

Debt-at-Risk

EFB 2025: Sustainability in Times of National Escape Clauses

Davide Furceri^{1,2} **Domenico Giannone**^{2,3} **Faizaan Kisat**¹
W. Raphael Lam¹ **Hongchi Li**¹

¹International Monetary Fund ²CEPR ³Johns Hopkins University

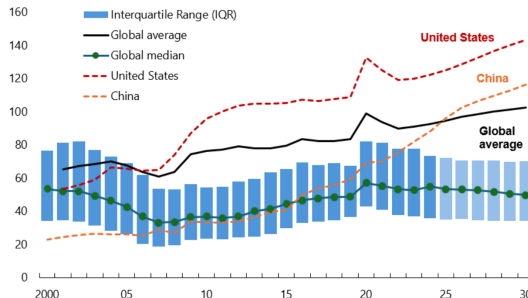
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Global debt is elevated and is projected to increase

- High debt reduces fiscal space and raises the risk of sovereign stress.
- Assessing the risks surrounding the debt outlook is thus essential.

Public Debt-to-GDP Ratio, 2000-30
(Percent of GDP)



The figure plots statistics for the historical and projected debt-to-GDP ratios.

Source: IMF World Economic Outlook database.

Debt-at-Risk (DaR)—novel framework to quantify risks around debt projections

Builds on the “growth-at-risk” methodology (Adrian, Boyarchenko, and Giannone 2019):

- Novel approach to examine the role of macroeconomic factors and policies in affecting the level and the uncertainty surrounding debt.
- Construct predicted quantiles of future debt at a forecast horizon of one to five years.
- Estimates fitted to a skewed t -distribution.
- Densities conditional on multiple variables are combined to a single distribution based on the individual factors’ predictive power.

Contribution of DaR to existing tools

- Goes beyond proximate drivers to consider underlying factors—e.g., financial stress.
- Examines their asymmetric and nonlinear effects on the debt distribution.
- Gauges how high debt could rise in an extreme adverse, but plausible, scenario.
- Strong predacity power of fiscal crises.

Road map

- Constructing DaR for a large sample of countries.
- Predictability of fiscal crises.
- DaR for countries with limited or high-frequency data

Data

Data structure:

- Country x year panel.
- Years: 1980-2024, Countries: 90 advanced and emerging and developing economies (>90 percent of global debt)

Key variables:

- Financial variables: Financial Conditions Index (IMF), Financial Stress Index (Ahir et al. 2023), spreads (Global Financial Data).
- Political variables: World Uncertainty Index (Ahir, Bloom, and Furceri 2022), Reported Social Unrest Index (Barrett et al. 2022).
- Economic variables: Debt-to-GDP, primary balance, real GDP growth, inflation (WEO database).

Empirical framework—Quantile regression specification

Estimate the following panel location-scale model (Machado and Santos Silva 2019):

$$d_{i,t+h} = \alpha_i + X'_{i,t}\beta + (\delta_i + X'_{i,t}\gamma)\varepsilon_{i,t+h} \quad (1)$$

- $d_{i,t+h}$: h year-ahead debt-to-GDP ratio (h :1 to 5 years), of country i in year t .
- α_i and δ_i : Country fixed effects.
- $X_{i,t}$: Vector of predictors (initial debt included in all specifications).
- β : Location parameter—“shift” in the entire distribution of future debt as a regressor moves.
- γ : Scale parameter—captures whether this shift differs across quantiles.

The τ -th quantile of future debt, $Q_d(\tau)$ is given by:

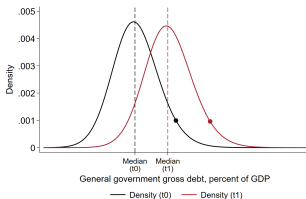
$$Q_{d_{i,t+h}}(\tau|X_{i,t}) = (\alpha_i + \delta_i q(\tau)) + X'_{i,t}\beta + X'_{i,t}\gamma q(\tau) \quad (2)$$

where $q(\tau) = F_\varepsilon^{-1}(\tau)$. Quantile regression coefficient for predictor x : $\beta_x + \gamma_x q(\tau)$.

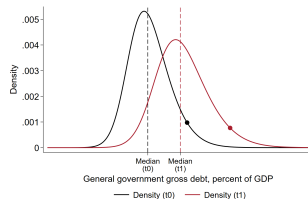
Effects of a conditioning variable on the future debt distribution depends on the location and scale parameters

Impact of Conditioning Variable on Density Based on Location (β) and Scale (γ) Coefficients

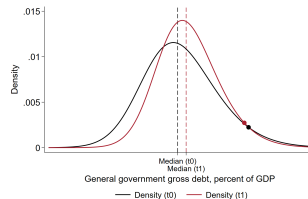
A. $\beta > 0, \gamma = 0$



B. $\beta > 0, \gamma > 0$



C. $\beta > 0, \gamma < 0$



The figures plot illustrative changes in the predicted conditional debt densities when the conditioning variable increases by one standard deviation. t_0 refers to period zero, and t_1 refers to period one (after the change in the conditioning variable). In Panel A, β is positive but γ is zero; In Panel B, both β and γ are positive (same signs); In Panel C, β is positive while γ is negative (opposite sign). Dots indicate the predicted 95th quantile of the debt-to-GDP ratio.

Fitting and combining densities

Fitting densities: [Details](#)

- Quantiles re-centered such that predicted median conditional on initial debt matches WEO 2025-30 projection.
- Predicted quantiles fitted to a skewed t -distribution (Azzalini and Capitanio 2003).

Combining densities:

- For a particular country, year, and forecast horizon, we pool densities using a weighted sum of the densities based on individual predictors m :

$$\hat{f}_{i,t+h}^{pooled}(d) = \sum_m \eta_{i,h}^m \hat{f}_{i,t+h}^m(d) \quad (3)$$

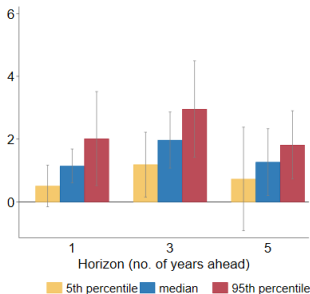
- Weights $\eta_{i,h}^m$ sum to one and maximize out-of-sample predictive accuracy of the combined distribution (Crump et al. 2023). [Details](#)

Quantiles aggregated to global or country-group level using GDP weights [Details](#). Global sample has 47 countries [List](#).

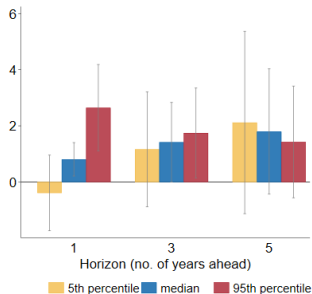
Adverse financial and political developments are associated with higher debt-at-risk

Quantile Regression Results: Forward Debt-to-GDP Ratio and Financial and Political Variables

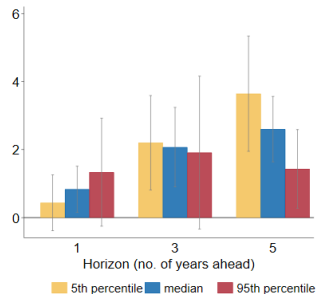
A. Financial Conditions



B. Spread

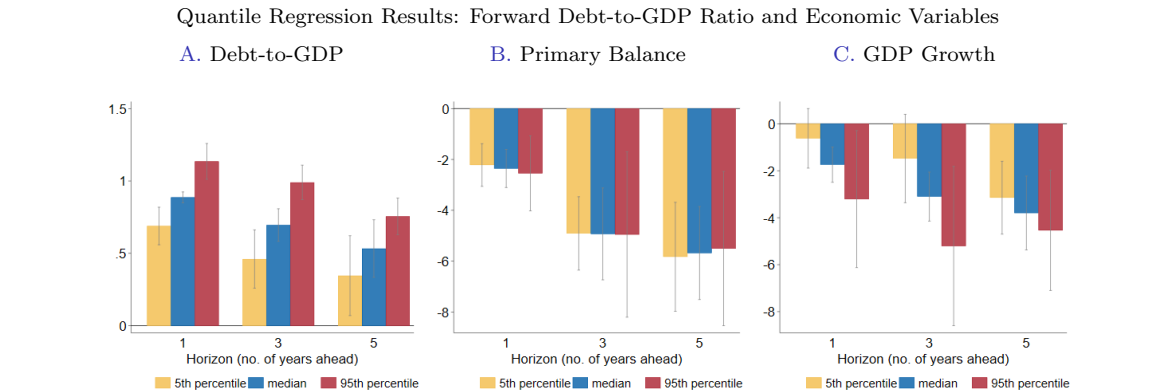


C. Social Unrest



The figure displays the estimated quantile regression coefficients for 5th, 50th, and 95th percentile based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables (Equation (1)). Bars denote estimated coefficients, and the whisker in each bar shows the associated 90 percent confidence interval. 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) are standardized to have a mean of zero and a standard deviation of one to ensure comparability across coefficients. Standard errors are clustered at the country level.

Economic factors have persistent and asymmetric effects on the debt distribution

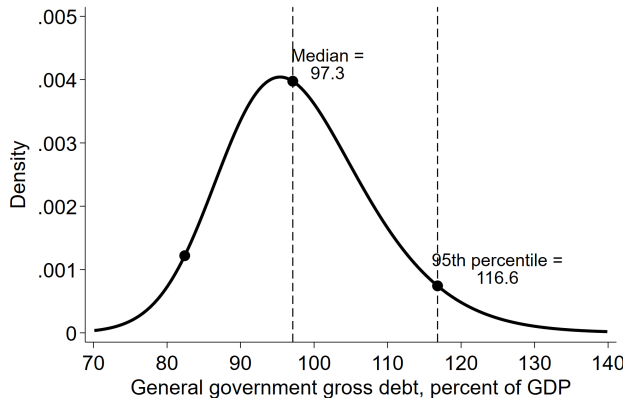


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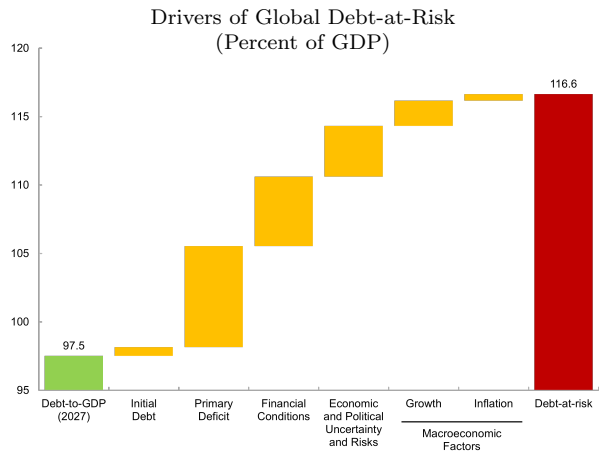
Global debt-at-risk for 2027 is estimated at 117 percent of GDP, nearly 20 percentage points higher than projections

Global Debt-at-Risk 2027
(Probability density of three-year-ahead government debt-to-GDP ratio)



The figure plots the predicted density of the three-year-ahead global debt-to-GDP ratio. The probability density functions are estimated using panel quantile regressions of the debt-to-GDP ratio on various political, economic, and financial variables. The global sample comprises 47 countries for which data on the conditioning variables are available. The quantile estimates are fitted to a skewed t -distribution. Dots indicate the predicted 5th, 50th (median), and 95th quantile of the debt-to-GDP ratio.

Primary deficits and tight financial conditions are the main factors contributing to upside risks to global debt

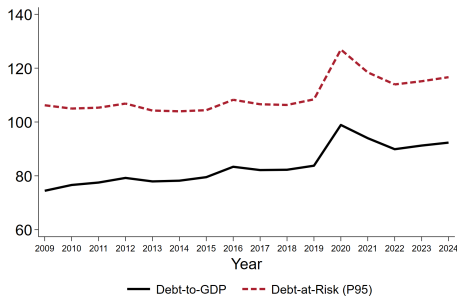


The figure plots the contributions from the conditioning variables used for the debt-at-risk model to the estimated level of global debt-at-risk. The green bar denotes the baseline debt projection for 2027 from the World Economic Outlook database. Yellow bars refer to contribution from the conditioning variables. The red bar indicates the value of the debt-at-risk.

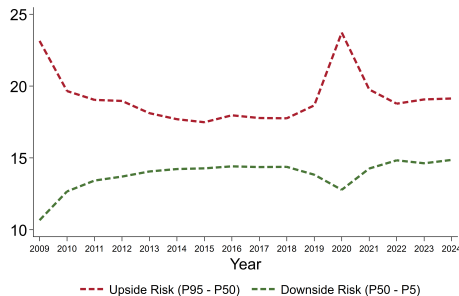
Global debt-at-risk has risen since 2009, and upside risks are consistently higher than downside risks

Evolution of Global Debt and Debt Risks
(Percent of GDP)

A. Debt-to-GDP and Debt-at-Risk



B. Upside and Downside Risks

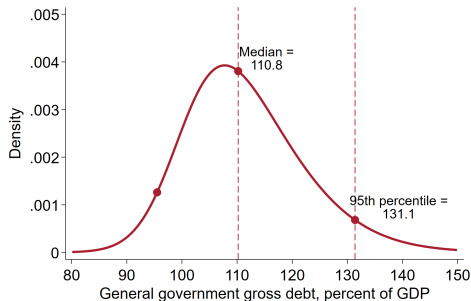


The figures plot the evolution of global GDP weighted debt-to-GDP and debt-at-risk (Panel A), and the evolution of upside and downside debt risks (Panel B) at a three-year forecast horizon. Debt-at-risk is defined as the predicted 95th quantile (P95) of the combined distribution. Upside risks are calculated as the difference between the predicted 95th quantile of the combined distribution and the predicted 50th quantile (median) of the distribution conditional on initial debt (P95 - P50). Downside risks are the difference between the predicted median conditional on initial debt and the predicted 5th quantile of the combined distribution (P50 - P5).

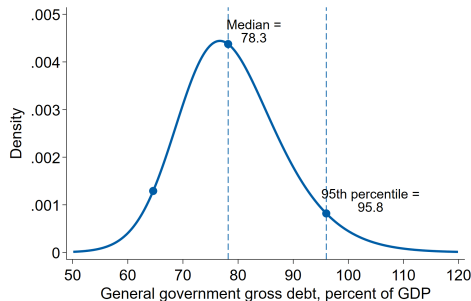
Debt-at-risk differs across country income groups...

Debt-at-Risk by Income Groups 2027
(Probability density of three-year-ahead government debt-to-GDP ratio)

A. Advanced Economies



B. Emerging Market and Developing Economies

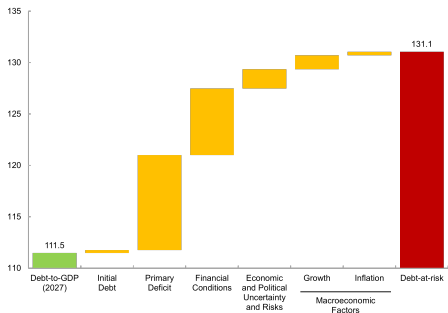


The figure plots the predicted density of the three-year-ahead global debt-to-GDP ratio for Advanced Economies (Panel A) and Emerging Market and Developing Economies (Panel B). The probability density functions are estimated using panel quantile regressions of the debt-to-GDP ratio on various political, economic, and financial variables. The global sample comprises 47 countries for which data on the conditioning variables are available. The quantile estimates are fitted to a skewed t -distribution. Dots indicate the predicted 5th, 50th (median), and 95th quantile of the debt-to-GDP ratio.

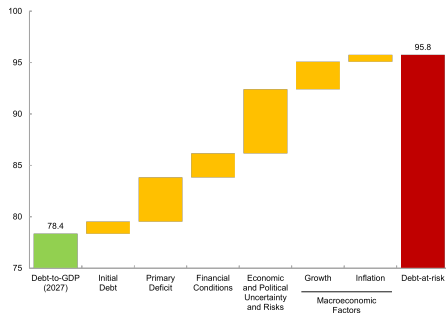
... with primary deficits driving debt risks for AEs and economic and political uncertainty more important for EMDEs

Drivers of Global Debt-at-Risk by Income Groups
(Percent of GDP)

A. Advanced Economies



B. Emerging Market and Developing Economies



The figure plots the contributions from the conditioning variables used for the debt-at-risk model to the estimated level of debt-at-risk for Advanced Economies (Panel A) and Emerging Market and Developing Economies (Panel B). The green bar denotes the baseline debt projection for 2027 from the World Economic Outlook database. Yellow bars refer to contribution from the conditioning variables. The red bar indicates the value of the debt-at-risk.

Debt-at-Risk and fiscal crises

- 1 Do the debt-at-risk measures help predict fiscal crises?
- 2 If so, how well do they perform relative to other economic variables?

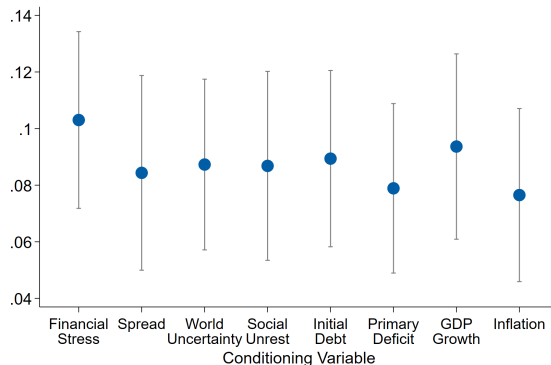
To address these, we:

- Construct a binary fiscal crisis variable (Moreno Badia et al. 2022). [Details](#)
- Correlate crisis variable with debt-at-risk measure:
 - Logit model.
 - Bayesian Model Averaging (BMA) model.
 - Random forest machine learning model.

1. Do the debt-at-risk measures help predict fiscal crises?

Debt-at-Risk correlates strongly and positively with a future fiscal crisis.

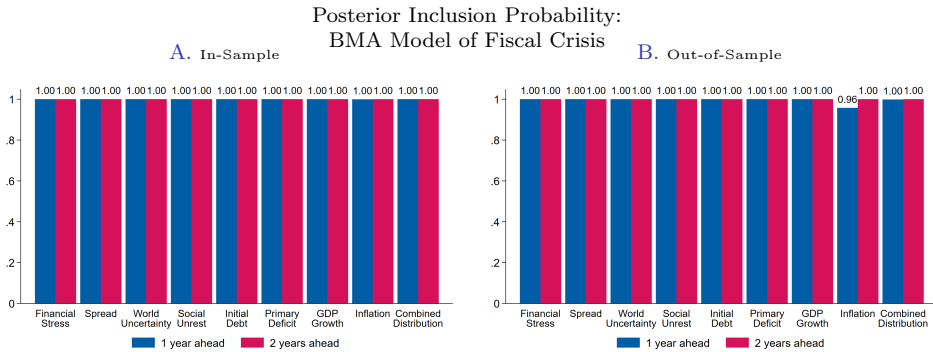
Logistic Regression Coefficients:
Fiscal Crisis vs. One-Year Ahead Debt-at-Risk



The figure shows estimated coefficients from a panel logit regression of a fiscal crisis indicator against debt-at-risk. Each point denotes the coefficient from a separate regression. The independent variable is the difference between the predicted 95th quantile of one-year-ahead debt-to-GDP and the 50th quantile conditional on the variables displayed on the horizontal axis. Whiskers show the 90 percent confidence intervals.

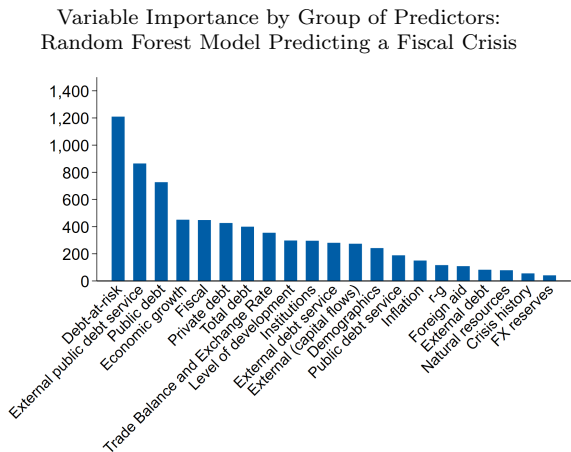
2. How well do the measures perform in predicting crises relative to other economic variables?

Debt-at-risk is one of the most robust metrics in predicting a fiscal crisis.



The figure shows the posterior inclusion probability (PIP) for the interaction of (P95-P50) with P95 from a Bayesian model averaging (BMA) model of a fiscal crisis indicator against debt-at-risk and other macroeconomic variables. The independent variables include the one- and two-year-ahead predicted debt quantiles (p95, p95-p50, p95*(p95-p50)) conditional on the variables displayed on the horizontal axis, the conditional variables themselves, the one-year-ahead debt-to-GDP and primary balance-to-GDP ratios, and additional economic variables (total debt to GDP, public debt to GDP, public debt service to revenue, public debt to revenue, public external debt to exports, and public debt service to exports). For these additional variables, we include contemporaneous values, first and second lags, and the (historical) 1-year and 3-year growth rates. PIP measures the likelihood that a particular predictor variable is to be included in the “true” model based on the data, indicating its importance within the model space across all possible combinations of variables.

2. How well do the measures perform in predicting crises relative to other economic variables? (continued)

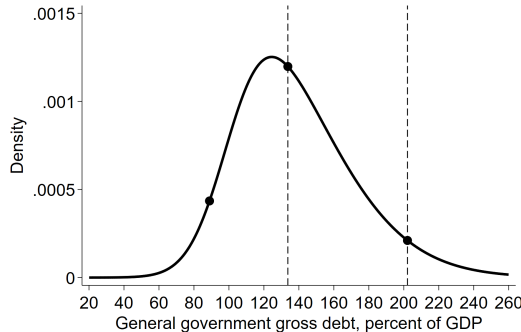


The figure displays (grouped) variable importances from a random forest model used to predict a fiscal crisis. The independent variables are similar to those used for the BMA. Higher values indicate that a variable has a higher predictive power. Variable importance is calculated using an in-built out of bag permuted predictor importance function in R using a random forest with the variables selected by Boruta.

Extended Sample

- Construct measure of debt-at-risk for based on more widely available economic variables. Sample extended to 175 countries, including many low-income economies.

Debt-at-Risk 2027 for Selected Low Income Developing Country in Extended Sample
(Probability density of three-year-ahead government debt-to-GDP ratio)



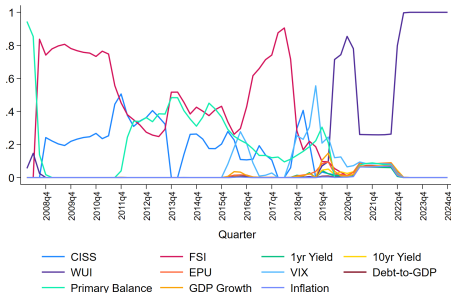
The figure plots the predicted density of the three-year-ahead global debt-to-GDP ratio for a selected highly indebted low income developing economy in the extended sample. The economy has coverage for the economic variables but does not have any data for the considered financial and political variables. The probability density functions are estimated using panel quantile regressions of the debt-to-GDP ratio on economic variables. The quantile estimates are fitted to a skewed t -distribution. Dots indicate the predicted 5th, 50th (median), and 95th quantile of the debt-to-GDP ratio.

Debt-at-Risk for the US

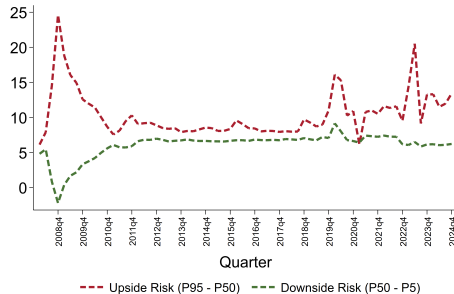
- Higher frequency data, more conditioning variables available for some countries.
- Use location-scale model to estimate quarterly debt-at-risk for the US.

Debt-at-Risk for the US: Four Quarters Ahead

A. Time-Varying Weights for US Distribution



B. Upside and Downside Risks (Percent of GDP)



Panel A plots the weights used to combine predicted distributions conditional on each of the conditioning variables (Equation (5)). Panel B plots the evolution of upside (P95 - P50) and downside risks (P50 - P5), defined as in the main section. The conditioning variables are: Composite Indicator of Sovereign Stress (ECB), Financial Stress Index (Ahir et al. 2023), 1 year Yield, 10 year Yield, World Uncertainty Index (Ahir, Bloom, and Furceri 2022), Economic Policy Uncertainty Index (Baker, Bloom, and Davis 2016), VIX, Initial Debt, Primary Balance, GDP Growth, and Inflation.

Correlation of US Debt-at-Risk Based Uncertainty with Policy Uncertainty Measures

Uncertainty Measure	Correlation with Debt-at-Risk (1)
Economic Policy Uncertainty Index (EPU)	0.670***
EPU Fiscal Policy	0.489***
EPU Tax Policy	0.486***
EPU Government Spending Policy	0.289***
Fiscal Volatility Shock (FGKR 2015)	0.268*
World Uncertainty Index: Overall	0.468***
World Policy Uncertainty Index	0.220*
VIX Index	0.511***

The table displays the correlation coefficients for the uncertainty of the US debt-at-risk (four quarters ahead) and selected other uncertainty measures. Debt-at-risk based uncertainty is defined as the difference between the predicted 95th and 5th percentiles. Economic Policy Uncertainty indices are from Baker, Bloom, and Davis (2016). Fiscal volatility shock is the fiscal volatility shock to capital tax rate from Fernández-Villaverde et al. (2015). World Uncertainty indices are from Ahir, Bloom, and Furceri (2022). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. .

Conclusion

Conclusion:

- Debt risks are elevated and tilted to the upside.
- Global debt-at-risk in 2027 is estimated at around 117 percent of GDP, with significant heterogeneity across countries.
- Debt-at-risk is the most robust predictor of fiscal crises.

Implications and potential use:

- Use DaR to quantify the size of debt risks in a severely adverse scenario; compare risks over time and across countries.
- DaR as an early-warning tool to monitor fiscal crises.

Additional Slides

Fitting densities to a skewed t -distribution

- Distribution depends on four parameters: the location μ , scale σ , fatness ν , and the shape α .
- Choose parameters to fit predicted quantiles to the quantile function of the distribution:

$$\{\hat{\mu}_{i,t+h}^m, \hat{\sigma}_{i,t+h}^m, \hat{\alpha}_{i,t+h}^m, \hat{\nu}_{i,t+h}^m\} = \underset{\mu, \sigma, \alpha, \nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{Q}_{d_i, t+h}^m(\tau) - F^{-1}(\tau; \mu, \sigma, \alpha, \nu) \right)^2 \quad (4)$$

where:

- $\hat{Q}_{d_i, t+h}^m(\tau)$ is predicted quantile from quantile regression (2).
- $F^{-1}(\tau; \mu, \sigma, \alpha, \nu)$ is the quantile function of the skewed t -distribution.
- $\tau \in \{5, 25, 75, 95\}$

Weighting methodology to combine conditional distributions

Two steps:

- Compute out-of-sample predictive densities conditional on each explanatory variable m using data from the *prior* 20 years (from 2005 onwards).
 - E.g., $\hat{p}_{2007|2005}^m(d)$ is density for 2007 conditional on information from 1986 to 2005.
- Weights are the values (positive and summing to one) that maximize these probability scores across all years:

$$\eta_{i,h}^1, \dots, \eta_{i,h}^M = \operatorname{argmax} \sum_{t=2005+h}^{2024} \sum_{m=1}^M \eta_{i,h}^m \hat{p}_{T+h|T}^m(d) \quad (5)$$

s.t. $\eta_{i,h} > 0$; $\sum_{m=1}^M \eta_{i,h}^m = 1$

Back

Aggregating to global levels or country groups

- For each model m , approximate the quantile of the global distribution with the weighted average of the country-level quantiles:

$$\hat{Q}_{d_{global,t+h}}^m(\tau) = \sum_{i=1}^I \omega_{i,t} \hat{Q}_{d_{i,t+h}}^m(\tau) \quad (6)$$

- $\omega_{i,t}$ is country i 's nominal GDP share.
- Re-center quantiles around WEO projections.
- Fit aggregate quantiles to skewed t -distribution to obtain global density $\hat{f}_{global,t+h}^m(d)$
- Pool densities by combining model-specific densities; global weights are the GDP-weighted average of the country-specific weights:

$$\hat{f}_{global,t+h}^{pooled}(d) = \sum_{m=1}^M \omega_{global,h}^m \hat{f}_{global,t+h}^m(d) \quad (7)$$

where $\omega_{global,h}^m = \sum_{i=1}^I \omega_{i,t} \eta_{i,h}^m$.

Country coverage for global debt distribution

Advanced Economies	Emerging Market and Developing Economies
Australia	Brazil
Austria	Bulgaria
Belgium	Chile
Canada	China
Denmark	Colombia
Finland	Hungary
France	India
Germany	Indonesia
Greece	Kenya
Hong Kong SAR	Malaysia
Ireland	Mexico
Israel	Morocco
Italy	Nigeria
Japan	Pakistan
Korea	Peru
Netherlands	Philippines
New Zealand	Romania
Norway	Russia
Portugal	South Africa
Spain	Tanzania
Sweden	Thailand
Switzerland	Vietnam
United Kingdom	Zambia
United States	

Significant and asymmetric effects of conditioning factors

Location-Scale Coefficients: Forward Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables

	Horizon (no. of years Ahead):					
	1		3		5	
	Location (1)	Scale (2)	Location (3)	Scale (4)	Location (5)	Scale (6)
Panel A: Financial Variables						
Financial Conditions	1.189***	0.314	2.002***	0.441**	1.256**	0.293
Spread	0.925***	0.693**	1.433**	0.148	1.792	-0.178
Panel B: Political Variables						
Social Unrest	0.860**	0.180	2.065***	-0.071	2.583***	-0.578*
Panel C: Economic Variables						
Debt-to-GDP	0.901***	0.092***	0.710***	0.126***	0.539***	0.105***
Primary Balance	-2.365***	-0.062	-4.928***	-0.010	-5.673***	0.082
GDP Growth	-1.816***	-0.507	-3.220***	-0.911	-3.815***	-0.356

The table displays the estimated location (β) and scale (γ) coefficients based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables (Equation (1)). All explanatory variables (except for initial debt) are standardized to have a mean of zero and a standard deviation of one to ensure comparability across coefficients. Standard errors (reported in parentheses) are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Defining a fiscal crisis

Fiscal crisis occurs if any one of four criteria are met over the next two years:

- ① A credit event (default, restructuring, or rescheduling).
- ② Exceptionally large official financing from the IMF or European Union.
- ③ Implicit default on domestic debt (high inflation, increase in domestic arrears).
- ④ Loss of market confidence (spike in spreads, loss of market access).

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Random Forest Model Variables

Table: Variables in the Random Forest Model

	Variable category	Number of factors (1)	Total number of permutation on factors (2)	Number of factors chosen in Boruta selection (3)
1	Debt-at-risk	8	32	31
2	External public debt service	4	58	22
3	r-g	1	10	2
4	Trade and Exchange Rate	9	83	15
5	Total debt	2	28	6
6	Private debt	5	50	13
7	Public debt	4	60	16
8	Institutions	3	33	4
9	Economic growth	4	27	10
10	External capital flows	2	43	4
11	Level of development	3	21	8
12	Fiscal	6	61	12
13	Public debt service	2	30	6
14	Inflation	5	17	7
15	Natural resources	2	42	3
16	External debt service	3	15	5
17	Demographics	5	40	9
18	External debt	2	20	4
19	Foreign aid	1	10	4
20	Crisis History	2	27	2
21	FX reserves	2	18	5
22	Country Category	–	6	–
23	Global Factor	–	48	–
Total		75	779	188

The table presents a summary of the variables used for the Random Forest model. Column (1) shows the number of selected factors chosen in the Boruta selection. Column (2) shows the total number of factors (including all their permutations) in the dataset (prior to Boruta selection). Column (3) shows the number of selected factors (including all their permutations) chosen in the Boruta selection. We consider the following functional forms for the variables: first and second lags, weighted average of last 5-year and 10-year, percent change from last period, and standard deviation.

References I



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