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Debt-at-Risk

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Prepared by Davide Furceri, Domenico Giannone, Faizaan Kisat, W. Raphael Lam, and Hongchi Li*

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ABSTRACT: This paper proposes a novel framework for analyzing the risks surrounding the public debt outlook, the "Debt-at-Risk." It employs a quantile panel regression framework to assess how current macro-financial and political conditions impact the entire spectrum of possible future debt outcomes. Many of these factors—including financial conditions and economic variables such as initial debt and GDP growth—predict both the expected level and the uncertainty of future debt, implying pronounced variations in risks, especially in the upper tail of the distribution. By combining the roles of these factors, we find that in a severely adverse scenario—the 95th percentile of the future debt distribution, or debt-at-risk—global public debt could be approximately 20 percentage points higher than currently projected. The magnitudes and sources of debt risks vary over time and across countries, with high initial debt amplifying the effects of economic and financial conditions on debt-at-risk. Furthermore, empirical estimates indicate that debt-at-risk is a key variable for predicting fiscal crises.

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Abstract

This paper proposes a novel framework for analyzing the risks surrounding the public debt outlook, the "Debt-at-Risk." It employs a quantile panel regression framework to assess how current macro-financial and political conditions impact the entire spectrum of possible future debt outcomes. Many of these factors—including financial conditions and economic variables such as initial debt and GDP growth—predict both the expected level and the uncertainty of future debt, implying pronounced variations in risks, especially in the upper tail of the distribution. By combining the roles of these factors, we find that in a severely adverse scenario—the 95th percentile of the future debt distribution, or debt-at-risk—global public debt could be approximately 20 percentage points higher than currently projected. The magnitudes and sources of debt risks vary over time and across countries, with high initial debt amplifying the effects of economic and financial conditions on debt-at-risk. Furthermore, empirical estimates indicate that debt-at-risk is a key variable for predicting fiscal crises.

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1 Introduction

Global public debt is currently very high and may rise further than anticipated. Debt levels exceeded $100 trillion in 2024 and are projected to approach 100 percent of global GDP by 2030, primarily driven by the world's two largest economies, China and the United States (see Figure 1). Looking ahead, rising trade tensions and geo-economic uncertainties, tighter financial conditions, and spending pressures—such as those related to aging populations and defense— could further complicate the debt outlook by exacerbating fiscal deficits and depressing growth. Additionally, debt surprises are both frequent and, in some cases, substantial (Estefania-Flores et al. 2023), leading to painful economic consequences, as observed during the European debt crisis.

Assessing the risk surrounding the debt outlook is thus essential. However, most available debt forecasts typically reflect average estimates of the future debt trajectory in an economy. Understanding the uncertainty surrounding debt dynamics requires quantifying both downside and upside risks to the forecast and monitoring their evolution over time. To address this need, this paper introduces a novel "debt-at-risk" framework to quantify the full distribution (and identify the sources) of risks around baseline projections for public debt.

The debt-at-risk framework builds on, and advances, the "growth-at-risk" methodology (Adrian, Boyarchenko, and Giannone 2019) and examines the dynamics of the global debt distribution over a projection horizon of one to five years. The analysis has several advantages compared to existing methods to forecast future debt. It examines debt risks by going beyond the "proximate" drivers of debt (e.g., interest-growth differentials and primary balances) to investigate salient underlying factors—such as financial stress or increased uncertainty regarding policies—that could affect government debt by acting on multiple proximate drivers at once. Second, it assesses whether these factors have asymmetric and nonlinear effects on the future distribution of debt-to-GDP. Third, it examines the effect of these factors on both the level of public debt and the uncertainty surrounding it. Ultimately, the framework helps policymakers gauge how high public debt could rise in a severe adverse scenario, in a way that allows for comparisons across countries and over time.

The empirical approach is based on a location-scale model to estimate the predictive distribution of debt-to GDP ratio. The model includes country fixed effects to fully control for non-time-varying country characteristics. The key parameters linking changes in a conditioning variable to the predicted quantile of future debt are the location and the scale. The location captures the "shift" in the entire distribution of future debt as a regressor moves. The scale captures whether this shift differs across quantiles—that is, if the regressor has asymmetric effects on the upper or lower tail of the predicted debt distribution. Thus, by allowing a conditioning factor to simultaneously influence both the mean and variance of the predictive debt density, the location-scale model can accommodate complex changes in the predictive density associated with changes in a conditioning factor.

In our baseline specification, future realized values of debt-to-GDP, up to a forecast horizon of five years, are regressed against contemporaneous values of financial, political, and economic variables of interest. As debt-to-GDP is a stock variable, initial debt levels are included as a conditioning variable in all specifications. Financial factors include a financial conditions index, a Financial Stress Index (Ahir et al. 2023), and sovereign spreads. Political variables include a World Uncertainty Index (Ahir, Bloom, and Furceri 2022) and a Reported Social Unrest Index (Barrett et al. 2022). Economic variables include the proximate drivers of debt such as initial debt, GDP growth, primary balance, and inflation. The sample is a country-year panel, spans from 1980 to 2024, and includes 90 advanced economies and emerging market and developing economies accounting for more than 90 percent of global government debt.

Debt-at-risk is defined at the predicted 95th quantile of a country or country aggregate's projected debt-to-GDP ratio. Upside risks are defined as the difference between the 95th and the 50th percentiles of the distribution. Downside risks are constructed as the difference between the 50th and 5th percentile of distribution. The 25th and 75th percentiles are additional percentiles that are estimated to fit predicted quantiles to a continuous probability distribution.

Quantile regression results show that unfavorable financial developments are consistently and asymmetrically associated with higher debt risks. Tighter financial conditions, higher sovereign spreads, and financial stress episodes disproportionately affect the right tail of the future debt distribution, with the strongest effects up to a forecast horizon of three years. In particular, tightening financial conditions are associated with a statistically significant and simultaneous increase in the mean and the variance of the predicted debt distribution, resulting in larger relative changes in the upper debt quantiles versus the lower ones. Specifically, a one-standard deviation increase in the financial conditions index is associated with a 3 percentage points of GDP increase in the three-year-ahead debt-at-risk (95th quantile). In contrast, the corresponding effect on the 5th quantile of future debt is only 1.2 percentage points of GDP. We replace debt realizations as the dependent variable with the future realized values of proximate debt drivers and find that adverse financial developments may raise debt risks by increasing growth-at-risk (consistent with the literature), deficit-at-risk, and interest rate-at-risk. Beyond financial variables, political developments such as social unrest raise debt risks in the near term by raising economic and policy uncertainty.

Economic factors have long-lasting effects on the debt distribution. Higher primary balances are associated with lower debt across all quantiles of the debt distribution. In contrast, higher initial debt and lower growth have asymmetric effects on the right tail of the future debt distribution up to a forecast horizon of five years, with the scale parameter on initial debt significant up to a five year horizon. This result differs from those found in the growth-at-risk literature, which indicates that current economic conditions help to forecast the median of the distribution but do not provide information about the other quantiles. In addition, it is striking that the relationship between contemporaneous economic conditions and future debt realizations remains strong even five years into the future.

Conditional quantiles are fitted to a density function and combined across conditioning variables using country-specific weights. This procedure follows two steps. First, we follow Adrian, Boyarchenko, and Giannone (2019) and fit the quantile predictions conditional on a single factor (e.g., financial stress) to a skewed t-distribution. Second, as the analysis considers multiple conditioning variables, we follow Crump et al. (2023) and Hengge (2024) to obtain a single "pooled" density function (for every country-year and forecast horizon) based on the individual variables' predictive power. The pooled density is calculated using a weighted sum of the densities based on individual predictors, where the (country-specific) weights sum to one and are computed to maximize the out-of-sample predictive accuracy of the combined distribution. This approach ensures that the pooled density is itself a density function, and enables the construction of densities based on the variables that most strongly drive debt dynamics for a country. Country-level distributions are aggregated to construct global and regional densities and distributions for other aggregates of interest—advanced economies and emerging market and developing economies.

Global debt-at-risk for 2027 (three years ahead) is estimated at 117 percent of GDP, about 20 percentage points of GDP higher than the corresponding projection in the IMF's World Economic Outlook database. In addition, global debt-at-risk remains as right-skewed as it was during the Global Financial Crisis (GFC), as primary deficits and debt levels—key driver of debt-at-risk—have worsened in recent years for many countries. Global debt risks have increased over time, mostly mirroring the path of public debt itself. However, upside risks spike noticeably—and more than the actual debt increase—during global economic shocks such as the GFC (2009) and COVID-19 pandemic (2020), highlighting the asymmetric effect of the conditioning factors on the right tail of the debt distribution.

Debt-at-risk differs markedly across countries and country income groups. For advanced economies, three-year-ahead debt-at-risk in 2024 is estimated at about 131 percent of GDP and has retreated from pandemic peaks. For emerging market and developing economies, the corresponding figure is about 96 percent of GDP and represents an increase relative to the pandemic. Differences in debt risks between the two country groups are attributed to the initially higher levels of debt in advanced economies and variations in the primary sources of debt-at-risk: in advanced economies, these sources include the primary deficit and financial conditions, while in emerging market and developing economies, they consist of the primary deficit and uncertainty.

The paper presents three extensions. First, we evaluate the usefulness of debt-at-risk in predicting fiscal crises and find that the debt-at-risk measure outperforms other economic variables as a leading indicator of oncoming fiscal stress. We begin by using a logit model to demonstrate that debt-at-risk has a strong positive correlation with a binary fiscal crisis variable. Next, we assess the robustness of debt-at-risk as a correlate of future fiscal crises using Bayesian Model Averaging, showing that debt-at-risk should always be included in the "true" model for predicting fiscal crises in a probabilistic sense. Finally, we employ a Random Forest model to predict fiscal crises and find that debt-at-risk has the highest variable importance among all predictors, suggesting it could serve as a useful early-warning sign of an impending crisis.

As a second extension, we expand our sample to provide measures of debt-at-risk for approximately 175 economies, where most of the additional countries included are emerging market and low-income economies. In particular, we estimate quantiles using only the available conditioning factors for a country while still retaining the panel data structure. Consistent with the results from the baseline quantile regressions, economic variables (which have the broadest country coverage) exert long-lasting and significant effects on the right tail of the future distribution. In addition, upside and downside debt risks across the extended sample also exhibit similar asymmetries as the baseline specification. This extension adds value by quantifying upside risks to the debt outlook for nearly every economy in the world, going beyond previous "at-risk" exercises in the literature.

Third, we assess potential non-linearity in the relationship between various financial, economic, and political factors and future debt. Specifically, we identify two primary sources of cross-country heterogeneity influencing debt-at-risk: the initial level of debt and income status (advanced vs. emerging market and developing economies). The results suggest that initial debt amplifies the impact of economic factors on debt-at-risk, and that sovereign spreads and uncertainty tend to have larger and more persistent effects in emerging markets and developing economies.

This paper contributes to three main strands of the literature. The first, and main motivation of the paper, is a quantification of sovereign debt vulnerabilities and risks. Measures proposed in the literature typically focus on the level of debt, debt service and composition, and factors affecting the evolution of debt over time—such as GDP growth, interest rate, primary deficit and exchange rate (see, for example,Berg and Sachs (1988), Berg and Pattillo

(1999), Sturzenegger and Zettelmeyer (2007), Reinhart and Rogoff (2011), and Blanchard (2019)). We contribute to this literature in two ways: First, the literature focuses on the level of debt and its drivers, and we contribute by studying the whole conditional distribution of future debt. Second, debt-at-risk encompasses many of the measures considered as well as additional factors—such as uncertainty and financial stress—that can directly affect debt and its drivers.

Our second contribution, is to consider a large set of both advanced and emerging market economies, exploit non-linearity based on cross-country heterogeneity, and develop a methodology to combine multiple conditional densities into a single distribution based on the conditioning factors' out-of-sample predictive power.

Our third contribution is to the literature on early warning exercises and prediction of fiscal crises. This literature has typically found that domestic and external debt, debt service and GDP growth are the most important predictors of fiscal crises (see Moreno Badia et al. (2022) for a review of the literature). In this paper, we show that the ability of debt-at-risk to predict fiscal crises surpasses that of other measures—that is, debt-at-risk is the most robust predictor of fiscal crises.

Finally, we hope to contribute to research on macro-fiscal issues by providing a dataset of annual measures of debt-at-risk for a sample of 175 economies. Our framework also develops a methodology which can flexibly incorporate additional conditioning variables and higher frequency of data for future research applications that can be tailored to country-specific factors and data availability.

The rest of the paper is organized as follows. Section 2 reviews the data sources, and Section 3 discusses the quantile regression estimation strategy. Section 4 presents the debt-at-risk results and discusses the driving factors, and the variation over time and across countries. Section 5 offers several extensions, including an assessment of the link between debt-at-risk and fiscal crises. Section 6 concludes.

2 Data

The sample is a country-year level and is constructed using a variety of data sources with extensive country and time coverage (see Table A.1). Data on economic variables is from the April 2025 vintage of the IMF's World Economic Outlook (WEO) database. Our preferred measure of debt is the ratio of (end-of-period) general government gross debt to nominal GDP, a commonly used statistic of a country's sovereign debt exposure.[1] This ratio evolves

1. While this measure may not fully capture off-balance sheet debt vulnerabilities (for example, due to contingent liabilities), the use of future realized values of the debt-to-GDP ratio in our estimation strategy

according to the following equation:

$$d_{i,t+h} = \frac{1}{[(1+g_{t,h})(1+\pi_{t,h})]^h} \left[d_t(1 + \sum_{j=1}^{h} i_{i,t+j}) - \sum_{j=1}^{h} pb_{i,t+j} \right] \tag{1}$$

where $d_{i,t}$ is the debt-to-GDP ratio for country i in year t. $g_{t,h}$ and $\pi_{t,h}$ denote the (geometric) average real GDP growth rate and inflation rate between years t and $t+h$, respectively. $\sum_{j=1}^{h} i_{i,t+j}$ and $\sum_{j=1}^{h} pb_{i,t+j}$ denote the ratio of cumulative interest payments and primary balances as a fraction of current debt levels, respectively. Motivated by the dynamics displayed in equation (1), the analysis incorporates the *contemporaneous* values of growth, interest, primary balance, and inflation as conditioning variables to study their impact on future debt risks.[2]

We also include a range of financial and political variables to go beyond the "proximate" drivers of debt in the debt dynamics equation and capture the underlying drivers of debt risks. The financial factors we consider include: (i) the IMF's Financial Conditions Index, which captures the pricing of risk by condensing various financial indicators into a single index; (ii) the Financial Stress Index from Ahir et al. (2023), an indicator of financial market stress based on text search methods; and (iii) sovereign spreads, defined as the difference between 10-year government bond yields and the 10-year United States treasury yield.[3] Political factors include: (i) the World Uncertainty Index from Ahir, Bloom, and Furceri (2022), an index of uncertainty also based on text search techniques; and (ii) the Reported Social Unrest Index from Barrett et al. (2022), a high frequency indicator of social unrest events based on media reports.[4]

The estimation sample includes 90 economies accounting for more than 90 percent of global sovereign debt (Table A.2). This group of countries includes those economies with existing and continuous sovereign bond yields, indicating market access for debt financing. As debt data for most of countries are only reliably available on a yearly basis, the sample is at an annual frequency, spanning from 1980 to 2024.

does incorporate upside debt revisions resulting from the *materialization* of off-balance sheet risks.

2. In addition, we use the realized future values of some of these variables as dependent variables to evaluate the mechanisms through which shocks to financial, political, and fiscal conditions affect debt risks.

3. Spreads based on 5-year bond yields are used for countries where 10-year yields are not available. For the United States, actual 10-year treasury yields are used in place of spreads.

4. The selection of these specific variables is driven by the goal of maximizing country coverage in the estimation. For instance, other variables that capture similar concepts, such as the Economic Policy Uncertainty Index developed by Baker, Bloom, and Davis (2016), are available for a significantly more limited set of countries compared to the WUI.

3 Empirical Framework

We use a location-scale model to estimate various quantiles of the future debt distribution: specifically, the 5th, 25th, 50th, 75th, and 95th. Debt-at-risk is defined as the 95th predicted quantile of the forward debt-to-GDP ratio over a specific time horizon (1 to 5 years ahead). Upside risks are defined as the difference between the 95th and the 50th percentiles of the distribution. Downside risks are constructed as the difference between the 50th and 5th percentile of distribution. The 25th and 75th percentiles are additional quartiles that are estimated to fit a continuous distribution.

Our baseline specification to estimate regression quantiles is the following model:

$$d_{i,t+h} = \alpha_i + X'_{i,t}\beta + (\delta_i + X'_{i,t}\gamma)\varepsilon_{i,t+h} \tag{2}$$

where $d_{i,t+h}$ is the h year-ahead debt-to-GDP ratio (h ranges from 1 to 5 years), of country i in year t. The parameters α_i and δ_i capture the country fixed effects. The vector $X_{i,t}$ includes the conditioning variable $x_{i,t}$—for example, GDP growth—as well as the initial debt-to-GDP ratio d_{it} to account for persistency.[5] The location parameter β captures the effect of a predictor across all quantiles–alike the regression coefficients estimated using the OLS estimates. The scale parameter γ makes the effect of a predictor vary across quantiles. Indeed, equation (2) implies that the τ-th quantile of future debt, $Q_d(\tau)$ is given by:

$$Q_{d_{i,t+h}}(\tau|X_{i,t}) = (\alpha_i + \delta_i q(\tau)) + X'_{i,t}\beta + X'_{i,t}\gamma q(\tau) \tag{3}$$

where $q(\tau) = F_{\varepsilon}^{-1}(\tau)$ is the inverse cumulative density function of the error term evaluated at the τ-quantile. The quantile regression coefficient for a particular conditioning variable x is therefore given by $\beta_x + \gamma_x q(\tau)$.

This simple location-scale is very flexible and powerful in capturing possible asymmetric effects of a conditioning variable on the projected debt distribution. Looking at equation (3), it is evident that the linear regression model is encompassed with $\gamma = 0$. Conversely, and as discussed in Adrian, Boyarchenko, and Giannone (2019), when γ is different from zero, the model features asymmetric risk. Figure 2 illustrates how these different values for β and γ determine how the predicted debt density evolves when there is a change in a conditioning variable. If γ is zero, changes in the predictors affect all quantiles of the predicted distribution by the same amount (Panel A). If γ has the same sign as β (Panel B), then the mean and the variance of the predictive distribution are positively correlated implying that upside risk

5. In formulas, we have $X'_{i,t}\beta = \beta_x x_{it} + \beta_d d_{it}$. We also estimate an "unconditional" model which only includes initial debt as a single conditioning factor.

moves more than downside risk when a conditioning factor increases; conversely, if γ has the opposite sign of β (Panel C), then mean and the variance of the predictive distribution are negatively correlated and changes in risk are more prominent in the downside.

Estimation of the location-scale model follows the three-step procedure proposed by Machado and Santos Silva (2019). In the first step, we estimate the location parameters α_i and β using a standard fixed effects estimator applied to the data. In the second step, we estimate the scale parameters δ_i and γ by applying a fixed effects estimator to the absolute residuals obtained from the first step, thereby capturing the conditional heteroskedasticity structure. Finally, in the third step, we account for non-normality in the residuals by estimating $q(\tau)$ directly from the sample quantiles of the standardized residuals—i.e., residuals divided by their estimated conditional scale. Inference is conducted using two-ways clustered standard errors at the country level, as outlined by Rios-Avila, Siles, and Canavire-Bacarreza (2024).

Once we estimate the various conditional quantiles for a given factor, we recover a probability density function (PDF) by fitting the predicted quantiles to the skewed t-distribution of Azzalini and Capitanio (2003). The distribution extends the standard t distribution by incorporating a shape parameter which determines the skewing effect of the cumulative density function on the PDF, and has been used in a variety of economics and finance applications to study tail risks. Nonetheless, our reported global debt-at-risk estimate, as well as its use in Section 5.1 to predict fiscal crises, is obtained directly from the quantile regression prediction (Equation (3)) and is therefore invariant to the choice of distribution used to smooth regression quantiles.

The quantiles are re-centered such that the predicted median for the unconditional distribution in 2024—the distribution obtained conditional only on current debt levels—matches the corresponding 2025-29 debt-to-GDP ratio forecast in the April 2025 projection vintage of WEO database. This approach ensures consistency with median debt projections in forecast years, as our primary objective is to recover the risk around the debt outlook.

The skewed t-distribution depends on four parameters: the location μ, scale σ, fatness ν, and the shape α. For each country, forecast horizon, year, and conditioning variable (indexed by m for simplicity), we choose these parameters to minimize the squared distance between the predicted quantile $\hat{Q}^m_{d_{i,t+h}}(\tau)$ obtained from equation (3) and the quantile function of the skewed t-distribution $F^{-1}(\tau; \mu, \sigma, \alpha, \nu)$ corresponding to the 5, 25, 75, and 95 percent quantiles:[6]

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

The fitted parameters are therefore based on an exactly-identified system of equations. As the skewed t-distribution is fully pinned down by the four estimated parameters, we are able to smooth the quantile function and obtain PDFs at the same level (i.e., country x year x forecast horizon x conditioning variable) as the quantile predictions.

We estimate the model for each predictor, including the initial debt-to-GDP ratio. There are two main reasons for estimating equation (2) for each predictor separately. First, including all predictors simultaneously would significantly reduce the number of observations in the estimation sample since the overlapping sample when all predictors are available is small. Second, we are not interested in estimating marginal or causal effects; our focus is on examining the role of each factor in predicting the future debt distribution.

In the final step, we combine all predictions with the weight selected according to the predictive content of each factor. We obtain a single "pooled" density function based on the individual variables' predictive power. Specifically, for any country, the pooled density is calculated using a weighted sum of the densities based on individual predictors m as follows:

$$\hat{f}^{poooled}_{i,t+h}(d) = \sum_m \eta^m_{i,h} \hat{f}^m_{i,t+h}(d) \tag{5}$$

where $\hat{f}^m_{i,t+h}(d)$ is the PDF conditional on a single conditioning variable (for example, financial stress) and $\hat{f}^{pooled}_{i,t+h}(d)$ is the pooled PDF.

The weights $\eta^m_{i,h}$ sum to one and are computed to maximize the out-of-sample predictive accuracy of the combined distribution, following Crump et al. (2023) and Hengge (2024). This process proceeds in two steps. First, for a particular country, for each year from 2005 onward (and for each forecast horizon h) we compute out-of-sample predictive densities conditional on each explanatory variable m using data from the *prior* 20 years. We denote the predictions as $\hat{p}^m_{T+h|T}(d)$, for $T = 2005, ..., 2024$. For example $\hat{p}^m_{2007|2005}(d)$ is predictive density "score" for 2007. It is a $2-$year out-of-sample prediction since it only uses information available up to 2005. Second, the weights are obtained as the values that maximize these

6. 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.

scores across all years:

$$\eta_{i,h}^{1}, ..., \eta_{i,h}^{M} = \text{argmax} \sum_{t=2005+h}^{2024} \sum_{m=1}^{M} \eta_{i,h}^{m} \hat{p}_{T+h|T}^{m}(d) \tag{6}$$

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

The above approach ensures that the pooled density is itself a PDF, and has several computational advantages. It addresses the limitation of predicting quantiles for each conditioning variable one-by-one, by combining all individual models based on their ability to predict country's debt risk in real time. In this way, the procedure makes optimal use of the joint information across predictors. The weights reflect the marginal contribution of each variable to forecasting the full distribution of debt, conditional on the others—similar to coefficients in a multiple regression, but applied to the entire predictive density rather than just the mean. The weighted combination adds to the already rich and flexible location-scale models used for the individual components, allowing the pooled distribution to exhibit more complex shapes, including multimodality, pronounced skewness, and fat tails. The use of rolling widows to compute probability scores also helps to capture how the role of conditioning factors varies over time, including during periods characterized by large shocks (GFC, COVID-19). In addition, as the weights vary by country, the methodology enables the construction of country-level PDFs based on the conditioning variables that most strongly drive debt dynamics for a country.

Optimally combining forecasts is a viable strategy even when the number of forecasts to be combined is large, as it is in our case. The constraints that the weights are nonnegative and sum to one introduce an implicit Lasso-type penalty that shrinks the weights and regularizes predictions (Brodie et al. 2009; Conflitti, De Mol, and Giannone 2015). This implicit shrinkage prevents any single forecast from dominating the combined result, thereby improving the overall robustness and accuracy of the forecasts. To compute these optimal weights, we use the recursive algorithm of Conflitti, De Mol, and Giannone (2015), which is computationally efficient and scales well with the number of models and predictors, making it practical for combining predictions based on several models and predictors.

3.1 Aggregation to Global Levels or Country Groups

Aggregating country-level distributions into a global or regional distribution is a non-trivial exercise. The distributions of debt-to-GDP ratios cannot simply be added or averaged across countries because each country's sovereign debt stocks vary widely in their contribution to global debt levels.

Our approach aggregates country-level predicted quantiles to the global level in three steps. First, for each model m, we follow Adrian et al. (2022) and approximate the quantile of the global predictive distribution with the weighted average of the estimated country-level quantiles:[7]

$$\hat{Q}^m_{d_{global,t+h}}(\tau) = \sum_{i=1}^{I} \omega_{i,t} \hat{Q}^m_{d_{i,t+h}}(\tau) \tag{7}$$

where the weighting factor $\omega_{i,t}$ is country i's nominal US dollar GDP share among in-sample countries. The resulting quantiles are re-centered so that the median corresponds to the WEO projections. Second, the quantiles are fitted to a skewed t-distribution—in the same way we as the country-level quantiles—to get the global predictive distribution $\hat{f}^m_{global,t+h}(d)$. Finally, the pooled global predictions are obtained by combining the model-specific densities where the global weights are the GDP-weighted average of the individual country weights $\eta^m_{i,h}$, as shown below:

$$\hat{f}^{poooled}_{global,t+h}(d) = \sum_{m=1}^{M} \omega^m_{global,h} \hat{f}^m_{global,t+h}(d) \tag{8}$$

where $\omega^m_{global,h} = \sum_{i=1}^{I} \omega_{i,t} \eta^m_{i,h}$.

We follow an identical approach to compute aggregate densities for country groups. The country groups of interest are advanced economies (AEs) and emerging market and developing economies (EMDEs). For the aggregate distributions to be comparable across historical years, conditioning variables need to be available for all countries across the periods of interest, defined as 2009 through 2024. Imposing this restriction reduces the sample to 47 countries, but the reduced sample still covers more than 90 percent of global debt.[8]

4 Results

4.1 Quantile Regression Results

We first present the empirical results from quantile regressions to examine how the conditioning factors affect the future debt distribution. The key takeaway is that several of the

7. This is an approximation since, in general, the quantiles are not linear, i.e., $Q_{X+Y}(\tau) \neq Q_X(\tau) + Q_Y(\tau)$

8. The restricted sample includes 47 countries, including 24 advanced economies and 23 emerging market and developing economies. The sample restriction also excludes countries that temporarily lose access to international bond markets following periods of high-inflation or an economic crisis. The global debt-at-risk estimate therefore is robust to potential distortions from these outliers.

economic and financial factors considered in the analysis are consistently and asymmetrically associated with higher debt upside risks up to a forecast horizon of three years.

Figure 3 plots the estimated quantile regression coefficients (i.e., the $\beta_x + \gamma_x q(\tau)$) values) associated with the various factors for the 5th, 50th, and 95th percentiles across forecast horizons.[9] To facilitate comparison of the estimates across factors, we standardize the conditioning factors so that the coefficient can be interpreted as the percentage point increase in a particular percentile of the future debt-to-GDP ratio associated with a one standard deviation increase in the regressors. Table 1 presents the corresponding estimates for the location and scale parameters. These estimates should not be interpreted as causal effects, but rather as the strength of the relation between current financial and economic factors and future debt.

Panel A of Figure 3 illustrates that tighter financial conditions disproportionately impact the right tail of the future debt distribution, with the most pronounced effects observed over a three-year horizon. Specifically, the Financial Conditions Index (FCI) demonstrates statistically significant effects on the location of the distribution at all horizons, while its effects on the scale of the distribution remain significant up to a three-year horizon. In essence, the FCI not only raises the level of the future debt-to-GDP ratio but also increases the uncertainty surrounding it. This effect is economically substantial; for instance, a one-standard deviation increase in the FCI—similar to what was experienced in Spain in 2011—correlates with a 3 percentage points of GDP increase in debt-at-risk. Similar results are observed for the Financial Stress Index (FSI), although the findings regarding the scale of the distribution are weaker (Figure 3, Panel B).

Adverse financial developments are associated with higher debt risks through their impact on raising growth, deficit, and interest rate risks. To examine the channels through which FCI affects future debt asymmetrically, we estimate equation (2) using as dependent variables key economic factors entering the debt dynamic equation: (i) growth; (ii) primary balance; (iii) interest rates (iv) and the residual term, "unidentified" debt—that is, the change in government debt that is not explained by primary budgetary deficits and interest-growth differentials. The results, shown in Table A.6, suggest that a worsening in financial conditions (financial stress) raise debt risks, largely through its effect on the left tail of the growth distribution; that is, by increasing "growth-at-risk". In particular, a one-standard deviation increase in the FSI is associated with an increase of growth-at-risk of about 0.2 percentage point. This aligns with existing literature, where Adrian, Boyarchenko, and Giannone (2019) demonstrate that adverse financial conditions predict downside risks to the growth outlook.[10]

9. Table A.3-A.5 report the estimated regressions coefficients for one-year, three-year and five-year future debt.

10. See also, Figueres and Jarociński (2020), Adrian et al. (2022), Chernis, Coe, and Vahey (2023), and

In addition, a deterioration in financial conditions is associated with an increase in the left tail of the future primary balance distribution and of the right tail of the future interest rate distribution. In other words, a worsening of financial conditions make the primary balance and interest rate distribution riskier. Finally, and consistent with the evidence in the IMF's October 2024 Fiscal Monitor (IMF 2024), an increase in financial stress is followed by a significant increase in upsides risks concerning "unidentified" debt, such as the materialization of contingent liabilities.

Increases in spreads are linked to asymmetric rises in debt-at-risk in the short term, as shown in Panel C of Figure 3. For instance, a one-standard deviation increase in sovereign spreads—similar to the spike observed in Sri Lanka in 2022—correlates with approximately a 2.6 percentage points increase in debt risks as a percentage of GDP after one year. The results in Table 1 illustrate that sovereign spreads have statistically significant effects on the location of the future debt distribution at both the 1-year and 3-year horizons, while their effects on the scale of the distribution are statistically significant only at the 1-year horizon. Our findings also indicate that sovereign spreads contribute to an increase in future growth-at-risk and the left tail of the primary balance distribution. This result aligns with existing literature, which demonstrates that higher sovereign spreads elevate government debt servicing costs, thereby increasing debt levels (Gourinchas, Philippon, and Vayanos 2017). Additionally, higher spreads raise borrowing costs for households and firms, which in turn dampens economic activity (Arellano, Bai, and Bocola 2024).

Next, we extend our analysis beyond financial variables and find that political conditions and uncertainty also influence the future debt distribution. Panel D of Figure 3 displays the results for the World Uncertainty Index (WUI), revealing that increases in the WUI are linked to asymmetric rises in the future debt distribution across all horizons. The results presented in Figure 3, Panel E indicate that a one standard deviation increase in the Reported Social Unrest Index (RSUI) is associated with a statistically significant increase of approximately 1.9 percentage points of GDP in the 3-year ahead debt-at-risk. However, this effect is not statistically different from those observed in other quartiles of the future debt distribution (γ=0; see Table 1).

Finally, we conclude the analysis by examining the role of economic factors and proximate drivers of the debt dynamic equation in shaping the future debt distribution; the results (Figure 3, Panels F-I) indicate that these factors exert persistent effects on the distribution of the debt outlook. Notably, initial debt levels and lower growth rates have long-lasting and larger effects on the right tail of the distribution (Panels F and H)—the scale parameter for initial debt is statistically significant across all horizons, while the parameter for GDP

Amburgey and McCracken (2023).

growth is modestly significant at the 3-year horizon (see Table 1). The effects are also economically substantial; for instance, a one-standard-deviation change in GDP growth is associated with an increase of more than 5 percentage points of GDP in the 3-year ahead debt-at-risk. This finding underscores the importance of economic conditions as a key driver of risks surrounding the debt outlook. Additionally, higher primary balances contribute to reducing debt across all quantiles of the debt distribution, emphasizing the positive impact of fiscal adjustments on both debt levels and debt risks.

While these results may not be surprising given that these debt drivers are integral to the evolution of debt, as illustrated in Equation (1), our new insight is that the factors influencing debt dynamics can meaningfully and persistently shift the debt distribution, often asymmetrically.

4.2 Aggregate Debt Distributions

Estimates from the analysis above are used to construct the conditional probability distribution of future debt for the world, as well as separate distributions for advanced and emerging economies.

Figure 4 plots the PDF of the predicted three-years ahead global debt-to-GDP ratio distribution for 2024, and shows that global debt-at-risk is estimated at 116.6 percent of GDP. The estimate is nearly 20 percentage points higher than the median projection of 97.5 percent (calibrated to the IMF WEO baseline) (P50).[11] In addition, these upside risks to public debt are greater than the downside risks of about 15 percentage points, underscoring that debt risks are tilted to the upside. The computation of debt quantiles conditional on each of the regressors and the use of weights to combine distributions also allows us to determine which of the conditioning factors are driving debt risks. Figure 5 plots the contributions from the conditioning variables used for the debt-at-risk model to the estimated level of global debt-at-risk. It shows that, on average for the entire sample, the main factors contributing to upsides risks to debt projections—that is, the difference between P95 and P50—are the primary deficit and financial conditions.

This aggregate picture masks significant variation in global debt risks over time and heterogeneity across different country groups. First, global debt-at-risk has steadily risen since 2009 (Figure 6, Panel A). The increase mostly mirrors the path of public debt itself but upside risks spike noticeably—and more than the actual debt increase—during global

11. The median displayed in the figure is slightly different from the WEO baseline as it corresponds to the median of the pooled distribution, whereas it is the median of the unconditional distribution that is calibrated to match the WEO baseline. Our measure of upside and downside risk is also based on differences relative to the median of the unconditional distribution.

economic shocks such as the GFC (2009) and COVID-19 (2020) (Figure 6, Panel B). These major shocks have not only resulted in a substantial rise in both public debt and debt-at-risk but have also diminished downside risks associated with debt. Regarding the contributions from conditioning factors, financial conditions were the primary influence in 2009, while growth and primary balance were more significant in 2020.

Second, debt-at-risk is greater in advanced economies compared to emerging market economies (Figure 7). For 2024, the projected three-year ahead debt-at-risk is estimated at 131.1 percent of GDP for advanced economies and 95.8 percent for emerging market economies, representing an increase of approximately 20 percentage points for advanced economies and 17 percentage points for emerging markets relative to the median projection. While upside risks (P95-P50) are higher in absolute terms in advanced economies—due to their elevated initial debt levels—the distributions exhibit similar positive skewness, albeit slightly higher for advanced economies (0.15) than for emerging market economies (0.13).[12]

The contribution of conditioning factors differs between advanced and emerging market economies (Figure 8). In advanced economies, primary deficits and financial conditions emerge as the two largest contributors to upside risks. Conversely, in emerging market economies, uncertainty and primary deficits are the most significant factors.

Finally, whereas debt-at-risk in advanced economies as a group has broadly retreated from pandemic peaks, it has increased in emerging market economies due to higher projected debt levels as well as higher risks stemming from lower growth and higher primary deficits (Figure 9).

5 Extensions

This section presents three extensions of the debt-at-risk framework. The first extension evaluates the effectiveness of debt-at-risk in predicting fiscal crises, comparing it with other commonly used macroeconomic variables in the literature, such as debt levels and debt servicing costs (Moreno Badia et al. 2022). The second extension offers measures of debt-at-risk utilizing a reduced set of conditioning factors, thereby expanding the sample coverage to 175 countries. The third extension enhances the quantile regression framework to accommodate non-linear effects of conditioning factors that vary according to country characteristics.

12. The skewness for country or country group i at an h year forecast horizon is computed as $\frac{\hat{Q}^{pooled}_{d_{i,t+h}}(95)-\hat{Q}^{pooled}_{d_{i,t+h}}(50)}{\hat{Q}^{pooled}_{d_{i,t+h}}(95)-\hat{Q}^{pooled}_{d_{i,t+h}}(5)} - \frac{\hat{Q}^{pooled}_{d_{i,t+h}}(50)-\hat{Q}^{pooled}_{d_{i,t+h}}(5)}{\hat{Q}^{pooled}_{d_{i,t+h}}(95)-\hat{Q}^{pooled}_{d_{i,t+h}}(5)}$, where *pooled* refers to the predicted quantiles for the pooled distribution.

5.1 Debt–at–Risk and Predicting Fiscal Crises

The analysis thus far quantifies how high debt could rise in a severely adverse scenario but has not considered the economic implications of such a potential surge in public debt. In particular, does the debt-at-risk measure presage economic or fiscal distress? And if so, how well does the measure perform in predicting fiscal or sovereign debt crises in the next 1 to 2 years relative to other macro-fiscal variables frequently used in the literature? This section addresses these critical questions in three steps. First, it examines the strength of the correlation between fiscal crises and debt-at-risk. Second, it assesses the robustness of this correlation while accounting for model uncertainty. Finally, it evaluates the relative significance of debt-at-risk as a leading indicator of fiscal crises.

Our measure of a fiscal crisis is a binary discreet variable–at the country-year level—which is set to one if a fiscal crisis occurs over the next two years and zero otherwise. While there isn't a common definition of a fiscal crisis in the literature, we follow Moreno Badia et al. (2022) and define a fiscal crisis to have occurred if any of the following four criteria are met:

1. A credit event in which a fiscal crisis is triggered when debt service is not repaid on the due date or creditors incur losses including through debt restructuring;

2. Exceptionally large official financing from the IMF or European Union;

3. Implicit default on domestic debt either with periods of high inflation (often associated with monetary financing of the budget) or accumulation of domestic arrears;

4. Loss of market confidence to capture episodes associated with loss of market access or very large spikes in sovereign yields.

5.1.1 Logit estimation

First starting with simple bivariate correlations, a simple logit model of the fiscal crisis indicator against the debt-at-risk measure reports a strong positive correlation between the two variables. We consider the upside risk to the debt projection—that is, the difference between the debt-at-risk (the 95th predicted quantile) and the median at a one and two-year forecast horizon—as the independent variable.[13] This metric is the key contribution of our debt-at-risk framework as it captures the risk *around* the baseline debt projection. Figure 10 plots the logit coefficients for the upside debt risk conditional on each of the eight

13. Similar results are obtained using the debt-at-risk as well as the product of debt-at-risk (or debt) and upside debt risks.

variables used to construct debt-at-risk. The figure shows that upside risks to debt across all models are positive and statistically significantly correlated with the fiscal crisis variable. For example, across all models, a one percentage point of GDP increase in the difference between the 95th and 50th percentile of predict debt is associated with a 8-10 percentage points increase in the probability of a fiscal crisis within the next two years. The magnitude is non-trivial, as the current estimated gap between the 95th percentile and the median for the (one-year ahead) global debt distribution is about 20 percentage points of GDP, and the frequency of a crisis in the sample is just 5 percent.

5.1.2 Bayesian model averaging estimation

Having established a strong correlation between debt-at-risk and fiscal crises, we then employ Bayesian model averaging (BMA) to examine the robustness of this correlation. BMA is particularly well-suited for addressing model uncertainty and assessing the robustness of numerous potential correlates across the entire model space (see Steel (2020) for a comprehensive review of the properties of BMA and its applications in economics.).

We consider three predicted debt-at-risk quantile measures (the P95 level, difference between P95 and P50, and the interaction of (P95-P50) with P95), for each of the conditioning factors as well as the combined distribution. In each BMA regression, the dependent variable is the fiscal crisis indicator defined above. Independent variables include the three predicted debt-at-risk quantile measures as computed above, the conditioning variables themselves (a total of 8 variables), and additional control variables such as the projected debt-to-GDP ratio and primary balance-to-GDP ratios. For these additional control variables, we include various functional forms such as contemporaneous values, lags, and historical growth rates (adding to a total of 24 control variables) (see Table A.7 for the full list of variables). We estimate the BMA model using in-sample debt-at-risk estimates for the period 1986-2024, and find that debt-at-risk is a robust predictor of fiscal crises. Figure 11 (left chart) plots the posterior inclusion probability (PIP) for the interaction term of (P95 - P50) with P95 for each of the conditioning variables and the combined distribution. The PIP measures the likelihood that the particular selected 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. As shown in the figure, the debt-at-risk measure for all variables has a posterior inclusion probability of 1 at both a 1-year and 2-years forecast horizon, implying that the debt-at-risk measure, along with the chosen conditioning variables, is a key indicator of impending fiscal distress.

Our results remain robust to estimating the BMA model with out-of-sample debt-at-risk measures. For this exercise, the debt-at-risk forecasts (1- and 2-years ahead) are based on a 20-year rolling window. For example, the 2006 and 2007 forecasts in 2005 are based on data from 1986-2005. The out-of-sample estimation shows that the PIPs remain high and significant across all conditioning variables, at levels staying at 1 for all cases except one on inflation for the the one-year ahead estimation (Figure 11, right chart). Overall, the BMA estimation results suggest that the inclusion of debt-at-risk measures—in addition to their conditioning variables—is important when predicting an oncoming fiscal crisis.

5.1.3 Random Forest model

Finally, we follow Moreno Badia et al. (2022) and apply machine learning techniques to compare the relative power of debt-at-risk measure in predicting a fiscal crisis versus a vast range of other variables used in the literature. We conduct the exercise in two steps:

1. First, we use the Boruta "feature selection algorithm" (Kursa and Rudnicki 2010) to reduce this large set of predictors to those that most strongly predict a fiscal crisis.[14] The set of macro-fiscal variables to be included span across 23 categories, including debt-at-risk, debt levels, growth, capital flows, external debt, demographics, among others (see Table A.8 for the full list). Each category of variables contains several factors for different measures. For example, the category of demographics will include factors such as the total working age population, the share of working age relative to total population, age dependency ratios, population density and several others). The full set of variables to be considered for potential predictors add up to nearly 780 because they include several permutations for each of the factors in different functional forms, including first and second lags, weighted average of last 5 years or 10 years, percent change from last period, and standard deviations. Applying the Boruta method, we significantly reduce potential predictors by more than four-fold to 188 factors (see Table A.8).

2. Second, we use a Random Forest (RF) model (Breiman 2001) to determine which (Boruta-selected) variables are most useful in predicting crises.[15] Specifically, we compute the *out of bag permuted predictor importance*, a variable scaled between 0 and 100 that measures the increase in prediction error if an explanatory variable is randomly permuted.[16] As we consider various functional forms of the same variable (and include

14. The Boruta method removes variables by comparing model performance with randomly permuted copies of the variables.

15. In a simple sense, an RF model can flexibly consider higher-order interactions among observable characteristics, keeping those interactions with the highest predictive power.

16. A variable has a higher importance if randomly permuting its values increases the model's prediction error. A variable's importance therefore increases in its predictive power.

multiple debt-at-risk models), we sum their importance by variables to report their overall predictive power by each set of category variable (see Table A.8).

The RF model shows that the debt-at-risk measure is the most useful metric in predicting a fiscal crisis among a wide range of economic variables. Figure 12 plots the aggregate variable importance for the top explanatory variables in the RF model. As shown, debt-at-risk has the highest variable importance, with both the predicted 95th quantile as well as the difference between predicted 95th and 50th quantiles being key predictive measures. This result is significant in two ways. First, it further extends previous research by Moreno Badia et al. (2022), which concludes that public debt levels and public debt service are important predictors of fiscal crises. Our results are one of the first empirical studies to robustly show that the evolution of risks surrounding the debt outlook is critical when predicting a fiscal crisis, and at times has even stronger predictive power than just considering baseline debt levels. Second, it is striking that introducing debt at risk as a predictor reduces the relative importance of other variables such as the debt-to-GDP level. The results imply that the debt-at-risk measure could indeed be useful as a warning sign for an impending crisis.

5.2 Extended Sample

Country coverage can be expanded further using the available conditioning factors. As previously discussed, the baseline sample includes 90 economies. The sample restriction corresponds to the countries for which sovereign bond yields are available. However, it is possible to construct measures of debt-at-risk using only the conditioning variables that are available for a country. For example, if a country has coverage for 7 out of the 8 variables, then it is feasible to create predicted quantiles conditional on this subset and combine distributions using variable weights for each available conditioning factor. In practice, this approach relies on using more widely available economic variables, such as GDP growth and primary balance (see Table A.2 for the availability of various variables across countries). Notably, the results from the previous section indicate that these variables exert long-lasting and significant effects on the right tail of the future distribution, making them valuable for quantifying upside risks to the debt outlook.

Specifically, using only the available conditioning variables allows us to extend the sample to 175 countries, many of which are low-income. Figures 13 and 14 illustrate two examples of debt-at-risk for the extended sample. The first figure presents the PDF for a highly indebted low-income country which only has coverage for the economic variables, demonstrating that the debt distribution remains asymmetric even without financial variables. The second figure depicts the evolution of debt-at-risk along with upside and downside risks as a world simple average. It shows that the trends in debt-at-risk and downside risks closely follow those of the world GDP-weighted average shown in Figure 5, with the changes in upside and downside risks being only less pronounced during the GFC, as financial stress measures are unavailable for several countries.

5.3 Heterogeneity Analysis

This section assesses potential non-linearity in the relationship between various financial, economic, and political factors and future debt. Specifically, we identify two primary sources of heterogeneity likely to influence debt-at-risk. The first is the initial level of debt; as demonstrated in Equation (1), the impact of economic factors, such as growth and inflation, on the future debt distribution increases with higher initial debt levels. To evaluate the role of initial debt, the baseline equation (2) is modified as shown follows:

$$X'_{it}\beta = \sum_{k=1}^{4} \beta_{1,k} x_{i,t} \times \mathbf{1}\{Q(d_{i,t} = k)\} + \sum_{k=1}^{4} \beta_{2,k} d_{i,t} \times \mathbf{1}\{Q(d_{i,t} = k)\} \tag{9}$$

where $x_{i,t}$ is the conditioning variable as before (for example, GDP growth) and $d_{i,t}$ is the (current) debt-to-GDP ratio. $\mathbf{1}\{Q(d_{i,t} = k)\}$ is an indicator that equals one if the quartile of the contemporaneous debt-to-GDP ratio equals k, where $k \in \{1, 2, 3, 4\}$. We define "low initial debt" and "high initial debt" as the first and fourth quartile of the debt-to-GDP ratio, respectively.[17] All remaining variables are identical to those in Equation (2). This approach is a semi-parametric way of estimating the heterogeneous effects of conditioning factors depending on initial debt and does not impose any restrictive assumptions on the functional forms of non-linearity.

Tables 2 and 3 report the estimated scale and location parameters associated with low and high initial debt, respectively. The results indicate that: (i) consistent with Equation (1), the location parameters of several economic variables—such as growth, primary balance, and inflation—tend to be statistically significantly larger for countries with higher initial debt; (ii) while the scale parameter does not systematically vary with the initial debt level, in a few cases—specifically for the spread at the one-year horizon and growth at the three-year horizon—it is larger and more precisely estimated for higher debt levels. Overall, these results suggest that initial debt amplifies the impact of economic factors on the entire future debt distribution (including debt-at-risk), with effects that are typically not significantly different between the left and right tails of the distribution.

The second source of heterogeneity we consider is the country income group, as the

17. These corresponds to debt values of 33 and 69 percent of GDP, respectively.

previous section highlighted significant variations in debt-at-risk across different income categories. We evaluate heterogeneity by country group by estimating the following modified specification:[18]

$$X_{it}'\beta = \sum_{j=\{AE,EMDE\}} \beta_{1,j} x_{i,t} \times \mathbf{1}\{country\, i \in j\} + \sum_{j=\{AE,EMDE\}} \beta_{2,j} d_{i,t} \times \mathbf{1}\{country\, i \in j\} \tag{10}$$

where $\mathbf{1}\{country\, i \in j\}$ is an indicator equaling one if a country is classified as an AE or EMDE, respectively.

Tables 4 and 5 show the estimated scale and location parameters associated with AEs and EMDEs, respectively. Regarding the location parameter, the results indicate that various factors influence the overall future debt distribution differently between AE and EMDE. Sovereign spreads tend to have statistically significant effects in AE in the short term, while in EMDE, their effects are more pronounced in the medium term. Consistent, with the empirical evidence suggesting that EMDEs are less resilient to uncertainty shocks (Ahir, Bloom, and Furceri 2022), uncertainty tends to have larger and more persistent effects in EMDEs. Initial debt appears to have larger effects in AEs, probably reflecting the higher debt values in this group of countries. Finally, while the point estimates for primary balance and growth tend to be larger in EMDEs, the difference compared to AEs is not statistically significantly different from zero. In contrast, the results for the scale parameters do not indicate systematic differences between AEs and EMDEs. One notable exception is the initial debt level, which suggests that initial debt tends to have larger asymmetric effects on the right tails of the future distribution for EMDEs compared to AEs.

6 Conclusion

Global public debt is set to rise over the medium term. In this paper, we show that shocks such as those experienced during the COVID-19 pandemic (weak growth, uncertainty, and financial stress) do not only increase the level of debt, but even more so the right tail of the current and future debt distribution.

To quantify risks surrounding public debt projections, we construct a novel measure of debt vulnerability to shocks—the debt-at-risk—by estimating the entire future debt distri-

18. There could also be potential heterogeneity in both the levels and drivers of debt risks *within* advanced and emerging market economies. The analysis could be extended to consider additional interactions for specific sub-groups within AEs and EMDEs.

bution conditional on a set of economic, financial, and political variables, for a large group of 90 countries since 1980.

Global debt-at-risk is estimated to be nearly 20 percentage points of GDP higher three years ahead than currently projected, reaching nearly 117 percent of GDP in a severely adverse scenario. Elevated debts levels today amplify the negative effects of weaker growth or tighter financial conditions on future debt ratios. We extend our analysis to: (i) examine the role of debt-at-risk in predicting fiscal crises, (ii) produce debt-at-risk measures for an expanded sample of 175 economies, and (iii) explore non-linearities based on initial debt levels and country characteristics.

Our analysis can be expanded in several ways. Our framework and methodology is flexible enough to potentially incorporate additional conditioning factors and consider further interaction effects (for example, state dependencies around periods of economic downturns). In addition, debt-at-risk can be combined with complementary tools to monitor risk, and in particular with predictive scenarios routinely developed for existing debt sustainability analyses (IMF 2022). These analyses quantify and provide a narrative on how debt risks could evolve under alternative macro-financial conditions or fiscal consolidation paths. As discussed by Adrian et al. (2025), the predictive density developed in this paper can also be used to estimate the likelihood of alternative scenarios.

We believe that this measure can be extremely valuable to policymakers and researchers. First, the framework enables policymakers to quantify the size of debt risks in severely adverse scenarios and assess the main determining factors. Second, our analysis indicates that debt-at-risk is the most robust predictor of fiscal crises, suggesting that policymakers can utilize this framework as an important early-warning tool to monitor and prevent crises. Third, the annual dataset of debt-at-risk measures for 175 countries since 2009 has the potential for use in various empirical applications, particularly given its substantial coverage across countries and over time.

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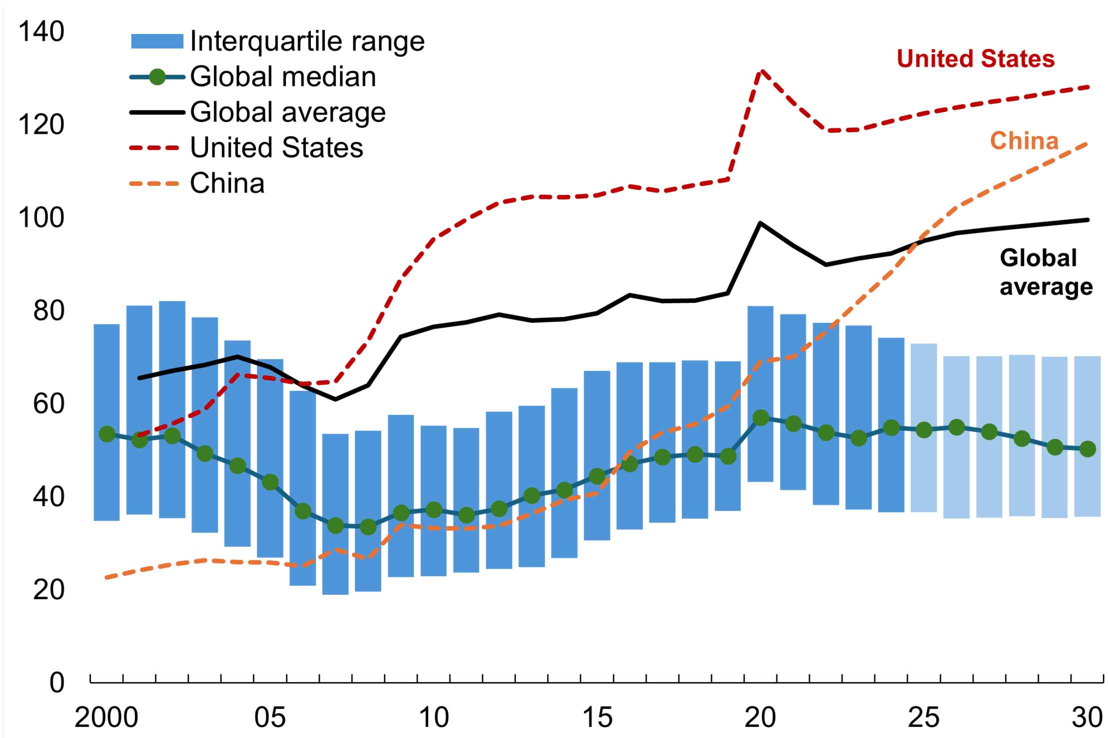
Figures

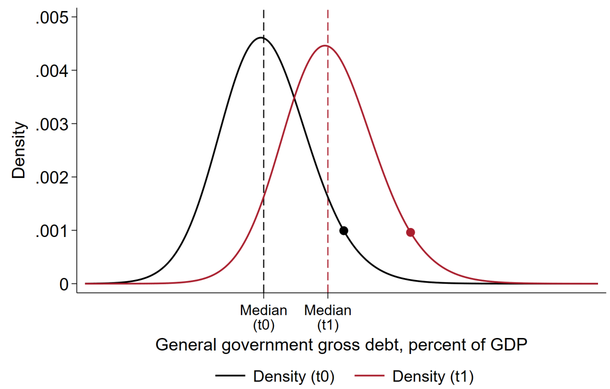
Figure 1: Public Debt-to-GDP Ratio, 2000-30
(Percent of GDP)



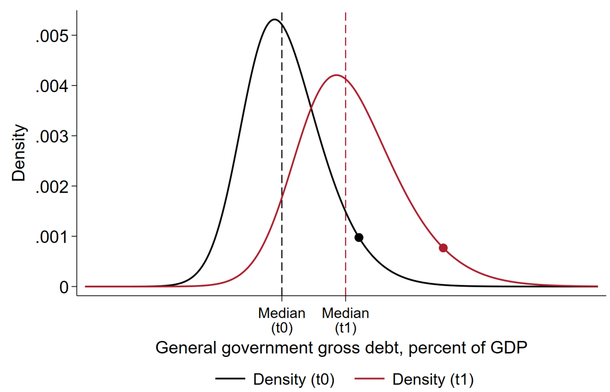
The figure plots statistics for the historical and projected debt-to-GDP ratios.
Source: IMF World Economic Outlook database.

Figure 2: Impact of Conditioning Variable on Density Based on Location (β) and Scale (γ) Coefficients

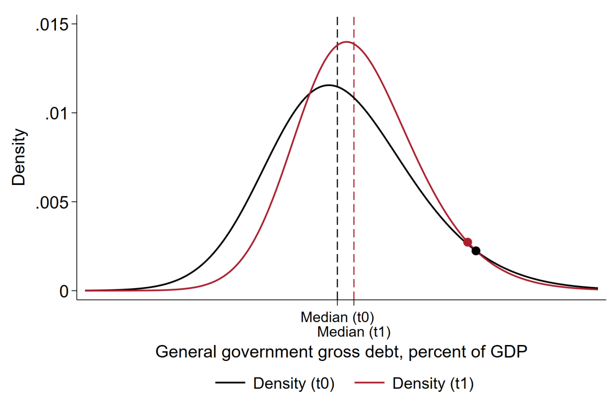
A. $\beta > 0, \gamma = 0$



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

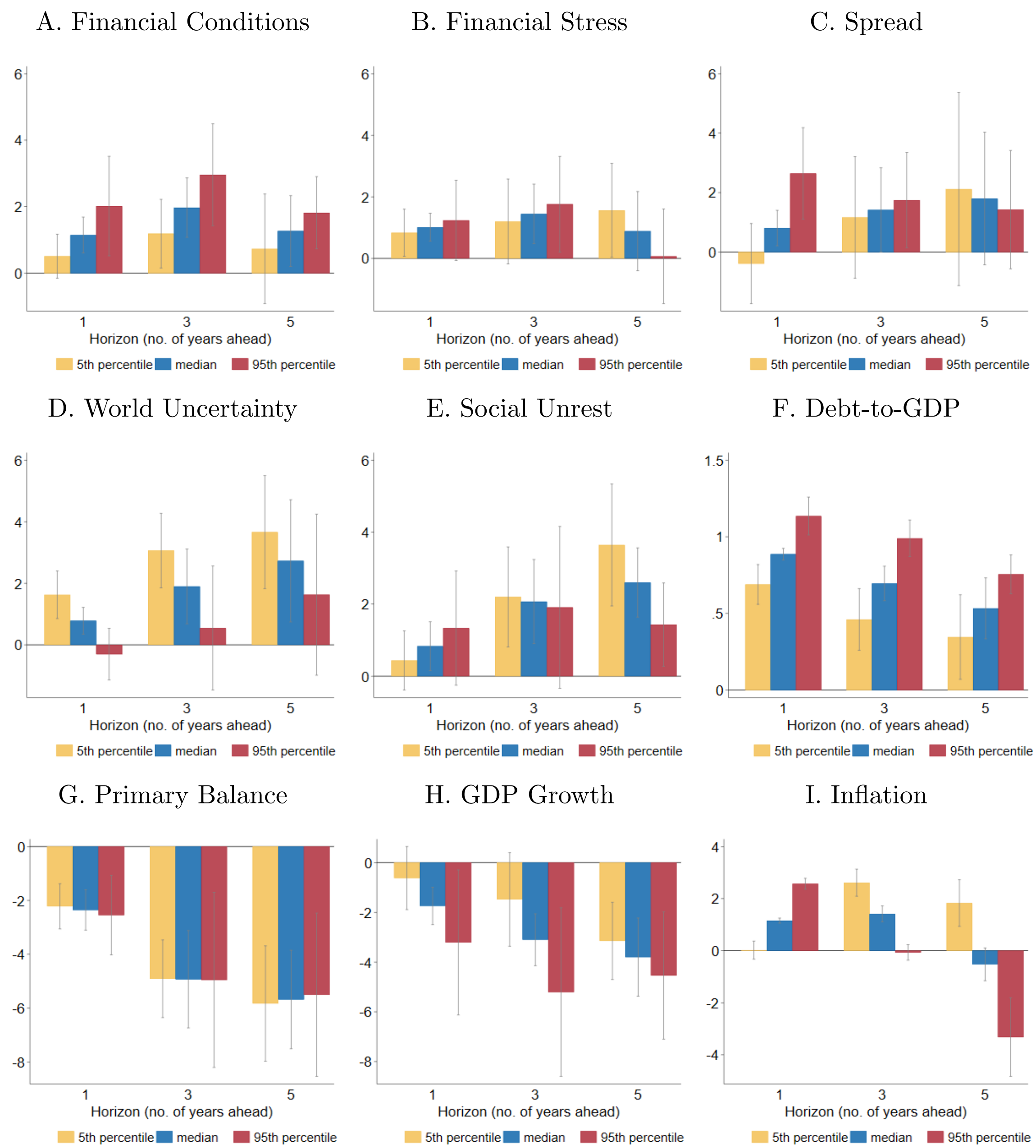


C. $\beta > 0, \gamma < 0$



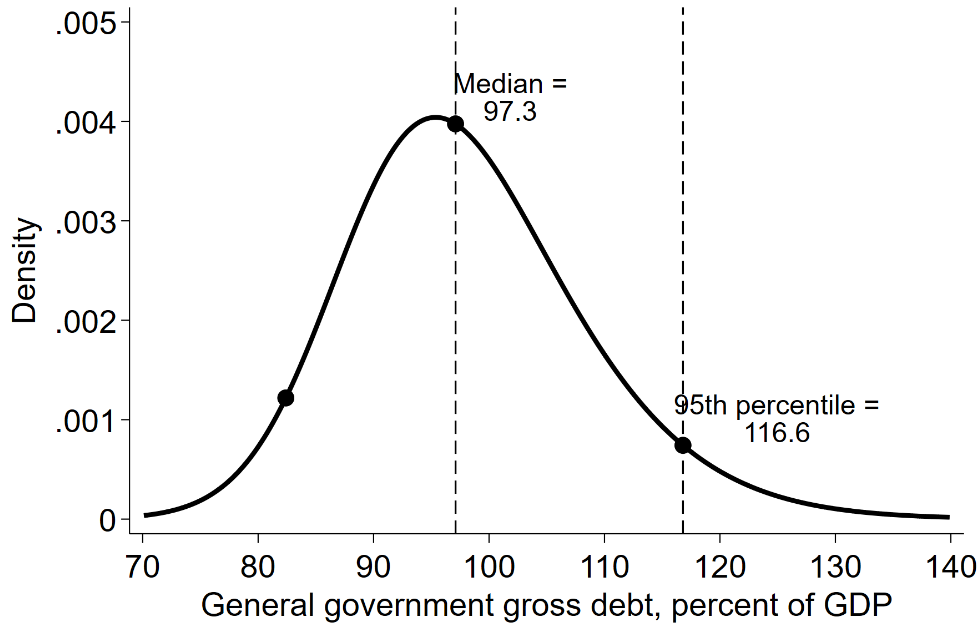
The figures plot illustrative changes in the predicted conditional debt densities when the conditioning variable increases by one standard deviation. $t0$ refers to period zero, and $t1$ refers to period one (after the change in the conditioning variable). In Panel A, β is positive but γ is zero; In 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.

Figure 3: Quantile Regression Results: Forward Debt-to-GDP Ratio and Financial, Economic, and Political Variables



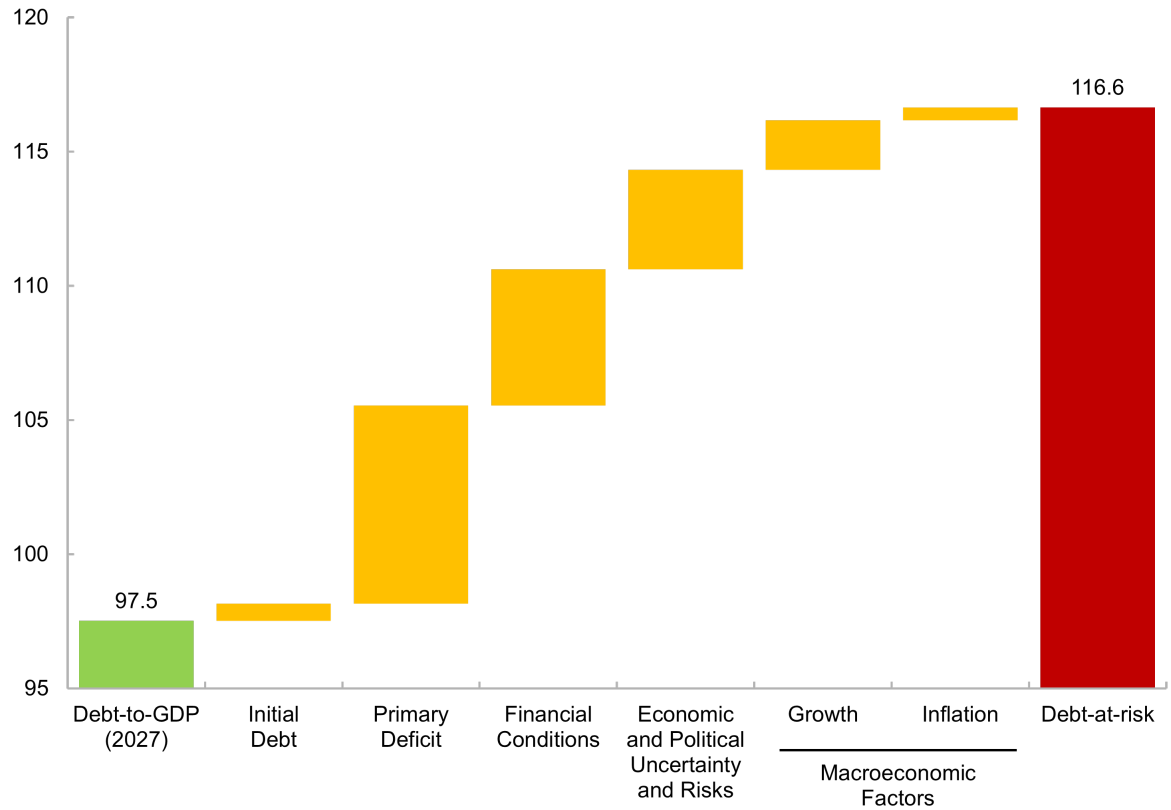
The figure displays the estimated quantile regression coefficients for 5th, 50th, and 95th percentile based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables (Equation (2)). Bars denote estimated coefficients, and the whisker in each 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.

Figure 4: 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.

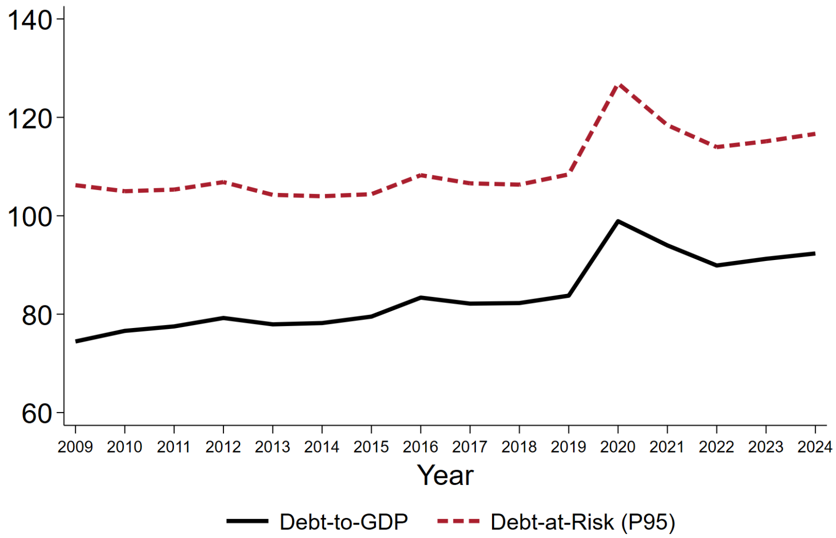
Figure 5: Drivers of Global Debt-at-Risk
(Percent of GDP)



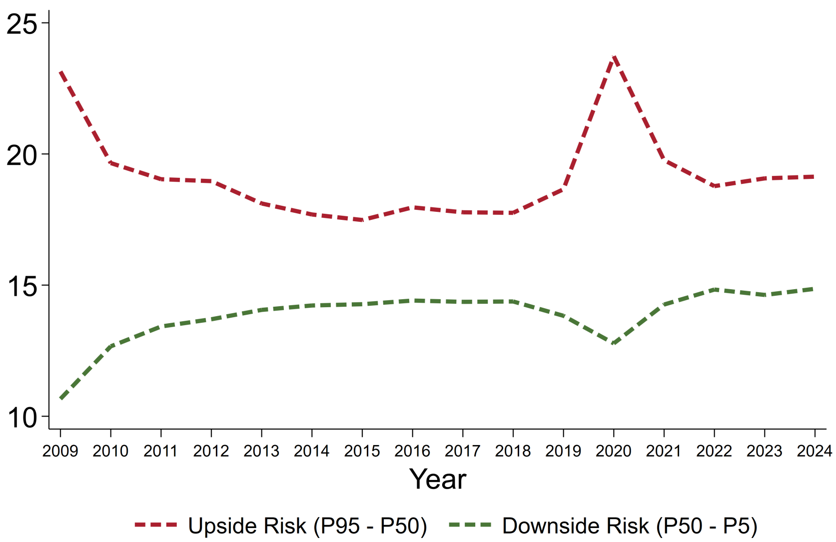
The figure plots the contributions from the conditioning variables used for the debt-at-risk model to the estimated level of global debt-at-risk. The green bar denotes the baseline debt projection for 2027 from the World Economic Outlook database. Yellow bars refer to contribution from the conditioning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

Figure 6: Evolution of Global Debt and Debt Risks
(Percent of GDP)

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



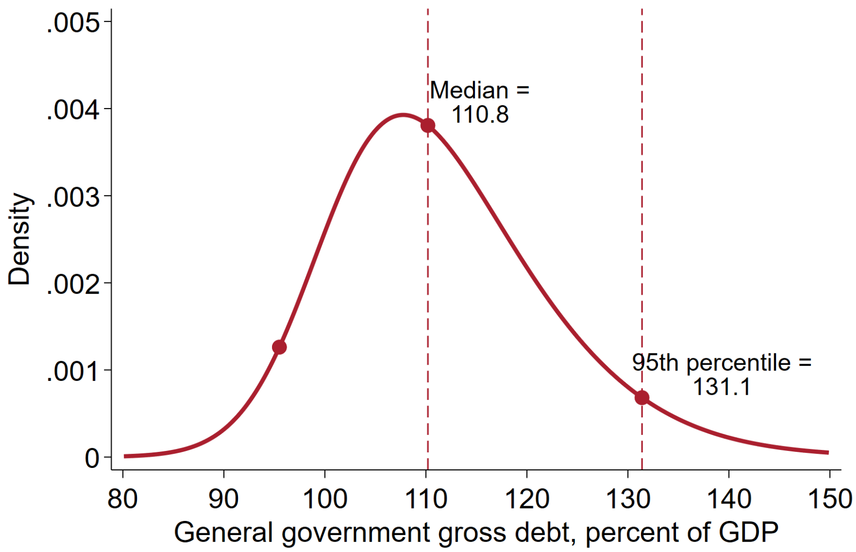
B. Upside and Downside Risks



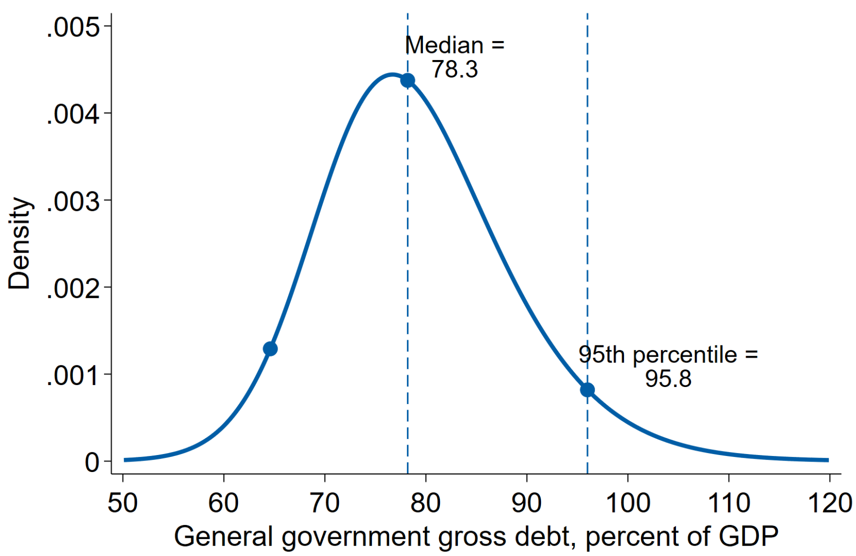
The figures plot the evolution of global GDP weighted debt-to-GDP and debt-at-risk (Panel A), and the evolution of upside and downside debt risks (Panel B) at a three-year forecast horizon. Debt-at-risk is defined as the predicted 95th quantile (P95) of the combined distribution. Upside risks are calculated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

Figure 7: Debt-at-Risk by Income Groups 2027
(Probability density of three-year-ahead government debt-to-GDP ratio)

A. Advanced Economies



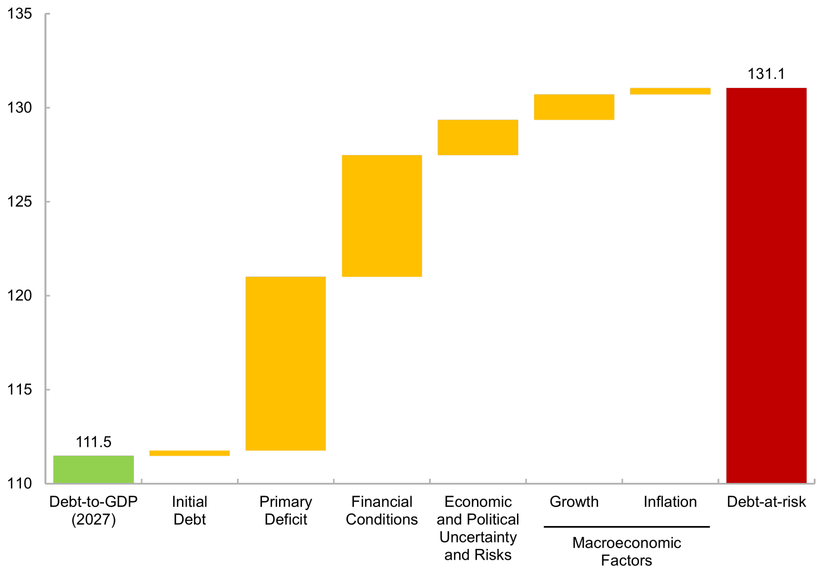
B. Emerging Market and Developing Economies



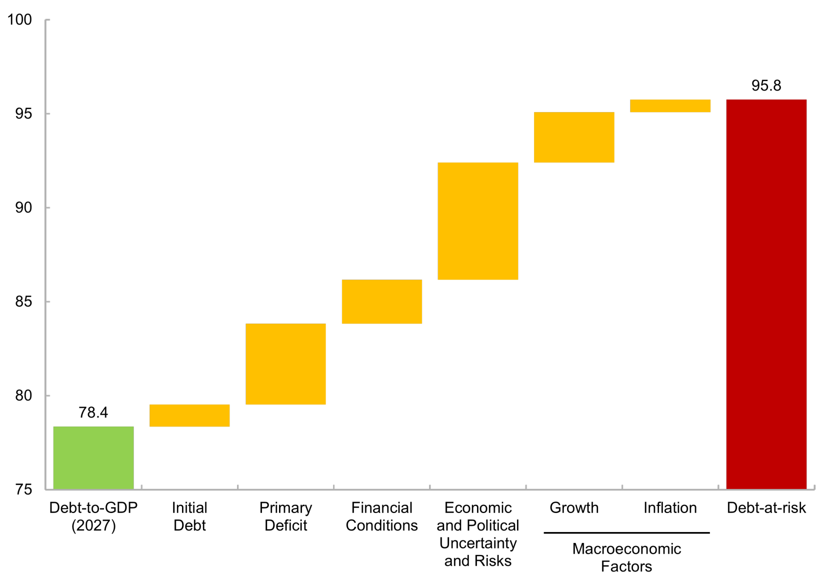
The figure plots the predicted density of the three-year-ahead global debt-to-GDP ratio for Advanced Economies (Panel A) and Emerging Market and Developing Economies (Panel B). The probability density functions are estimated using panel quantile regressions of the debt-to-GDP ratio on various political, 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.

Figure 8: Drivers of Global Debt-at-Risk by Income Groups
(Percent of GDP)

A. Advanced Economies

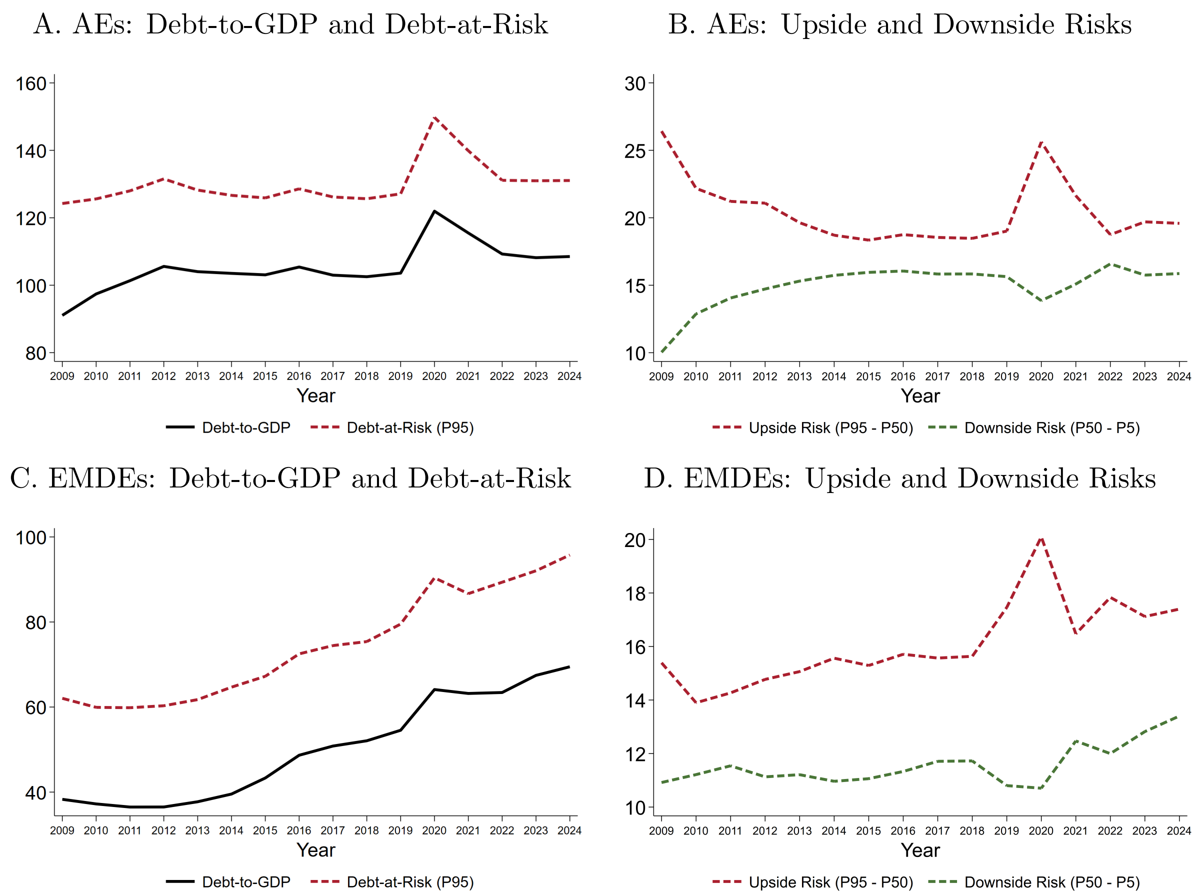


B. Emerging Market and Developing Economies



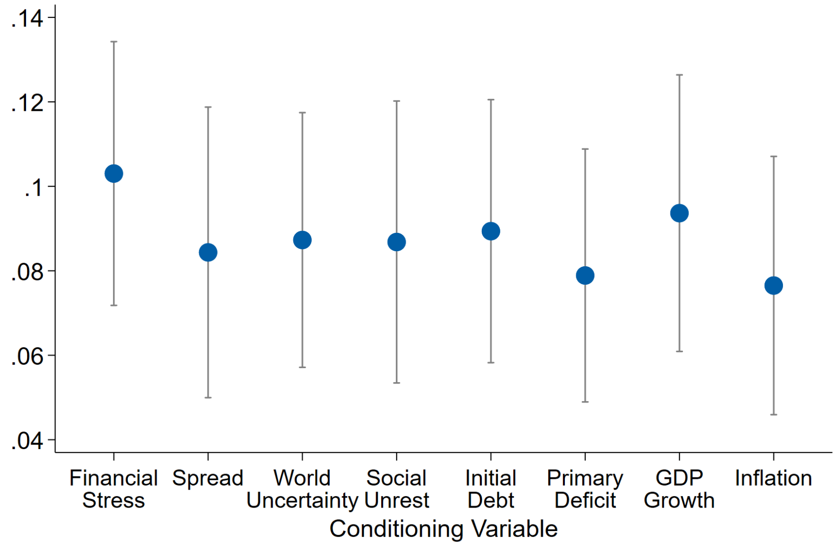
The figure plots the contributions from the conditioning variables used for the debt-at-risk model to the estimated level of debt-at-risk for Advanced Economies (Panel A) and Emerging Market and Developing Economies (Panel B). The green bar denotes the baseline debt projection for 2027 from the World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

Figure 9: Evolution of Global Debt and Debt Risks
(Percent of GDP)



Panels A and C plot the evolution of debt-to-GDP and (three-year-ahead) debt-at-risk for Advanced Economies (AEs) and Emerging Market and Developing Economies (EMDEs), respectively. Panels B and D plot the evolution of three-year-ahead upside and downside debt risks for AEs and EMDEs, respectively. 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).

Figure 10: Logistic Regression Coefficients:
Fiscal Crisis vs. One-Year Ahead Debt-at-Risk

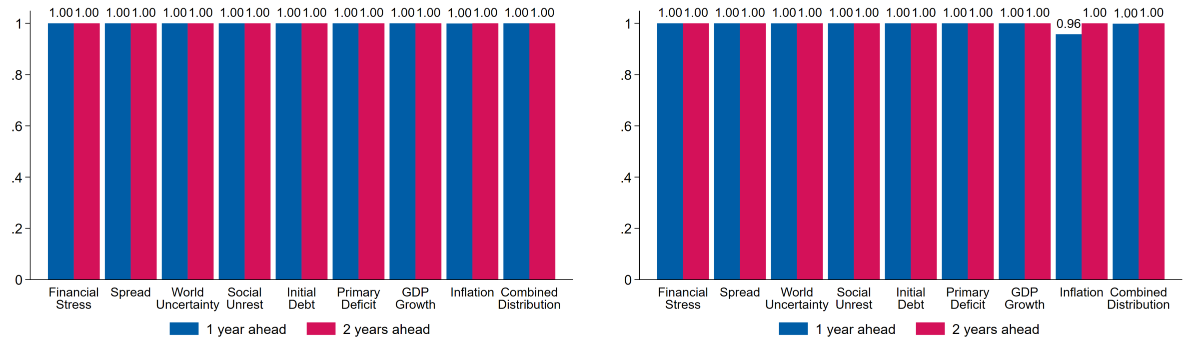


The figure shows estimated coefficients from a panel logit regression of a fiscal crisis indicator against debt-at-risk. Each point denotes the coefficient from a separate regression. The independent variable is the difference between the predicted 95th quantile of one-year-ahead debt-to-GDP and the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

Figure 11: Posterior Inclusion Probability:
BMA Model of Fiscal Crisis

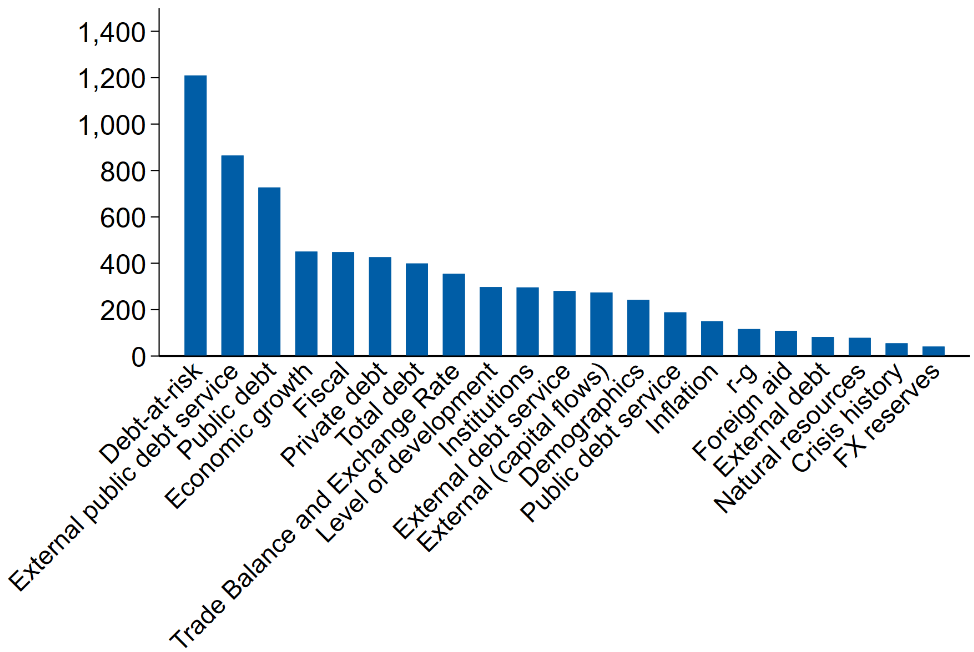
A. In-Sample

B. Out-of-Sample



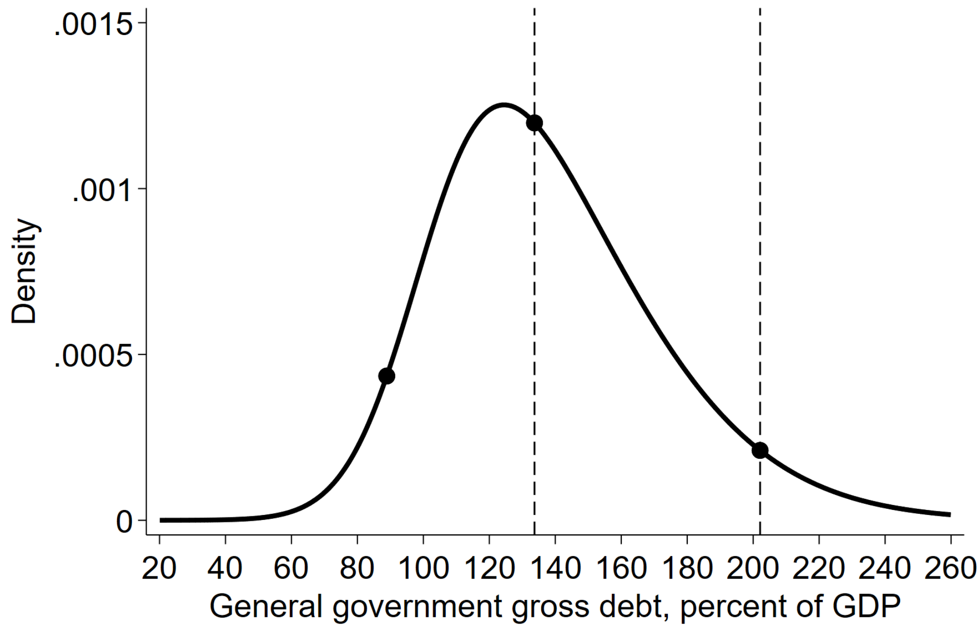
The figure shows the posterior inclusion probability (PIP) for the interaction of (P95-P50) with P95 from a Bayesian model averaging (BMA) model of a fiscal crisis indicator against debt-at-risk and other macroeconomic variables. The independent variables include the one- and two-year-ahead predicted 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.

Figure 12: Variable Importance by Group of Predictors:
Random Forest Model Predicting a Fiscal Crisis



The figure displays (grouped) sum of variable importances from a Random Forest model used to predict a fiscal crisis. 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. The predictors are as follows: (1) Debt-at-risk: predicted 95th quantile, difference between predicted 95th and 50th quantiles across the 8 conditioning variables at a one- and two-year forecast horizon; (2) External public debt service: amortization of external public debt in percent of GDP; amortization of external public debt in percent of reserves; (3) Public debt: public debt in percent of GDP; public debt in percent of general government revenue; general government short-term external debt in percent of GDP; general government short-term external debt in percent of reserves; public external debt in percent of GDP; public external debt to export; (4) Economic growth: real GDP per capita; real GDP; nominal GDP; domestic private savings; (5) Fiscal: general government expenditures in percent of GDP; general government primary expenditures in percent of GDP; overall balance in percent of GDP; general government primary balance in percent of GDP; general government revenues in percent of GDP; stock and flow adjustment; (6) Private debt: one sided credit gap based on the GDD loans and securities; total debt, loans and securities in percent of GDP; credit gap; domestic credit to private sector by banks in percent of GDP; external debt stocks, private nonguaranteed in percent of GDP; (7) Total debt: total debt (public plus private debt) in percent of GDP; (8) Trade and exchange rate: current account balance in percent of GDP; export of goods and services in percent of GDP; import of goods and services in percent of GDP; current account excluding imports; sum of export and import of goods and services; exchange rate; real exchange rate; log of PPP exchange rate; (9) Level of development: urban population (percent of total); log of real GDP per capita (in PPP dollars, Units), relative to US; log of nominal GDP in USD, relative to US; (10) Institutions: revised combined polity score; bureaucracy quality; corruption; estimates of political stability and absence of violence/terrorism; estimates of regulatory quality; (11) External debt service: external gross financing needs; debt service on total external debt in percent of GDP; debt service on total external debt in percent of export; debt service on total external debt in percent of reserves; (12) External (capital flows): personal remittances in percent of GDP; net foreign direct investment in percent of GDP; other investment, net (loans, deposits, insurance, pensions, trade credits, SDR) in percent of GDP; portfolio investment, net; terms of trade (of goods and services) index; trading partner growth; trading partner import demand; external assets in percent of GDP; (13) Demographics: log of population relative to US; population ages 15-64, total; age dependency ratio in percent of working-age population; population density (people per sq. km of land area); (14) Public debt service: general government interest expenses in percent of GDP; public debt service in percent of revenue; public debt service in percent of expenditure; (15) Inflation: consumer price index; (16) r-g: r minus g; (17) Foreign aid: net official development assistance in percent of GDP; (18) External debt: short-term external debt in percent of GDP; short-term external debt in percent of reserves; total external debt in percent of GDP in USD; total external debt, percent of export; (19) Natural resources: value of oil export in percent of GDP in USD; mineral rents in percent of GDP; oil rent in percent of GDP; total natural resources rent in percent of GDP; agriculture, forestry, and fishing, value added in percent of GDP; (20) Crisis history: average crisis history, year since last crisis; (21) FX reserves: total reserves in terms of the number of months of imports. Additionally, 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.

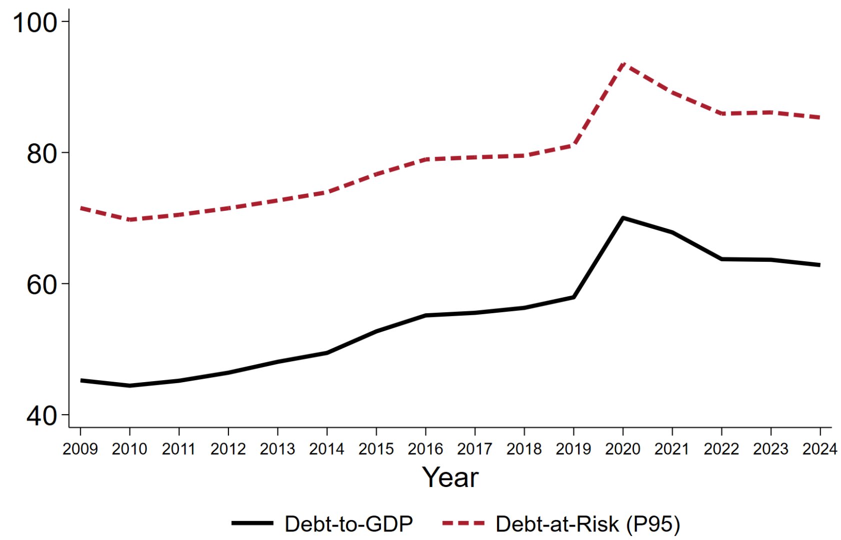
Figure 13: Debt-at-Risk 2027 for Selected Low Income Developing Country in Extended Sample
(Probability density of three-year-ahead government debt-to-GDP ratio)



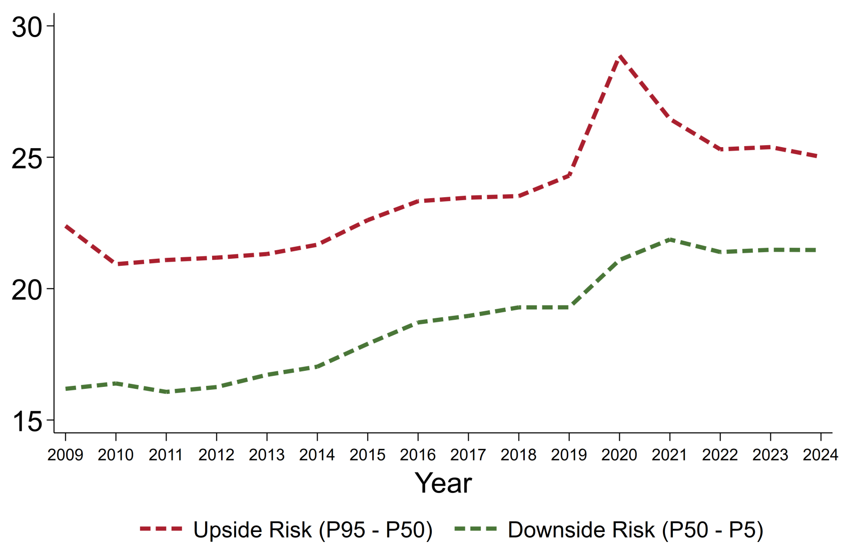
The figure plots the predicted density of the three-year-ahead global debt-to-GDP ratio for a selected highly indebted low income developing economy in the extended sample. The economy has coverage for the economic variables but does not have any data for the considered financial and political variables. 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.

Figure 14: Evolution of Global Debt and Debt Risks for Expanded Sample of Countries (Percent of GDP)

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



B. Upside and Downside Risks



The figures plot the evolution of global simple average 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).

Tables

Table 1: 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
	(0.294)	(0.194)	(0.472)	(0.219)	(0.550)	(0.247)
Financial Stress	1.021***	0.079	1.458***	0.129	0.860	-0.380*
	(0.241)	(0.187)	(0.494)	(0.257)	(0.656)	(0.218)
Spread	0.925***	0.693**	1.433**	0.148	1.792	-0.178
	(0.302)	(0.303)	(0.713)	(0.317)	(1.129)	(0.420)
Yield	0.607*	0.762**	0.371	0.364	-0.431	0.389
	(0.310)	(0.352)	(1.275)	(0.403)	(2.337)	(0.574)
Panel B: Political Variables						
World Uncertainty	0.720***	-0.393***	1.828***	-0.606**	2.685***	-0.524**
	(0.216)	(0.143)	(0.635)	(0.264)	(1.026)	(0.260)
Social Unrest	0.860**	0.180	2.065***	-0.071	2.583***	-0.578*
	(0.364)	(0.207)	(0.607)	(0.350)	(0.480)	(0.302)
Panel C: Economic Variables						
Debt-to-GDP	0.901***	0.092***	0.710***	0.126***	0.539***	0.105***
	(0.016)	(0.026)	(0.051)	(0.034)	(0.098)	(0.031)
Primary Balance	-2.365***	-0.062	-4.928***	-0.010	-5.673***	0.082
	(0.391)	(0.170)	(0.955)	(0.384)	(0.942)	(0.476)
GDP Growth	-1.816***	-0.507	-3.220***	-0.911	-3.815***	-0.356
	(0.434)	(0.404)	(0.584)	(0.598)	(0.811)	(0.352)
Inflation	1.235***	0.537***	1.338***	-0.640***	-0.587*	-1.309***
	(0.046)	(0.055)	(0.132)	(0.087)	(0.304)	(0.289)

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 (2)). 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.

Table 2: Location Coefficients: Forward Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables Interacted with Initial Debt

	Horizon (no. of years Ahead):								
	1			3			5		
	Q1	Q4	Diff: Q4 - Q1	Q1	Q4	Diff: Q4 - Q1	Q1	Q4	Diff: Q4 - Q1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Financial Variables									
Financial Conditions	1.570***	2.055**	0.485	2.741***	3.084***	0.343	2.621*	1.313	-1.308
	(0.302)	(0.840)	(0.829)	(0.771)	(1.166)	(1.404)	(1.367)	(1.209)	(1.831)
Financial Stress	6.849	7.553**	0.704	7.049	5.980	-1.068	7.084	-1.598	-8.682
	(4.253)	(3.363)	(5.167)	(8.225)	(8.004)	(11.425)	(11.076)	(10.016)	(14.858)
Spread	0.087***	0.137	0.050	0.207***	-0.281	-0.488	0.248**	-0.431	-0.679
	(0.020)	(0.220)	(0.213)	(0.071)	(0.307)	(0.314)	(0.122)	(0.525)	(0.551)
Yield	0.049	0.108	0.059	0.099	-0.250	-0.350	0.068	-0.594	-0.662
	(0.041)	(0.189)	(0.184)	(0.140)	(0.290)	(0.303)	(0.236)	(0.439)	(0.485)
Panel B: Political Variables									
World Uncertainty	2.654	10.613**	7.959	12.970***	10.141	-2.830	18.988***	7.407	-11.582
	(1.731)	(4.583)	(5.446)	(4.469)	(12.262)	(13.941)	(6.436)	(14.481)	(15.271)
Social Unrest	0.003***	0.014	0.011	0.008***	0.035**	0.026	0.014**	0.031***	0.017*
	(0.001)	(0.009)	(0.009)	(0.003)	(0.017)	(0.017)	(0.005)	(0.008)	(0.010)
Panel C: Economic Variables									
Debt-to-GDP	0.783***	0.884***	0.102**	0.572***	0.689***	0.117	0.515**	0.534***	0.020
	(0.067)	(0.022)	(0.049)	(0.180)	(0.065)	(0.127)	(0.250)	(0.111)	(0.165)
Primary Balance	-0.373***	-1.009***	-0.636***	-0.412***	-2.141***	-1.729***	-0.387	-2.342***	-1.956***
	(0.062)	(0.194)	(0.189)	(0.141)	(0.495)	(0.482)	(0.243)	(0.462)	(0.483)
GDP Growth	-0.284***	-0.587***	-0.303	-0.404**	-1.031***	-0.627***	-0.242	-1.836***	-1.594***
	(0.079)	(0.223)	(0.193)	(0.170)	(0.208)	(0.236)	(0.221)	(0.363)	(0.406)
Inflation	-0.087*	0.001***	0.088*	-0.228	0.001***	0.229	-0.446**	-0.001**	0.445**
	(0.049)	(0.000)	(0.049)	(0.153)	(0.000)	(0.153)	(0.212)	(0.000)	(0.213)

The table displays the estimated location (β) coefficients based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables interacted with the quartile of initial debt (Equation (9)). Q1 and Q4 refer to the first and fourth quartile of initial debt, respectively. Diff reports the difference between the Q4 and Q1 coefficients. Standard errors (reported in parentheses) are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3: Scale Coefficients: Forward Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables Interacted with Initial Debt

	Horizon (no. of years Ahead):								
	1			3			5		
	Q1	Q4	Diff: Q4 - Q1	Q1	Q4	Diff: Q4 - Q1	Q1	Q4	Diff: Q4 - Q1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Financial Variables									
Financial Conditions	0.122	1.139**	1.017	0.199	0.653	0.455	0.116	0.084	-0.033
	(0.235)	(0.544)	(0.628)	(0.423)	(0.681)	(0.797)	(0.708)	(0.629)	(0.846)
Financial Stress	0.319	-2.297	-2.615	-3.578	-2.919	0.659	-10.901	-6.580	4.320
	(3.856)	(3.050)	(5.584)	(6.353)	(3.209)	(8.091)	(7.089)	(4.187)	(8.553)
Spread	0.005	0.446***	0.441***	0.007	-0.007	-0.014	-0.054	0.264	0.318
	(0.013)	(0.127)	(0.128)	(0.024)	(0.228)	(0.228)	(0.039)	(0.291)	(0.292)
Yield	0.020	0.362***	0.342***	0.026	0.088	0.063	-0.005	0.418*	0.423*
	(0.013)	(0.117)	(0.116)	(0.031)	(0.203)	(0.202)	(0.042)	(0.248)	(0.248)
Panel B: Political Variables									
World Uncertainty	-3.745*	-4.158	-0.414	-5.650**	-11.149**	-5.499	-7.009**	-10.435**	-3.426
	(1.912)	(3.475)	(4.410)	(2.880)	(4.859)	(5.939)	(3.541)	(4.849)	(6.323)
Social Unrest	-0.000	0.006	0.006	-0.001	0.002	0.003	-0.004	-0.011	-0.007
	(0.001)	(0.004)	(0.004)	(0.002)	(0.009)	(0.008)	(0.003)	(0.007)	(0.008)
Panel C: Economic Variables									
Debt-to-GDP	0.089	0.090***	0.001	0.129	0.128***	-0.002	0.120	0.110***	-0.010
	(0.071)	(0.031)	(0.043)	(0.084)	(0.038)	(0.057)	(0.078)	(0.033)	(0.058)
Primary Balance	-0.061	-0.009	0.052	0.063	-0.129	-0.192	-0.045	-0.058	-0.013
	(0.047)	(0.099)	(0.106)	(0.109)	(0.224)	(0.249)	(0.133)	(0.314)	(0.370)
GDP Growth	0.026	-0.309	-0.335	-0.004	-0.548*	-0.544	-0.230*	-0.120	0.111
	(0.064)	(0.236)	(0.251)	(0.098)	(0.331)	(0.379)	(0.129)	(0.194)	(0.267)
Inflation	-0.043	0.000***	0.043	-0.182*	-0.001***	0.182*	-0.235*	-0.001***	0.234*
	(0.040)	(0.000)	(0.040)	(0.109)	(0.000)	(0.109)	(0.129)	(0.000)	(0.129)

The table displays the estimated scale (γ) coefficients based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables interacted with the quartile of initial debt (Equation (9)). Q1 and Q4 refer to the first and fourth quartile of initial debt, respectively. Diff reports the difference between the Q4 and Q1 coefficients. Standard errors (reported in parentheses) are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: Location Coefficients: Forward Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables Interacted with Country Group

	Horizon (no. of years Ahead):								
	1			3			5		
	AE	EM	Diff: AE - EM	AE	EM	Diff: AE - EM	AE	EM	Diff: AE - EM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Financial Variables									
Financial Conditions	2.181***	1.518*	0.663	3.475***	2.756**	0.719	2.089***	2.121	-0.032
	(0.479)	(0.790)	(0.924)	(0.716)	(1.271)	(1.458)	(0.758)	(1.406)	(1.597)
Financial Stress	13.755***	1.737	12.019**	22.196***	-6.013	28.209***	16.308***	-16.792**	33.100***
	(1.750)	(4.965)	(5.265)	(3.450)	(6.797)	(7.622)	(5.350)	(8.469)	(10.017)
Spread	0.464***	0.067**	0.397***	0.378**	0.153**	0.225	-0.416*	0.288***	-0.704***
	(0.089)	(0.028)	(0.093)	(0.166)	(0.077)	(0.183)	(0.234)	(0.054)	(0.240)
Yield	0.168***	0.049	0.118**	0.038	0.078	-0.040	-0.614***	0.165	-0.779***
	(0.050)	(0.033)	(0.060)	(0.133)	(0.135)	(0.189)	(0.221)	(0.140)	(0.262)
Panel B: Political Variables									
World Uncertainty	3.956***	3.772**	0.185	-1.523	16.509***	-18.032***	-1.031	23.657***	-24.688**
	(1.531)	(1.869)	(2.416)	(4.675)	(4.982)	(6.832)	(6.998)	(7.429)	(10.206)
Social Unrest	0.008***	0.005	0.003	0.013***	0.013**	-0.000	0.010*	0.019***	-0.009
	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.004)	(0.007)
Panel C: Economic Variables									
Debt-to-GDP	0.965***	0.844***	0.121***	0.858***	0.580***	0.278***	0.770***	0.320***	0.450***
	(0.009)	(0.024)	(0.026)	(0.041)	(0.048)	(0.063)	(0.078)	(0.107)	(0.133)
Primary Balance	-0.463***	-0.776***	0.313	-0.796***	-1.720***	0.924*	-0.989***	-1.931***	0.943*
	(0.111)	(0.169)	(0.202)	(0.198)	(0.430)	(0.474)	(0.278)	(0.427)	(0.510)
GDP Growth	-0.465***	-0.437***	-0.029	-0.689***	-0.887***	0.199	-0.855***	-1.043***	0.188
	(0.071)	(0.167)	(0.182)	(0.195)	(0.197)	(0.277)	(0.314)	(0.251)	(0.402)
Inflation	0.025	0.001***	0.024	0.011	0.001***	0.010	-0.252	-0.000	-0.252
	(0.033)	(0.000)	(0.033)	(0.137)	(0.000)	(0.137)	(0.204)	(0.000)	(0.204)

The table displays the estimated location (β) coefficients based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables interacted with a country group indicator (Equation (10)). AE and EM refer to advanced economies and emerging market and developing economies, respectively. Diff reports the difference between the AE and EM coefficients. Standard errors (reported in parentheses) are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: Scale Coefficients: Forward Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables Interacted with Country Group

	Horizon (no. of years Ahead):								
	1			3			5		
	AE	EM	Diff: AE - EM	AE	EM	Diff: AE - EM	AE	EM	Diff: AE - EM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Financial Variables									
Financial Conditions	0.505**	0.042	0.464	0.523	0.589	-0.066	0.090	0.690	-0.599
	(0.210)	(0.663)	(0.696)	(0.416)	(0.507)	(0.656)	(0.378)	(0.483)	(0.614)
Financial Stress	2.823*	-4.413	7.236	3.296	-4.348	7.644	-2.645	-11.679***	9.035*
	(1.489)	(5.718)	(5.909)	(3.008)	(8.357)	(8.882)	(2.331)	(4.499)	(5.067)
Spread	0.068	0.041*	0.028	-0.149	-0.012	-0.138	-0.356*	-0.030	-0.326*
	(0.054)	(0.022)	(0.059)	(0.172)	(0.031)	(0.175)	(0.189)	(0.030)	(0.191)
Yield	0.010	0.056*	-0.046	-0.038	0.001	-0.040	-0.055	-0.023	-0.032
	(0.037)	(0.031)	(0.048)	(0.113)	(0.028)	(0.116)	(0.169)	(0.030)	(0.172)
Panel B: Political Variables									
World Uncertainty	1.486	-3.411***	4.896**	-4.572*	-0.837	-3.735	-7.109**	-0.294	-6.814
	(1.769)	(0.776)	(1.932)	(2.513)	(2.293)	(3.402)	(3.432)	(2.772)	(4.412)
Social Unrest	0.003***	0.001	0.002	-0.005*	0.002	-0.007	-0.009***	-0.002	-0.006
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Panel C: Economic Variables									
Debt-to-GDP	0.030***	0.140***	-0.110***	0.029*	0.176***	-0.146***	-0.005	0.144***	-0.149***
	(0.009)	(0.026)	(0.027)	(0.017)	(0.026)	(0.031)	(0.028)	(0.025)	(0.038)
Primary Balance	-0.051	-0.033	-0.018	-0.065	-0.104	0.039	0.056	-0.019	0.075
	(0.062)	(0.077)	(0.098)	(0.128)	(0.168)	(0.211)	(0.155)	(0.215)	(0.265)
GDP Growth	-0.094*	-0.094	0.000	-0.165	-0.228	0.063	-0.019	-0.081	0.062
	(0.056)	(0.117)	(0.130)	(0.176)	(0.164)	(0.241)	(0.225)	(0.085)	(0.241)
Inflation	-0.061**	0.000***	-0.062**	-0.150***	-0.001***	-0.149**	-0.335***	-0.001***	-0.333***
	(0.028)	(0.000)	(0.028)	(0.058)	(0.000)	(0.058)	(0.092)	(0.000)	(0.092)

The table displays the estimated scale (γ) coefficients based on panel quantile regressions of the future debt-to-GDP ratio on selected financial, political, and economic variables interacted with a country group indicator (Equation (10)). AE and EM refer to advanced economies and emerging market and developing economies, respectively. Diff reports the difference between the AE and EM coefficients. Standard errors (reported in parentheses) are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

A Appendix Tables

Table A.1: Summary Statistics

Variable	Mean (1)	Median (2)	SD (3)	Obs (4)	Description and Source (5)
Panel A: Financial Variables					
Financial Conditions	0.008	-0.045	0.694	1,262	The Financial Conditions Index captures the pricing of risk. It incorporates various pricing indicators, including real house prices. Higher values indicate tighter financial conditions. Source: IMF, Financial Conditions Index.
Financial Stress	0.031	0.000	0.098	2,844	The Financial Stress Index is computed by looking for wording indicating increased frictions in credit provision, reduced availability of credit, and increases in intermediation costs in the Economist Intelligence Unit (EIU) country reports. The indices are normalized by total number of words and rescaled by multiplying by 1,000. A higher number means higher financial stress and vice versa. Source: Ahir et al. (2023).
Spread	3.557	1.531	9.812	2,487	Difference between 10-year government bond yield and 10-year US Treasury yield. 5-year yield used if 10-year maturity not available. For US, 10-year Treasury yields are used. Source: Global Financial Data (Finaeon), Eikon.
Yield	7.878	6.279	9.872	2,487	10-year government bond yield. 5-year yield used if 10-year maturity not available. Source: Global Financial Data (Finaeon), Eikon.
Panel B: Political Variables					
World Uncertainty	0.159	0.121	0.144	3,417	The World Uncertainty Index (WUI) is computed by counting the percent of word uncertain (or its variant) in the Economist Intelligence Unit country reports. The WUI is then rescaled by multiplying by 1,000,000. A higher number means higher uncertainty. Source: Ahir, Bloom, and Furceri (2022)
Social Unrest	102.294	64.681	134.142	3,033	The Reported Social Unrest Index captures the fraction of all articles which are about unrest in a country. Source: Barrett et al. (2022).
Panel C: Economic Variables					
Debt-to-GDP	55.527	48.677	35.728	2,876	End-of-period general government gross debt to nominal GDP. Source: IMF, World Economic Outlook (WEO) Database.
Primary Balance	-0.496	-0.581	3.660	2,922	General government primary balance as a percent of GDP. Source: IMF, World Economic Outlook (WEO) Database.
GDP Growth	3.406	3.564	4.311	3,721	Real GDP growth rate. Source: IMF, World Economic Outlook (WEO) Database.
Inflation	49.931	4.230	1,142.129	3,719	Consumer Price Index Inflation. Source: IMF, World Economic Outlook (WEO) Database.

The table presents a summary of the variables used for the debt-at-risk analysis.

Table A.2: Variable Coverage

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Afghanistan	–	–	–	–	✓	–	✓	✓	–	–	–	✓
Albania	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Algeria	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Andorra	–	–	–	–	–	–	–	–	✓	–	✓	✓
Angola	–	✓	✓	–	–	✓	✓	–	✓	✓	✓	✓
Antigua and Barbuda	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Argentina	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Armenia	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Aruba	–	–	–	–	✓	–	✓	✓	–	–	–	✓
Australia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Austria	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Azerbaijan	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Bahamas, The	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Bahrain	–	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Bangladesh	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Barbados	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Belarus	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Belgium	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Belize	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Benin	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Bhutan	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Bolivia	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Bosnia and Herzegov-ina	–	–	✓	–	–	–	✓	–	✓	✓	✓	✓
Botswana	–	✓	✓	–	✓	✓	✓	–	✓	✓	✓	✓
Brazil	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Brunei Darussalam	–	–	–	–	–	–	–	–	–	✓	✓	✓
Bulgaria	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Burkina Faso	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Burundi	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Cabo Verde	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Cambodia	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Cameroon	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Canada	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Central African Republic	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Chad	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Chile	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
China	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Colombia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Comoros	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Congo, Republic of	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Costa Rica	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Cote d'Ivoire	–	✓	✓	–	✓	✓	✓	–	✓	✓	✓	✓
Croatia	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Cyprus	–	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Czech Republic	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Democratic Republic of the Congo	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Denmark	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Djibouti	–	–	–	–	–	–	–	–	–	✓	✓	✓
Dominica	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Dominican Republic	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Ecuador	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Egypt	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
El Salvador	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Equatorial Guinea	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Eritrea	–	–	–	–	–	–	✓	–	–	–	–	✓
Estonia	–	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Eswatini	–	–	✓	–	–	–	–	✓	✓	✓	✓	✓
Ethiopia	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Fiji	–	✓	✓	–	–	✓	–	–	✓	✓	✓	✓
Finland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
France	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Gabon	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Gambia, The	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Georgia	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Germany	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Ghana	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Greece	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Grenada	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Guatemala	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Guinea	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Guinea-Bissau	–	–	✓	–	–	–	✓	–	✓	✓	✓	✓
Guyana	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Haiti	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Honduras	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Hong Kong SAR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hungary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Iceland	–	✓	✓	–	✓	✓	–	–	✓	✓	✓	✓
India	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Indonesia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Iran	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Iraq	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Ireland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Israel	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Italy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jamaica	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Japan	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jordan	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Kazakhstan	–	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓
Kenya	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Iran	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Iraq	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Ireland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Israel	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Italy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jamaica	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Japan	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Jordan	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Kazakhstan	–	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓
Kenya	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Kiribati	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Korea	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Kosovo	–	–	–	–	–	–	–	✓	–	✓	✓	✓
Kuwait	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Kyrgyz Republic	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Lao P.D.R.	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Latvia	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Lebanon	–	–	✓	✓	✓	–	✓	✓	✓	✓	✓	✓
Lesotho	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Liberia	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Lithuania	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Luxembourg	–	✓	✓	✓	–	✓	–	–	✓	✓	✓	✓
Macao SAR	–	–	–	–	–	–	–	–	–	–	✓	✓
Madagascar	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Malawi	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Malaysia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Maldives	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Mali	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Malta	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Marshall Islands	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Mauritania	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Mauritius	–	✓	✓	–	–	✓	–	–	✓	✓	✓	✓
Mexico	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Micronesia, Fed. States of	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Moldova	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Mongolia	–	–	–	–	–	–	✓	–	–	✓	✓	✓
Montenegro, Rep. of	–	–	✓	–	–	–	–	✓	✓	✓	✓	✓
Morocco	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Mozambique	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Myanmar	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Namibia	–	✓	✓	–	–	✓	✓	–	✓	✓	✓	✓
Nauru	–	–	–	–	–	–	–	–	–	–	✓	✓
Nepal	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Netherlands	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
New Zealand	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Nicaragua	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Niger	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Nigeria	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
North Macedonia	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Norway	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Oman	–	–	✓	–	–	–	✓	–	✓	✓	✓	✓
Pakistan	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Palau	–	–	–	–	–	–	–	–	✓	–	✓	✓
Panama	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Papua New Guinea	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Paraguay	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Peru	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Philippines	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Poland	–	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓
Portugal	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Puerto Rico	–	–	–	–	–	–	–	✓	–	–	✓	✓
Qatar	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Romania	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Russia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Rwanda	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Samoa	–	–	–	–	–	–	–	–	✓	–	✓	✓
San Marino	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Sao Tome and Principe	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Saudi Arabia	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Senegal	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Serbia	–	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Seychelles	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Sierra Leone	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Singapore	–	✓	–	✓	✓	✓	✓	✓	✓	–	✓	✓
Slovak Republic	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓
Slovenia	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
Solomon Islands	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Somalia	–	–	–	–	–	–	–	✓	–	–	–	✓
South Africa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
South Sudan	–	–	–	–	–	–	–	–	–	–	–	✓
Spain	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sri Lanka	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
St. Kitts and Nevis	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
St. Lucia	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
St. Vincent and the Grenadines	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Sudan	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Suriname	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Sweden	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Switzerland	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Syria	–	–	–	–	–	–	–	✓	–	–	–	✓
Taiwan Province of China	–	✓	–	–	✓	✓	✓	✓	✓	–	✓	✓
Tajikistan	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Tanzania	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Thailand	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Timor-Leste, Dem. Rep. of	–	–	–	–	–	–	–	✓	–	✓	✓	✓
Togo	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓
Tonga	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Trinidad and Tobago	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Tunisia	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Turkiye	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Turkmenistan	–	–	–	–	–	–	✓	–	✓	–	✓	✓
Tuvalu	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Uganda	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Ukraine	–	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓
United Arab Emirates	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
United Kingdom	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.2: Variable Coverage (continued)

Country	Global	Regres-sion	Ex-tended	FCI	FSI	Spread	WUI	RSUI	Debt-to-GDP	Primary Balance	Growth	Infla-tion
United States	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uruguay	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Uzbekistan	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Turkiye	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Turkmenistan	–	–	–	–	–	–	✓	–	✓	–	✓	✓
Tuvalu	–	–	✓	–	–	–	–	–	✓	✓	✓	✓
Uganda	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Ukraine	–	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓
United Arab Emirates	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
United Kingdom	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United States	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uruguay	–	–	✓	–	✓	–	✓	–	✓	✓	✓	✓
Uzbekistan	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Vanuatu	–	✓	✓	–	–	✓	–	–	✓	✓	✓	✓
Venezuela	–	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Vietnam	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
West Bank and Gaza	–	–	–	–	–	–	–	✓	–	–	–	✓
Yemen	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓
Zambia	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Zimbabwe	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓

The table displays the sample and variable coverage by country. "Global" is the sample of 47 countries used to aggregate to the global distribution. "Regression" is the sample of 90 countries (for which sovereign yield data are available) used for the quantile regression results. "Extended" is the extended sample of 175 countries which report debt-to-GDP, primary balance, and GDP growth continuously from 2005 to 2024. ✓ indicates that a country is included in a sample or is covered by the conditioning variables.

Table A.3: Quantile Regression Results: One-Year Ahead Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables

	Dependent Variable: General government gross debt, percent of GDP: 1 periods ahead			
	Q5	Q50	Q95	Obs
	(1)	(2)	(3)	(4)
Panel A: Financial Variables				
Financial Conditions Index	0.508	1.147***	2.017***	1,164
	(0.339)	(0.275)	(0.764)	
General government gross debt, percent of GDP	0.770***	0.885***	1.043***	
	(0.083)	(0.037)	(0.054)	
Financial Stress Index	0.833**	1.013***	1.237*	2,066
	(0.390)	(0.231)	(0.665)	
General government gross debt, percent of GDP	0.693***	0.896***	1.149***	
	(0.076)	(0.020)	(0.084)	
Sovereign Spread (Percentage Point)	-0.391	0.807***	2.645***	2,208
	(0.688)	(0.304)	(0.786)	
General government gross debt, percent of GDP	0.876***	0.951***	1.065***	
	(0.034)	(0.013)	(0.028)	
Sovereign Bond Yield (Percent)	-0.817	0.480	2.497***	2,208
	(0.774)	(0.314)	(0.891)	
General government gross debt, percent of GDP	0.875***	0.953***	1.076***	
	(0.035)	(0.014)	(0.029)	
Panel B: Political Variables				
World Uncertainty Index: Overall	1.626***	0.784***	-0.305	2,481
	(0.394)	(0.220)	(0.428)	
General government gross debt, percent of GDP	0.691***	0.885***	1.136***	
	(0.068)	(0.018)	(0.071)	
Reported Social Unrest Index	0.435	0.833**	1.336*	2,410
	(0.420)	(0.345)	(0.811)	
General government gross debt, percent of GDP	0.659***	0.874***	1.146***	
	(0.068)	(0.020)	(0.070)	
Panel C: Economic Variables				
General government gross debt, percent of GDP	0.689***	0.887***	1.135***	2,786
	(0.066)	(0.019)	(0.063)	
General government primary net lending/borrowing, percent of GDP	-2.219***	-2.356***	-2.546***	2,658
	(0.428)	(0.380)	(0.753)	
General government gross debt, percent of GDP	0.672***	0.868***	1.139***	
	(0.068)	(0.020)	(0.071)	
Real GDP Growth Rate (percent)	-0.622	-1.742***	-3.210**	2,764
	(0.647)	(0.385)	(1.488)	
General government gross debt, percent of GDP	0.681***	0.875***	1.129***	
	(0.066)	(0.020)	(0.067)	
CPI Inflation	0.020	1.155***	2.568***	2,757
	(0.178)	(0.049)	(0.107)	
General government gross debt, percent of GDP	0.696***	0.880***	1.108***	
	(0.067)	(0.023)	(0.051)	

The dependent variable is the one-year-ahead debt-to-GDP ratio. 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 (2)). 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. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. .

Table A.4: Quantile Regression Results: Three-Year Ahead Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables

	Dependent Variable: General government gross debt, percent of GDP: 3 periods ahead			
	Q5	Q50	Q95	Obs
	(1)	(2)	(3)	(4)
Panel A: Financial Variables				
Financial Conditions Index	1.188**	1.970***	2.959***	1,083
	(0.526)	(0.456)	(0.781)	
General government gross debt, percent of GDP	0.596***	0.679***	0.785***	
	(0.109)	(0.070)	(0.062)	
Financial Stress Index	1.198*	1.446***	1.762**	1,938
	(0.704)	(0.493)	(0.791)	
General government gross debt, percent of GDP	0.463***	0.708***	1.020***	
	(0.119)	(0.064)	(0.075)	
Sovereign Spread (Percentage Point)	1.165	1.417**	1.747**	2,046
	(1.045)	(0.723)	(0.816)	
General government gross debt, percent of GDP	0.759***	0.826***	0.914***	
	(0.073)	(0.053)	(0.053)	
Sovereign Bond Yield (Percent)	-0.287	0.332	1.148	2,046
	(1.769)	(1.296)	(1.104)	
General government gross debt, percent of GDP	0.761***	0.830***	0.920***	
	(0.075)	(0.053)	(0.051)	
Panel B: Political Variables				
World Uncertainty Index: Overall	3.062***	1.898***	0.545	2,321
	(0.617)	(0.619)	(1.028)	
General government gross debt, percent of GDP	0.450***	0.688***	0.964***	
	(0.110)	(0.061)	(0.064)	
Reported Social Unrest Index	2.202***	2.071***	1.910*	2,250
	(0.707)	(0.596)	(1.147)	
General government gross debt, percent of GDP	0.434***	0.670***	0.961***	
	(0.106)	(0.056)	(0.070)	
Panel C: Economic Variables				
General government gross debt, percent of GDP	0.461***	0.695***	0.990***	2,606
	(0.103)	(0.057)	(0.061)	
General government primary net lending/borrowing, percent of GDP	-4.908***	-4.926***	-4.950***	2,482
	(0.735)	(0.921)	(1.658)	
General government gross debt, percent of GDP	0.453***	0.653***	0.925***	
	(0.098)	(0.058)	(0.060)	
Real GDP Growth Rate (percent)	-1.479	-3.101***	-5.210***	2,584
	(0.960)	(0.531)	(1.730)	
General government gross debt, percent of GDP	0.455***	0.652***	0.907***	
	(0.101)	(0.064)	(0.044)	
CPI Inflation	2.610***	1.410***	-0.069	2,577
	(0.265)	(0.157)	(0.152)	
General government gross debt, percent of GDP	0.448***	0.685***	0.977***	
	(0.110)	(0.060)	(0.061)	

The dependent variable is the three-year-ahead debt-to-GDP ratio. 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 (2)). 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. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. .

Table A.5: Quantile Regression Results: Five-Year Ahead Debt-to-GDP Ratio vs. Financial, Political, and Economic Variables

	Dependent Variable: General government gross debt, percent of GDP: 5 periods ahead			
	Q5	Q50	Q95	Obs
	(1)	(2)	(3)	(4)
Panel A: Financial Variables				
Financial Conditions Index	0.730	1.267**	1.816***	1,001
	(0.842)	(0.542)	(0.554)	
General government gross debt, percent of GDP	0.424**	0.476***	0.528***	
	(0.172)	(0.114)	(0.113)	
Financial Stress Index	1.562**	0.885	0.066	1,810
	(0.776)	(0.656)	(0.784)	
General government gross debt, percent of GDP	0.365**	0.554***	0.782***	
	(0.160)	(0.115)	(0.068)	
Sovereign Spread (Percentage Point)	2.118	1.799	1.426	1,880
	(1.656)	(1.139)	(1.015)	
General government gross debt, percent of GDP	0.686***	0.722***	0.764***	
	(0.123)	(0.090)	(0.081)	
Sovereign Bond Yield (Percent)	-1.132	-0.444	0.376	1,880
	(3.072)	(2.350)	(1.883)	
General government gross debt, percent of GDP	0.687***	0.723***	0.767***	
	(0.123)	(0.089)	(0.080)	
Panel B: Political Variables				
World Uncertainty Index: Overall	3.662***	2.728***	1.629	2,161
	(0.935)	(1.013)	(1.334)	
General government gross debt, percent of GDP	0.351**	0.521***	0.720***	
	(0.149)	(0.111)	(0.074)	
Reported Social Unrest Index	3.642***	2.602***	1.433**	2,090
	(0.864)	(0.491)	(0.589)	
General government gross debt, percent of GDP	0.303**	0.483***	0.685***	
	(0.146)	(0.098)	(0.069)	
Panel C: Economic Variables				
General government gross debt, percent of GDP	0.346**	0.533***	0.755***	2,426
	(0.141)	(0.101)	(0.064)	
General government primary net lending/borrowing, percent of GDP	-5.825***	-5.678***	-5.504***	2,306
	(1.091)	(0.933)	(1.547)	
General government gross debt, percent of GDP	0.322**	0.494***	0.699***	
	(0.133)	(0.099)	(0.067)	
Real GDP Growth Rate (percent)	-3.149***	-3.800***	-4.541***	2,404
	(0.793)	(0.802)	(1.304)	
General government gross debt, percent of GDP	0.310**	0.496***	0.707***	
	(0.145)	(0.104)	(0.068)	
CPI Inflation	1.831***	-0.524	-3.324***	2,397
	(0.458)	(0.322)	(0.771)	
General government gross debt, percent of GDP	0.336**	0.535***	0.771***	
	(0.147)	(0.104)	(0.076)	

The dependent variable is the five-year-ahead debt-to-GDP ratio. 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 (2)). 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. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. .

Table A.6: Quantile Regression Results: Conditioning Variables and Three-Year-Ahead Growth, Primary Balance, Interest Rate, and Unidentified Debt-at-Risk

	Dependent Variable:			
	Growth	Primary Balance	Interest	Unidentified Debt
	Q5	Q5	Q95	Q95
	(1)	(2)	(3)	(4)
Panel A: Financial Variables				
Financial Conditions Index	-0.020	-2.343***	1.465**	0.809
	(0.091)	(0.476)	(0.638)	(0.653)
Financial Stress Index	-0.212**	-1.006**	-1.398***	0.940**
	(0.087)	(0.397)	(0.459)	(0.434)
Sovereign Spread (Percentage Point)	-0.301**	-1.005*	3.401	-0.606
	(0.144)	(0.588)	(3.237)	(0.416)
Sovereign Bond Yield (Percent)	-0.137	-0.140	5.948	-0.325
	(0.234)	(0.994)	(4.848)	(0.621)
Panel B: Political Variables				
World Uncertainty Index: Overall	0.061	-1.049**	-1.900***	-0.597*
	(0.113)	(0.460)	(0.585)	(0.346)
Reported Social Unrest Index	-0.328***	-1.504***	-0.865	-0.849***
	(0.104)	(0.406)	(0.582)	(0.286)
Panel C: Economic Variables				
General government gross debt, percent of GDP	-0.003	-0.001	-0.110**	0.077
	(0.006)	(0.032)	(0.055)	(0.049)
General government primary net lending/borrowing, percent of GDP	0.301**	4.306***	-1.230*	0.209
	(0.129)	(0.701)	(0.673)	(0.637)
Real GDP Growth Rate (percent)	0.590***	1.915***	-0.877	1.135
	(0.154)	(0.717)	(0.824)	(0.943)
CPI Inflation	-0.021	0.158**	0.506***	-0.250**
	(0.013)	(0.077)	(0.138)	(0.121)

The table displays the estimated coefficients based on panel quantile regressions (Equation (2)). The dependent variables are the 5th percentile of real GDP growth (Column 1), the 5th percentile of the primary balance to GDP ratio (Column 2), the 95th percentile of the effective interest rate (Column 3), and the 95th percentile of unidentified debt (Column 4). The coefficients refer to the percentage point change in the dependent variable 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%, 5% and 10% levels, respectively. .

Table A.7: Variables in the BMA Model

Variable	Description
Panel A: DaR Measurements	
DaR quantiles	Predicted debt quantiles (Q95, Q95-Q50, Q95*(Q95-Q50)) conditional on the conditioning factors and the combined distribution.
Panel B: Conditioning Factors	
Financial stress index Spread World uncertainty index Social unrest index Initial debt Primary deficit GDP growth Inflation	
Panel C: Additional Variables	
Total debt	Total debt in percent of GDP.
Public debt	Public debt in percent of GDP and general government revenue, and public external debt in percent of exports.
Public debt service	Public debt service in percent of general government revenue and expenditure.
Fiscal projection	One-year-ahead debt-to-GDP and primary balance-to-GDP ratios.

The table presents a summary of the variables used for the BMA model. For these additional variables, we include functional forms of contemporaneous values, first and second lags, and the (historical) 1-year and 3-year growth rates. For conditioning factors, see Table A.1.

Table A.8: Variables in the Random Forest Model

	Variable category	Number of factors	Total number of permutation on factors	Number of factors chosen in Boruta selection
		(1)	(2)	(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.

PUBLICATIONS

Debt-at-Risk

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