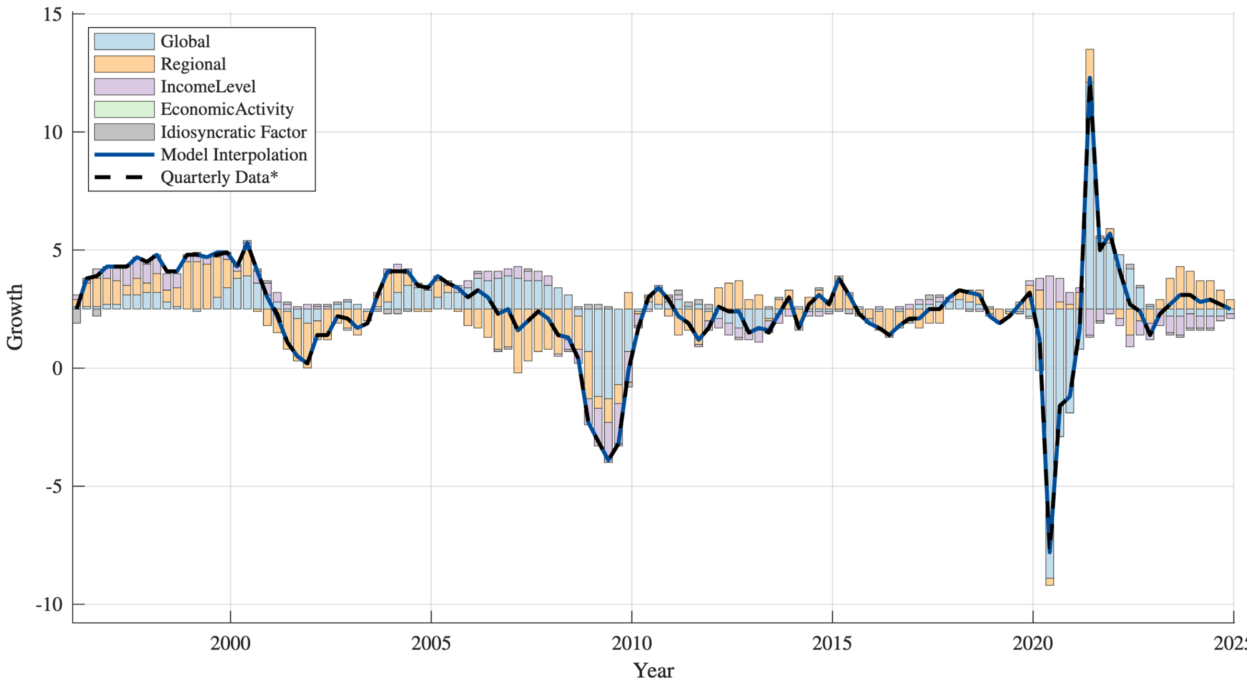

Figure 12: North America GDP Data, Model Estimate and Factor Contributions

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.

D. Trade Shares of Economies with Quarterly Data

Consider a universe of countries partitioned into two sets:

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

$$EX_t^{NQ} = \sum_{i\in\Omega^{NQ}} \sum_{j} X^t_{i\to j}$$

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:

$$SHARE_t^{NQ\to S} = \frac{\sum_{i\in\Omega^{NQ}} \sum_{k\in S} X^t_{i\to k}}{EX_t^{NQ}}$$

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

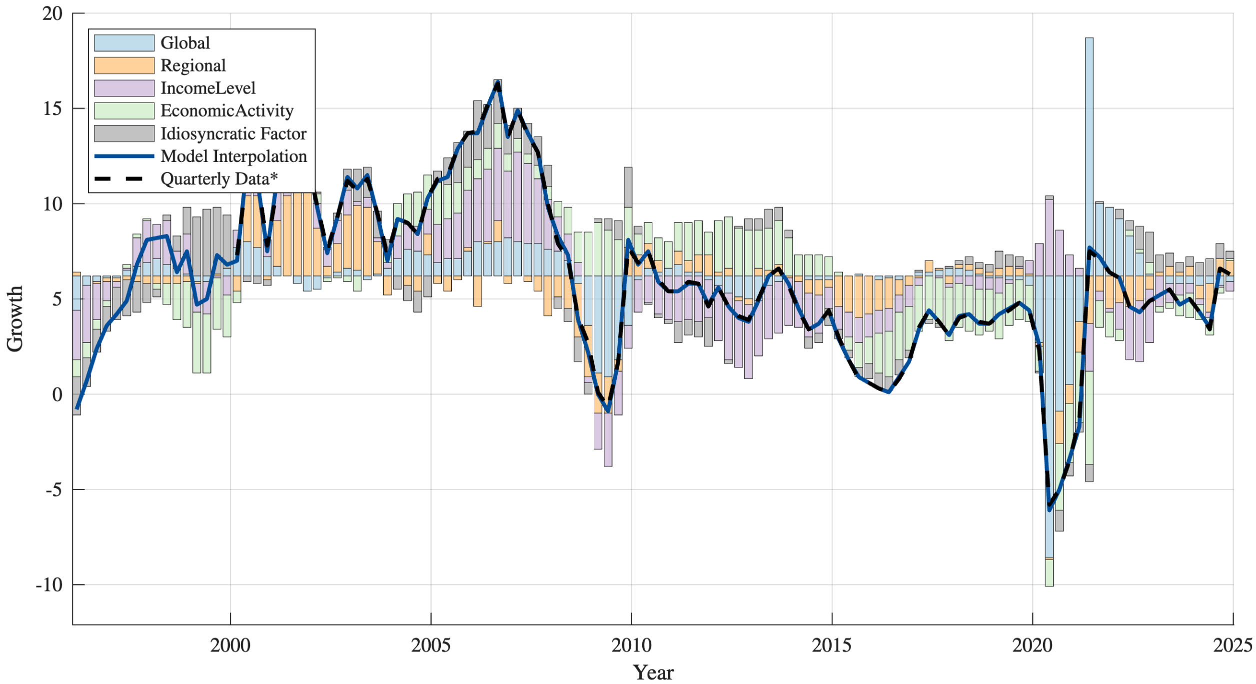

Figure 13: The Caucasus GDP Data, Model Estimate and Factor Contributions

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.

E. Quarterly Data Availability in Global Statistics

Table 5. Release lags of national accounts statistics for annual GDP economies

Economy	**Rel. Lag**	**Economy**	**Rel. Lag**
San Marino, Republic of	136	Eritrea, The State of	522
Haiti	337	Ethiopia, The Federal Democratic Republic of	375
Antigua and Barbuda	401	Gambia, The	123
Anguilla, United Kingdom-British Overseas Territory	167	Guinea	120
Aruba, Kingdom of the Netherlands	406	Liberia	555
Barbados	34	Malawi	60
Dominica	167	Mali	91
Grenada	167	Niger	56
Montserrat, United Kingdom-British Overseas Territory	167	Zimbabwe	86
St. Kitts and Nevis	167	São Tomé and Príncipe, Democratic Republic of	149
St. Lucia	167	Sierra Leone	182
St. Vincent and the Grenadines	167	Somalia	181
Suriname	68	South Sudan, Republic of	336
Cayman Islands	235	Eswatini, Kingdom of	158
Iraq	124	Burkina Faso	89
Bhutan	65	Solomon Islands	423
Myanmar	283	Kiribati	320
Cambodia	701	Nauru, Republic of	228
Timor-Leste, Democratic Republic of	78	Vanuatu	355
Lao People's Democratic Republic	151	Papua New Guinea	312
Palau, Republic of	121	Tonga	640
Burundi	90	Tuvalu	517
Cabo Verde	94	Kyrgyz Republic	13
Chad	78	Tajikistan, Republic of	135

Note: Release lags are computed as the difference, in days, between the publication date and the end of the calendar year.

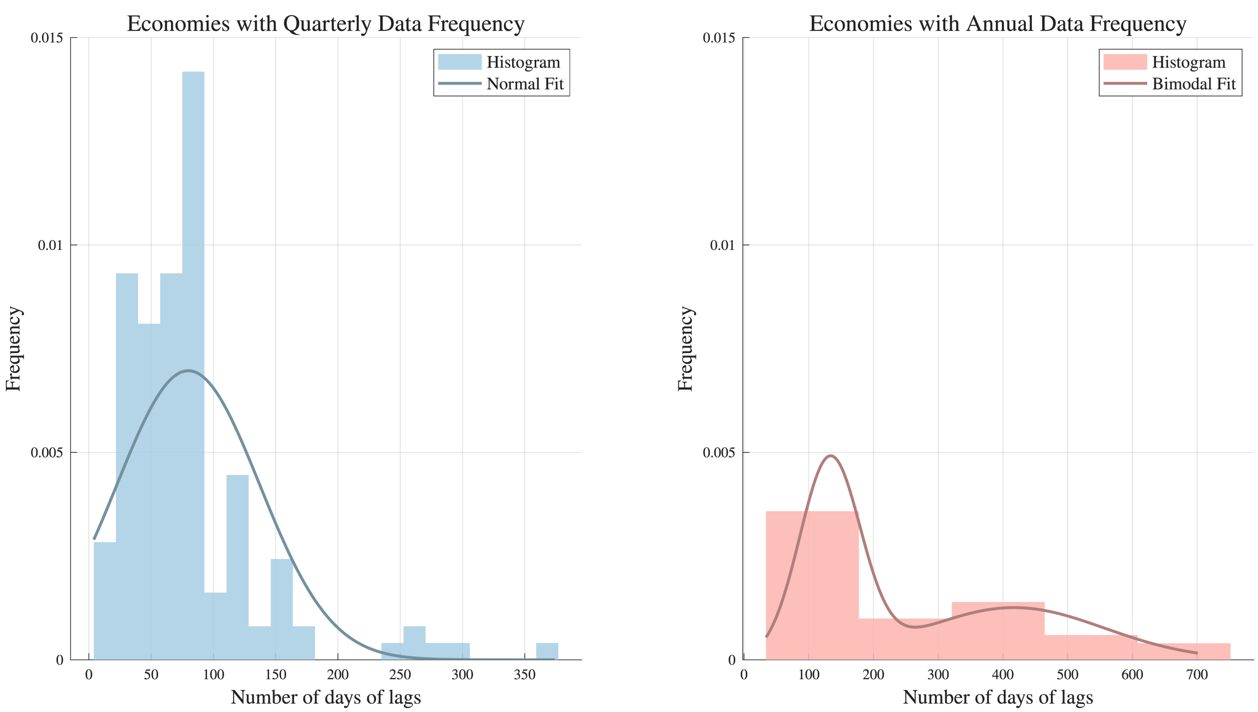

Figure 14: Distribution of Data Lags for Economies Publish National Accounts in Quarterly and Annual Frequency

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

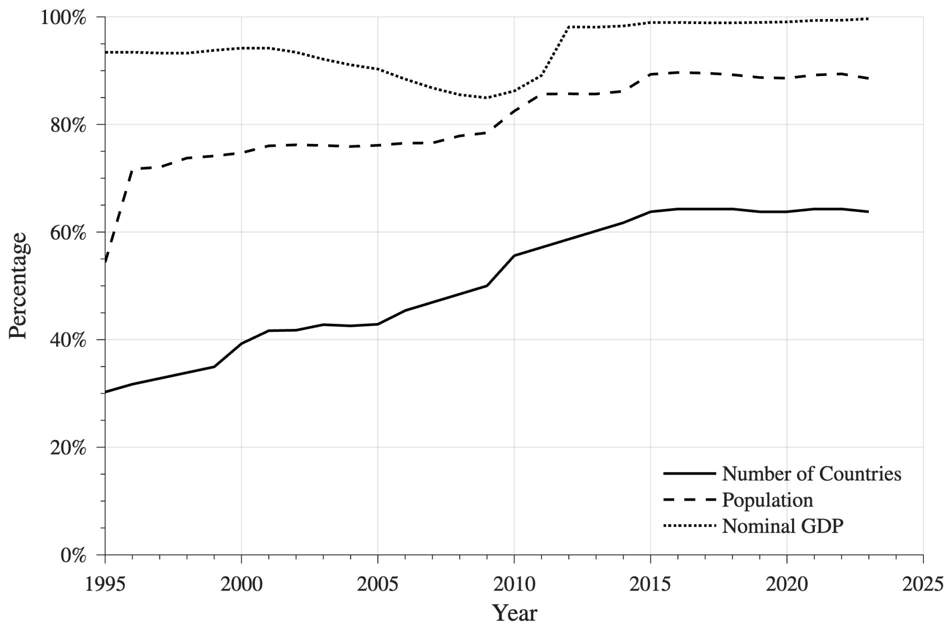

Figure 15: Global ratios of quarterly GDP data availability

Source: Author calculations, Haver Analytics.

PUBLICATIONS

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