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Online Annex 1.1. Debt-at-Risk Framework[1]

This Online Annex presents the data sources, empirical methodology, and additional results for the "debt-at-risk" framework used in the main chapter.

Data and Sample

The sample is a country-by-year panel constructed using a variety of data sources. Data on government debt, GDP growth, and other economic variables is from the April 2024 vintage of the IMF World Economic Outlook database. The Financial Conditions Index captures the pricing of risk, with higher values indicating tighter financial conditions (Online Annex 1.1 in the October 2018 *Global Financial Stability Report)*. The Financial Stress Index (Ahir and others 2023), World Uncertainty Index (Ahir, Bloom, and Furceri 2022), and Reported Social Unrest Index (Barrett and others 2022) use text search methods to construct indicators for financial market stress, uncertainty, and social unrest, respectively. Sovereign spreads are defined as the difference between 10-year government bond yields and the 10-year *United States* treasury yield.[2] Election year data is sourced from the National Elections under Democracy and Autocracy database. Fiscal rules data are obtained from the IMF Fiscal Rule database and Davoodi and others (2022).[3] The inclusion of financial and economic variables attempts to go beyond the debt dynamics equation and capture the underlying drivers of debt risks. The selected variables have wide country coverage and have been used in the growth-at-risk literature.

The country coverage includes 74 economies—comprising 37 advanced economies, 30 emerging markets, and 7 low-income developing countries—for which bond yield data are available (Online Annex Table 1.1.4). The coverage approximates those economies that have some level of market access for sovereign debt financing. The sample is at an annual frequency and spans from 1980 to 2023.[4]

Methodology

Following Machado and Santos Silva (2019), panel quantile regressions are estimated with country fixed effects to control for time-invariant country characteristics. The baseline estimating equation is the following location-scale model:

$$d_{i,t+h} = \alpha_i + X_{i,t}'\beta + \left(\delta_i + X_{i,t}'\gamma\right)\varepsilon_{i,t+h} \qquad \text{(A1.1.1)}$$

where $d_{i,t+h}$ denotes the h year-ahead government debt-to-GDP ratio for country i in year t (h ranges from 1 to 5 years). The parameters α_i and δ_i capture the country fixed effects. $X_{i,t}$ is the vector containing the conditioning variable of interest $x_{i,t}$—for example, GDP growth. As the debt-to-GDP ratio is a stock variable and likely non-stationary, $X_{i,t}$ includes the *contemporaneous* debt-to-GDP ratio (i.e., $d_{i,t}$) in every specification—that is, $X_{i,t}'\beta = \beta_1 x_{i,t} + \beta_2 d_{i,t}$. The scale parameter is γ and $\varepsilon_{i,t+h}$ is the error term. The coefficient(s) of interest are β.[5] The model implies that the τ-th quantile of future debt, $Q_d(\tau)$, is given by:

$$Q_{d_{i,t+h}}\left(\tau | X_{i,t}\right) = \left(\alpha_i + \delta_i q(\tau)\right) + X_{i,t}'\beta + X_{i,t}'\gamma q(\tau) \qquad \text{(A1.1.2)}$$

---

[1] Prepared by Faizaan Kisat.

[2] For the *United States*, actual 10-year Treasury yields are used in place of spreads. Data is obtained from Global Financial Data.

[3] The election year variable is an indicator that equals one if a country has an election scheduled in the current or preceding year, and zero otherwise (see Online Annex 1.3 in the April 2024 *Fiscal Monitor*).

[4] Debt data are reliably available only at an annual frequency for some countries. Average values for the year are used for conditioning variables (for example, spreads) that are reported at a higher frequency.

[5] The parameters of interest are estimated sequentially using a series of moment conditions (Machado and Santos Silva 2019). Robust and clustered standard errors (at the country level) are obtained by using the *mmqreg* Stata command (Rios-Avila 2022).

where $q(\tau) = F_\varepsilon^{-1}(\tau)$ is the inverse cumulative density function of the error term evaluated at the quantile τ.

As in Adrian, Boyarchenko, and Giannone (2019), the predicted quantiles are fitted to a skewed *t*-distribution (Azzalini and Capitanio 2003) to recover a probability density function.[6] For any country (or country group), a pooled density forecast is calculated using a weighted sum of the densities based on individual predictors m (for example, financial stress) as follows:[7]

$$\hat{f}_{i,t}^{pooled}(d) = \sum_m \mu_i^m \hat{f}_{i,t}^m(d) \qquad \text{(A1.1.3)}$$

The weights μ_i^m sum to one and are computed as follows to maximize the out-of-sample predictive accuracy of the combined distribution, following the work of Crump and others (2023): first, for a particular country in a given year (from 2006 onward), probability density functions are obtained conditional on each explanatory variable using data from the *prior* 20 years; second, each conditional density function is evaluated at the ex post realized value of debt-to-GDP at the corresponding horizon; third, the weights are obtained as the values (positive and summing to one) that maximize these out-of-sample probabilities across all years.[8]

Quantile predictions at the country-year level, denoted by $\hat{Q}_{d_{i,t+h}}$, are aggregated to the global level in three steps. First, a weighted average of the estimated quantiles is computed as follows:

$$\hat{Q}_{d_{global,t+h}}(\tau) = \sum_{i=1}^{I} \omega_{i,t}\, \hat{Q}_{d_{i,t+h}}(\tau) \qquad \text{(A1.1.4)}$$

where the weighting factor $\omega_{i,t} = \frac{GDP_{i,t}}{\sum_{i=1} GDP_{i,t}}$ is country i's nominal US dollar GDP share among in-sample countries. Second, the global quantiles across all years and conditioning variables are re-centered. This ensures the predicted median for the unconditional distribution in 2023—the distribution obtained from the quantile regression of future debt *only on* current debt levels—matches the corresponding 2024–28 global debt-to-GDP ratio forecast in the World Economic Outlook database. For the global distribution to be comparable across historical years, conditioning variables need to be available for all countries across the periods of interest, defined as 2009 through 2023. Imposing this restriction reduces the sample to 44 countries, but the reduced sample still covers more than 90 percent of global debt.[9] Finally, the pooled global distribution is calculated using a weighted sum of the fitted densities, similar to the approach for pooling country-level densities. The global weights are the GDP-weighted average of individual countries, as shown below (an identical approach is followed for country groups):

$$\hat{f}_{global,t}^{pooled}(d) = \sum_m \left(\sum_i \omega_{i,t} \mu_i^m\right) \hat{f}_{global,t}^m(d) \qquad \text{(A1.1.5)}$$

Debt-at-risk in a particular year is defined as the 95th predicted quantile of respective debt-to-GDP ratios. The model displays a decent out-of-sample fit. The predicted median global debt-to-GDP for 2026 is 98.4 percent, close to the comparable World Economic Outlook database forecast. The mean absolute percentage error across all years in the sample for global debt is less than 5 percent, indicating a fairly accurate model fit.

[6] The inputs for this step are the 5th, 25th, 75th, and 95th predicted quantiles.

[7] For this exercise, the following eight predictors with the most complete coverage in the sample are used: initial debt, financial stress index, spread, world uncertainty index, reported social unrest index, primary balance-to-GDP ratio, real GDP growth, and inflation.

[8] As a concrete example, consider how weights are produced for the *United States* at a one-year-ahead forecast horizon. Using data from 1986-2005, density functions are obtained which are evaluated at the actual realized value of the debt-to-GDP ratio in 2006. This procedure is repeated until probabilities are calculated for every explanatory variable and every year (2006–23). The weights are the solution to a constrained optimization problem that sums these probabilities across all explanatory variables and years, where the weights are constrained to be positive and sum to one.

[9] The restricted sample comprises 44 countries, including 23 advanced economies, 17 emerging markets, and 4 low-income developing countries.

The baseline equation (A1.1.1) is modified to consider heterogeneity by existing debt levels and country groups. For the former, the vector of conditioning variables is modified to include nonlinear interactions with existing debt levels, as shown below:

$$X'_{i,t}\beta = \sum_{k=1}^{4} \beta_{1,k} x_{i,t} \times \mathbf{1}\{Q(d_{i,t}) = k\} + \sum_{k=1}^{4} \beta_{2,k} d_{i,t} \times \mathbf{1}\{Q(d_{i,t}) = k\} \quad \text{(A1.1.6)}$$

where $x_{i,t}$ is the conditioning variable as before (for example, GDP growth) and $d_{i,t}$ is debt-to-GDP ratio. $\mathbf{1}\{Q(d_{i,t}) = k\}$ is an indicator that equals one if the quartile of contemporaneous debt-to-GDP ratio equals k, where $k \in \{1,2,3,4\}$. "Low initial debt" and "high initial debt" are defined as the first and fourth quartile of the contemporaneous debt-to-GDP ratio, respectively.

Heterogeneity by country group is evaluated by estimating the following modified specification:

$$X'_{i,t}\beta = \sum_{j=\{AE,EMDE\}} \beta_{1,j} x_{i,t} \times \mathbf{1}\{country\ i \in j\} + \sum_{j=\{AE,EMDE\}} \beta_{2,j} d_{i,t} \times \mathbf{1}\{country\ i \in j\} \quad \text{(A1.1.7)}$$

Where $\mathbf{1}\{country\ i \in j\}$ is an indicator that equals one if a country is classified as an advanced economy (AE) or emerging market and developing economy (EMDE), respectively. The analysis also explores heterogeneity by whether a country in a particular year is following a fiscal rule using an equation similar to (A1.1.7).

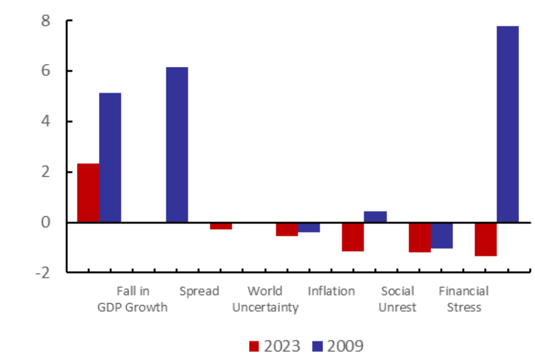
Results

Online Annex Table 1.1.1 displays the quantile regression coefficients for the three-year-ahead debt-to-GDP ratio corresponding to the results reported in Figure 1.3 in the main text. Most of the conditioning variables have an asymmetric effect on the debt distribution, with typically larger coefficients for the 95th quantile versus the median. The signs of the coefficients are also intuitive—tighter financial conditions increase the debt-at-risk whereas higher GDP growth or stronger primary balance lowers it.

To assess the relative importance of these variables in shifting the debt distribution, we can compare the difference between the debt-at-risk conditional on each variable relative to the debt-at-risk conditional only on initial debt (Online Annex Figure 1.1.1). At the current juncture, primary deficits are the largest driver of debt risks for the world. In particular, higher primary deficits raise the three-year-ahead global debt-at-risk by around 2 percentage points of GDP. The variable contributing to elevated debt risks changes over time, further substantiating the finding in the main text that debt risks change over time. In contrast and as expected, in 2009—the immediate aftermath of the global financial crisis—financial stress is the largest driver of debt risks (Online Annex Figure 1.1.1, blue bars).

Online Annex Figure 1.1.1. Conditioning Variables Contributing to Three-Year-Ahead Global Debt-at-Risk: 2023

(Percent of GDP)



Source: IMF staff estimates.
Note: The figure plots the difference between the predicted 95th quantile of three-year-ahead global debt-to-GDP conditional on the variables displayed on the horizontal axis and initial debt relative to the 95th quantile conditional on initial debt only.

The global five-year-ahead debt distribution (Online Annex Figure 1.1.2) follows a similar trajectory as the three-year-ahead distribution plotted in Figure 1.4 in the main text. The global debt-at-risk is at 119 percent of GDP five years ahead, about 20 percentage points higher than the current baseline projection by 2028. The corresponding distributions for advanced economies and emerging market and developing economies are displayed in Online Annex Figure 1.1.3. The debt-at-risk five years ahead is about 139 percent of GDP and 94 percent of GDP for advanced economies and emerging market and developing economies, respectively. Consistent with the main text, they show rising debt risks in emerging market and developing economies over time and a contraction of debt risks in advanced economies relative to the pandemic.

Online Annex Table 1.1.1. Quantile Regression Results: Three-Year-Ahead Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables

ıex Table 1.1.1. Quantile Regression Results: Three-Year-Ahead Debt-to-GDP Ratio vs.

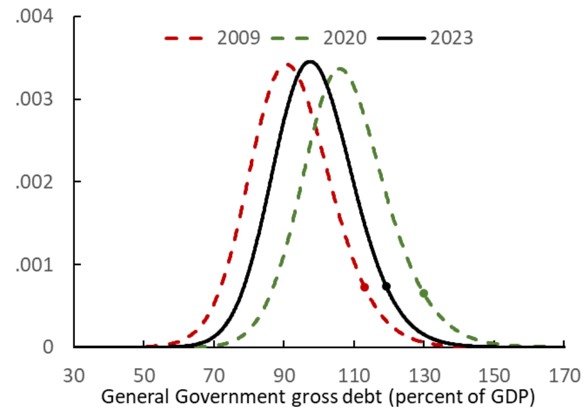
	Dependent variable: General government gross debt, percent of GDP: three-year-ahead		
	Q5	Q50	Q95
	(1)	(2)	(3)
Panel A: Financial Variables			
Financial conditions index	1.471***	2.150***	3.063***
	(0.556)	(0.485)	(0.859)
Initial debt, percent of GDP	0.591***	0.671***	0.777***
	(0.123)	(0.079)	(0.059)
Financial stress index	1.305*	1.718***	2.272***
	(0.707)	(0.380)	(0.724)
Initial debt, percent of GDP	0.626***	0.744***	0.903***
	(0.118)	(0.085)	(0.042)
Sovereign spread	1.218	1.616**	2.161***
	(1.209)	(0.811)	(0.735)
Initial debt, percent of GDP	0.794***	0.834***	0.888***
	(0.080)	(0.058)	(0.041)
World uncertainty index	2.370***	1.934***	1.388
	(0.738)	(0.749)	(0.937)
Initial debt, percent of GDP	0.640***	0.742***	0.869***
	(0.117)	(0.083)	(0.045)
10-year Government Bond Yield	-0.242	0.431	1.345
	(1.994)	(1.490)	(1.214)
Initial debt, percent of GDP	0.795***	0.838***	0.895***
	(0.082)	(0.058)	(0.039)
Panel B: Political Variables			
Election year indicator	0.346	0.537	0.793
	(0.844)	(0.339)	(1.075)
Initial debt, percent of GDP	0.640***	0.725***	0.838***
	(0.129)	(0.087)	(0.036)
Reported social unrest index	2.425***	2.186***	1.879***
	(0.701)	(0.409)	(0.518)
Initial debt, percent of GDP	0.624***	0.702***	0.801***
	(0.123)	(0.083)	(0.039)
Panel C: Economic Variables			
Initial debt, percent of GDP	0.648***	0.749***	0.883***
	(0.108)	(0.076)	(0.040)
Primary balance, percent of GDP	-4.068***	-3.667***	-3.117***
	(0.696)	(0.617)	(1.006)
Initial debt, percent of GDP	0.623***	0.713***	0.836***
	(0.104)	(0.080)	(0.050)
Real GDP growth rate	-2.084***	-2.834***	-3.861***
	(0.646)	(0.675)	(1.480)
Initial debt, percent of GDP	0.623***	0.715***	0.842***
	(0.111)	(0.082)	(0.047)
CPI inflation	-68.879*	-77.182***	-87.741***
	(35.635)	(26.919)	(33.785)
Initial debt, percent of GDP	0.646***	0.738***	0.856***
	(0.109)	(0.077)	(0.040)

Source: IMF staff estimates.
Note: The table shows the estimated coefficients for 5th, 50th, and 95th percentile based on panel quantile regressions (A1.1.1) on selected financial, political, and economic variables based on 74 countries for the period 2009–23. The coefficients refer to the percentage point change in the government debt-to-GDP ratio when the explanatory variable changes by one unit. All explanatory variables (except for initial debt and election year) are standardized to have a mean of zero and a standard deviation of one to ensure comparability across coefficients. Standard errors, clustered at the country level, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

The framework is at a country-year level allowing the above analysis to be conducted for individual countries that have available data. As an example, the three-year-ahead debt distribution for the *United States* shows elevated debt risks at the current juncture, consistent with the country's rising debt trajectory (Online Annex Figure 1.1.4). For the *United States*, the primary deficit is the largest driver of debt risks in 2023 and consistently has the highest weight in the combined distribution (Online Annex Table 1.1.2). Conditional on deficits, the three-year-ahead debt-at-risk exceeds 150 percent of GDP in 2023, more than 20 percentage points higher than the baseline projection of debt-to-GDP ratio in the World Economic Outlook database.

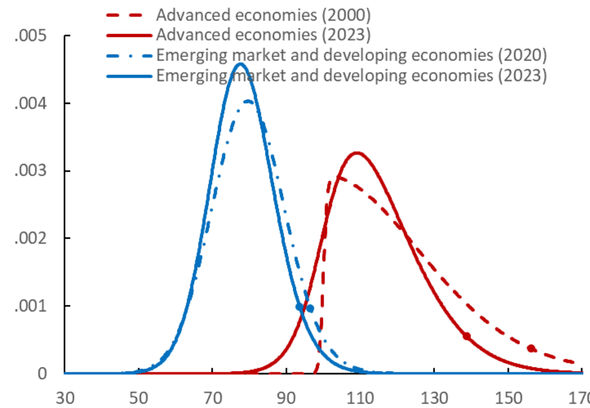
Online Annex Figure 1.1.2. Global Debt-at-Risk and Its Evolution

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



Online Annex Figure 1.1.3. Debt-at-Risk across Income Groups

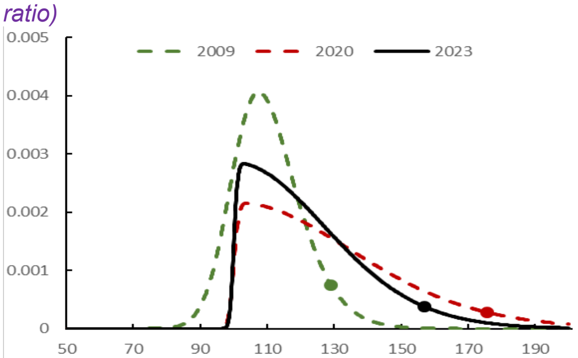
(Probability density of five-year-ahead debt-to-GDP ratio, 2023)



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 based on equation (A1.1.1). 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.

Online Annex Figure 1.1.4. Debt-at-Risk for the United States

(Probability density of three-year-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 based on equation (A1.1.1). 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.

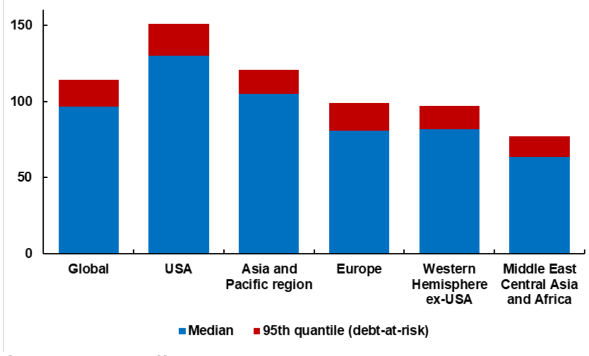
Online Annex Table 1.1.2. Weights Used to Combine United States Distribution

	Conditioning Variables							
Forecast Horizon (Years)	Initial Debt	Financial Stress Index	Spread	World Uncertainty Index	Social Unrest Index	Primary Balance	GDP Growth	Inflation
1	0.00	0.62	0.00	0.00	0.00	0.38	0.00	0.00
2	0.00	0.35	0.00	0.00	0.00	0.65	0.00	0.00
3	0.00	0.22	0.00	0.00	0.00	0.78	0.00	0.00
4	0.00	0.23	0.00	0.00	0.00	0.77	0.00	0.00
5	0.00	0.58	0.00	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 and others (2023).

Online Annex Figure 1.1.5. Debt-at-Risk by Region

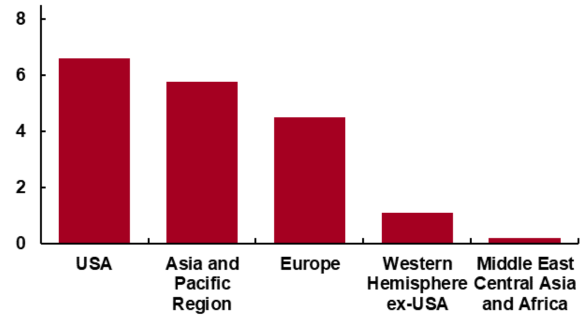
(Predicted median and 95th quantile of three-year-ahead debt-to-GDP ratio, in percent of GDP)



Source: IMF staff estimates.
Note: The regional aggregates only include the countries in the 44 country sample that are used to create the global distribution. The figure plots the three-year-ahead predicted median and 95th quantile debt-to-GDP ratio by region.

Online Annex Figure 1.1.6. Regional Contribution to Global Debt-at-Risk

(Percent of GDP)



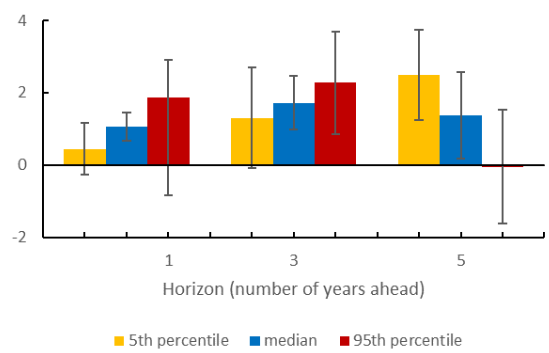
Source: IMF staff estimates.
Note: The regional aggregates only include the countries in the 44 country sample that are used to create the global distribution. The figure plots the difference between the predicted 95th quantile and the (unconditional) predicted median for each region. This difference 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 (A1.1.4).

Debt risks also exhibit some regional differences (Online Annex Figure 1.1.5). The *United States’* elevated debt risks and its high relative share in global GDP mean that the country contributes to around one-third of global debt-at-risk at the current juncture (Online Annex Figure 1.1.6).

The analysis also considers the impact of conditioning variables on the proximate drivers of debt (Online Annex Table 1.1.3). As noted in the main text, financial and political variables increase growth-at-risk in the near term. These variables also raise the “deficit-at-risk”—that is, adverse financial and political developments asymmetrically reduce the *fifth* quantile of the future primary balance-to-GDP distribution up to a forecast horizon of two years. In addition, the right tail of the “unidentified debt” distribution, where it refers to future realizations of unidentified debt, increases asymmetrically in the near term with financial stress episodes (Online Annex Figure 1.1.7). The result is in line with the finding that unidentified debt rises sharply following a financial crisis.

Online Annex Figure 1.1.7. Unidentified Debt and Financial Stress

(Coefficient on financial stress index in panel quantile regressions across forecast horizons)



Source: IMF staff estimates.
Note: The figure shows the estimated coefficients for 5th, 50th, and 95th percentile based on panel quantile regressions (A1.1.1) of future realizations of stock-flow adjustments on the financial stress index. The dependent variable is the cumulative unidentified debt (stock-flow adjustment excluding valuation changes in exchange rates) as a percent of GDP across a one-, three-, and five-year forecast horizon, respectively. Bars denote estimated coefficients. Whiskers in bars show 90 percent confidence intervals for estimated coefficients.

Online Annex Table 1.1.3. Conditioning Variables and Growth, Primary Balance, Interest Rate, and Hidden Debt-at-Risk

	Dependent Variable							
	Three years ahead				Five years ahead			
	Growth (5th percentile)	Primary balance (5th percentile)	Interest (95th percentile)	Unidentified debt (95th percentile)	Growth (5th percentile)	Primary balance (5th percentile)	Interest (95th percentile)	Unidentified debt (95th percentile)
Panel A: Financial Variables								
Financial conditions index		-				-	+	
Financial stress index	-	-	-	+			-	
Sovereign spread	-	-						
World uncertainty index		-	-	-		-	-	
10-year government bond yield								
Panel B: Political Variables								
Election year indicator	-	-						
Reported social unrest index	-	-		-	-	-		-
Panel C: Economic Variables								
Initial debt, percent of GDP			-			+	-	
Primary balance, percent of GDP		+	-			+	-	+
Real GDP growth rate	+	+			+	+		
Headline inflation			+		+		+	

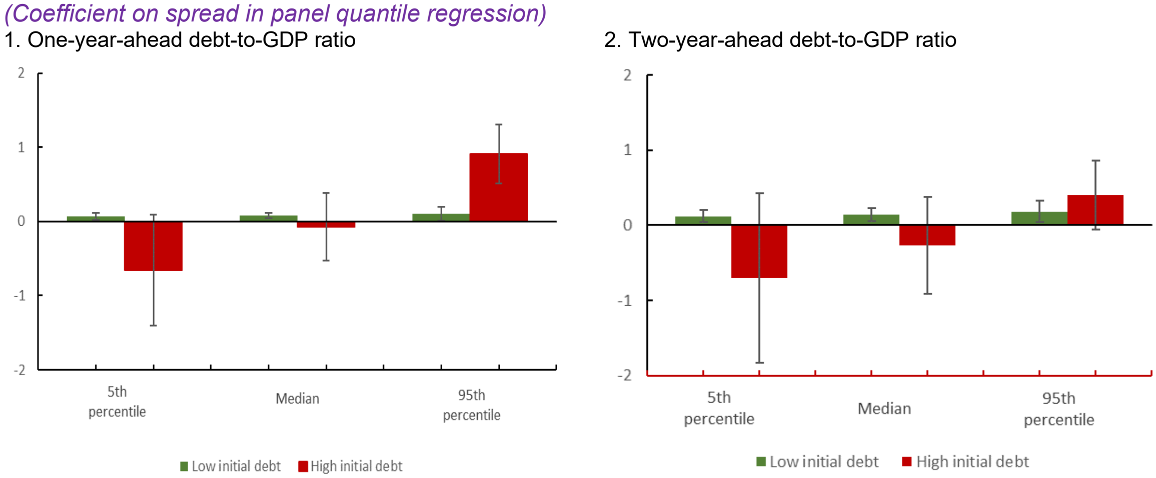
Source: IMF staff estimates.
Note: The table shows the signs of estimated coefficients and their statistical significance from the panel quantile regressions (A1.1.1). Economic growth and primary balance are shown for the 5th percentiles (downside risks) and interest rates and unidentified debt are shown at the 95th percentile (upside risks), which could raise the debt risk. "+" denotes a positive sign of the estimated coefficient and "-" denotes a negative sign of the estimated coefficients. Shades in the selected cells show the statistical significance, with dark red, light red, and pink indicating statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Results by Initial Debt Levels and Country Groups

Higher government borrowing costs increase near-term debt risks disproportionately when initial debt is high. Consistent with the results shown in the main text for GDP growth (Figure 1.5), a 1 percentage point increase in sovereign spreads is associated with a 0.9 percentage point increase in the one-year-ahead debt-at-risk when debt is high (above 70 percent of GDP) versus a comparable increase of only 0.1 percentage point when debt is low (Online Annex Figure 1.1.8, panel 1). The result also holds when sovereign bond yields are used instead of spreads—that is, when overall borrowing costs rather than spreads are considered. The findings are relevant at the current juncture, as both debt levels and debt servicing costs remain elevated.

Online Annex Figure 1.1.8. Sovereign Spreads, Initial Debt, and Debt-at-Risk

(Coefficient on spread in panel quantile regression)



Source: IMF staff estimates.
Note: The figure shows estimated coefficients for the 5th, 50th, and 95th percentile based on panel quantile regressions of debt-to-GDP ratio on spreads based on equation (A1.1.6). Panels 1 and 2 display the results for a forecast horizon of one and two years, respectively. Bars denote estimated coefficients. Whiskers in bars show 90 percent confidence intervals for estimated coefficients.

Online Annex Figure 1.1.9 displays the heterogeneity in the results by country income group as described in the main text. Consistent with the literature such as Ahir, Bloom, and Furceri (2022) and Ahir and others (2023), financial variables (spreads, world uncertainty) have a larger medium-term impact on debt-at-risk for emerging market and developing economies.

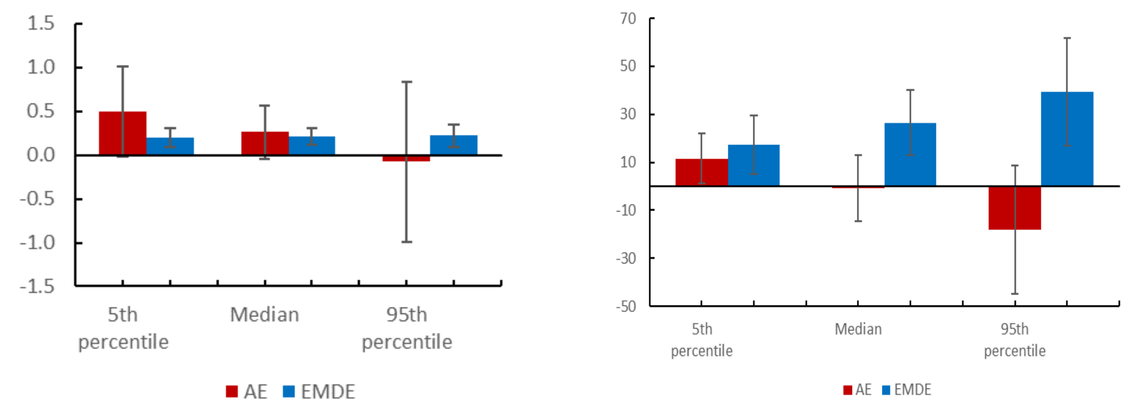
Online Annex Figure 1.1.9. Heterogeneity in Results by Country Groups

1. Spreads and Debt-at-Risk by Country Income Group

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

2. World Uncertainty Index 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.

Online Annex Table 1.1.4. Economies Coverage: Debt-at-Risk Analysis

Advanced Economies	Emerging Market and Middle-Income Economies	Low Income Developing Countries
Australia	Argentina	Bangladesh
Austria	Armenia	Côte d'Ivoire
Belgium	Botswana	Kenya
Canada	Brazil	Nigeria
Croatia	Bulgaria	Tanzania
Cyprus	Chile	Uganda
Czech Republic	China	Zambia
Denmark	Colombia	
Estonia	Ecuador	
Finland	Egypt	
France	Hungary	
Germany	India	
Greece	Indonesia	
Hong Kong SAR	Kazakhstan	
Iceland	Malaysia	
Ireland	Mexico	
Israel	Morocco	
Italy	Namibia	
Japan	Pakistan	
Korea	Peru	
Latvia	Philippines	
Lithuania	Qatar	
Luxembourg	Romania	
Malta	Russia	
Netherlands	South Africa	
New Zealand	Sri Lanka	
Norway	Thailand	
Portugal	Tunisia	
Singapore	Türkiye	
Slovak Republic	Vietnam	
Slovenia		
Spain		
Sweden		
Switzerland		
Taiwan Province of China		
United Kingdom		
United States		

Note: The table displays the countries included in the sample of 74 economies used for the debt-at-risk analysis.

Online Annex 1.2. Global and Local Drivers of Sovereign Bond Yields[1]

This Online Annex presents the methodology used to quantify the contribution of global factors to the fluctuations of sovereign bond yields and identify robust determinants of the sovereign yields volatility that is driven by global factors.

Methodology

A dynamic factor model is used to decompose the global factors:

$$y_{ijt} = A^G_{ijt}F^G_t + A^C_{ijt}F^C_{jt} + v_{ijt} \quad \text{(A1.2.1)}$$

for variable i in country *j* at a time t. Each series is assumed to be affected by a set of N^G global unobserved factors $F^G_t = \left[f^G_{1t}, \dots, f^G_{N^G t}\right]'$, a set of N^c country-specific unobserved factors $F^C_{jt} = \left[f^C_{1jt}, \dots, f^C_{N^C jt}\right]'$, and the unobserved idiosyncratic components v_{ijt}. $A^G_{ijt} = \left[a^G_{1ijt}, \dots, a^G_{N^G ijt}\right]$ and $A^C_{ijt} = \left[a^C_{1ijt}, \dots, a^C_{N^C ijt}\right]$ are row vectors of global and country-specific factor loadings, respectively. The global factors affect all variables for all countries, but the strength of their impact (i.e., a factor loading) is a country-specific variable, depending on factors such as economic conditions and the structure of the economy. In contrast, country-specific factors only affect variables in the corresponding country. The model includes N countries.

Each global and country-specific factor (*l*-th factor) is assumed to follow a standard autoregressive process (Diebold and others 2008; Kose and others 2012):

$$f^G_{lt} = c_l + \sum_{k=1}^{P} b_{lk} f^G_{lt-k} + \sqrt{\sigma_{lt}}e_{lt}, \text{ where } e_{lt} \sim N(0,1) \quad \text{(A1.2.2)}$$

$$f^C_{ljt} = c_{lj} + \sum_{k=1}^{P} b_{ljk} f^C_{ljt-k} + \sqrt{\sigma_{ljt}}e_{ljt}, \text{ where } e_{ljt} \sim N(0,1) \quad \text{(A1.2.3)}$$

where the error terms are heteroscedastic, following a stochastic volatility framework. This framework captures potential changes in the volatility of the variables, for example, high volatility driven by significant shocks versus periods of low volatility:[2]

$$\ln \sigma_{lt} = \ln \sigma_{lt-1} + \sqrt{\varphi_l}\epsilon_{lt} \text{ where } \epsilon_{lt} \sim N(0,1) \quad \text{(A1.2.4)}$$
$$\ln \sigma_{ljt} = \ln \sigma_{ljt-1} + \sqrt{\varphi_{lj}}\epsilon_{ljt} \text{ where } \epsilon_{ljt} \sim N(0,1) \quad \text{(A1.2.5)}$$

Similarly, each idiosyncratic component is modeled as:

$$v_{ijt} = \sum_{k=1}^{Q} b_{ijk}\, v_{ijt-k} + \sqrt{h_{ijt}}e_{ijt}, \text{ where } e_{ijt} \sim N(0,1) \quad \text{(A1.2.6)}$$
$$\ln h_{ijt} = \ln h_{ijt-1} + \sqrt{g_{ij}}\,\epsilon_{ijt}, \text{ where } \epsilon_{ijt} \sim N(0,1) \quad \text{(A1.2.7)}$$

To capture the impact of global and country-specific factors over time, the factor loadings are allowed to be time-varying, where each loading A_{lijt} follows:

$$A_{lijt} = A_{lijt-1} + \sqrt{q_{lij}}\tau_{lijt}, \text{ where } \tau_{lijt} \sim N(0,1) \quad \text{(A1.2.8)}$$

Consistent with the assumption used in the literature, all shocks are assumed to be orthogonal to each other.

The analysis applies the method described in Mumtaz (2017) and Mumtaz and Musso (2021) and uses the Gibbs sampling to estimate a nonlinear state space model featuring time-varying parameters and stochastic volatilities. The estimation covers 45 countries, consisting of 26 advanced economies and 19 emerging market

[1] Prepared by Anh Dinh Minh Nguyen and Alexandra Solovyeva.

[2] The inclusion of stochastic volatility is justified by several significant events associated with heightened volatility during the sample period, including the global financial crisis, the COVID-19 pandemic, and the postpandemic high inflation. Jurado, Ludvigson, and Ng (2015) provides evidence of changes in the volatility of the US macroeconomic variables and Comunale and Nguyen (2023) for the euro area.

and developing economies, from January 2005 until December 2022. The set of observed variables y include 10-year local currency sovereign yields, foreign currency sovereign yields, two-year local currency sovereign yields, corporate bond yields, the industrial production index, the consumer price index, and the nominal effective exchange rate.[3] Variables on bond yields are expressed in first differences, while the other three series are in first log differences.

The number of global factors is set at seven, the maximum number of variables for each country, which is consistent with the GVAR approach (Chudik and Pesaran 2016) and supported by the criteria of Bai and Ng (2002). The number of country-specific factors is limited to two, given that the number of series per country is only seven. The lag length of autoregressive processes is set to three ($P=Q=3$) in line with Mumtaz (2017) and Kose and others (2003). The first 36 months are used to construct the prior.

We use the variance decomposition in Kose and others (2003) to measure the relative contributions of global and local factors to the fluctuations of sovereign yields, adjusting for the time-varying parameters and stochastic volatilities. With orthogonal factors, the variance of each variable at each time t is as follows (country subscript j omitted for brevity):

$$var(y_{it}) = \sum_{l=1}^{N^G}(a_{lit}^G)^2 var(f_{lt}^G) + \sum_{l=1}^{N^C}(a_{lit}^C)^2 var(f_{lt}^C) + var(v_{it}) \qquad \text{(A1.2.9)}$$

The volatility of each series at time t is thus driven by movements in global factors (first term on the right-hand side), country-specific factors (second term), and the idiosyncratic component (third term) in equation (A1.2.9).

In line with Del Negro and Otrok (2008) and Mumtaz and Musso (2021), the decomposition is derived under the assumption that at each period in time the factor loadings are fixed based on their estimates in this decomposition (Cogley and Sargent 2008). The variance driven by global factors is $GV_{it} = \sum_{l=1}^{N^G}(a_{lit}^G)^2 var(f_{lt}^G)$, whereas the variance driven by local factors is the sum of country-specific factors and idiosyncratic factors: $LV_{it} = \sum_{l=1}^{N^C}(a_{lit}^C)^2 var(f_{lt}^C) + var(v_{it})$. The global factor share is then calculated as:

$$Global\ factor\ share_{it} = \frac{GV_{it}}{var(y_{it})} \qquad \text{(A1.2.10)}$$

The global factor share in equation (A1.2.10) changes over time due to time-varying factor loadings, time-varying volatility in the error terms associated with the global factors, country-specific factors, and the idiosyncratic component.[4]

Role of Global Factors

Results show that global factors are the main drivers of fluctuations in sovereign yields for advanced economies and foreign-currency sovereign yields for emerging market and developing economies (Online Annex Figure 1.2.1). In contrast, global factors explain only about 30 percent of variation in local-currency yields of emerging market and developing economies, on average. The role of global factors has been

[3] Data on sovereign and corporate bond yields are compiled from several sources, including Global Financial Data, IMF *International Financial Statistics,* J.P. Morgan, and OECD. Other macroeconomic variables are based on data from Haver Analytics, IMF *International Financial Statistics*, and the World Bank.

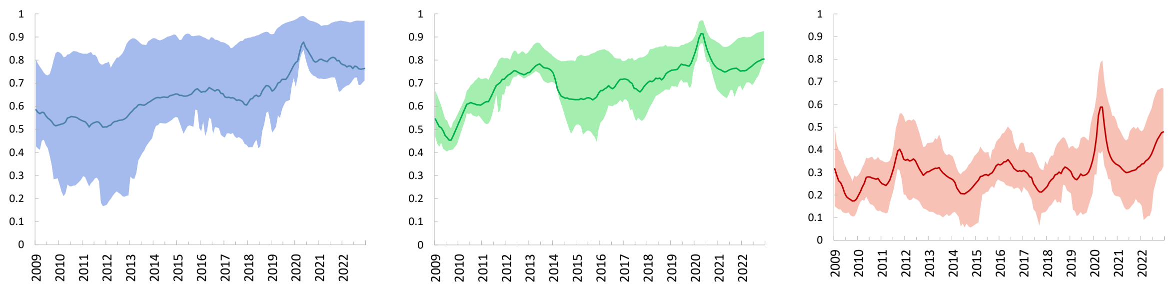
[4] The model is subject to the typical scale and sign identification problems affecting factor models. First, the scale of the factors is not identified. Following Mumtaz (2017) and Del Negro and Otrok (2008), this is addressed by fixing the value for the initial condition for the stochastic volatilities. Second, the signs of factors and factor loadings are not identified separately. However, the analysis uses either the product of factors and their factor loadings or the squared terms of the loadings, therefore it does not require a separate estimate of factors and their loadings.

increasing gradually across all sovereign bond markets, particularly at times of crisis during global shocks—such as the euro area sovereign debt crisis, the COVID-19 pandemic, and the postpandemic global inflation.[5]

Online Annex Figure 1.2.1. Global Factor Share

(Share of total variance)

1. Advanced economies, 10-year
2. Emerging market and developing economies, foreign currency
3. Emerging market and developing economies, 10-year local currency



Sources: Global Financial Data, Haver Analytics, IMF *International Financial Statistics,* J.P. Morgan, OECD, World Bank, and Nguyen, Solovyeva, and Zhang (forthcoming).
Note: Solid lines correspond to simple average contributions of global factor to the variance of sovereign bond yields across country groups (Equation A1.2.10). 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.

Globally Driven Variance of Sovereign Bond Yields

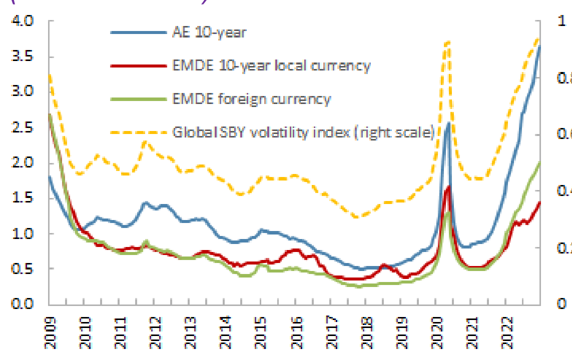
A composite index of global sovereign bond yield volatility (GSBYV) is constructed by averaging the variance driven by global factors (GV) across different bond types and across countries based on the methodology in Jurado, Ludvigson, and Ng (2015). Specifically, the GSBYV index is computed as:[6]

$$GSBYV_t = \frac{1}{M}\sum_j \sum_i \sqrt{GV_{ijt}} \qquad \text{(A1.2.11)}$$

where GV_{ijt} is the globally driven variance of a sovereign bond yield i in a country j at a time t.[7] The use of the globally driven component aims to directly capture the influence of global factors. The index captures well the periods of significant uncertainty, such as the global financial crisis, the COVID-19 pandemic, and the recent inflation surge. It is also strongly correlated to the variance of

Online Annex Figure 1.2.2. Sovereign Bond Yield Volatility

(Total variance)



Sources: Global Financial Data, Haver Analytics; *IMF International Financial Statistics;* J.P. Morgan; OECD; World Bank; and IMF staff calculations.
Note: The figure shows the median total variance of sovereign bond yields (SBYs) across country groups (Equation A1.2.9) and the index of the global sovereign bond yield volatility, defined as a simple average of sovereign bond yield volatilities (that is, standard deviations) driven by global factors calculated across all countries and bond types (Equation A1.2.11). AE = advanced economy, EMDE = emerging market and developing economy.

[5] An increasing role of global factors in explaining sovereign yields across bond types and countries' income groups could be explained by several economic forces, including increasing economic interconnectedness across countries and increasingly integrated capital markets across the world where global institutional investors play a major role (Longstaff and others 2011).

[6] Using the weighted average is an alternative option, but this requires specifying the weighting scheme. Another approach is to take the first principal component of the square root of (contemporaneous) forecast error variance of sovereign yields driven by global factors.

[7] The simple average is taken over 100 available series (M=100): 10-year local-currency and 2-year local-currency sovereign yields for both advanced economies and emerging market and developing economies, and foreign-currency sovereign yields for emerging market and developing economies.

sovereign yields across different bond instruments (Online Annex Figure 1.2.2).

Robust Drivers of Globally Driven Volatility

The contribution of global factors to the volatility of sovereign yields varies considerably across countries and over time. To examine the drivers of these sources of heterogeneity, the following specification is estimated:

$$\overline{GV}_{it} = \alpha_i + \eta_t + \beta' X_{it} + \gamma' P_{it} + \varepsilon_{it} \qquad \text{(A1.2.12)}$$

where $\overline{GV}_{it}$ is the average global-factor-driven variance of sovereign bond yields in county i in year t. X_{it} is a vector of covariates reflecting macroeconomic and structural characteristics, including real GDP growth and inflation rate (also squared terms of both variables to capture nonlinear effects on output and price), the inflation surprise (calculated as the difference between the actual and one-year-ahead projected inflation), trade openness (defined as the sum of a country's exports and imports as a share of GDP), reserve assets as a share of GDP, as well as the level of institutional quality (calculated as an average of six World Governance Indicators). P_{it} is a vector of variables that can be affected by fiscal policy, including government expenditure as a share of GDP, net interest payments as a share of tax revenues, changes in the government debt-to-GDP ratio, the primary deficit surprise (the difference between the actual and one-year-ahead projected primary deficit in percent of GDP), as well as public debt composition and maturity (foreign- and nonbank-investor shares from the IMF Sovereign Debt Investor Database and the short-term debt share from the World Bank Cross-Country Database of Fiscal Space) and the measure of fiscal policy uncertainty (captured by the Fiscal Policy Uncertainty Index constructed by Hong, Ke, and Nguyen (2024). The regression also includes country and year fixed effects, α_i and η_t , respectively.

Equation (A1.2.12) is estimated using the weighted-average least squares estimator (WALS), during the period 2009–22 for 10-year sovereign bond yields of 26 advanced economies, 10-year local-currency sovereign yields of 16 emerging market economies, and foreign-currency sovereign yields of 13 emerging market and developing economies. The WALS is well suited to address model uncertainty and identify the robust set of explanatory variables over all possible model specifications (Magnus and others 2010).[8]

Results suggest that several factors contribute to explaining differences in the contribution of global factors across countries and over time (Online Annex Table 1.2.1).[9] Higher inflation is associated with higher volatility, while an inflation surprise—since it reduces the debt-to-GDP ratio—is negatively associated with volatility. Trade openness and measures related to economic volatility (such as the square of GDP growth) are positively correlated with global volatility of yields in emerging market and developing economies. The share of sovereign bonds held by foreign and nonbank investors is associated with a higher level of globally driven volatility, partly because those investors are particularly sensitive to changes in bond yields (Fang and others 2023; European Central Bank 2023). Finally, deficit surprises, increases in debt-to-GDP ratio, and fiscal policy uncertainty are associated with higher globally driven volatility of sovereign yields.[10]

[8] For example, Furceri and Ostry (2019) apply this approach to identify a set of robust determinants of inequality across countries and over time.

[9] A regressor is considered to be a robust driver if the associated *t*-statistics is larger than 1 in absolute value.

[10] These findings contribute to studies of the role of determinants of sovereign bond yields (Dell'Erba and others 2013; Poghosyan 2014; Cimadomo and others 2016; Georgoutsos and Migiakis 2024) by identifying robust determinants of the volatility of sovereign yields driven by global factors.

Online Annex Table 1.2.1. Regression Estimates of the Key Determinants of the Variance of Sovereign Yields Driven by Global Factors

Dependent variable: Variance of bond yields driven by global factors	Advanced economies	Emerging markets and developing economies, local currency	Emerging markets and developing economies, foreign currency
Real GDP growth	0.0010	-0.0012	**-0.0278**
	(0.15)	(-0.26)	**(-2.51)**
Inflation	**0.0732**	**0.0087**	**0.0228**
	(2.99)	**(1.04)**	**(1.21)**
Real GDP growth (squared term)	-0.0002	0.0002	**0.0041**
	(-0.59)	(0.40)	**(3.56)**
Inflation rate (squared term)	**-0.0044**	-0.0005	**-0.0014**
	(-4.22)	(-0.89)	**(-1.18)**
Trade openness	**-0.0014**	**0.0029**	**0.0044**
	(-1.01)	**(1.66)**	**(1.07)**
Inflation surprise	**-0.0599**	-0.0024	**-0.0226**
	(-2.53)	(-0.30)	**(-1.32)**
Reserve assets, percent of GDP	-0.0024	**-0.0032**	-0.0041
	(-0.73)	**(-1.42)**	(-0.87)
Institutional quality	**-0.8365**	0.0005	0.0705
	(-4.12)	(0.01)	(0.43)
Government expenditure to GDP ratio	0.0012	**0.0066**	-0.0105
	(0.20)	**(1.08)**	(-0.93)
Interest expense to tax revenue ratio	**0.0124**	**0.0041**	0.0016
	(1.57)	**(1.55)**	(0.29)
Change in government debt to GDP ratio (3-year moving avgerage)	-0.0054	0.0016	**0.0125**
	(-1.00)	(0.29)	**(1.08)**
Government debt held by foreign investors, percent of total debt	**0.0029**	-0.0013	**0.0076**
	(1.12)	(-0.63)	**(1.58)**
Government debt debt held by domestic nonbank investors, percent of total debt	**0.0055**	-0.0010	**0.0058**
	(1.43)	(-0.48)	**(1.08)**
Short-term debt, percent of total debt	0.0000	-0.0005	0.0001
	(0.02)	(-0.80)	(0.06)
Primary deficit surprise	-0.0018	**0.0075**	-0.0093
	(-0.22)	**(1.38)**	(-0.81)
Fiscal Policy Uncertainty Index	**0.0356**	-0.0152	-0.0196
	(1.55)	(-0.71)	(-0.41)
Observations	306	174	144
Year fixed effect	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes

Sources Global Financial Data, Haver Analytics, IMF *International Financial Statistics*, IMF Sovereign Debt Investor Database. J.P. Morgan, OECD, World Bank, IMF World Economic Outlook Database, Hong, Ke, and Nguyen (2024), and Nguyen, Solovyeva, and Zhang (forthcoming).

Note: The table reports coefficient estimates and *t*-statistics (in parentheses) from regressions estimated using the weighted-average least squares (WALS) method over 2009–22. The dependent variable is the annual average of the global-factor-driven variance of the corresponding sovereign bond yields. Numbers in bold are regressors that are considered to be robust drivers, with the associated *t*-statistics larger than 1 in absolute value. Inflation (or primary deficit) surprise is the difference between the actual and one-year-ahead projected inflation (or primary deficit).

Online Annex 1.3. Unpacking Unidentified Debt in Debt Dynamics[1]

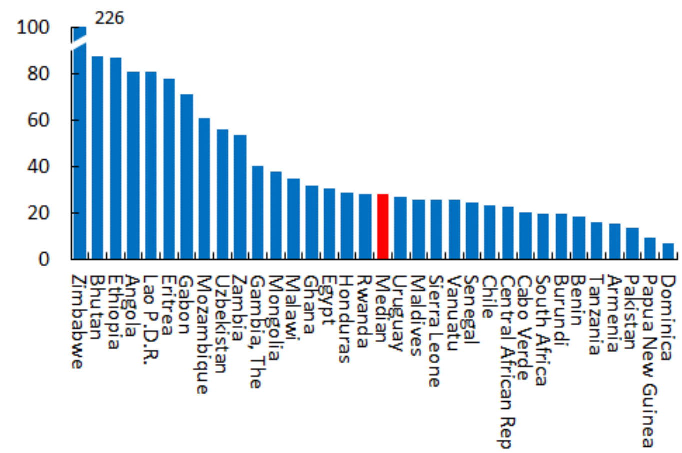
This Online Annex explains the methodology used to identify the sources of unidentified debt, as shown in Figures 1.14–1.15 of the main chapter, as well as the empirical framework to estimate the impact of crises and financial stress on unidentified debt in Figure 1.16 and how it is shaped by the role of fiscal instituions in Figure 1.23-24.

Unidentified debt—that is, the change in public debt that is not explained by the primary balance, interest-growth differentials, and valuation changes arising from exchange rate movements—could be a key driving factors in the debt dynamics.[2] Positive unidentified debt is debt-creating flows that stem from issues such as the materialization of contingent liabilities, arrears, and the underestimation of public debt by reporting a narrower debt perimeter. In some cases, unidentified debt can also reflect accumulation of financial assets. In contrast, negative number is associated with privatization of public corporations or haircuts from debt restructuring.

Selection of Country Cases

The analysis first computes the unidentified debt based on the debt composition for all countries using the IMF World Economic Outlook database for the period 2010–23. Thirty-three countries are initially selected for their large positive unidentified debt, with the median cumulative size being around 30 percent of GDP (Online Annex Figure 1.3.1).[3] These countries are predominantly emerging market and developing economies: out of the total 33 countries, 17 countries have sufficient information in IMF Country Reports to identify at least 30 percent of unidentified debt calculated based on the debt dynamics from the IMF World Economic Outlook database.[4] The rest of the countries where the IMF country reviews explain less than 30 percent of the unidentified debt is excluded in the full analysis on the grounds of insufficient information.

Online Annex Figure 1.3.1. Cumulative Unidentified Debt for Selected Countries, 2010–23
(Percent of GDP)



Sources: IMF World Economic Outlook database and IMF staff compilation. Unidentified debt refers to the change in public debt that is not explained by the primary balance, interest-growth differentials, and valuation changes arising from exchange rate movements. Positive unidentified debt could arise from the materialization of contingent liabilities, arrears, and the underestimation of public debt by reporting a narrower debt perimeter. In some cases, unidentified debt can also reflect accumulation of financial assets.

Methodology to Identify the Sources of Unidentified Debt

The exercise conducts a review of all annual IMF Country Reports (including both Article IV staff reports and IMF Program Review staff reports) for these 17 countries over the period 2010–23. To identify the sources of the unidentified debt, a mix of quantitative and qualitative methods is used—including the quantitative references to "Other debt creating flows" in the debt

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[1] Prepared by Camilo Gomez Osorio, Felipe Palmeira Bardella, Bryn Welham, and Zhonghao Wei.

[2] The *Fiscal Monitor* defines unidentified debt/stock-flow adjustments to exclude valuation changes due to exchange rate movements. Estimates of the unidentified debt are sensitive to the assumptions on the share of foreign currency debt and the applicable interest cost on debt.

[3] The countries are *Angola, Armenia, Benin, Bhutan, Burundi, Cabo Verde, Central African Republic, Chile, Dominica, Egypt, Eritrea, Ethiopia, Gabon, The Gambia, Ghana, Honduras, Lao P.D.R., Malawi, Maldives, Mongolia, Mozambique, Pakistan, Papua New Guinea, Rwanda, Senegal, Sierra Leone, South Africa, Tanzania, Uruguay, Uzbekistan, Vanuatu, Zambia, and Zimbabwe.*

[4] The list of the selected countries includes *Armenia, Burundi, Dominica, The Gambia, Ghana, Honduras, Lao P.D.R., Malawi, Mongolia, Mozambique, Pakistan, Papua New Guinea, Senegal, South Africa, Tanzania, Vanuatu, and Zambia.*

sustainability analysis, as well as the narrative policy discussion in the reports where unidentified debt -related events are discussed.

The sources of unidentified debt for each country are classified into one of the following categories, representing the common types of transactions: (1) materialization of contingent liabilities or fiscal risks; (2) arrears; (3) extrabudgetary spending; (4) unaccounted debt or statistical discrepancy arising from errors and omissions (or differences between fiscal accounts and cash balances); and (5) institutional changes arising from a change in the perimeter of public debt instruments and debt revisions or reconciliations. The materialization of contingent liabilities or fiscal risks is a broad category, which is further divided into those related to state-owned enterprises (SOEs), loan guarantees, recapitalization of banks and nonbank financial institutions, below-the-line operations for natural disasters, and pending legal claims against the state.

Two country examples—*Honduras* and *Mozambique*—can help illustrate how the narrative approach is used to identify the sources (Online Annex Table 1.3.1). First, unidentified debt in Honduras was primarily driven by the materialization of fiscal risks related to its state-owned enterprises. Several events resulted from delays in recognizing operational losses of its state-owned electricity company—la Empresa Nacional de Energía Eléctrica (ENEE). Governments issued bonds to pay for its liabilities of about 2 percent of GDP in 2017 (IMF 2018). The Honduras 2019 Article IV Staff Report indicated that "the deteriorating financial situation in ENEE has given place to a sharp increase in debt" (IMF 2019). The state-owned electricity company also accumulated domestic arrears of 1.9 percentage points of GDP during 2020–21. Finally, the closing of trust funds in 2022, to make expenditure execution more transparent, helps explain the unidentified debt in that year. These trust funds had been used for expenditure execution for many years prior, and some had accumulated debts. In *Mozambique*, the increase in unidentified debt was primarily owing to the weakness in governance and fiscal institution control, most notably debt management, and the materialization of fiscal risks from natural disasters. During the period 2014–16, three public corporations contracted loans with sovereign guarantees (11 percent of GDP). Later assessments made by the Commission of Enquiry concluded that the guarantees and other agreements had not been approved by the Parliament, had received no opinion from the public prosecutor, and were in breach of Mozambique's budget law (IMF 2015, 2017). The liabilities were ultimately incorporated into the budget as public debt.

The sources of unidentified debt are aggregated across each country for each category in each year, either through a simple cumulative percentage point of GDP or weighted average based on 2023 nominal GDP in U.S. dollars.

Online Annex Table 1.3.1. Selected Country Examples on the Sources of Unidentified Debt
(Percent of GDP)

Honduras

Comments	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Total	2010-19	2020-23
Residual in debt sustainability assessment	1.9	2.6	-0.4	2.8	-2.8	0.2	0.7	2.0	0.8	0.8	2.9	2.2	7.1	0.5	21.3	8.6	12.7
Statistical discrepancy	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Domestic arrears															0.0	0.0	0.0
Domestic Debt Regularization (2022)													2.6		2.6	0.0	2.6
Arrears from ENEE to private generators (2020/2021)											0.7	1.2			1.9	0.0	1.9
Imbalances from ENEE (2016/2017/2018)									1.5						1.5	1.5	0.0
Bond issueance to offset ENEE's liabilities								2.0							2.0	2.0	0.0
Central government arrears and public-private partnership liabilities						2.5									2.5	2.5	0.0
Total															**10.5**	**6.0**	**4.5**

Mozambique

Comments	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Total	2010-19	2020-23
SOE hidden debts, EMATUM (2014), ProIndicus and MAM (2015)					1	10	0	0	0	0	0	0	0	0	11.0	11.0	0.0
Guarantees called (domestic, debt issued)						0.7	1.2	1.7	2.2	2.7	3.2				11.7	8.5	3.2
Natural Disasters										4.6					4.6	4.6	0.0
Domestic arrears (flows)		2.1					1.3	0.3	0.3	0.2	0.5	0	0.1	1	5.8	4.2	1.6
Statistical discrepancy (extra-budgetary spending)							0.4	1	0.6		0.3	1.1			3.4	2.0	1.4
Total															**36.5**	**30.3**	**6.2**

Sources: IMF Country Reports and IMF staff compilations.
Note: DSA = debt sustainability assessment; SOE = state-owned enterprise.

Results

The narrative approach from the IMF Country Reports is able to explain well between 67 and 70 percent of the cumulative unidentified debt derived using the WEO data for these 17 countries. Results suggest that the three main sources of unidentified debt is related to: (1) the materialization of fiscal risks and contingent liabilities, predominantly from public corporations but also from loans and guarantees; (2) arrears; and (3) institutional changes—such as revisions to the definition of debt and the parameters of governments, and revisions to nominal GDP (Online Annex Table 1.3.2). Nearly 40 percent of unidentified debt is related to the materialization of contingent liabilities—such as losses from state-owned enterprises and public guarantees (Online Annex Figure 1.3.2). The ranking of primary sources remains the same regardless of different averaging methods, although the relative shares among the three main sources change across weighting methods.

Online Annex Table 1.3.2. Identified Sources of Unidentified Debt, by Category

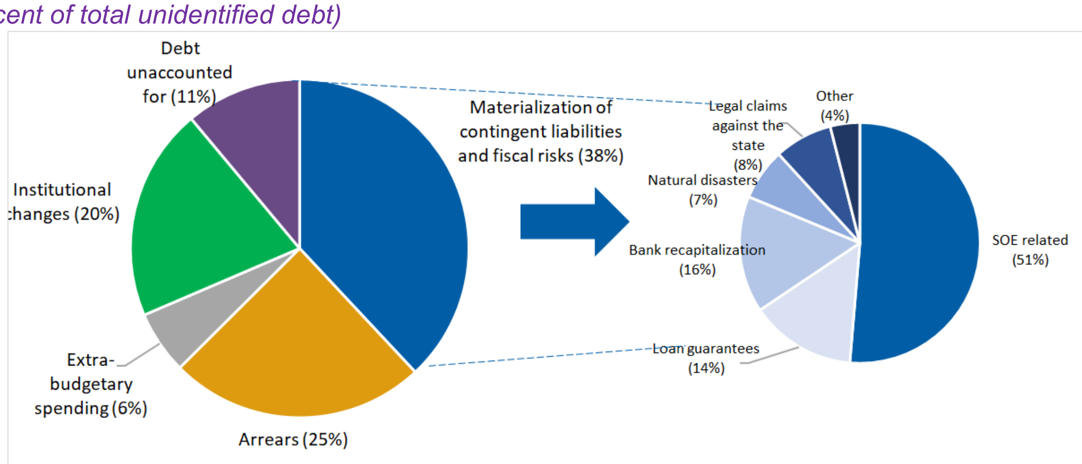
(Cumulative percentage points of national GDP)

	Annual average (percent GDP)			Share of SFAs documented in the IMF country reports (percent)		
	2010-23	2010-19	2020-23	2010-23	2010-19	2020-23
Annual average share of unidentified debt explained in IMF reports	**1.5**	**1.5**	**1.5**	**100**	**100**	**100**
Materialization of contingent liabilities / fiscal risks	**0.6**	**0.5**	**0.7**	**38.0**	**35.1**	**45.3**
SOE-related	0.3	0.2	0.4	19.5	15.9	28.4
Loan guarantees	0.1	0.1	0.1	5.4	6.4	7.4
Bank recapitalization	0.1	0.1	0.1	6.0	4.9	8.5
Natural disasters	0.0	0.1	0.0	2.6	3.7	0.0
Legal claims against the state	0.0	0.1	0.0	3.0	4.2	0.0
Other	0.0	0.0	0.1	1.5	0.0	5.3
Arrears	**0.4**	**0.3**	**0.5**	**24.5**	**20.9**	**33.3**
Extra-budgetary spending	**0.1**	**0.1**	**0.1**	**6.0**	**5.6**	**7.0**
Debt unaccounted for	**0.2**	**0.2**	**0.1**	11.1	13.0	6.3
of which: hidden debt	0.0	0.1	0.0	3.0	4.2	0.0
of which: statistical discrepancy (erros and omissions)	0.1	0.1	0.1	8.1	8.8	6.3
Institutional changes	**0.3**	**0.4**	**0.1**	**20.4**	**25.3**	**8.0**
Change in debt perimeter	0.2	0.3	0.0	12.7	17.8	0.0
Debt revision/reconciliation	0.1	0.1	0.0	3.6	4.1	2.5
Other	0.1	0.1	0.1	4.0	3.4	5.6

Sources: IMF Country Reports and IMF staff compilations.
Note: SOE = state-owned enterprise.

Online Annex Figure 1.3.2. Components of Unidentified Debt, 2010−23

(Percent of total unidentified debt)



Sources: IMF Country Reports and IMF staff compilations.
Note: Unidentified debt is based on a review of IMF Country Reports for each of the 17 countries selected in the sample. Unidentified debt refers to the change in debt excluding interest-growth differentials, primary balance, and valuation effects from exchange rate movements. SOE = state-owned enterprises.

The sources of unidentified debt have changed since the COVID-19 pandemic. The large unprecedented fiscal support implemented since 2020 has contributed to a larger share of SOE-related losses, bank recapitalization, and arrears. Based on the countries reviewed, the share of materialization of contingent liabilities and fiscal risks—possibly driven by the liquidity support on those loans and guarantees—has risen from 35 percent of total unidentified debt during 2010–19 to 45 percent of total during 2020–23.

The Role of Fiscal Institutions in Mitigating Unidentified Debt

The analysis in this section assesses the impact of banking crises (financial stress) on unidentified debt. Two econometric specifications are used. The first establishes whether crises (financial stress) have statistically and economically significant effects on unidentified debt. The second assesses whether these effects vary with the quality of fiscal institutions across countries.

The statistical method follows the approach in Jordà (2005) to estimate impulse-response functions. This approach is particularly suited to estimating nonlinearities (including interactions between shocks and other variables of interest) in the dynamic response. The first regression specification is estimated as follows:

$$SFA_{i,t+h} = \sum_{l=0}^{2} \beta_{l,h} Shock_{i,t-l} + \sum_{l=1}^{2} \theta_{l,h} SFA_{i,t-l} + \delta_{i,h} + \gamma_{t,h} + \epsilon_{i,t,h}, \qquad \text{(A1.3.1)}$$

in which *SFA* is the ratio of stock-flow adjustments (unidentified debt excluding movements of exchange rates) to nominal GDP; *Shock* denotes banking crises (or changes in financial stress); δ_i and γ_t are country and time fixed effects, respectively. In the second specification, the response is allowed to vary with quality of fiscal institutions:

$$SFA_{i,t+h} = F(z_i)\left[\sum_{l=0}^{2} \beta_{l,h}^{L} Shock_{i,t-l} + \sum_{l=1}^{2} \beta_{l,h}^{L} SFA_{i,t-l}\right] + \left(1 - F(z_i)\right)\left[\sum_{l=0}^{2} \beta_{l,h}^{H} Shock_{i,t-l} + \sum_{l=1}^{2} \beta_{l,h}^{H} SFA_{i,t-l}\right] + \delta_{i,h} + \gamma_{t,h} + \epsilon_{i,t,h}, \qquad \text{(A1.3.2)}$$

with $F(z_i) = \frac{\exp(-1.5z_i)}{1+\exp(-1.5z_i)}$ in which *z* is an indicator of fiscal institutions (budget transparency and compliance with fiscal rule) normalized to have zero mean and unit variance.

Equations (A1.3.1) and (A1.3.2) are estimated using a sample of 149 economies during the period 2000–23, for each $h = 0, \ldots, 2$. Impulse-response functions are computed using the estimated coefficients, and the confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients, based on clustered robust standard errors.

Data on SFAs are computed from IMF World Economic Outlook database using the debt dynamic equation. Data on banking crises are taken from Laeven and Valencia (2020). The financial stress index comes from Ahir and others (2023). Fiscal transparency is a time-variant index using the Open Budget Index (OBI) from the Open Budget Survey published by the International Budget Partnership. The index ranks from 0–100 (100 = best) and is assessed based on three interrelated components of a budget accountability system: public availability of budget information; opportunities for the public to participate in the budget process; and the role and effectiveness of formal oversight institutions, including the legislature and the national audit office. The fiscal rules and compliance data are based on the IMF 2021 Fiscal Rules Dataset developed in Davoodi and others (2022). The frequency of compliance is defined as the ratio of the years in which debt is within the rule limit relative to total number of years that the debt rule is in place.

Online Annex 1.4. Optimal Fiscal Reaction Function[1]

This Online Annex uses a New Keynesian DSGE model with unemployment risks and endogenous sovereign default to examine how fiscal policy should balance macroeconomic stabilization and sovereign risks in the current context of elevated debt vulnerabilities.

Model

The model is based on Bianchi and others (forthcoming), which uses a New Keynesian dynamic stochastic general equilibrium model with endogenous sovereign default from Bianchi, Ottonello, and Presno (2023).[2] It features a small open economy with a fixed exchange rate subject to shocks to its endowment of tradable goods. Households consume a bundle of tradable and nontradable goods. Domestic firms produce nontradable goods, whereas the supply of tradable goods is given by an exogenous stochastic endowment. The interaction of those shocks with downward nominal wage rigidities leads to unemployment. Households are modeled as "hand-to-mouth" and are not able to insure against unemployment risks. The government chooses discretionary expenditure each period to maximize household welfare, given a constant income tax rate and unemployment insurance system.[3] It borrows from risk-neutral foreign investors by issuing long-term bonds and may decide to default on its debt in each period. Sovereign default leads to a temporary cutoff from access to capital markets, which carries a cost.

Higher discretionary government expenditure—that is, the part of government expenditure that is not related to automatic stabilizers—helps to reduce unemployment by expanding aggregate demand, especially during recessions. At the same time, higher expenditure increases the fiscal deficit, leading to a higher probability that the government chooses to default. Even if default happens infrequently in equilibrium, a higher probability of default increases sovereign borrowing rates. This trade-off between macroeconomic stabilization and sovereign risks constitutes the core of the model.

Fiscal Reaction Function

To illustrate and quantify the balance between the macroeconomic stabilization and sovereign risks objectives, the optimal fiscal response is approximated with a simple rule. The rule specifies discretionary expenditure as a linear function of a sovereign risk indicator and an output gap indicator:

$$g_{i,t} = \alpha_i + \beta_i * r_{i,t-1} + \gamma_i * y_{i,t-1}, \qquad \text{(A1.4.1)}$$

where g denotes discretionary expenditure; r a sovereign risk indicator; y an output gap indicator; α denotes the average discretionary spending for the country, and β and γ are the weights given to the sovereign risk and output gap indicators, respectively. The subscript i indicates the country and t the year. The explanatory variables enter with a lag to reflect delays in fiscal policy implementation.

The rule coefficients are estimated by using the following steps: (1) simulating the economy for 1,000 series of 32 years each; (2) computing the level of discretionary expenditure in each period that maximizes

[1] Prepared by Daniel Garcia-Macia, with input from Javier Bianchi, Pablo Ottonello, and Ignacio Presno.

[2] The model distinguishes from the framework in Fournier (2019) and Fournier and Lieberknecht (2020) by incorporating endogenous sovereign default, and from Hatchondo and others (2022a, 2022b) by considering the New-Keynesian macroeconomic stabilization objective.

[3] The model focuses on discretionary expenditure as the short-term fiscal operational measure because governments typically have more direct control over it than over primary expenditure or fiscal balances, which include automatic stabilizers and cyclical tax revenues, respectively (Caselli and others 2022).

household utility; and (3) approximating the process for optimal discretionary expenditure with an ordinary least squares regression on a sovereign risk indicator and an output gap indicator.[4]

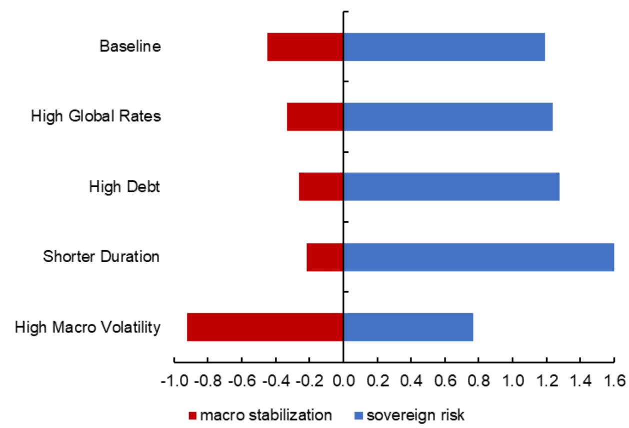
Various specifications are explored, including alternative indicators for sovereign risks such as the public-debt-to-GDP ratio and sovereign spreads. The specification in the main text of the *Fiscal Monitor* chapter is a linear rule based on sovereign spreads and the tradable goods level (normalized to 0 to be interpreted as an output gap), which is found to deliver the best fit of the unconstrained optimal policy solution among all linear specifications considered. This rule is used to illustrate the properties of optimal policy in a simplified way. In practice, countries may not target the level of sovereign spreads, partly because those are less well defined or unavailable in many cases.

Calibration of Scenarios

The fiscal reaction function is first estimated using simulated data from the same calibration as in Bianchi, Ottonello, and Presno (2023), which targets key statistical moments of the *Spanish* economy, a small open economy, using available data up to 2015. Under this baseline calibration, the fiscal response suggests that discretionary expenditure should increase by 0.4 percentage point of GDP if tradable output falls by one standard deviation (or 0.9 percent of GDP) and will need to tighten by 1 percentage point of GDP if sovereign spreads rise by one standard deviation (or 1.1 percentage points) (Online Annex Figure 1.4.1). Hence, in this calibration, fiscal policy should on average react more actively against increases in sovereign risks than output fluctuations.

Online Annex Figure 1.4.1. 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)



Sources: Bianchi and others (forthcoming) and IMF staff calculations.
Note: Simulations based on a New Keynesian DSGE model with endogenous sovereign default calibrated to *Spain*. A "macro stabilization" coefficient equal to –1 means that discretionary spending is increased by 1 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 spending is lowered by 1 percentage point of GDP if sovereign spread rates increase by one standard deviation (1.1 percentage points). Thus, bars shifting to the right imply more weight on sovereign risk containment and less on macro stabilization. “High global rate“ increases interest rates by 1 percentage point. “High debt” shows external debt above 20 percent of GDP. “Shorter duration” assumes a duration of 2 instead of 5 years. “High macro volatility” increases the standard deviation of output shocks by about one-third.

The analysis considers a range of scenarios with alternative structural parameters, to illustrate how fiscal policy should respond across different economic conditions (Online Annex Table 1.4.1). Departing from the baseline calibration, Online Annex Figure 1.4.1 shows how the coefficients of fiscal responses vary after changing key model parameters, one at a time.

The first alternative scenario considers a global risk-free interest rate 1 percentage point higher than in the baseline, in line with the increase in the US 10-year real sovereign rates between 2021 and 2022. The second scenario focuses on periods with high debt (i.e., with external debt above 20 percent of GDP). The third scenario considers a rise in the bond coupon decaying rate, equivalent to lowering debt duration from five to two years. Finally, the fourth scenario considers an increase in aggregate output volatility—a rise in the standard deviation of the tradable endowment shock by one-third.[5]

[4] The regression sample excludes those observations where the government eventually chooses to default, under the assumption that governments deviate from this fiscal reaction function upon default.

[5] The tradable endowment follows a first-order autoregressive (AR(1)) process. This fourth scenario increases the variance of the error term so as to increase the overall standard deviation of the AR(1) process by one-third.

According to the model simulations, the optimal weight on containing sovereign risk is greater when: (1) global interest rates rise, (2) initial debt levels are high, or (3) debt maturity is shorter (which accelerates the pass-through of higher interest rates). For instance, the fiscal contraction implied by the model after an increase in spreads is one-third larger in an economy with shorter debt duration (two years versus five years in the baseline). In contrast, in economies exposed to higher macroeconomic volatility (for example, commodity exporters), the weight on macroeconomic stabilization is larger.

Online Annex Table 1.4.1. Calibration of Alternative Scenarios

Parameter	Baseline	Alternative	Rationale
Risk-free rate (percent)	2.0	3.0	Similar to the increase in US real interest rates from 2021 to 2022 (a monetary tightening period)
External debt (percent of GDP)	22.0	23.0	Subsample of observations with external sovereign debt above 20 percent of GDP
Bond coupon decaying rate	0.18	0.49	A reduction of debt duration from five to two years
Tradable endowment, standard deviation of error term (percent)	2.9	4.0	Increases standard deviation of external shock by about one-third

Source: IMF staff calculations.
Note: The full baseline calibration to *Spain* is available in Bianchi, Ottonello, and Presno (2023). The scenario with a higher average external debt level (second row in the table) is obtained as the subsample of observations in the baseline calibration with external debt above 20 percent of GDP, without changing model parameters.

Online Annex 1.5. Fiscal Adjustments and Probability of Debt Stabilization[1]

This Online Annex describes the stochastic analysis of debt dynamics using the bootstrap approach—based on an extension of the IMF's Sovereign Risk and Debt Sustainability Framework (SRDSF) (IMF 2022)—*and explains the methodology to quantify the size of fiscal adjustments presented in Figures 1.18 and 1.19 of the chapter.*

Stochastic Analysis of Debt Dynamics

The bootstrap approach relies on the standard debt dynamic equation, in which public debt in year *t* is a function of debt of the previous year, interest bill, exchange rate changes (if part of the debt is denominated in foreign currency), primary balance, and stock-flow adjustments:

$$D_t = \frac{e_t}{e_{t-1}} D^f_{t-1} + D^d_{t-1} + i_t D_{t-1} - PB_t + SFA_t \qquad \text{A1.5.1}$$

where D^f_{t-1} and D^d_{t-1} are foreign- and domestic-currency-denominated debt respectively, e_t is the nominal exchange rate (defined as the price of foreign currency in terms of domestic currency). The term $i_t D_{t-1}$ is the interest payment. Finally, PB_t denotes primary balance (defined as noninterest revenue net of noninterest expenditure) and SFA_t denotes stock-flow adjustments, excluding the valuation effects of exchange rate movements. Equation (A1.5.1) can be transformed into key drivers of change in the public-debt-to-GDP ratio:

$$\Delta d_t = \frac{z_t d^f_{t-1}}{(1+g_t)(1+\pi^f_t)} + \frac{\pi^d_t - \pi^f_t}{(1+\pi^f_t)\rho_t} d^f_{t-1} + \frac{r_t - g_t}{1+g_t} d_{t-1} - pb_t + sfa_t \qquad (A1.5.2)$$

where d^f_{t-1} and d_{t-1} are the ratios of foreign-currency-denominated and total debt to GDP; pb_t and sfa_t are primary balances and stock flow adjustments expressed as a ratio to GDP; z_t is the real exchange rate effect defined as $1 + z_t = \frac{e_t}{e_{t-1}} \times \frac{1+\pi^f_t}{1+\pi^d_t}$; ρ_t is the nominal GDP growth rate $\rho_t = (1+g_t)(1+\pi^d_t)$; g_t is the real GDP growth rate; π^d_t is the domestic GDP deflator; π^f_t is foreign GDP deflator; and r_t is the real effective interest rate defined as: $1 + r_t = \frac{1+i_t}{1+\pi^d_t}$.

The first term in equation (A1.5.2) corresponds to the real exchange rate effect, and the second term to the relative inflation component. The third term is the interest-growth differential in real terms, which is typically considered the main driver of automatic debt dynamics. From equation (A1.5.2), the *debt-stabilizing* primary balance can be computed by setting $\Delta d_t = 0$ and assuming no change in real exchange rate ($z_t = 0$)[2]:

$$pb^*_t = \frac{\pi^d_t - \pi^f_t}{(1+\pi^f_t)\rho_t} d^f_{t-1} + \frac{r_t - g_t}{1+g_t} d_{t-1} + sfa_t \qquad (A1.5.3)$$

Bootstrap Method

The bootstrap algorithm requires historical series for each component in equation (A.1.5.2): $p_t = [r_t, g_t, pb_t, z_t, \pi^d_t, \pi^f_t, sfa_t]$, where *p* is a vector containing each variable. The first six drivers are observable from the data, while the stock-flow adjustment is computed as a residual from equation (A1.5.2). Key variables are obtained from the World Economic Outlook database. Data on the currency composition of public debt is based on the dataset by Arslanalp and Tsuda (2014), updated in December 2023). A simplifying assumption that all foreign currency debt is issued in US dollars is used. Hence, the corresponding π^f_t is the US GDP deflator and z_t is calculated using the exchange rate of national currency to the US dollar. This

[1] Prepared by Sergejs Saksonovs.

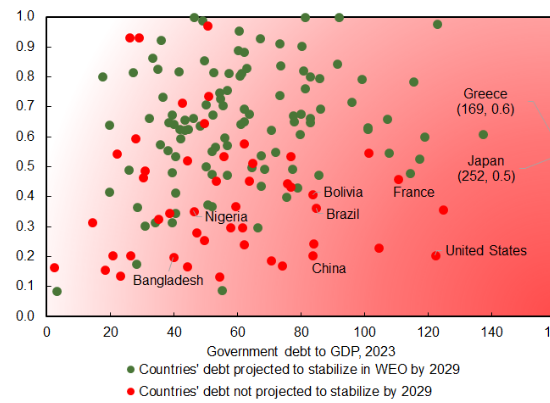
[2] Other derivations of the debt dynamic equation in the literature sometimes combine nominal exchange rate effects into the definition of effective interest rate (see for example, Escolano and others 2017).

means that the measured stock-flow adjustment will include some residual effects of exchange rate movements if the actual foreign debt structure of a country is denominated in currencies other than US dollars.[3]

The bootstrap relies on generating multiple debt paths for the projection horizon 2024–29 in the World Economic Outlook (WEO). For a given country, the probability of debt stabilization is calculated with the following algorithm:

1. Subtracts historical means from each driver of debt in equation (A1.5.2) for that country (except for the SFA term). The starting period for the analysis is 1991, but data availability implies countries may have a shorter sample period in practice.[4]
2. Selects two random (based on a uniform distribution) *consecutive* vectors of debt drivers for periods *t* and *t+1* and adds them to the baseline projections of these variables. Drawing two consecutive periods allows capturing correlations not only across variables (for example, higher growth levels being associated with higher primary balances), but also accounting for potential persistency of variables across time (for example, lower growth levels being followed by higher growth in next period owing to persistence and reversion to the mean).
3. These augmented baseline projections, together with the SFA terms drawn from the same periods, are used to generate debt values in the next period using equation (A1.5.2). The fact that the SFAs are drawn from the country's history assumes that their magnitude in the future is similar to the one in the past.[5]
4. Steps 2 and 3 are repeated three more times to generate a simulated debt path from 2023 until 2029.
5. For each debt trajectory, a debt stabilizing primary balance is computed by using the last generated value of the debt-to-GDP ratio and the *average* drawn debt drivers, including stock-flow adjustments. This calculation reflects a hypothetical steady state in which debt drivers are equal to the average of their simulated medium-term values.

Online Annex Figure 1.5.1. Probability of Debt Stabilization and Debt Levels
(probability in percent)



Sources: IMF World Economic Outlook database and IMF staff estimates.
Note: Countries' debt projection is based on WEO. The probability of debt stabilization is estimated based on the bootstrap method.

[3] The potential residual effects do not affect the results for the following reasons. Most foreign-currency-denominated debt is issued in US dollars. For debt issued in other currencies, the relative bilateral exchange rates with the US dollar are relatively stable compared with local currencies of the issuing countries.

[4] The fact that variables are used as their deviations from the mean to add to the baseline in step 2 creates an issue for some countries, notably those with a history of hyperinflation, where one very large change in the GDP deflator can lead to a series with one positive deviation from the mean and the rest of the prospective "shocks" being deflationary. The time series for every country was adjusted to ensure that there is a minimum of five observations above or below zero in the demeaned series, typically by excluding episodes of hyperinflation, which tend to occur at the beginning of the time series, from the data.

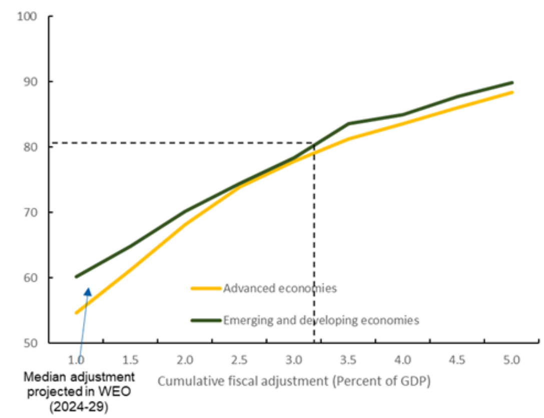
[5] A limitation of this assumption is that a country with no history of large stock-flow adjustments could nevertheless experience one (for example, a large, unexpected bank recapitalization). An alternative way could draw SFA shocks from the estimated probability density function by income group instead (with fatter upside tail risk for low-income developing countries). The disadvantage of this approach, however, is that the presence of SFAs would have a nearly uniform effect on all countries depending just on their income group.

6. Finally, the baseline 2029 primary balance forecast is compared to the debt-stabilizing value computed in step 5. If the baseline debt forecast from the bootstrap method is higher than the debt-stabilizing level, the trajectory is considered to be stabilizing; otherwise, it is considered nonstabilizing. The probability of keeping debt from rising is calculated as the share of debt-stabilizing trajectories in the total of 10,000 replications.[6]

Intuitively, the bootstrap produces a confidence interval around the baseline projection of debt levels based on past variability and correlations of the main debt drivers. Results show that the probability of debt stabilization, on average, is lower for those countries where debt is not projected to stabilize by 2029 (Online Annex Figure 1.5.1).

To determine the probability of debt stabilization with different fiscal adjustments in Figure 1.18 in the main chapter, equation (A1.5.2) is augmented by a fiscal adjustment term and the algorithm is run separately for different magnitudes of cumulative fiscal adjustments from 1 to 5 percent of GDP over six years (assumed to be evenly spread over years). The effect of the additional fiscal adjustment on median probability of debt stabilization is very similar between advanced economies and emerging market and developing economies (Online Annex Figure 1.5.2). Figure 1.19 presents the required fiscal adjustment consistent with 80 percent probability of stabilizing debt. For the debt-stabilizing trajectories, the required fiscal adjustment is set the same as the fiscal adjustment in the WEO projection. For trajectories where debt is not stabilizing at the end of sample horizon by 2029, the required adjustment is the difference between the debt-stabilizing primary balance and the primary balance in 2023. The bootstrap produces a distribution of required adjustments, and the 80th percentile is reported in Figure 1.19.

Online Annex Figure 1.5.2. Median Fiscal Adjustment and Probability of Stabilizing or Reducing Debt by 2029
(Percent of GDP)



Sources: 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 keeping debt from rising is calculated as the number of debt paths, where the baseline primary balance is higher than or equal to the debt-stabilizing primary balance

[6] In that sense, "stabilizing" here refers to nonincreasing debt rather than remaining constant over time. Any primary balance that exceeds debt-stabilizing primary balance will result in a gradually declining debt.

Online Annex 1.6. Fiscal Adjustments under the Heterogeneous Agent New Keynesian (HANK) Model[1]

This Online Annex presents a Heterogeneous Agent New Keynesian (HANK) model to assess the impact of fiscal adjustments across households and on the economy and explains the technical details o the simulations in Figures 1.20-22 in the chapter.

Key Model Features

The model extends that developed by Auclert, Rognlie, and Straub (2024) to assess the impact of fiscal adjustments across different households and on the economy as a whole. The extension includes various types of fiscal instruments: government consumption, public investment, subsidies, transfers (both targeted and untargeted), and progressive income taxes. The government faces a budget constraint and uses these instruments to balance the budget:

$$G_{c,t} + \mathrm{I}_{\mathrm{G,t}} \ + Tr_t + (1 + r_{t-1})B_{t-1} = B_t + T_t \qquad (A1.6.1)$$

where $T_t = W_t N_t - Z_t$.

Public investment is used to improve the overall production:

$$Y_t = \Theta_t \, F(K_{G,t}, \, K_t, N_t) = \Theta_t \, K_{G,t}^{\alpha^G} K_t^{\alpha} N_t^{1-\alpha} \qquad (A1.6.2)$$

where: $K_{G,t} = I_{G,t} \ + (1 - \delta_G)K_{G,t-1}$

Households make consumption and labor decisions while facing an idiosyncratic income process, alongside financial frictions. Two financial frictions are considered: (1) households are not able borrow; and (2) agents are not able to adjust illiquid assets whenever needed, which implies that returns for liquid assets are lower than or illiquid assets. Households receive various transfers and are subject to progressive income taxes (on labor income). In detail, households maximize lifetime utility $u(c,n) = u(c_t) - \ v(N_t) = \frac{c_t^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - \ v(N_t)$, with intertemporal elasticity σ, by choosing optimal levels of consumption, labor supply, and holdings of liquid and illiquid assets. The model differentiates between households who can adjust their asset portfolios (*adj = 1*) and those who cannot (*adj = 0*). When households can adjust the illiquid asset (adj = 1), their lifetime utility can be expressed as the value function below:

$$V_t\left(1, \epsilon, a_{-,t}^{liq}, a_{-,t}^{illiq}\right) = \max_{c, a_t^{liq}, a_t^{illiq}} u(\,\tilde{c}) + \beta \, E\left[\, V_{t+1}\left(adj', \epsilon', a_t^{liq}, a_t^{illiq}\right) \middle| \epsilon \,\right] \qquad (A1.6.3)$$

$$\tilde{c} + \ a_t^{liq} + a_t^{illiq} = \epsilon \, Z_t + (1 + r_{t-1})(1 - \zeta)a_{-,t}^{liq} + (1 + r_{t-1})a_{-,t}^{illiq} + Tr_t \qquad (A1.6.4)$$

$$a_t^{liq} \geq 0, a_t^{illiq} \geq 0$$

Households who do not reallocate their asset portfolio *(adj = 0)* face a lifetime utility with the value function:

$$V_t\left(0, \epsilon, a_{-,t}^{liq}, a_{-,t}^{illiq}\right) = \max_{c, a_t^{liq}} u(\,\tilde{c}) + \beta \, E\left[\, V_{t+1}\left(adj', \epsilon', a_t^{liq}, a_t^{illiq}\right) \middle| \epsilon \,\right] \qquad (A1.6.5)$$

$$\tilde{c} + \ a_t^{liq} + a_t^{illiq} = \epsilon \, Z_t + (1 + r_{t-1})(1 - \zeta)a_{-,t}^{liq} + (1 + r_{t-1})a_{-,t}^{illiq} + Tr_t \qquad (A1.6.6)$$

$$a_t^{liq} \geq 0$$

where $V_t(.)$ represents time t value function, ϵ represents the individual labor skill units, a is asset holding with superscripts *liq* standing for liquid assets and *illiq* for illiquid assets, respectively; Z represents the after-tax aggregate wage rate; $\tilde{c}$ is household consumption, r is the interest rates on the asset, and ζ represents the spread between liquid and illiquid assets. Tr is the transfers received from the government that raise disposable income, including subsidies and targeted and untargeted transfers.

[1] Prepared by Yongquan Cao.

Household consumption is influenced by after-tax wage income (Z_t), government transfers (Tr_t), and idiosyncratic income shocks, with progressivity as detailed by Heathcote, Storesletten, and Violante (2017). The exogenous probability of adjusting the asset portfolio, $\Pr(adj' = 1)$, is denoted by ν, and the reallocation of assets incurs a flow cost of $\zeta(1+r)a_{it-1}^{liq}$. These financial frictions affect households' capabilities to smooth consumption over time, generating large differences in marginal propensity to consume (MPC) across households. The financial frictions will cause not only low-income households to behave like hand-to-mouth agents but also middle-income households who prefer to accumulate their wealth in illiquid assets for higher returns. However, when adverse shocks occur, they cannot convert illiquid assets in a timely manner, leading them to behave like hand-to-mouth agents (similar to the wealthy "hand-to-mouth" agents in Kaplan, Moll, and Violante (2018). Finally, output is produced from capital and labor—subject to rigidity in wage and price adjustments—and monetary policy is assumed to follow a Taylor rule.

Calibration

The model is calibrated for a representative advanced economy and emerging market economy. The calibration accounts for volatility and persistence of individual income shocks, greater financial frictions, and greater tax potentials (given lower tax rates and tax base) in the emerging market economy (Online Annex Table 1.6.1)—these differences affect the impact of fiscal measures and the choice of measures during the fiscal adjustment. In detail, the calibration parameters are based on the study of the *United States* in Auclert, Rognlie, and Straub (2024) for the advanced economy, and on Peru in Hong (2023) for the emerging market economy. The calibration of subsidies is based on energy consumption data from Coady and others (2015) and the U.S. Energy Information Administration.[2] Other potentially important differences—such as informality, social protection systems, and monetary policy stances—that could affect the distributional and aggregate effects of fiscal measures are not featured in the model.

Online Annex Table 1.6.1. Calibration of Alternative Scenarios

Parameters	Description	Emerging market economy	Source	Advanced economy	Source
$\boldsymbol{\sigma}$	Elasticity of intertemporal substitution	1	Auclert, Rognlie, and Straub (2024)	1	Auclert, Rognlie, and Straub (2024)
$\boldsymbol{r}$	Real interest rate (annual)	0.05	Auclert, Rognlie, and Straub (2024)	0.05	Auclert, Rognlie, and Straub (2024)
$\boldsymbol{\beta}$	Discount factor (annual)	0.929	matching $\frac{A}{Y}$	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)
$\boldsymbol{\theta}$	Retention function curvature	0.05	Tax brackets in Peru	0.181	Heathcote and others (2017)
$\frac{A}{Y}$	Capital to GDP	2.73	Hong (2023)	2.96	Auclert, Rognlie, and Straub (2024)
$\boldsymbol{\zeta\,(1+r)}$	Illiquid-liquid spread	0.1	Lending-deposit spread in Peru	0.08	Auclert, Rognlie, and Straub (2024)
$\boldsymbol{\nu}$	Adjustment probability	0.088	Matching marginal propensity to consume	0.089	Auclert, Rognlie, and Straub (2024)

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

Main channels of fiscal measures

Fiscal measures affect households' consumption and aggregate output through multiple channels: (1) disposable income, via wage income and transfers; (2) interest rate; and (3) asset revaluation. Each channel affects households differently, shaping the aggregate impact. The interplay of these channels, combined with

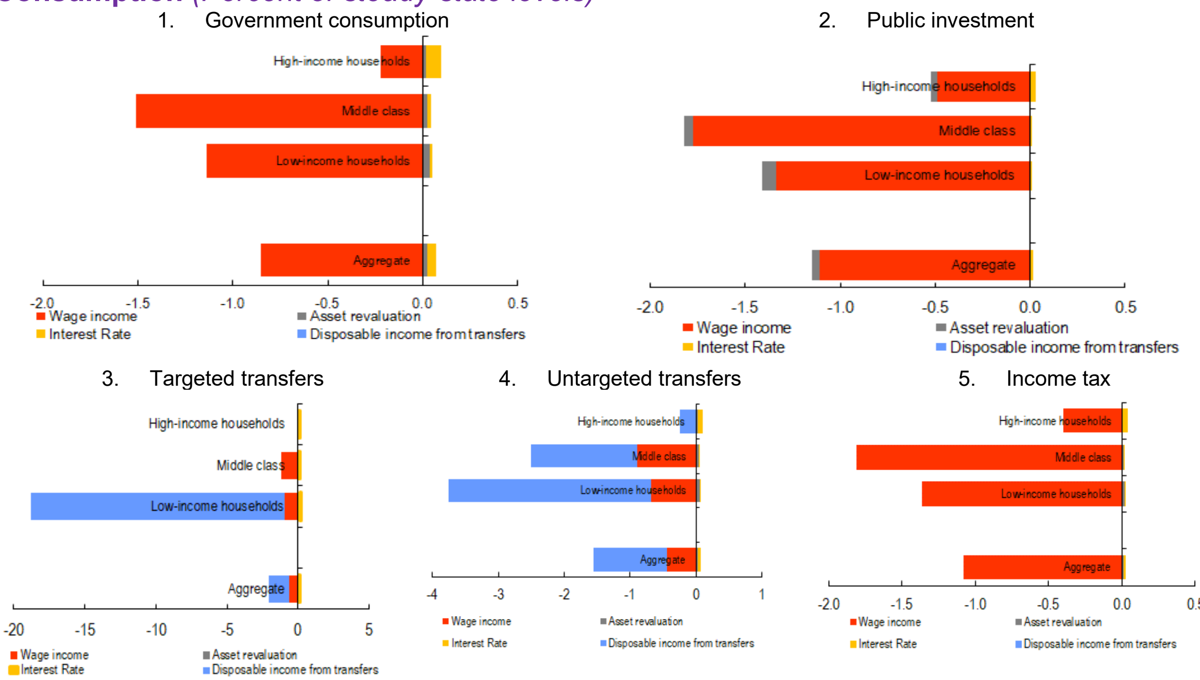
[2] Energy consumption is not modeled directly, and the results do not account for general equilibrium effects arising from changes in energy subsidies. The two sources of information are indicative. The model does not intend to match the precise moments in these two studies but highlights potential differences between advanced economy and emerging market and developing economies.

financial frictions faced by households, lead to large variations in propensity to consume among households, which amplify the aggregate economic effects.

- *Disposable income channel.* Wage income is a key component of disposable income. The channel operates through after-tax wage rates. A cut in government spending reduces the aggregate demand and puts pressure on wages, which in turn affects household income and consumption. In addition, government direct transfers provide households a cushion for income losses—especially for low-income households—and directly affect households' disposable income and consumption.
- *Interest rate channel.* It works through intertemporal substitution in which a decline in real interest rates will make current consumption relatively cheaper than that in the future, thereby encouraging households to consume more and save less today.
- *Asset valuation channel.* Households hold liquid and illiquid assets where their valuation could fluctuate with economic conditions. A decline in real interest rates raises the present value of those assets (from higher future income streams), increasing consumption owing to wealth effects, particularly for high-income households that have significant asset holdings.

The strength of each channel, for each measure (of the same size, of 1 percentage point of initial GDP), is shown in Online Annex Figure 1.6.1. Across all measures, the main channel at work is disposable income—through wages or government transfers. For example, a cut in government spending reduces aggregate demand, puts pressures on wages, and reduces household consumption. These effects are partly offset by the interest rate channel, in which monetary policy eases in response to lower inflationary pressures from less demand.

Online Annex Figure 1.6.1. Channels of Fiscal Measures Affecting Household Consumption *(Percent of steady-state levels)*



Source: IMF staff estimates.
Note: The simulation assumes a one-off consolidation in respective fiscal measures in the first year by 1 percentage point of steady-state GDP. The decomposition is based on the impact at the time of the adjustment. Low-income households refer to those at the bottom 5th percentile. Middle-class households refer to those with income in the 40th to 60th percentile. High-income households refer to those with income in the top 10th percentile.

The effect varies across households. Low- and middle-income households often bear disproportionate effects because they rely heavily on wage income and government transfers and do not have sufficient asset buffers.

A decline in wages leads to a substantial drop in consumption, exacerbating their financial strains. They are less able to offset this loss in income with lower interest rates either because of limited access to credit and/or small financial wealth. In contrast, high-income households are much less affected, despite a similar drop in wage income, because they can use their savings to smooth consumption. In the case of a cut in public investment, both the interest rate and asset valuation channels are smaller than those in other fiscal measures because a cut in public investment reduces the return of assets. Moreover, in the case of a cut in public investment, the interest rate does not fall much because of less inflationary pressure from a smaller aggregate supply. Raising progressive income tax reduces consumption across all households, although high-income households can buffer lower after-tax wages with income from financial assets to preserve their consumption.

Design of Fiscal Measures

This section underpins the technical details of the fiscal adjustment scenarios (*undesirable* and *preferred*) presented in the main text. For both scenarios. the size of the fiscal adjustment is set at a cumulative reduction of about 3 percent of initial GDP over six years (about 0.5 percent annually), which is consistent with debt stabilizing (or reducing) with high probability (see Online Annex 1.5).

For the *undesirable* adjustment package, the share of each type of fiscal measure is assumed to be 40 percent from a cut in public investment, 40 percent from a cut in government consumption, and 10 percent from a reduction in untargeted transfers, with the remaining 10 percent from income taxes (Online Annex Table 1.6.2). This composition is set as uniform for both advanced economies and emerging markets. Simulation results show the debt would reduce by about 4 percent of GDP (as output is endogenous in the model) by the end of the adjustment period and stabilize around that level (Online Annex Figure 1.6.2).[3]

Online Annex Table 1.6.2. Public-Debt-to-GDP across Country Income Groups
(Percent of initial GDP and share, percent)

Measures	Undesirable adjustment		Preferred adjustment (Advanced economies)		Preferred adjustment (Emerging markets economies)	
	percent of initial GDP	percent of total adjustment	percent of initial GDP	percent of total adjustment	percent of initial GDP	percent of total adjustment
Public Investment	0.26	40	-0.03	-5	-0.10	-15
Government Consumption	0.26	40	0.39	60	0.26	40
Untargeted Transfers	0.07	10	0.03	5	0.07	10
Income Taxes + Interest Rate	0.07	10	0.29	45	0.39	60
Targeted Transfers	0.00	0	-0.07	-10	-0.03	-5
Reduction in Subsidies	0.00	0	0.03	5	0.07	10

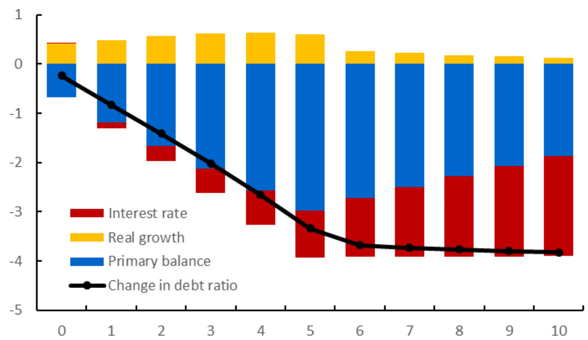
Source: IMF staff estimates.
Note: positive shares indicate a fiscal consolidation, negative shares a fiscal expansion.

In the *preferred* adjustment scenario, measures in advanced economies largely rely on a cut in government consumption (60 percent of the total adjustment). Public investment and targeted transfers are each raised slightly by about 0.07 and 0.03 percent of initial GDP, respectively (Online Annex Table 1.6.2). Subsidies are adjusted slightly (by 0.03 percent of initial GDP) to help cushion the impact on middle-income households. Income tax is also an important component of the adjustments and is raised by about 0.2–0.3 percent of initial GDP. The preferred adjustment scenario in emerging markets largely relies on revenue measures (accounting for 60 percent of the total). Public investment is raised (by 0.10 percent of initial GDP) to boost supply, while targeted transfers are expanded (by 0.03 percent of initial GDP) to protect vulnerable households. Regressive subsidies are reduced by 0.07 percent of initial GDP. The reliance on revenue measures (instead of a cut in government consumption), combined with reducing regressive subsidies, helps limit the aggregate output loss.

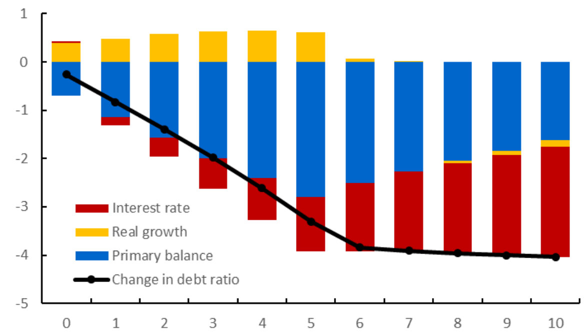
[3] The exercise does not solve for a transitional path from a high- to a low-debt steady state. Instead, it approximates the dynamics for the first 15 years and assume debt will return to its initial steady state over 200 years.

Online Annex Figure 1.6.2. Change in Public-Debt-to-GDP across Country Income Groups *(Percent of GDP)*

1. Emerging market economy



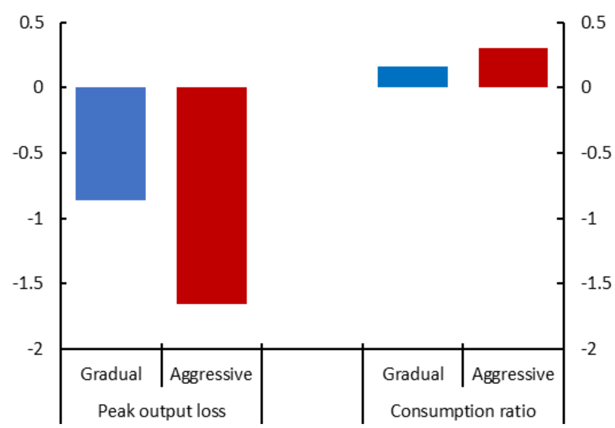
2. Advanced economy



Source: IMF staff estimates.
Note: the simulation is based on a cumulative fiscal adjustment of about 3 percent of GDP over six years in each economy, comprising measures in the preferred adjustment package noted in Figure 1.20 of the main chapter.

Model results also show that a fiscal adjustment of the same size but implemented more aggressively tends to intensify the adverse impact on output and inequality. For example, in the case of emerging market economies, a fiscal adjustment of 3 percent of GDP over three years (instead of six years) will lead to a much sharper (about doubled) reduction in output initially, and a rise in inequality as measured by the consumption ratio between the top 5th percentile of households relative to the bottom 50th percentile of households (Online Annex Figure 1.6.3).

Online Annex Figure 1.6.3. Impact of Fiscal Adjustments at Different Pace
(Percent of initial GDP and consumption ratio)



Source: IMF staff estimates.
Note: The simulation considers the same fiscal adjustment of 3 percent but over different horizons (three years in the aggressive scenario and six years in the gradual scenario). Consumption ratio refers to the consumption of the top 5th percentile and the bottom 50th percentile of households. Peak output loss refers to the change in output relative to the initial levels at the peak (3rd and 6th year in the aggressive and gradual scenarios, respectively).

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