

INTERNATIONAL MONETARY FUND

FISCAL MONITOR

Putting a Lid on Public
Debt

2024
OCT



FISCAL AFFAIRS

Fiscal Monitor

Presented by Davide Furceri

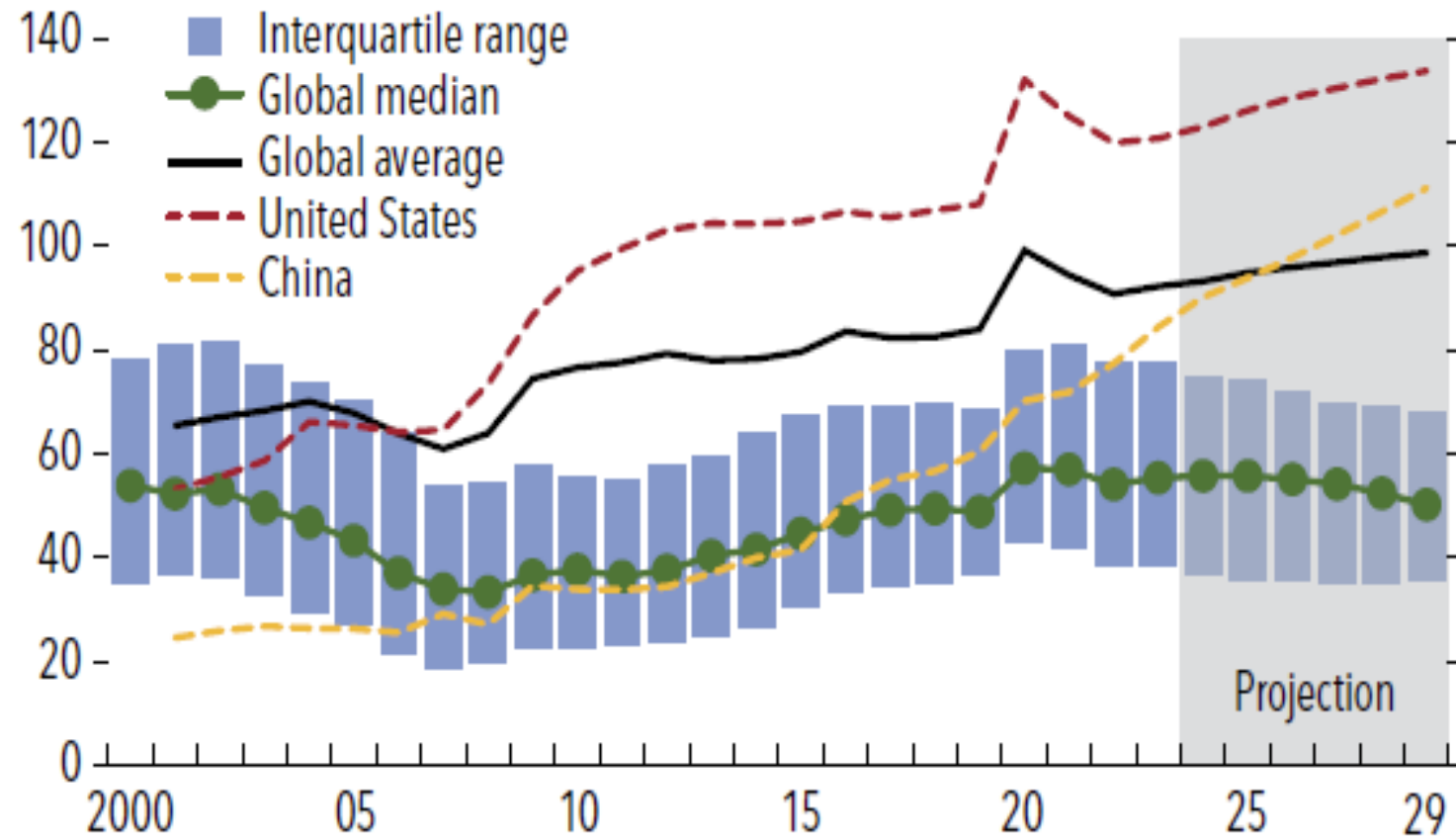
Fiscal Affairs Department

International Monetary Fund

SUERF BAFFI Bocconi e-lecture

Debt vulnerabilities are elevated

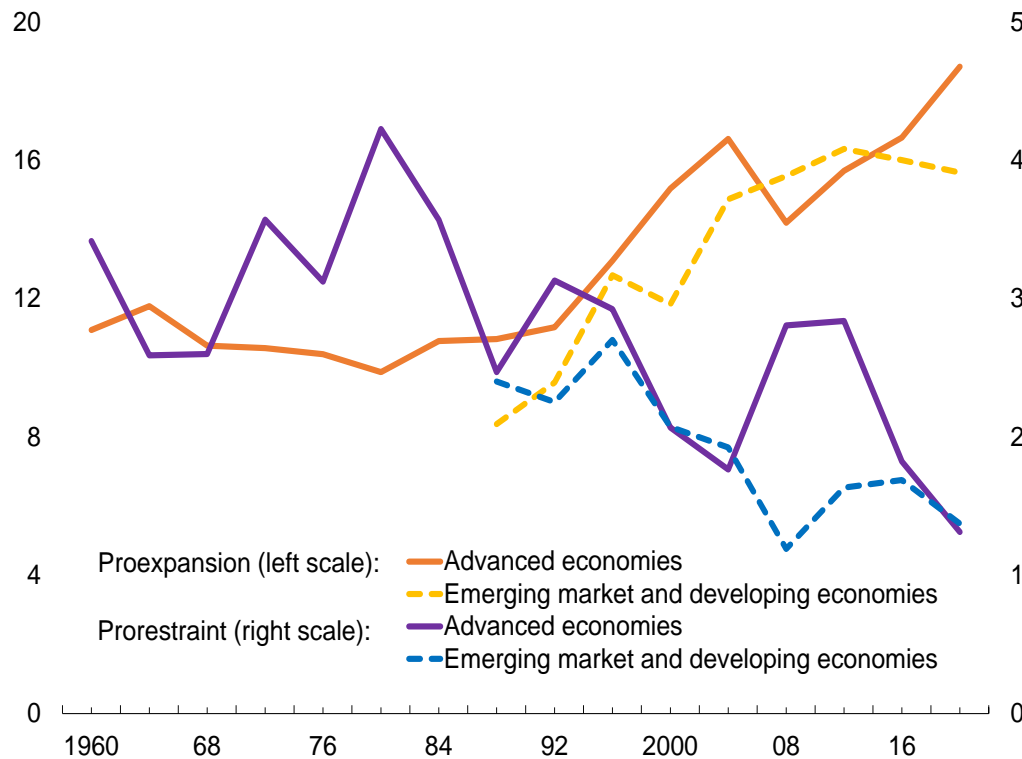
Global Public Debt, 2000–2029
(Percent of GDP)



Sources: IMF World Economic Outlook Database; and IMF staff estimates.

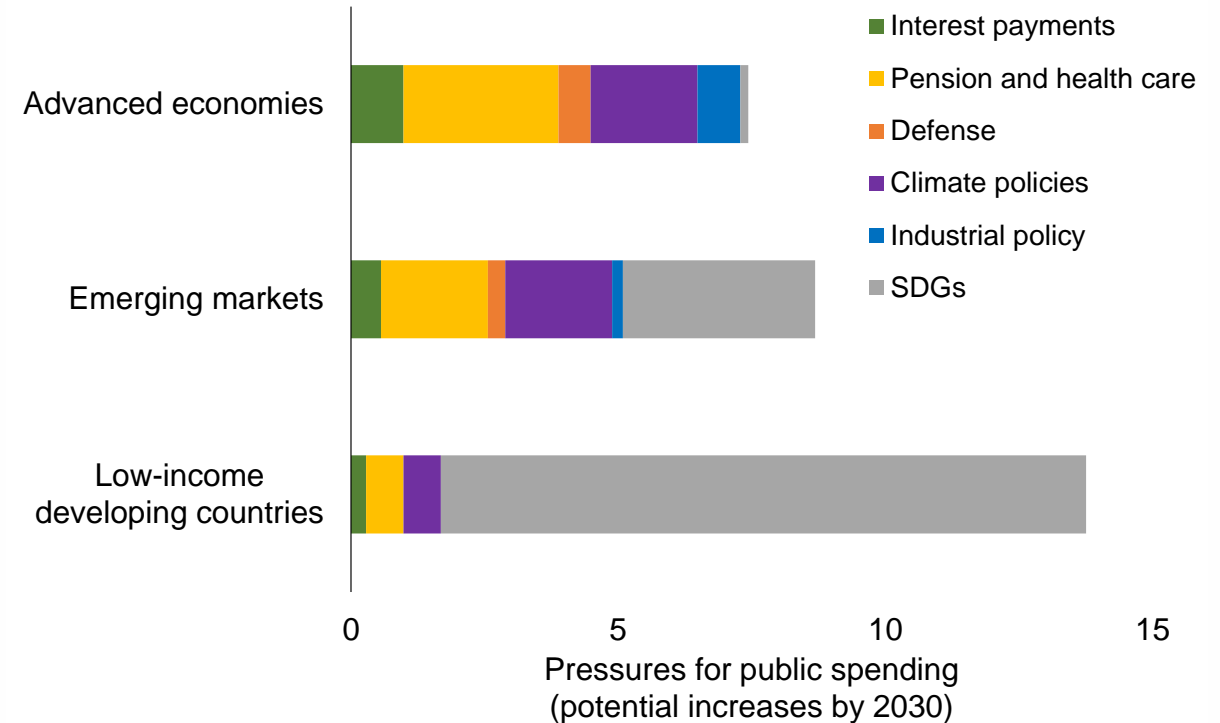
Expansionary fiscal discourse and mounting spending pressures ahead

Evolution of Fiscal Discourse by Country Groups (Percent of party platform content)



Sources: Cao, Dabla-Norris, and Di Gregorio (2024), Manifesto Project Database.

Potential Increases in Spending through 2030 (Percent of GDP)

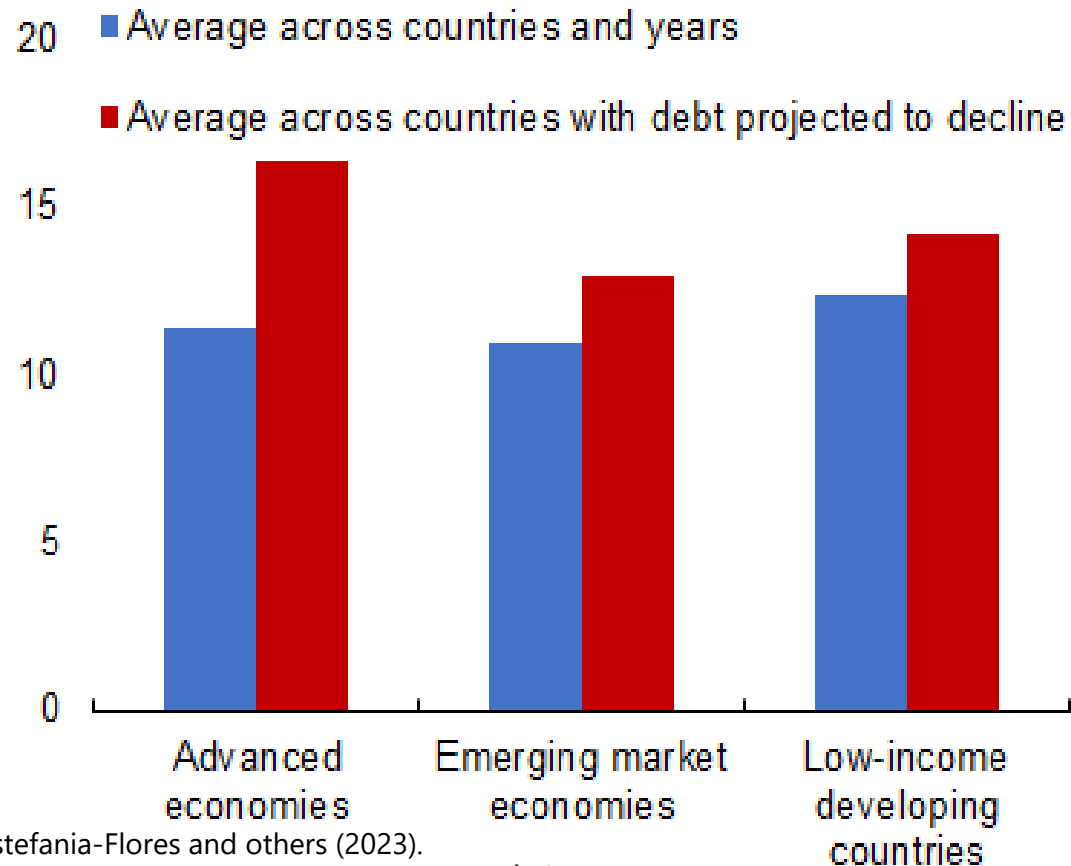


Sources: April 2024 Fiscal Monitor.

Note: For advanced and emerging market economies, climate policies include spending on both mitigation and adaptation. For low-income and developing countries, climate policies include spending only on adaptation. SDGs = UN Sustainable Development Goals.

Optimism bias in debt projections

Five-Year Forecast Errors of Public Debt Projections, 1990-2021
(Percent of GDP)



Sources: Estefania-Flores and others (2023).

Note: Forecast errors are defined as $FE_{c,h}^v = FE_{c,v,y+h}^{v,y+h+1} - FE_{c,v,y+h}^v$, where the first term refers to the forecast debt-to-GDP ratio for country c in vintage v at horizon h , and the second term is the realized debt-to-GDP ratio as reported one year after. The charts show average forecast errors at the 5-year horizon.

Key Questions

1. What is the **distribution of risks** around baseline projections for public debt?
2. How should fiscal policy be conducted to put public debt under control?
 - What is the **size of fiscal adjustments** to stabilize or reduce debt with high probability?
 - How should **fiscal adjustments be designed** to make them more socially acceptable?
 - How can governments tackle debt buildup arising from **unidentified debt**?

I. Risks Surrounding Debt Outlook

Introducing a novel Debt-at-Risk framework

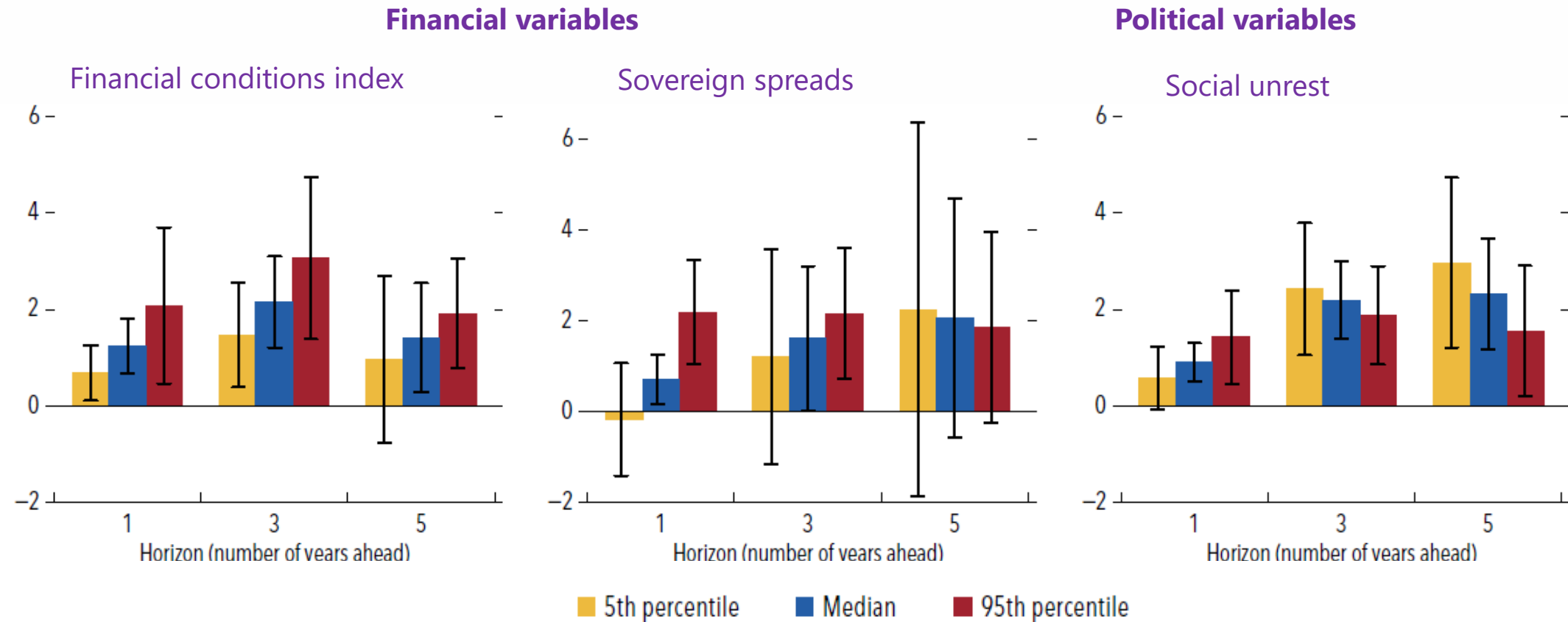
Why Debt-at-Risk?

Empirical strategy and contributions

1. Estimate panel quantile regressions for a range of financial, political, and economic variables over different horizons using a location-scale model
 - 74 advanced and emerging market economies covering more than 90 percent of global debt.
 - Debt-at-Risk (DaR) is the estimated future debt-to-GDP ratio in a severely-adverse scenario, i.e., the 95th quantile of the predicted debt level.
 - Country DaRs recentered around WEO debt forecasts.
2. Fit quantiles to a skewed t-distribution to recover the conditional density function
 - Combine densities into one using weights based on conditioning variables' out-of-sample fit.
3. Aggregate individual countries' predicted quantiles to create global distribution.
 - Recenter and combine densities for aggregates.

Adverse financial conditions and social unrest increase debt risk with asymmetric effects

Future Debt-to-GDP Ratio Predicted by Selected Financial, Political, and Economic Variables (Coefficient on Conditioning Variable in Panel Quantile Regressions Across Forecast Horizons)



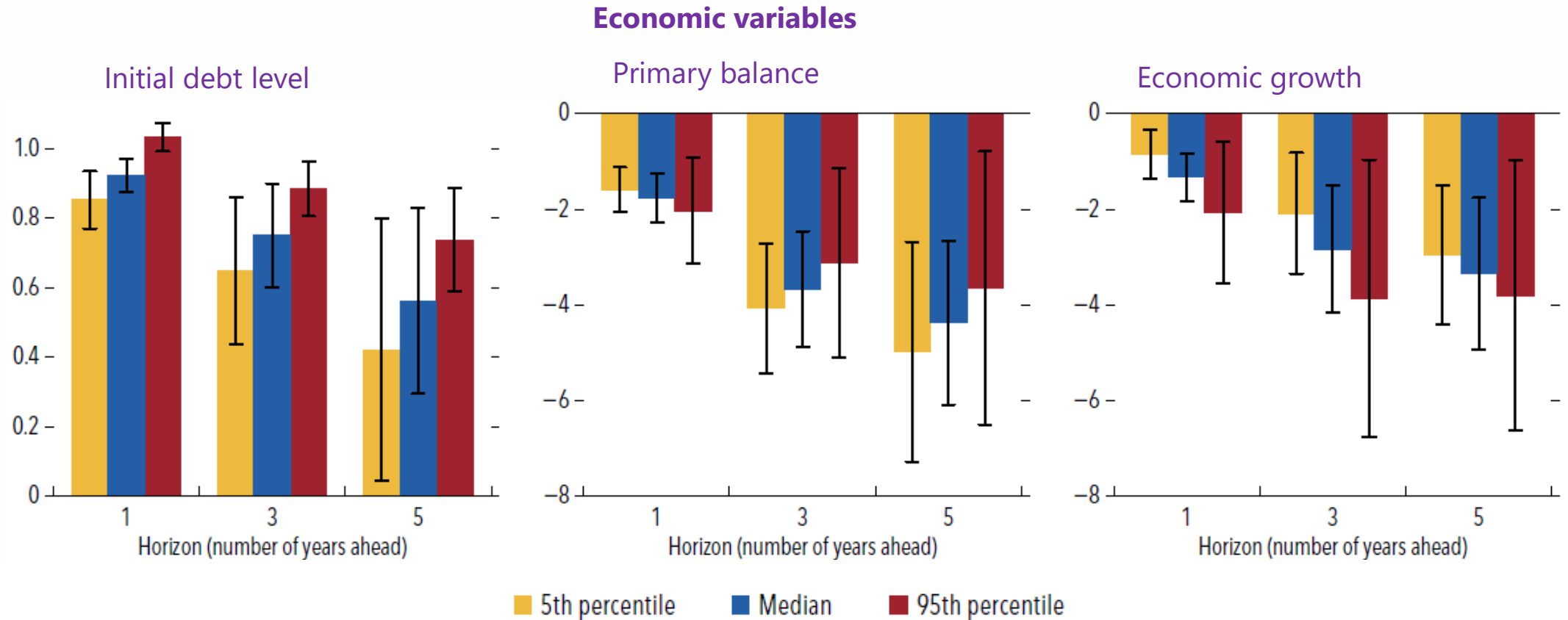
Source: IMF staff estimates.

The figure shows the estimated coefficients for 5th, 50th, and 95th percentile based on quantile regressions on selected financial, political, and economic variables. The line in each bar shows the 90 percent confidence interval of the estimated coefficient.

Initial debt level, deficits, and growth have persistent effects on debt risks

Future Debt-to-GDP Ratio Predicted by Selected Economic Variables

(Coefficient on Conditioning Variable in Panel Quantile Regressions Across Forecast Horizons)



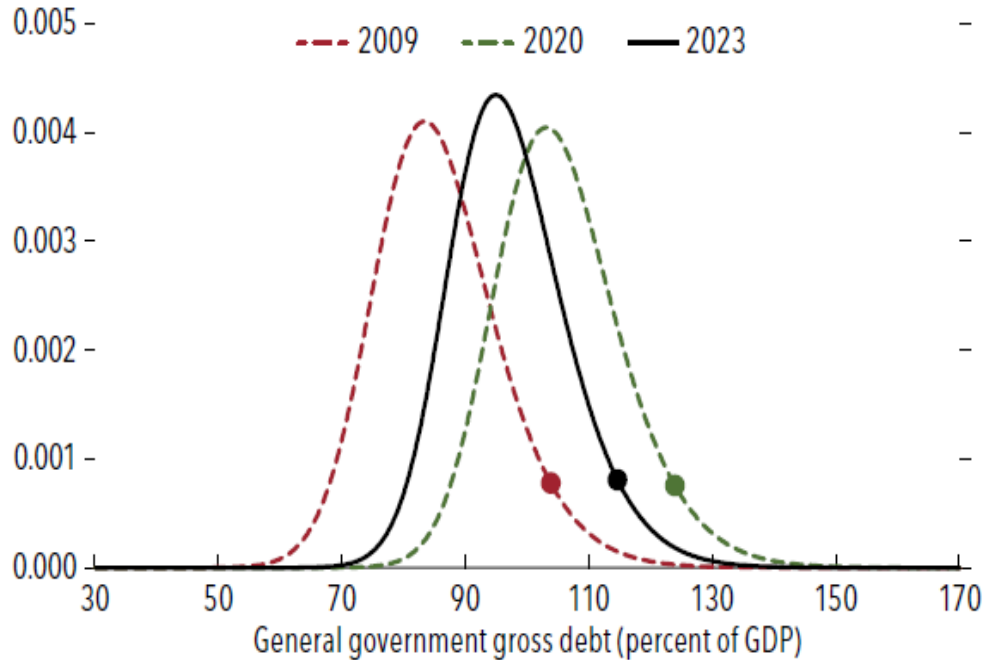
Source: IMF staff estimates.

The figure shows the estimated coefficients for 5th, 50th, and 95th percentile based on quantile regressions on selected financial, political, and economic variables. The line in each bar shows the 90 percent confidence interval of the estimated coefficient.

Global DaR is elevated and estimated at 115 percent of GDP in 2026, partly owing to high current debt levels

Global Debt-at-Risk

(Probability density of three-year-ahead government debt-to-GDP ratio)

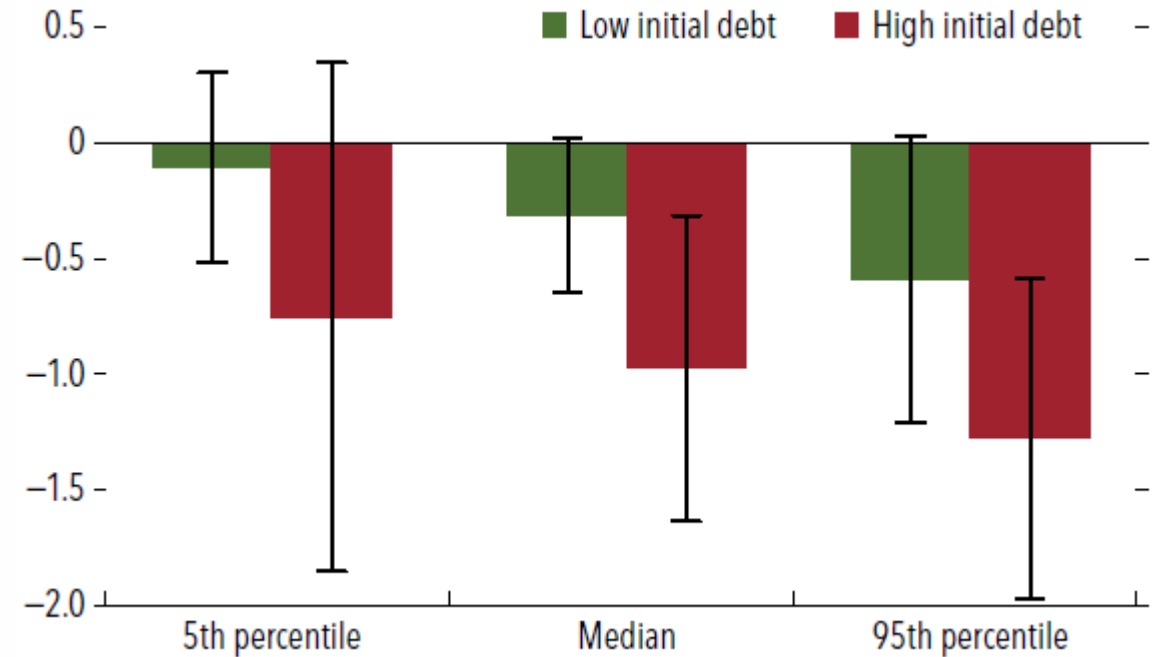


Source: IMF staff estimates.

Note: The probability density functions are estimated using panel quantile regressions of debt-to-GDP on various political, economic, and financial variables. The global sample includes 74 countries—accounting for more than 90 percent of global debt—for which data on the conditioning variables is available from 2009-2023. The quantile estimates are fitted to a skewed t distribution for every year in the sample.

Initial Debt and Debt-at-Risk

(Coefficient on real GDP growth in panel quantile regressions for three-year-ahead debt-to-GDP ratio)



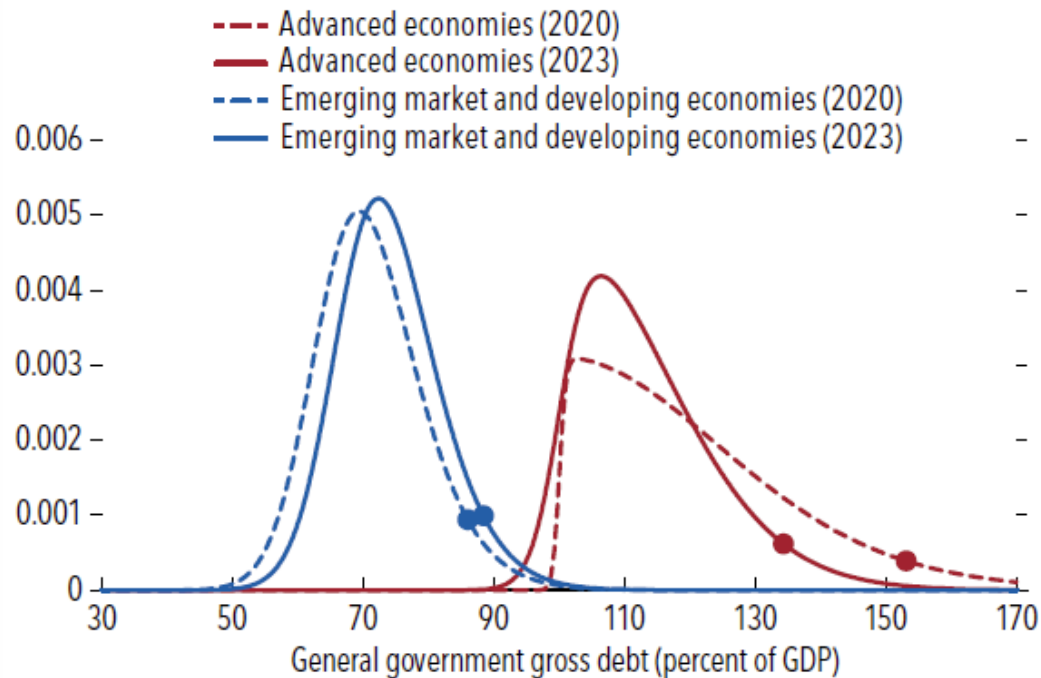
Source: IMF staff estimates.

Note: The figure shows estimated coefficients for 5th, 50th, and 95th percentiles based on panel quantile regressions of the debt-to-GDP ratio on real GDP growth differentiated by low initial debt (first quartile) and high initial debt (fourth quartile). Bars denote estimated coefficients. Whiskers in bars show 90 percent confidence intervals for estimated coefficients.

DaR varies significantly across country groups

Debt-at-Risk across Income Groups

(Probability density of three-year-ahead government debt-to-GDP ratio, 2023)

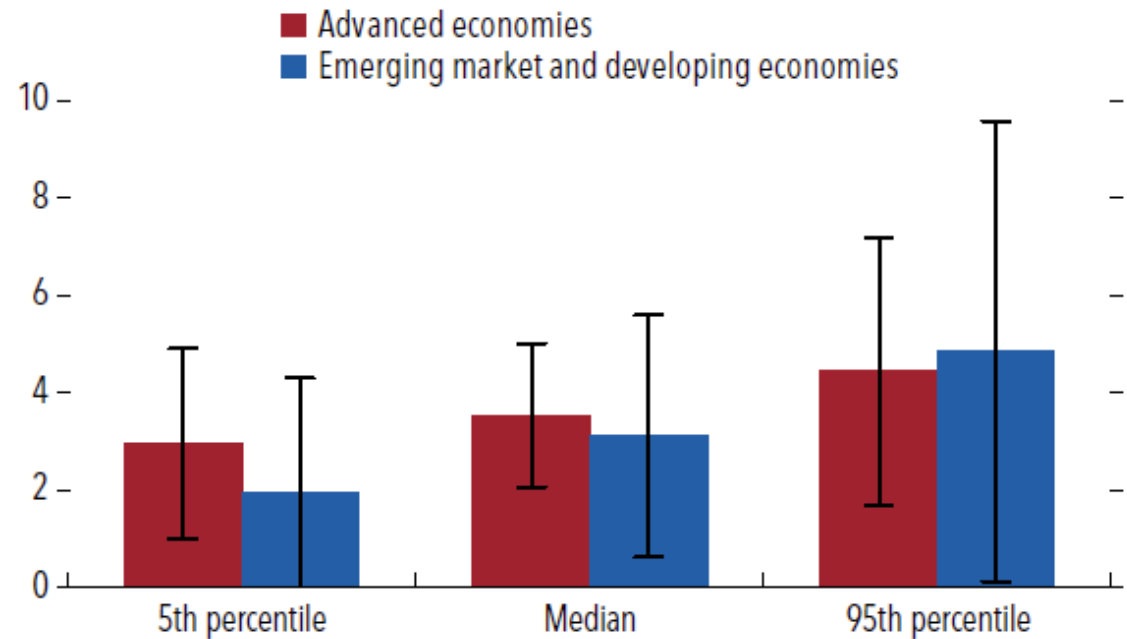


Source: IMF staff estimates.

Note: The probability density functions are estimated using panel quantile regressions of debt-to-GDP on various political, economic, and financial variables. The global sample includes 74 countries—accounting for over 90 percent of global debt—for which data on the conditioning variables is available for 2009–23. The quantile estimates are fitted to a skewed t distribution for every year in the sample. The dots indicate the predicted 95th quantile of debt-to-GDP ratio.

Financial Conditions and Debt-at-Risk across Income Groups

(Coefficients on financial conditions index for three-year-ahead debt-to-GDP ratio)



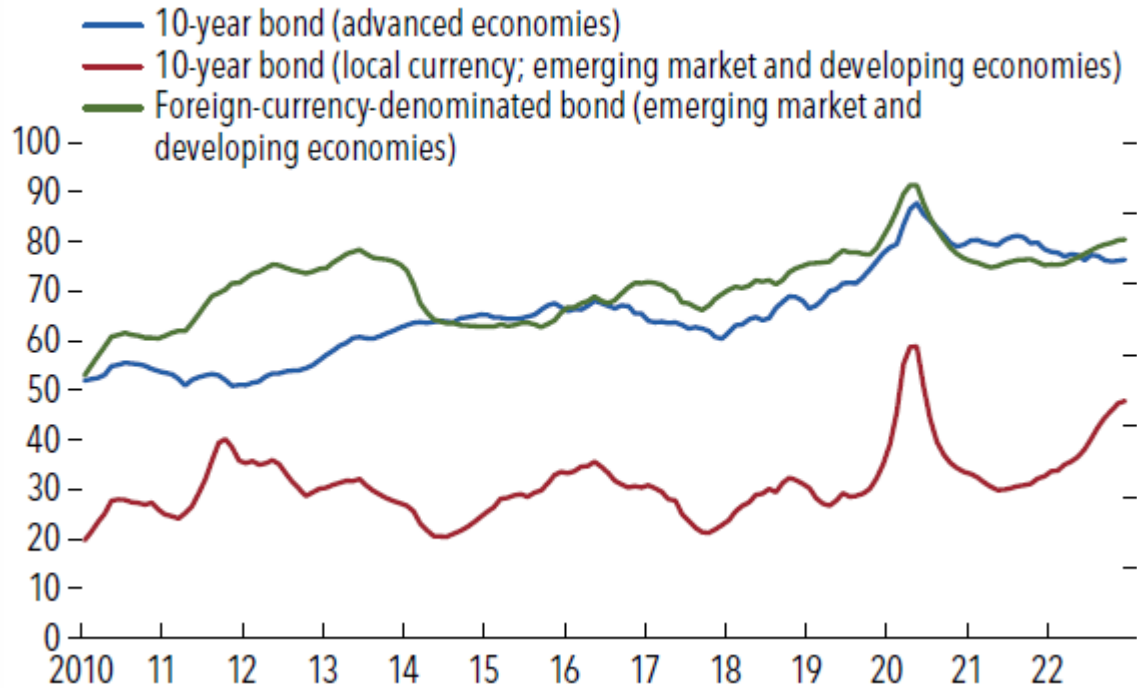
Source: IMF staff estimates.

Note: The figure shows estimated coefficients for 5th, 50th, and 95th percentiles based on panel quantile regressions of the debt-to-GDP ratio on the financial conditions index for advanced economies and emerging market and developing economies. Bars denote estimated coefficients. Whiskers in bars show 90 percent confidence intervals for estimated coefficients.

Increasing role of global factors pose negative spillovers from fiscal policy uncertainty in largest economies

Share of Total Variance in Sovereign Yields Explained by Global Factors

(Share of total variance)

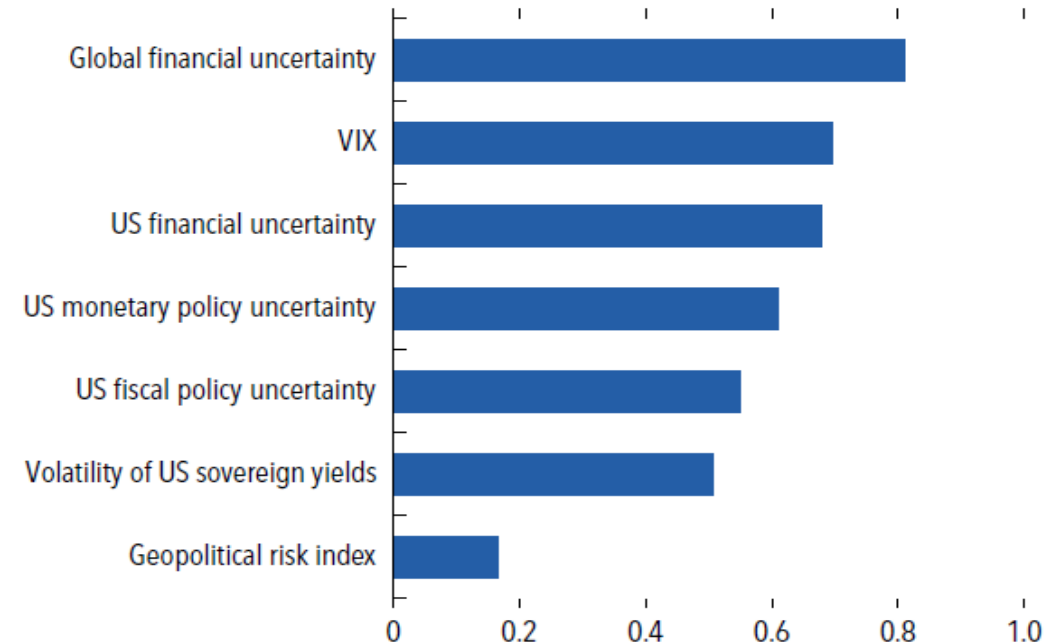


Sources: EUROPACE AG/Haver Analytics; Global Financial Data; IMF, International Financial Statistics; JPMorgan; Organisation for Economic Co-operation and Development; World Bank; and Nguyen and others (forthcoming).

Note: Figure shows the unweighted average contribution of global factors to the time-varying variance of sovereign bond yields across country groups. For each country, the contribution of global factors corresponds the median global factor share from retained Gibbs-sampling Draws.

Correlation of Selected Indicators with Global Sovereign Yield Volatility

(Pairwise correlation coefficients)



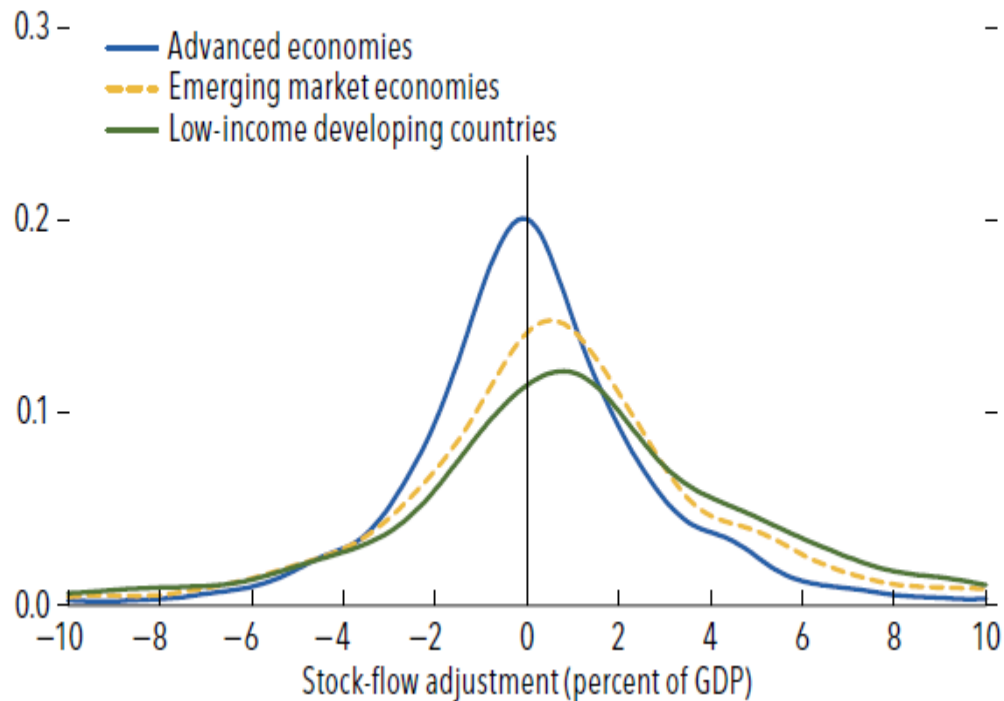
Sources: Baker and others (2016); Caggiano and Castelnuovo (2023); Caldara and Iacoviello (2022); EUROPACE AG/Haver Analytics; Global Financial Data; Hong and others (2024); IMF, International Financial Statistics; JPMorgan; Ludvigson and others (2021); OECD; World Bank; and IMF staff estimates.

Note: The figure shows pairwise correlation coefficients with the global sovereign bond yield volatility index, defined as simple averages of sovereign bond yield volatilities driven by global factors calculated across countries and bond instruments. The correlation coefficient for the geopolitical risk index is statistically significant at 5 percent level. All other correlation coefficients are significant at the 1 percent level.

Large unidentified debt could further contribute to higher debt

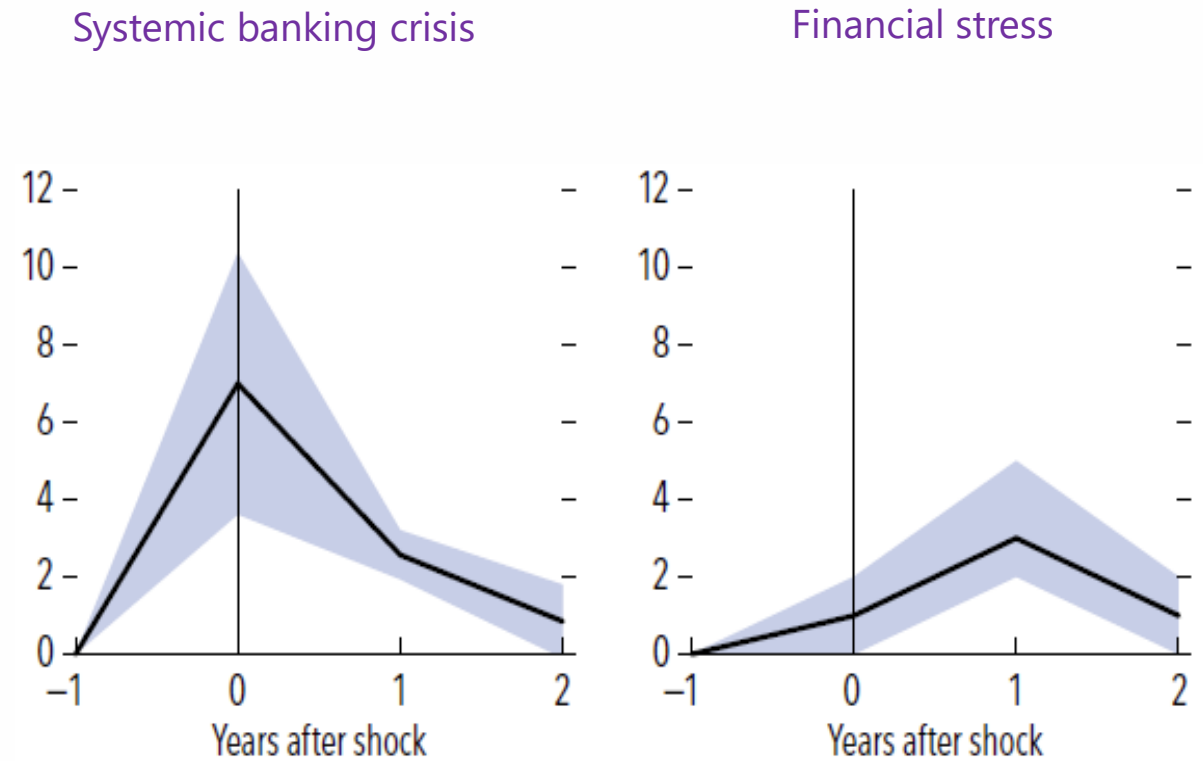
Distribution of Unidentified Debt Excluding Exchange Rate Movements, 1991–2023

(Density)



Sources: IMF World Economic Outlook Database; and IMF staff estimates.
 Note: Positive (negative) level contributes to higher (lower) debt-to-GDP ratios.

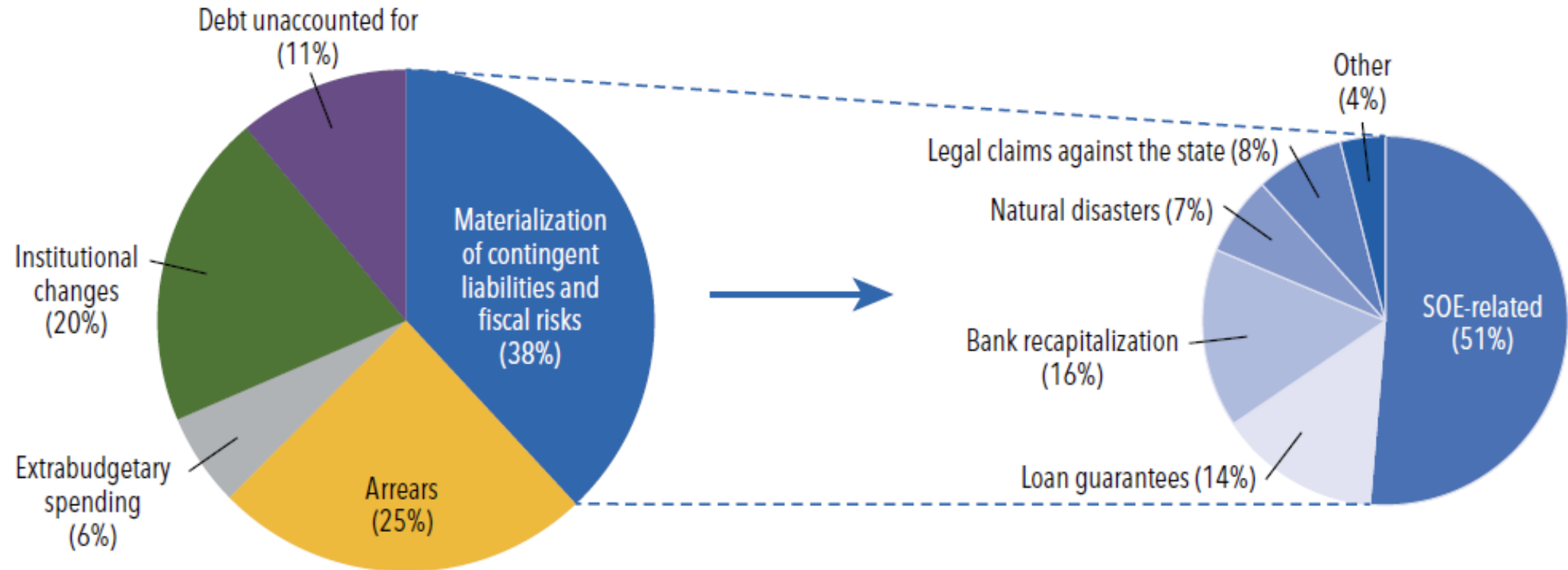
Increase in Unidentified Debt after Financial Stress or Banking Crisis
 (Percent of GDP)



Source: IMF staff estimates.
 Note: Results based on local projection of unidentified debt (in percent of GDP) against a financial stress indicator. Financial stress indicator is based on Ahir and others (2023) and banking crisis data are based on Laeven and Valencia (2020).

Two-thirds of unidentified debt stems from realization of contingent liabilities and arrears buildup

Components of Unidentified Debt, 2010–23
(Percent of total identified components; percentage points)



Source: IMF staff estimates.

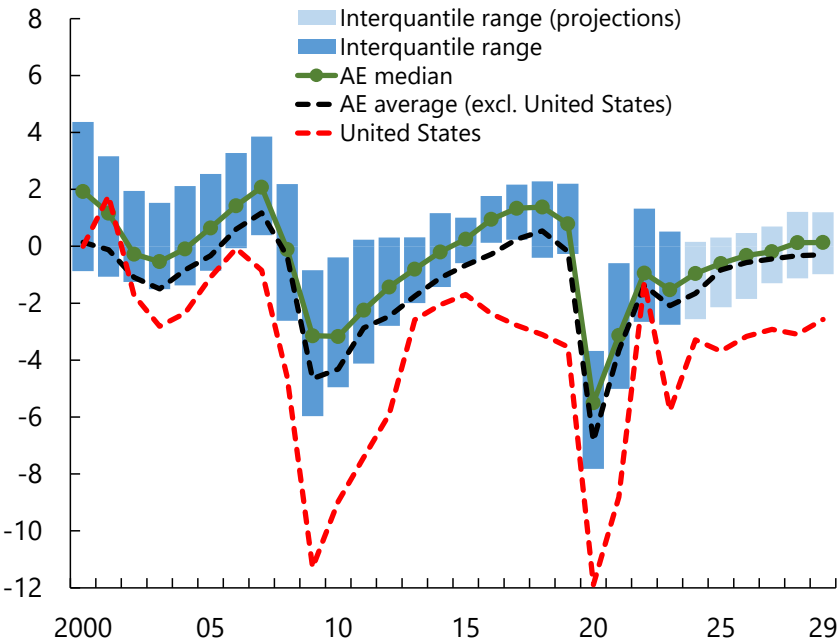
Note: Unidentified debt refers to the change in debt levels not explained by budgetary deficits, interest-growth differentials, and movements of exchange rates. Components are based on individual review of 17 countries' IMF Staff Reports. The set of countries are selected based on the size of unidentified debt (in percent of GDP) as well as the criterion that over 30 percent of the unidentified debt is explained by discussion in the IMF country documents.

II. Fiscal Policies to Get Debt under Control

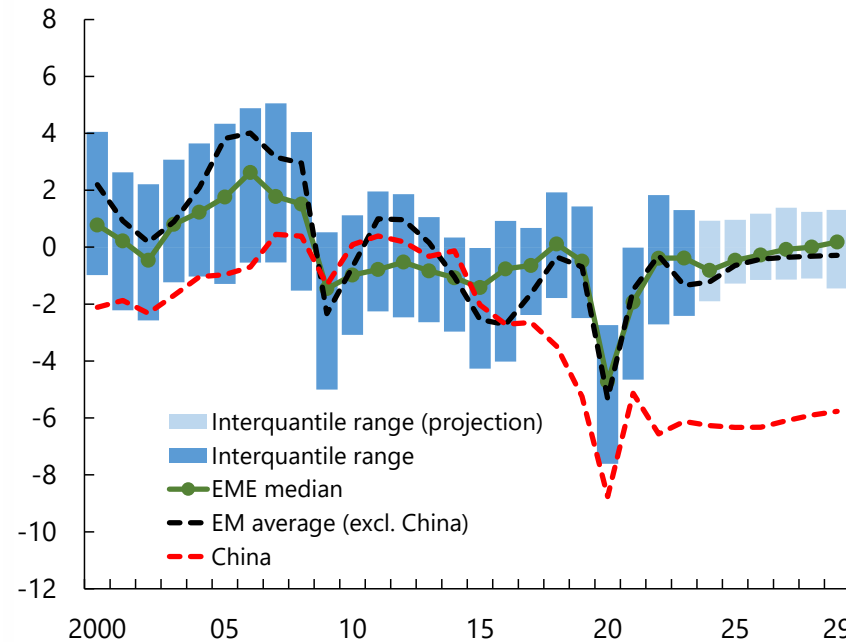
Modest fiscal adjustments anticipated in the current projection

Primary Balance (Percent of GDP)

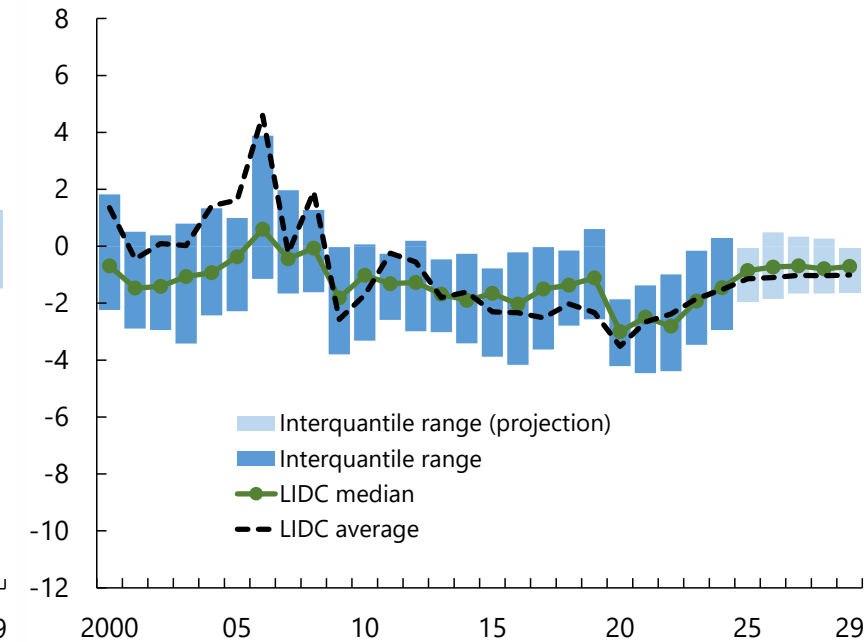
Advanced Economies



Emerging Market Economies



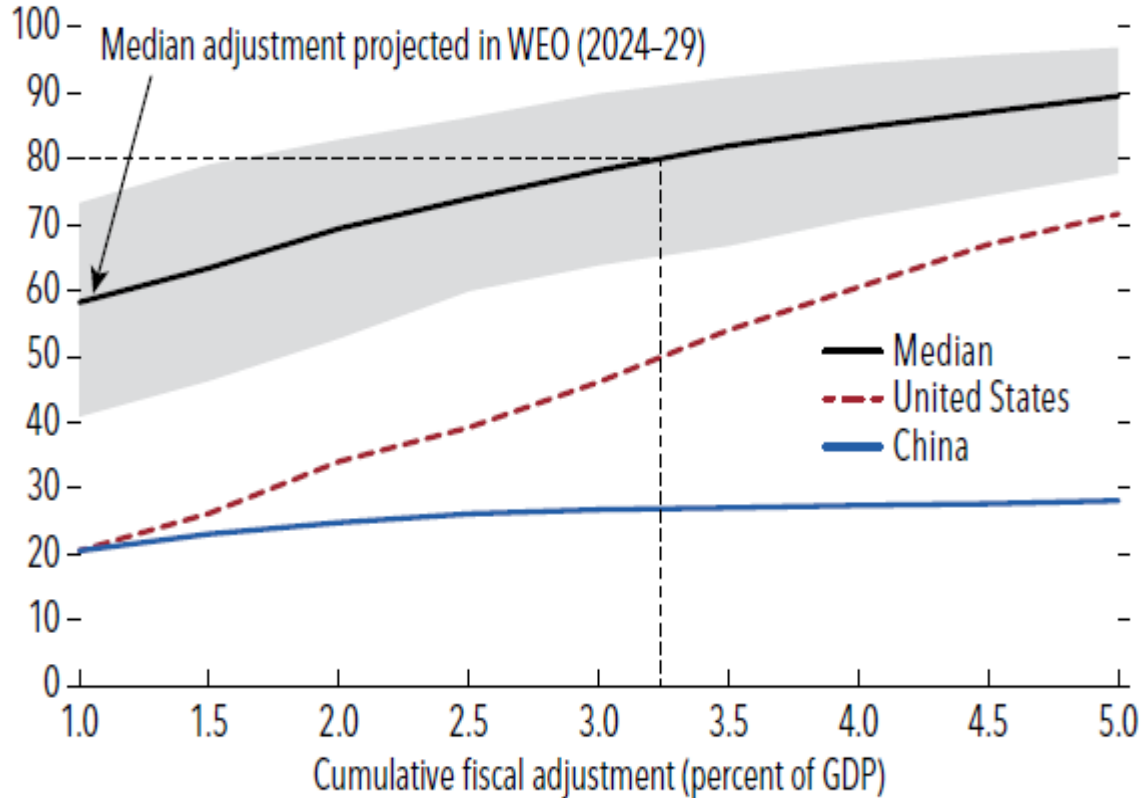
Low Income and Developing Countries



Sources: IMF World Economic Outlook Database.

Stabilizing (reducing) debt with high probability requires fiscal adjustments greater than projected

Median Fiscal Adjustment and Probability of Debt Stabilizing or Reducing Debt by 2029
(Probability for median and interquartile range in percent)



Source: IMF World Economic Outlook Database; and IMF staff estimates.
Note: The median fiscal adjustment in the WEO is about 1 percentage point of GDP cumulative over six years (2023–29). Additional fiscal adjustments are the same for all countries, applied to those countries' baseline projections. The probability of debt stabilization is calculated as the number of debt paths, where the baseline primary balance is higher than debt stabilizing primary balance.

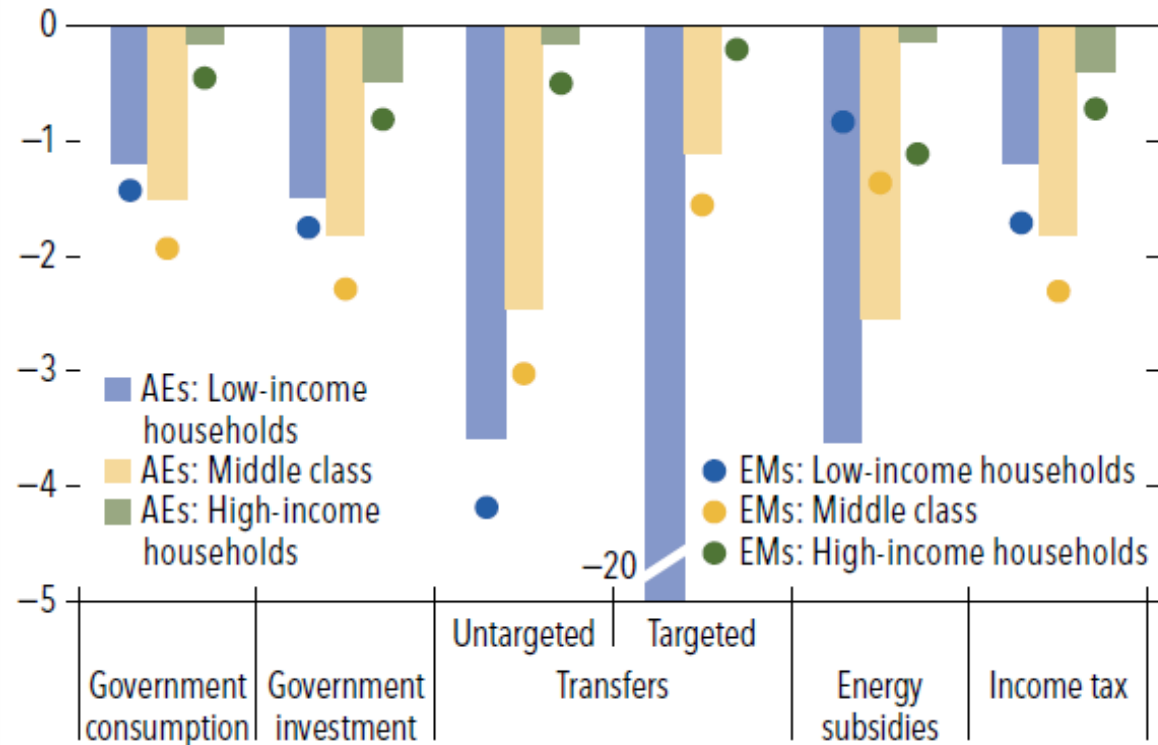
Median Fiscal Adjustments across Scenarios: Baseline, Historical, and High Probability to Stabilize Debt
(Percent of GDP)



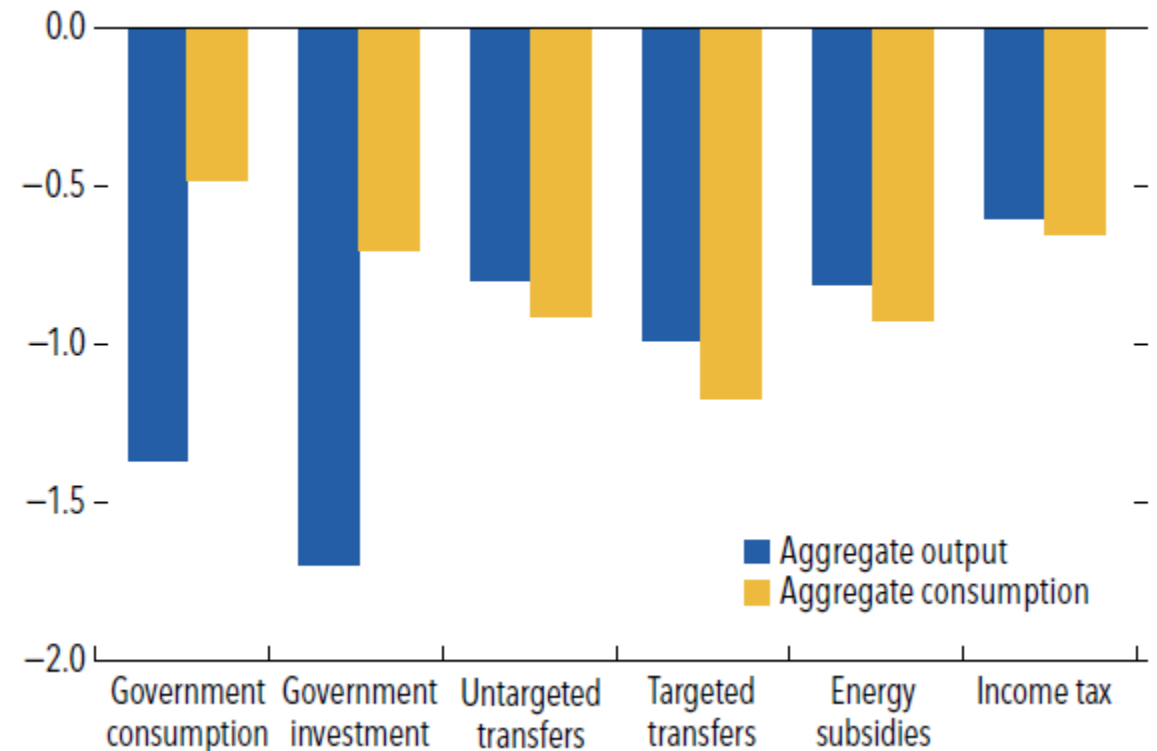
Source: IMF World Economic Outlook Database; and IMF staff estimates.
Note: Historical fiscal adjustment refers to the adjustments that have a positive change in primary balance over 6-year rolling window in a country. Baseline adjustment is the difference between projected primary balance between 2023 and 2029 in the WEO. Proactive adjustment sets the probability of stabilizing debt at the 80 percent, about one-third higher than that in the baseline.

Fiscal adjustments need to account for the adverse impact on output and inequality

Distributive Impact of Fiscal Adjustment across Households
(Percent of initial consumption)



Impact of Fiscal Adjustment on Aggregate Output and Consumption
(Percent of steady-state GDP)

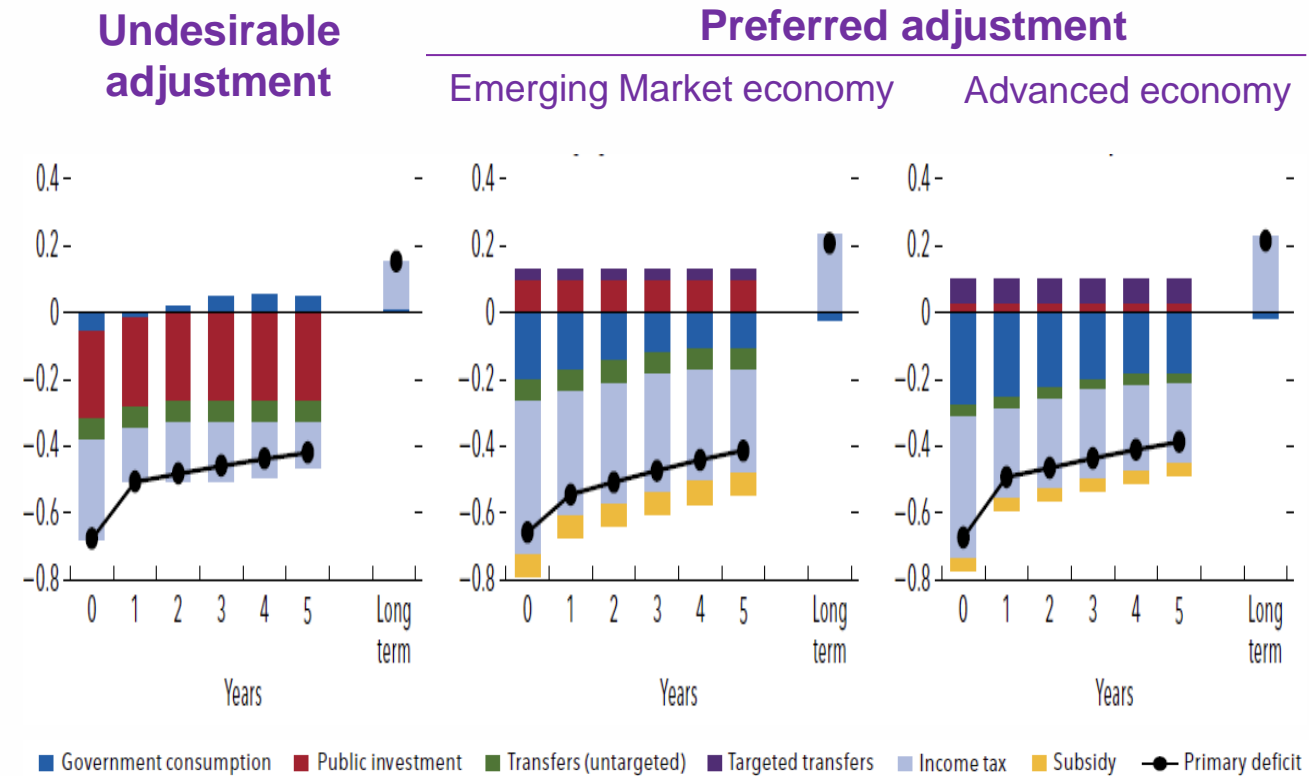


Source: IMF staff estimates.

Note: Simulation results are based on a temporary one-off fiscal adjustment of 1 percentage point of steady-state output for each measure in a representative advanced economy (see Online Annex 1.6). Transfers are separated into "Untargeted" (for all households) and "Targeted" (to low-income households: 5th percentile and below in the income distribution). Energy subsidies are calibrated based on energy consumption across households. Income tax is assumed to be progressive. Left figure shows the impact for each type of fiscal measure (an increase in taxes or an expenditure cut), measured in terms of initial consumption for each type of household. Bars (dots) show the effects for a representative advanced economy (emerging market economy). Right figure shows the impact for each type of fiscal measure (an increase in taxes or an expenditure cut), measured in terms of steady-state GDP.

Preferred fiscal adjustments should reflect differences across countries

- Illustrative case for representative AE and EM:
 - Cumulative adjustment of 3% of GDP over 6 years
- Two scenarios for fiscal adjustment packages:
 - **Undesirable adjustment:** rely on public investment cuts and untargeted measures (from past experience)
 - **Preferred adjustment:** (i) combine revenue and expenditure measures; (ii) protect vulnerable households; (iii) safeguard public investment; (iv) phase out untargeted subsidies
- Structural differences between AEs and EMs considered:
 - Capacity to insure against shocks
 - Volatility and persistence of shocks
 - Tax potentials



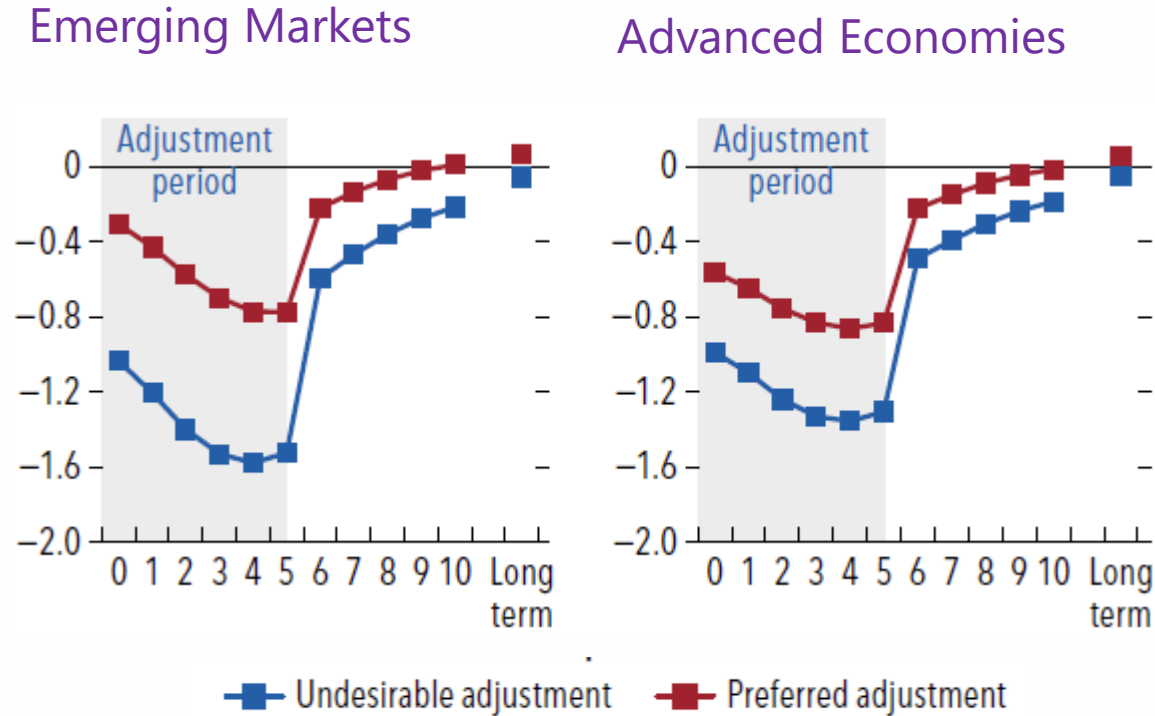
Source: IMF staff estimates.

Note: Estimation based on extended HANK model by Auclert, Rognlie and Straub (2024). Fiscal adjustment is set at a cumulative 3 percent of GDP over 5 years. The composition of the fiscal measures vary across advanced and emerging market economy as shown in the previous charts.

...while mitigating adverse impacts on output and inequality

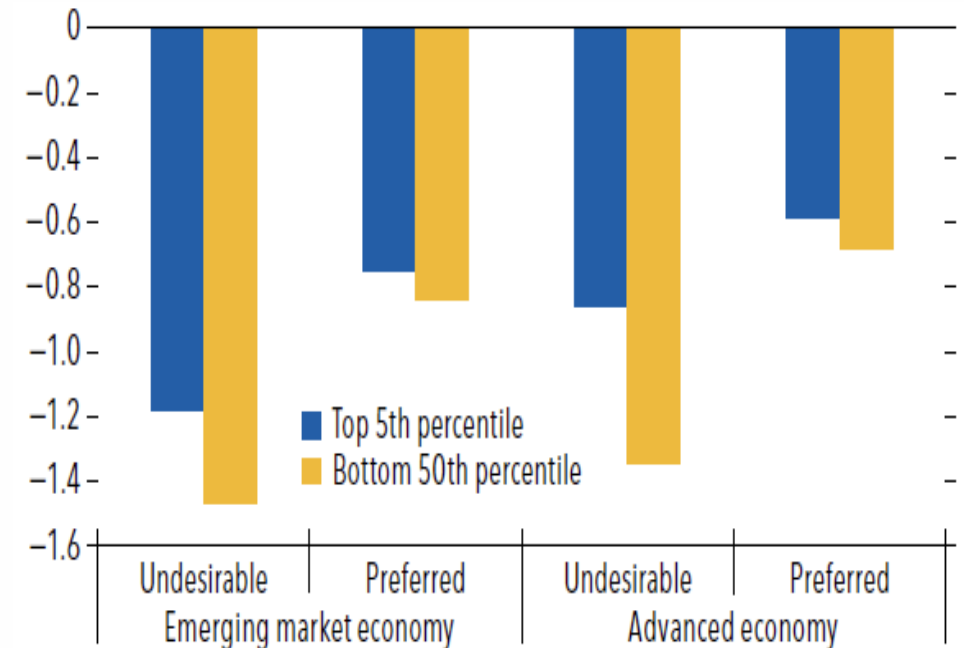
Adverse Impact on Output from Fiscal Adjustment

(Percent of steady state GDP)



Decline in Consumption across Income Groups and Fiscal Adjustment Scenarios

(Percent of initial consumption levels)



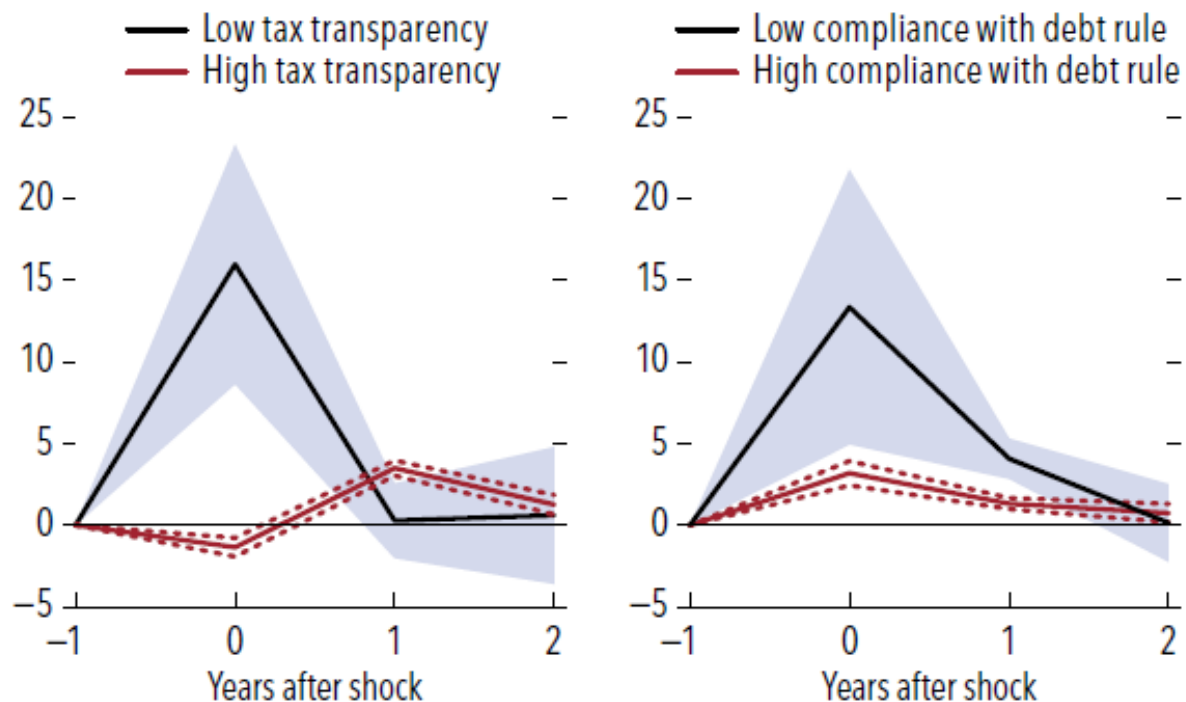
Source: IMF staff estimates.

Note: The simulation is based on extending the model of Auclert, Rognlie, and Straub (forthcoming). The model is calibrated to a representative advanced economy and emerging market economy by matching respective data (see Online Annex 1.6 for details). The size of the fiscal adjustment is set identically at a cumulative 3 percent of steady-state GDP over six years for comparison, but the composition varies across scenarios (undesirable and preferred) and income groups (advanced economy and emerging market economy).

Fiscal rules and transparency can mitigate buildup of unidentified debt

Unidentified Debt: Relationship with Budget Transparency and Compliance with Fiscal Rules

(Percent of GDP)



Government policies to mitigate the rise in unidentified debt

Assess and manage contingent liabilities

Broaden institutional coverage

Strengthen core expenditure control functions and fiscal rules framework

Improve fiscal transparency

Source: Davoodi and others 2022; IMF, Fiscal Rules Dataset, 1985–2021; International Budget Partnership, Open Budget Survey; and IMF staff estimates.

Note: “Compliance with fiscal rules” refers to the frequency of compliance with debt rules. Tax transparency is sourced from the Open Budget Survey Index. Year 0 is the year of a banking crisis. Solid black (red) lines denote the response to a banking crisis; shaded areas (dashed lines) denote 90 percent confidence bands.

Key Takeaways

Public debt is high and could be even higher

- Risks to the debt outlook are heavily tilted to the upside, stemming from weaker growth, tighter financing conditions, and greater policy uncertainty. High debt today also amplifies the risks.
- Negative spillovers from high debt and policy uncertainty in systemically important countries will raise volatility of borrowing cost and debt risks in other countries.
- Large unidentified debt could add to the buildup of debt, especially for emerging market and developing economies.

Larger fiscal adjustments needed to get public debt under control

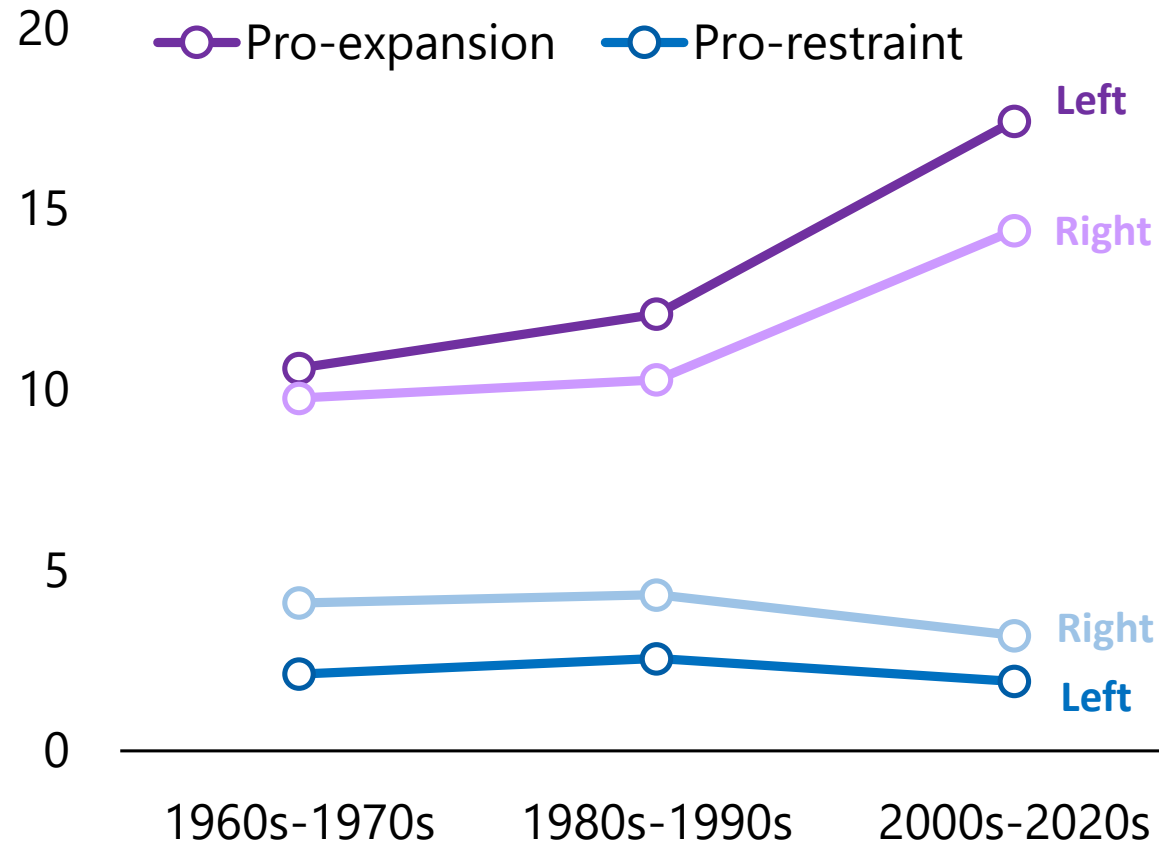
- Now opportune time to pivot to fiscal adjustments to contain debt risks
- Larger than currently planned fiscal adjustments are required to stabilize (or reduce) debt with high probability
- A judicious mix of revenue and expenditure measures needed to mitigate the adverse impact of fiscal adjustments on output and inequality. AEs should prioritize expenditures within an overall cut in spending, while EMs should rely on revenue measures and scale up public investment and targeted transfers
- Strengthening fiscal transparency and compliance of fiscal rules can mitigate the buildup of unidentified debt

Thank you

Background Slides

Rising expansionary discourse across political parties

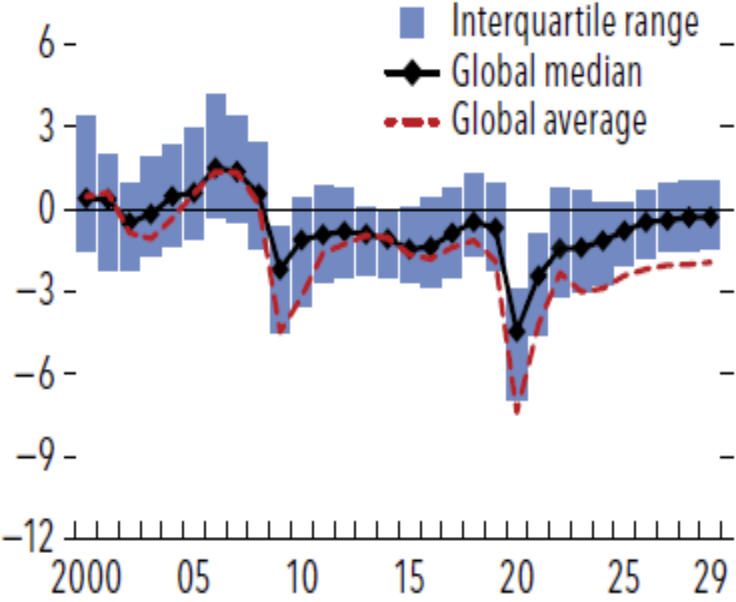
Evolution of Fiscal Discourse by Party Family
(Percent of party platform content)



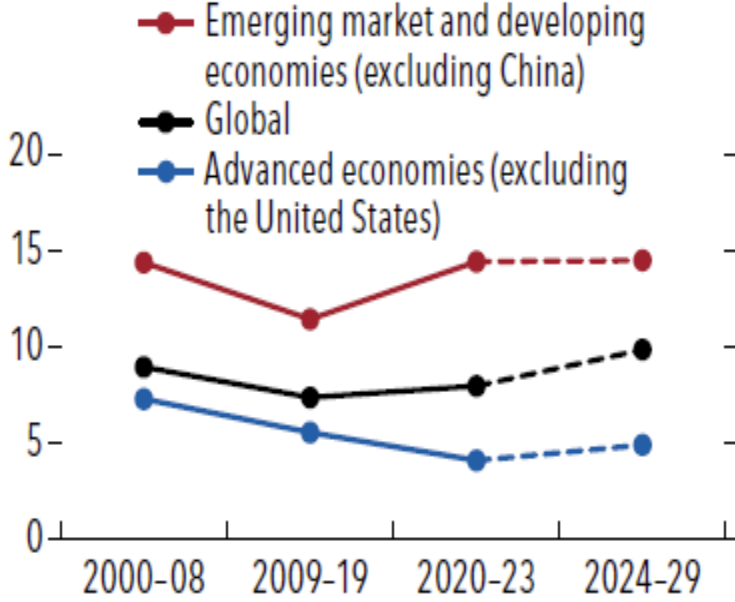
Sources: Cao, Dabla-Norris, and Di Gregorio (2024), Manifesto Project Database.

Selected key indicators of debt vulnerabilities

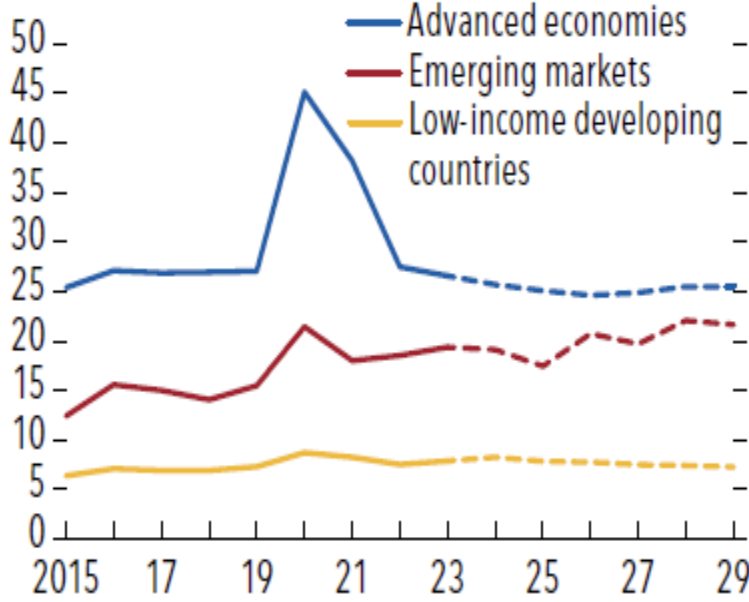
Primary Balance
(Percent of GDP)



Interest Payment to Total Revenues
(Percent)



Gross Financing Needs
(Percent of GDP)



Sources: IMF World Economic Outlook Database.

Debt-at-Risk framework: empirical strategy (1/2)

Step 1: Estimate panel quantile regressions (Machado and Santos Silva 2019) with country fixed effects. Estimate the following location-scale model:

$$d_{i,t+h} = \alpha_i + X'_{i,t}\beta + (\delta_i + X'_{i,t}\gamma)\varepsilon_{i,t+h}$$

- i : country, t : year, h : horizon (1 to 5 years).
- $d_{i,t+h}$: Debt-to-GDP ratio h years ahead for country i
- X_{it} : Vector containing the conditioning variable (e.g., sovereign spreads, GDP growth); also includes current public debt ($d_{i,t}$)
- α_i, δ_i : Country fixed effects, γ : scale parameter, $\varepsilon_{i,t}$: error term.
- β : coefficient of interest.

Model implies that for quantile τ : $Q_{d_{i,t+h}}(\tau|X_{i,t}) = (\alpha_i + \delta_i q(\tau)) + X'_{i,t}\beta + X'_{i,t}\gamma q(\tau)$, where $q(\tau) = F_{\varepsilon}^{-1}(\tau)$

Define debt-at-risk (DaR) as the 95th quantile of predicted debt-to-GDP.

Step 2:

- Recenter around WEO projections.
- Fit predicted quantiles to a skewed t-distribution (Azzalini and Capitanio 2003) to obtain density $\hat{f}(d)$.
- Pool conditional densities using a weighted sum: $\hat{f}_{i,t}^{pooled}(d) = \sum_m \mu_i^m \hat{f}_{i,t}^m(d)$
 - Weights μ_i^m maximize the out-of-sample predictive accuracy of each conditioning variable (Crump et al. 2023).

Debt-at-Risk framework: empirical strategy (2/2)

Step 3: Aggregate quantiles to the global level:

$$\hat{Q}_{d_{global,t+h}}(\tau) = \sum_{i=1}^I \omega_{i,t} \hat{Q}_{d_{i,t+h}}(\tau)$$

- Where $\omega_{i,t} = \frac{GDP_{i,t}}{\sum_{i=1}^I GDP_{i,t}}$ is a country's nominal GDP share.
- Recenter and fit to a skewed t-distribution as for individual countries.

Step 4: Pool conditional densities using a weighted sum of the conditional densities:

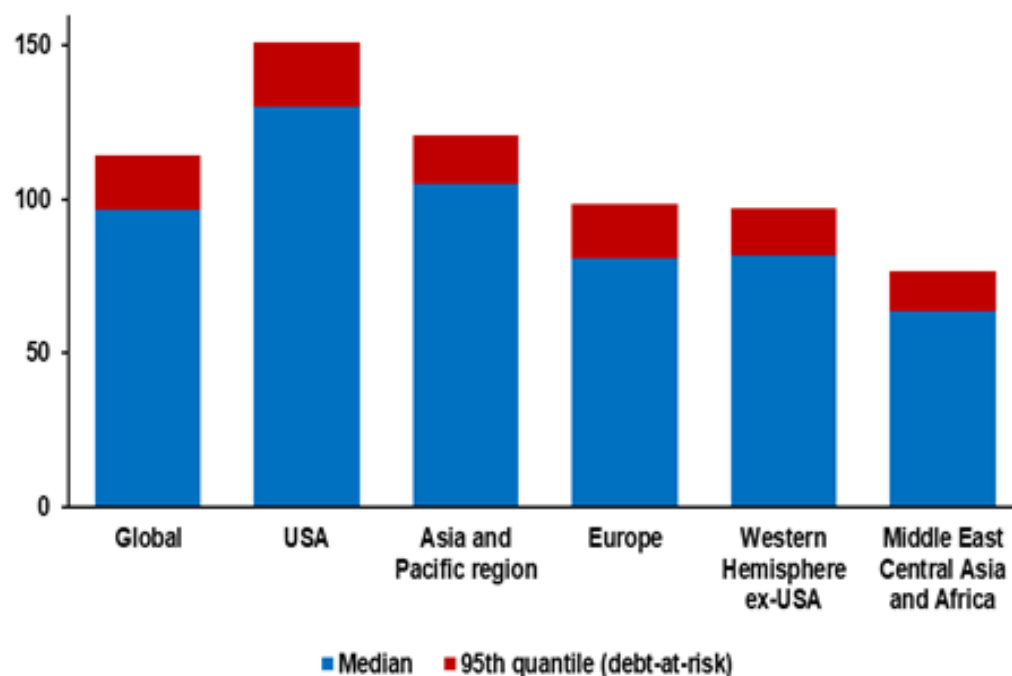
$$\hat{f}_{global,t}^{pooled}(d) = \sum_m (\sum_i \omega_{i,t} \mu_i^m) \hat{f}_{global,t}^m(d)$$

- Global weights are the GDP-weighted average of individual country weights
- Follow a similar approach for country groups (e.g., advanced economies, emerging markets and developing economies)

Debt-at-Risk differs across regions, with the United States contributing about a third of global Debt-at-Risk

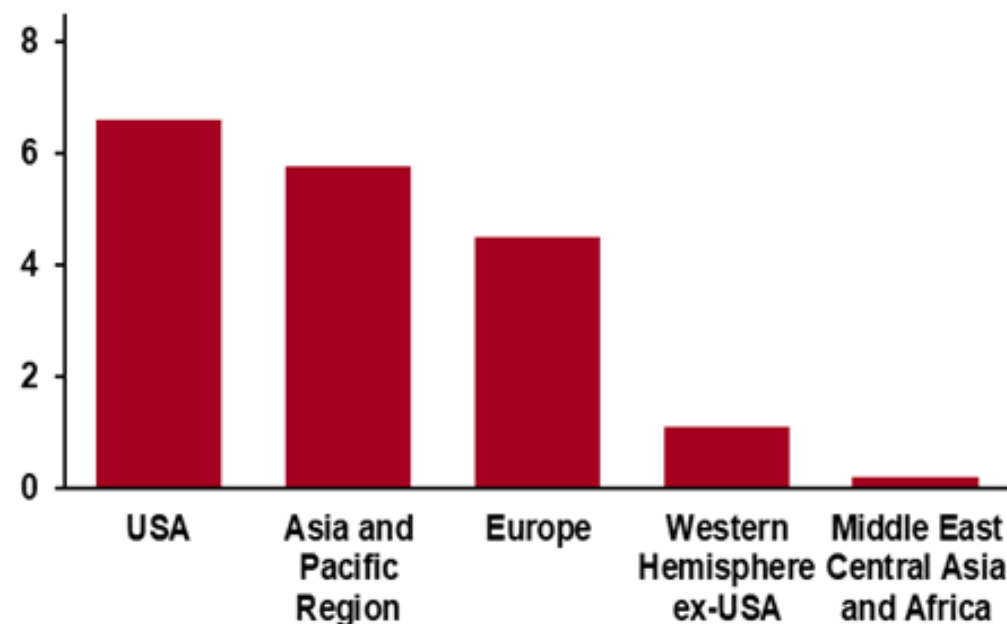
Debt-at-Risk by Region

(Predicted median and 95th quantile of three-year-ahead debt-to-GDP ratio, in percent of GDP)



Regional Contribution to Global Debt-at-Risk

(Percent of GDP)



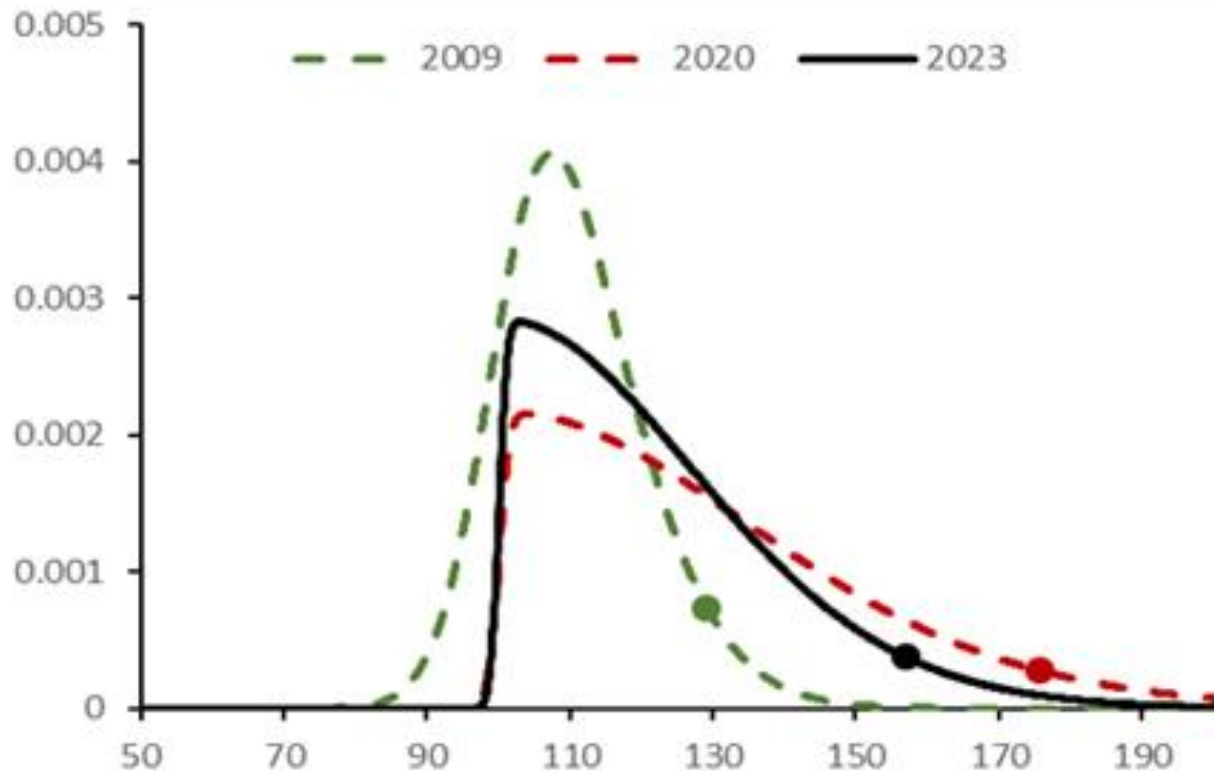
Source: IMF staff estimates.

The regional aggregates only include the countries in the sample that are used to create the global distribution. The left figure plots the three-year-ahead predicted median and 95th quantile debt-to-GDP ratio by region. The right figure plots the difference between the predicted 95th quantile and the (unconditional) predicted median for each region. This difference is then weighted by the region's nominal GDP to create a contribution to global debt-at-risk that aligns with the approach used to create the global quantiles.

For the United States, the primary deficit is the largest driver of debt risks at the current juncture

US Debt-at-Risk

(density of 3-years ahead debt-to-GDP ratio)



Source: IMF staff estimates.

Note: The probability density functions are estimated using panel quantile regressions of debt-to-GDP on various political, economic, and financial variables. The quantile estimates are fitted to a skewed t-distribution for every year in the sample. The dots indicate the predicted 95th quantile of debt-to-GDP ratio.

Weights Used to Combine United States Distribution

Forecast Horizon (Years)	Initial Debt	Financial Stress Index	World Uncertainty Index	Social Unrest Index	Primary Balance	GDP Growth	Inflation
1	0.00	0.62	0.00	0.00	0.38	0.00	0.00
2	0.00	0.35	0.00	0.00	0.65	0.00	0.00
3	0.00	0.22	0.00	0.00	0.78	0.00	0.00
4	0.00	0.23	0.00	0.00	0.77	0.00	0.00
5	0.00	0.58	0.00	0.00	0.42	0.00	0.00

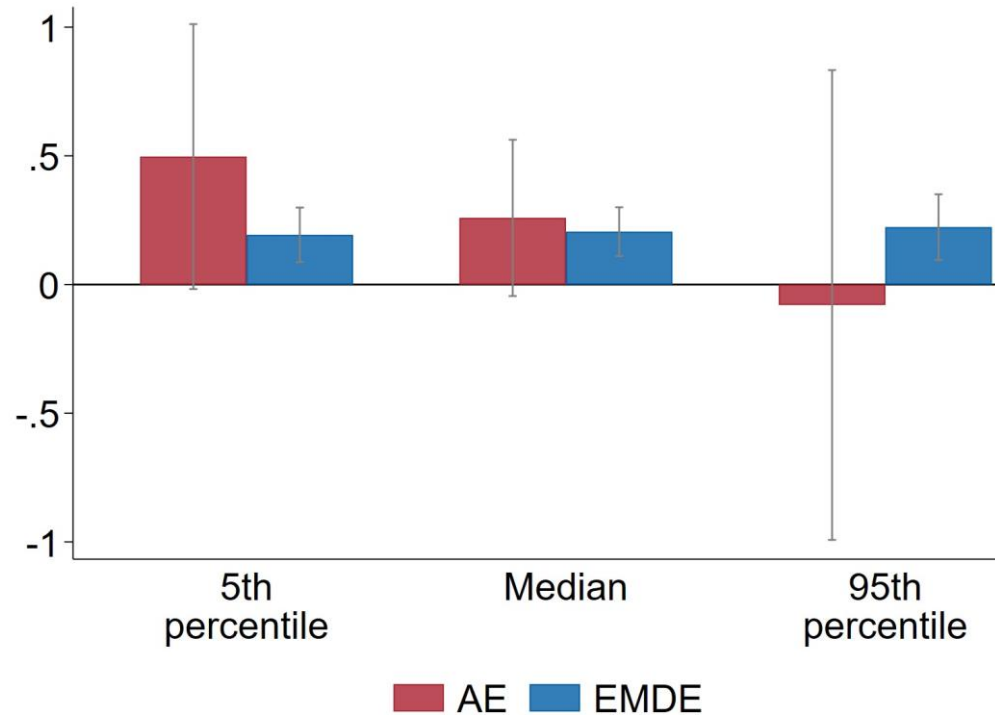
Source: IMF staff estimates.

Note: The table displays the weights used to combine the conditional distributions based on each conditioning variable into a single distribution for the United States. The procedure used to compute the weights follows Crump et al. (2023).

Financial conditions and world uncertainty have larger medium-term effects on Debt-at-Risk for emerging markets and developing economies

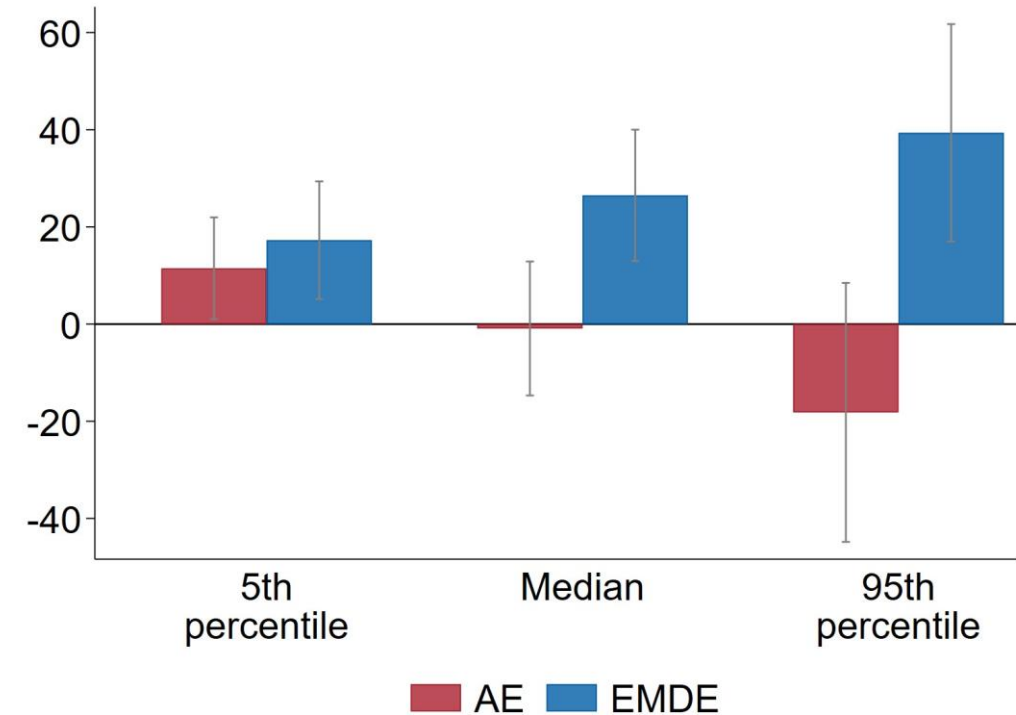
Spreads and Debt-at-Risk by Country Income Group

(Coefficient on three-year-ahead debt-to-GDP)



World Uncertainty and Debt-at-Risk by Country Income Group

(Coefficient on five-year-ahead debt-to-GDP)

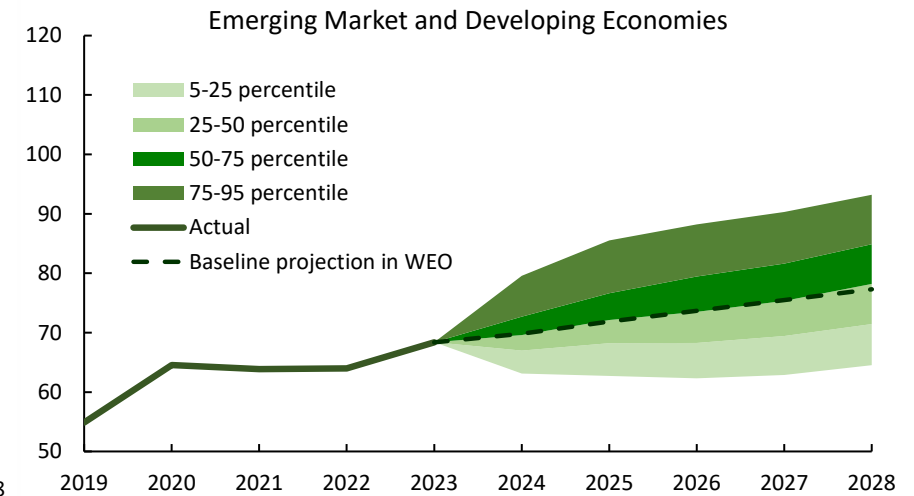
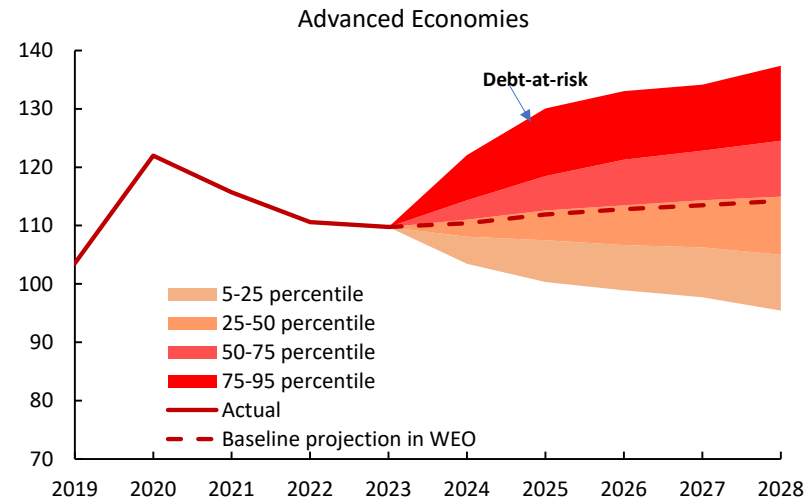
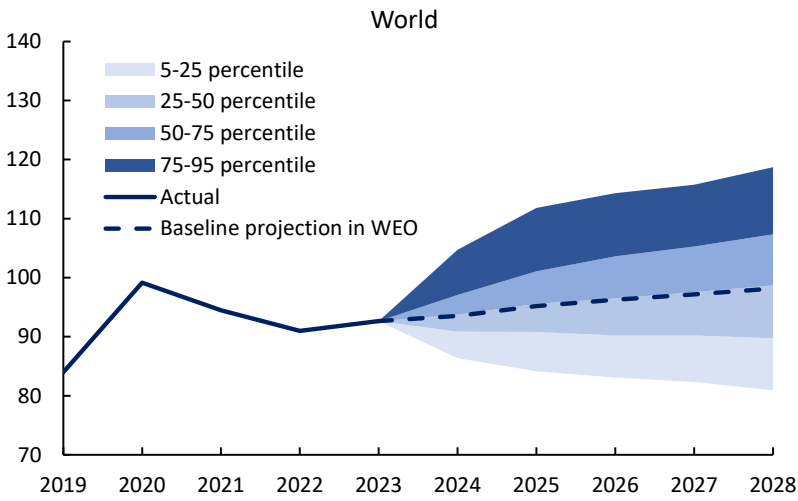


Source: IMF staff estimates.

Note: The figure shows the estimated coefficients for 5th, 50th, and 95th percentile based on panel quantile regressions based on equation (A1.1.7). Panels 1 and 2 display results for sovereign spreads and world uncertainty, respectively, differentiated across country income groups. Bars denote estimated coefficients. Whiskers in bars show 90 percent confidence intervals for estimated coefficients. AE = advanced economy; EMDE = emerging market and developing economy.

Risks surrounding WEO baseline public debt-to-GDP projections

Public Debt Ratio Projections (Percent of GDP)



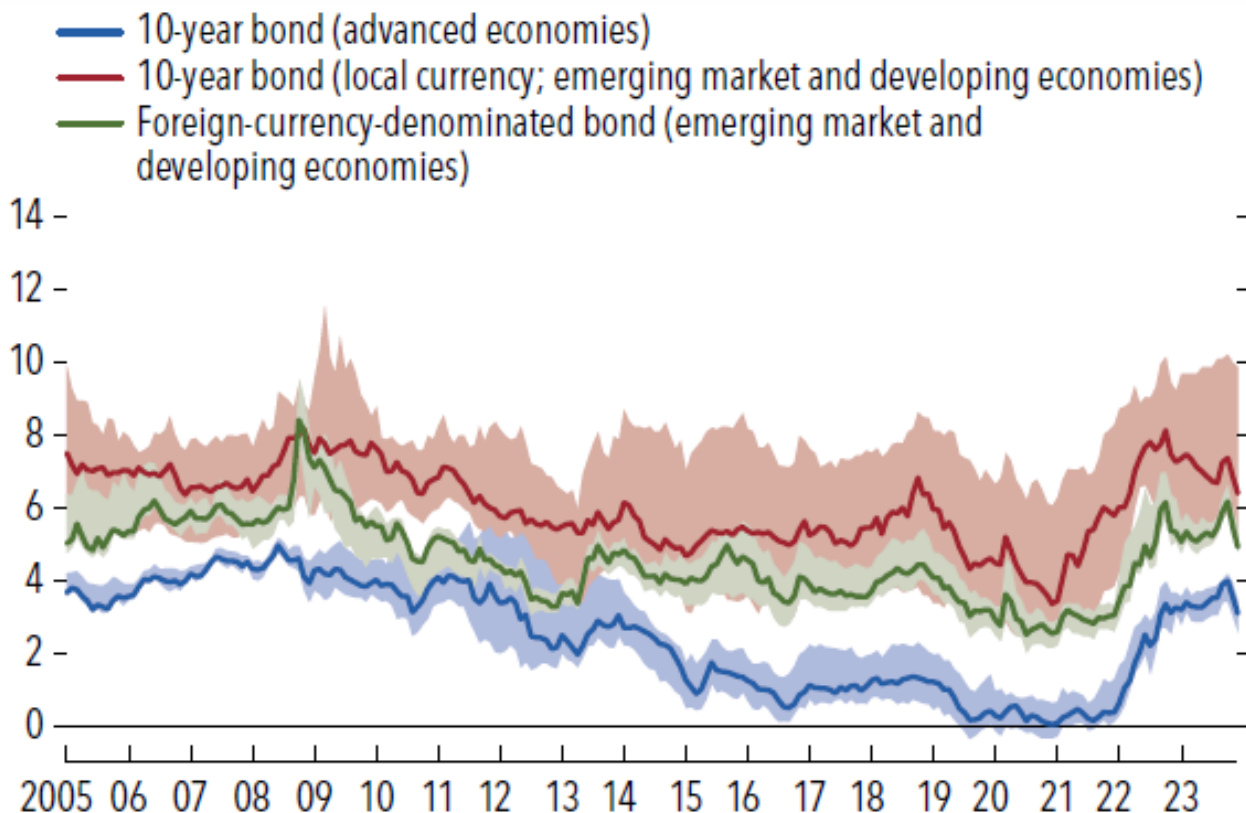
Sources: IMF staff estimates.

Note: Debt-at-risk is the estimated level of future debt-to-GDP ratio in a severely adverse scenario (95th percentile).

Fluctuations in sovereign yields exhibit strong co-movement

- Sovereign spreads—key predictor of Debt-at-Risk—co-move strongly, suggesting global factors drive their fluctuations
- Quantify the role of global factors in driving fluctuations of sovereign yields
- Methodology: a dynamic factor model with time-varying parameters and stochastic volatility for 50 AEs and EMDEs:
 - *Global unobserved factors*
 - *Country-specific unobserved factors*

Sovereign Bond Yields (Percent)



Sources: Global Financial Data, OECD, and IMF staff estimates.

Note: The figure shows medians, with shaded areas corresponding to the interquartile range.

Sovereign bond yields: Dynamic factor model (1/2)

Dynamic factor model to decompose the importance of global factors:

$$y_{it} = A_{it}^G \mathbf{F}_t^G + A_{it}^c \mathbf{F}_t^c + v_{it}$$

for variable i , at time t

Each series is affected by a set of N^g **global unobserved factors** \mathbf{F}_t^G , a set of N^c **country-specific unobserved factors** \mathbf{F}_t^c , and the unobserved **idiosyncratic components** v_{it}

Example: with 2 countries, each has 5 variables, 2 global factors, and 2-country specific factors

$$\begin{array}{l}
 \text{Country 1's variables} \\
 \text{Country 2's variables}
 \end{array}
 \begin{pmatrix}
 y_{1t} \\
 y_{2t} \\
 y_{3t} \\
 y_{4t} \\
 y_{5t} \\
 y_{6t} \\
 y_{7t} \\
 y_{8t} \\
 y_{9t} \\
 y_{10t}
 \end{pmatrix}
 =
 \begin{pmatrix}
 A_{1t}^{1G} & A_{1t}^{2G} \\
 A_{2t}^{1G} & A_{2t}^{2G} \\
 A_{3t}^{1G} & A_{3t}^{2G} \\
 A_{4t}^{1G} & A_{4t}^{2G} \\
 A_{5t}^{1G} & A_{5t}^{2G} \\
 A_{6t}^{1G} & A_{6t}^{2G} \\
 A_{7t}^{1G} & A_{7t}^{2G} \\
 A_{8t}^{1G} & A_{8t}^{2G} \\
 A_{9t}^{1G} & A_{9t}^{2G} \\
 A_{10t}^{1G} & A_{10t}^{2G}
 \end{pmatrix}
 \begin{pmatrix}
 f_{1t}^G \\
 f_{2t}^G
 \end{pmatrix}
 +
 \begin{pmatrix}
 A_{11t}^1 & A_{12t}^1 & 0 & 0 \\
 A_{21t}^1 & A_{22t}^1 & 0 & 0 \\
 A_{31t}^1 & A_{32t}^1 & 0 & 0 \\
 A_{41t}^1 & A_{42t}^1 & 0 & 0 \\
 A_{51t}^1 & A_{52t}^1 & 0 & 0 \\
 0 & 0 & A_{61t}^2 & A_{62t}^2 \\
 0 & 0 & A_{71t}^2 & A_{72t}^2 \\
 0 & 0 & A_{81t}^2 & A_{82t}^2 \\
 0 & 0 & A_{91t}^2 & A_{92t}^2 \\
 0 & 0 & A_{101t}^2 & A_{102t}^2
 \end{pmatrix}
 \begin{pmatrix}
 f_{1t}^1 \\
 f_{2t}^1 \\
 f_{1t}^2 \\
 f_{2t}^2
 \end{pmatrix}
 +
 \begin{pmatrix}
 v_{1t} \\
 v_{2t} \\
 v_{3t} \\
 v_{4t} \\
 v_{5t} \\
 v_{6t} \\
 v_{7t} \\
 v_{8t} \\
 v_{9t} \\
 v_{10t}
 \end{pmatrix}$$

Sovereign bond yields: Dynamic factor model (2/2)

Dynamic factor model to decompose the importance of global factors:

for variable i , in country c , at time t .

$$y_{it} = A_{it}^G F_t^G + A_{it}^c F_t^c + v_{it}$$

- Each global and local factor has a time-varying volatility

$$f_{jt} = c_j + \sum_{k=1}^P b_{jk} f_{jt-k} + \sigma_{jt}^{1/2} e_{jt}, \quad \text{where } e_{jt} \sim N(0,1)$$

$$\ln \sigma_{jt} = \ln \sigma_{jt-1} + \varphi_j^{1/2} \epsilon_{jt}, \quad \text{where } \epsilon_{jt} \sim N(0,1)$$

➡ Stochastic volatility

- Idiosyncratic components

$$v_{it} = \sum_{k=1}^Q b_{jk} v_{it-k} + h_{it}^{1/2} e_{ict}, \quad \text{where } e_{it} \sim N(0,1)$$

$$\ln h_{it} = \ln h_{it-1} + \vartheta_{ic}^{1/2} \epsilon_{it}, \quad \text{where } \epsilon_{it} \sim N(0,1)$$

➡ Stochastic volatility

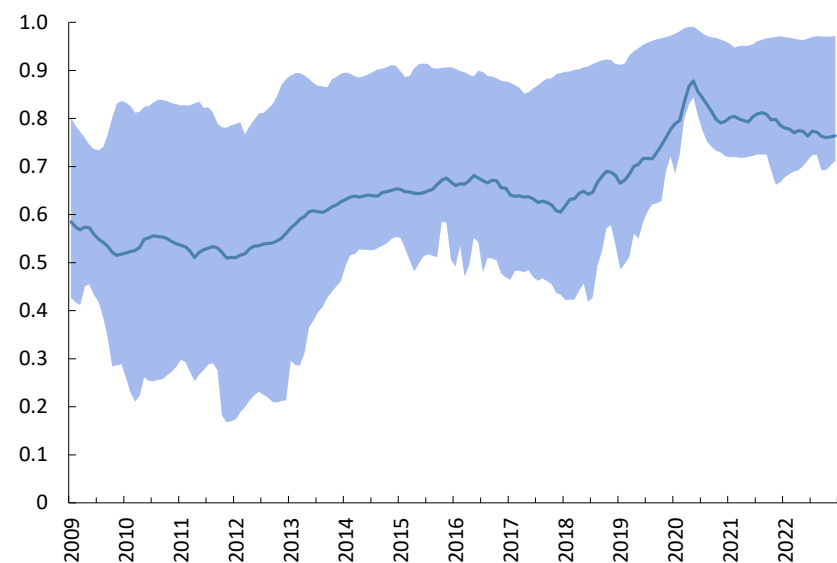
- Time-varying factor loadings $Z_{it} = [A_{it}^G \quad A_{it}^c]$ where each components of Z_{it} follows:

$$z_{ict} = z_{ict-1} + q_{ic}^{1/2} \tau_{it} \quad \text{where } \tau_{it} \sim N(0,1)$$

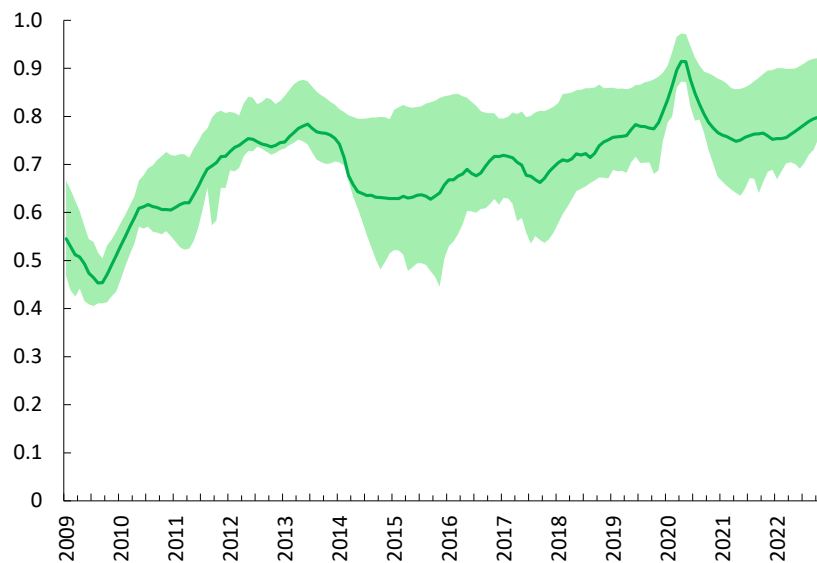
The role of global factors varies considerably across countries and over time

Global Factor Share (Share of total variance)

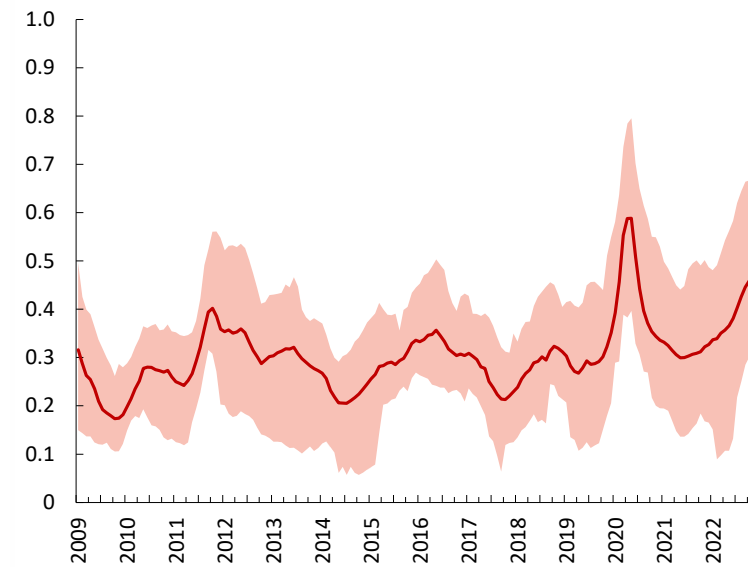
Advanced Economies, 10-year



Emerging Markets and Developing Economies, foreign currency



Emerging Markets and Developing Economies, 10-year local currency



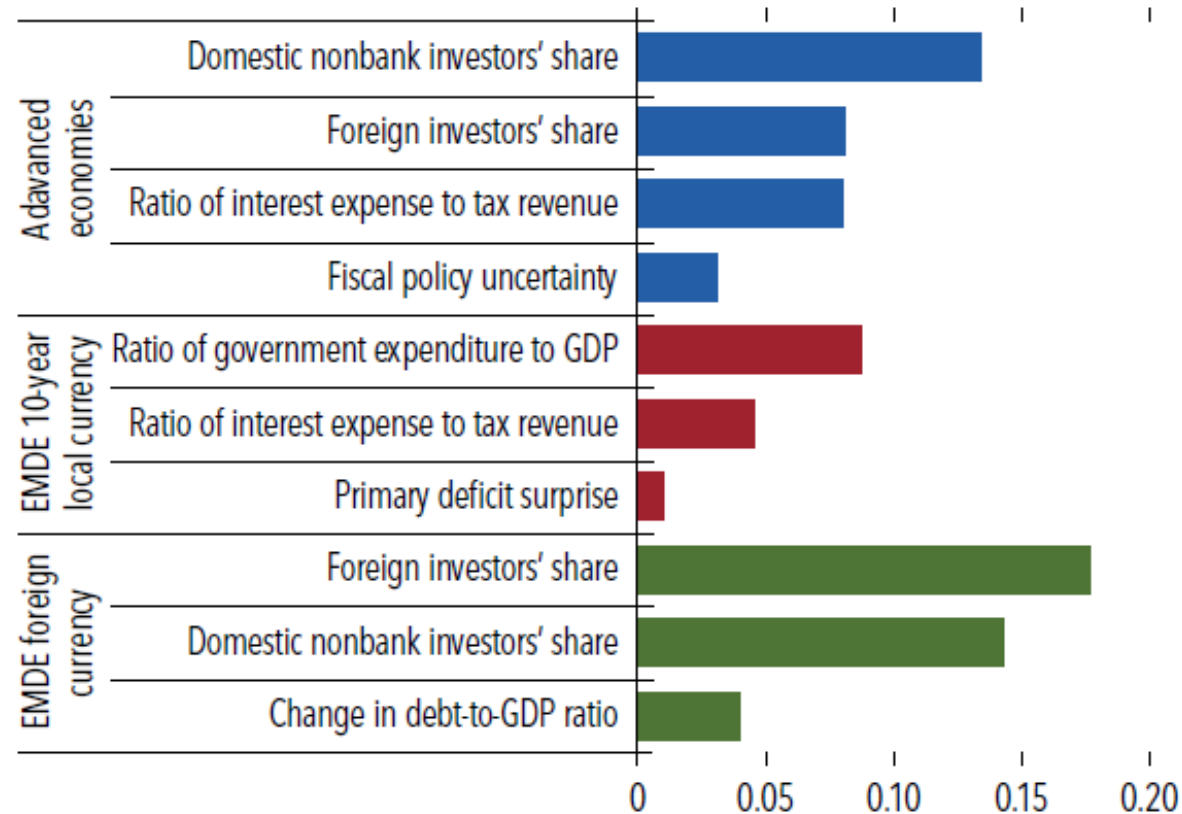
Sources: Global Financial Data, Haver Analytics, IMF International Financial Statistics, J.P. Morgan, OECD, World Bank; and IMF staff estimates.

Note: Solid lines correspond to simple average contributions of global factor to the variance of sovereign bond yields across country groups. For each country, the contribution of global factors corresponds to the median global factor share from retained Gibbs-sampling draws. Shaded areas around the solid line correspond to the interquartile range.

Fiscal policy and debt structure indicators are among the key drivers of the global volatility of sovereign yields

Key Drivers of Global Volatility of Sovereign Yields

(Effects on the volatility of sovereign bond yields explained by global factors given a change from 25th to 75th percentiles in selected)



Sources Europace AG/Haver Analytics; Global Financial Data; Hong, Ke, and Nguyen 2024; IMF, Sovereign Debt Investor Database; IMF, World Economic Outlook; JPMorgan; S&P Global Ratings; World Bank; and IMF staff estimates.

Note: The figure shows the differential impact on variance of sovereign bond yields driven by global factors when the variable of interest moves from the 25th to the 75th percentile. Estimates are obtained using the weighted-average least squares method for 26 advanced economies and 16 emerging market economies over 2009–22 (De Luca, Magnus, and Peracchi 2018), with a panel regression model estimated separately for each country group and bond instrument. The dependent variable is the average global component of the variance for respective sovereign yields. A variable is a “robust” contributing factor if the associated t-statistic is greater than one in absolute value. “Primary deficit surprise” is the difference between the actual primary deficit and that projected one year ahead. See Online Annex 1.2. EMDE = emerging market and developing economy.

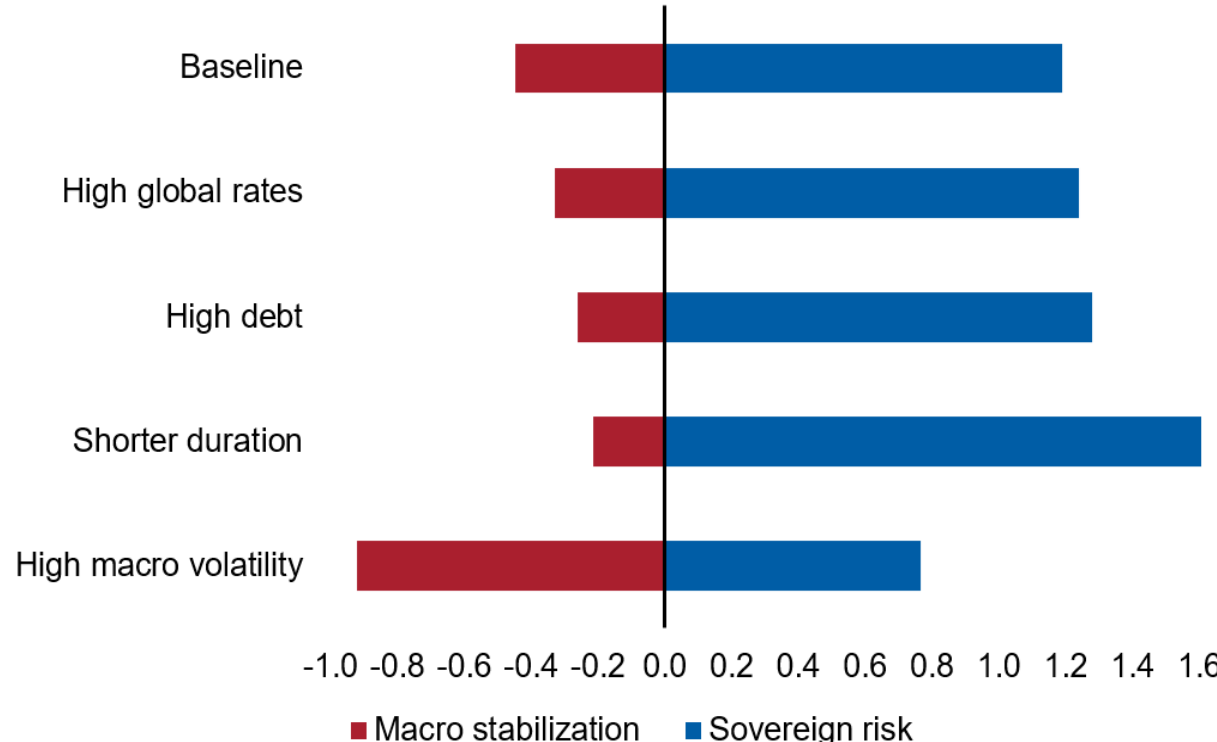
Optimal fiscal response warrants greater weight on sovereign risks

- Countries face tradeoffs between macroeconomic stabilization and debt sustainability.
- *Approach:* illustrate with a New-Keynesian-DSGE model with endogenous sovereign default.
- Approximate the optimal fiscal response:

$$\text{Discretionary expenditure}_{i,t} = \alpha_i + \beta_i * \left(\text{Sovereign risk} \right)_{i,t-1} + \gamma_i * \left(\text{Output gap} \right)_{i,t-1}$$

Optimal Fiscal Reaction: Balancing Macro Stabilization and Sovereign Risk

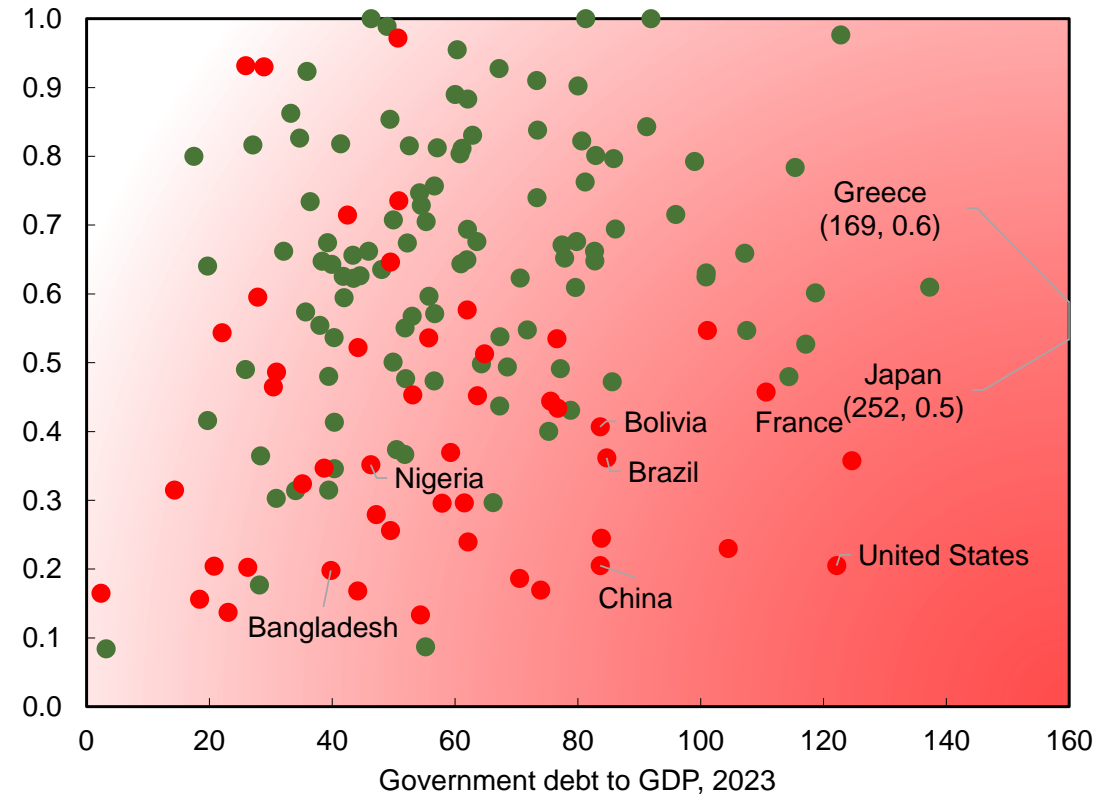
(Discretionary expenditure response to a one standard deviation change in each regressor, percentage points of GDP)



Source: Bianchi, Garcia-Macia, Ottonello, and Presno (forthcoming).
 Notes: The red (blue) bars denote the optimal weights associated with macro stabilization (sovereign risks). A "macro stabilization" coefficient equal to -1 means that discretionary expenditure is increased by one percent of GDP if tradable output falls by one standard deviation (0.9 percent of GDP). A "sovereign risk" coefficient equal to 1 means that discretionary expenditure is lowered by one percentage point of GDP if sovereign spreads rates increase by one standard deviation (1.1 percentage points).

Preventing debt from rising with a high probability requires a large fiscal adjustment for most countries

Probability of Debt Stabilization and Debt Levels
(Probability in percent)



- Countries' debt projected to stabilize in WEO by 2029
- Countries' debt not projected to stabilize by 2029

Source: IMF World Economic Outlook Database; and IMF staff estimates.

Note: The probability of debt stabilization is estimated based on the bootstrap method.

Fiscal adjustments needs to internalize household distribution, motivating the use of the HANK framework

Extend the **heterogeneous agent New-Keynesian (HANK)** model (Auclert, Rognlie and Straub, 2024) with additional fiscal instruments.

- **Households:** Consumption and labor choices, facing idiosyncratic income process
 - Liquid and illiquid asset (financial frictions)
 - Subject to (progressive) taxes and transfers
- **Production / supply side:** Output produced from capital and labor with wage and price rigidities
- **Fiscal policies**—government uses different expenditure (government consumption, public investment, subsidies, transfers) and tax measures (income tax) and debt to balance the budget
- **Monetary policy**—follow a ‘Taylor’ rule in response to inflation

Matching Key Moments

Calibration of Alternative Scenarios

Parameters	Description	Emerging market economy	Source	Advanced economy	Source
σ	Elasticity of intertemporal substitution	1	Auclert, Rognlie, and Straub (2024)	1	Auclert, Rognlie, and Straub (2024)
r	Real interest rate (annual)	0.05	Auclert, Rognlie, and Straub (2024)	0.05	Auclert, Rognlie, and Straub (2024)
β	Discount factor (annual)	0.929	matching $\frac{A}{\bar{Y}}$	0.93	Auclert, Rognlie, and Straub (2024)
(ρ_e, σ_e)	log(ϵ) persistence and standard deviation	0.90, 0.80	Hong (2023)	0.91, 0.92	Auclert, Rognlie, and Straub (2024)
θ	Retention function curvature	0.05	Tax brackets in Peru	0.181	Heathcote and others (2017)
$\frac{A}{\bar{Y}}$	Capital to GDP	2.73	Hong (2023)	2.96	Auclert, Rognlie, and Straub (2024)
$\zeta (1 + r)$	Illiquid-liquid spread	0.1	Lending-deposit spread in Peru	0.08	Auclert, Rognlie, and Straub (2024)
ν	Adjustment probability	0.088	Matching marginal propensity to consume	0.089	Auclert, Rognlie, and Straub (2024)

Source: Auclert, Rognlie, and Straub (2024), Heathcote, Storesletten, and Violante (2017), Hong (2023); and IMF staff estimates.

Key differences:

- Higher wealth inequality
- Tight financial frictions
- Stronger precautionary saving motives
- Higher MPC in EM than AE drives the key differences in the model dynamics

How can governments reduce and better manage risks from unidentified debt?

1. Assess and manage contingent liabilities

- Strengthen fiscal framework to identify, account, and manage risks, particularly from public corporations and natural disasters.
- Prioritize management based on the likelihood and impact of risks

2. Broaden institutional coverage

- Transition to cover general government or entire public sector
- Adopt/maintain broad coverage of budget aggregates and debt statistics

3. Strengthen core expenditure control functions

- Strengthen budget preparation and credibility
- Apply effective commitment control to limit overspending; active cash management
- Establish tracking systems for arrears; regular audits; strategy to clear arrears

4. Improve fiscal transparency

- Improve the quantity, quality, and timeliness of public fiscal and budgetary information