INTERNATIONAL MONETARY FUND

Market Access and High Spread Issuances

Raphael Espinoza, Metodij Hadzi-Vaskov, Luis Carlos Ibanez-Thomae, and Flora Lutz

WP/26/10

2026
JAN

WORKING PAPER

 WP/26/10

IMF Working Paper
Western Hemisphere Department

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Authorized for distribution by Fabian Valencia
January 2026

ABSTRACT: We investigate the factors determining emerging markets' likelihood to access international capital markets. First, we develop a simple model to outline the theoretical foundations of market access, highlighting the role of risk, spreads, net worth, and the cost of repaying debt. The model also shows a trade-off between risk insurance and moral hazard and underscores the relevance of unconventional instruments such as guarantees and macro-contingent debt. Second, we estimate a random forest model to assess the key predictors of market access. We find that outstanding obligations, reserves, short-term external debt, EMBIG spreads and the size of the economy are key predictors of market access. Important non-linear effects include an inverted U-curve for the effect of spreads on likelihood of issuance; a positive relationship between likelihood of issuance and external debt at low spreads that turns negative at high spreads; and a high sensitivity to governance only for high spreads. Finally, we collect a novel dataset and examine the characteristics of high spread issuances, which are often unconventional and include guarantees, contingencies or collateral, in line with what theory predicts.

RECOMMENDED CITATION: Espinoza, Raphael, Metodij Hadzi-Vaskov, Luis Carlos Ibanez Thomae, and Flora Lutz (202#), "Market Access and High Spread Issuances", IMF Working Paper WP/26/10

JEL Classification Numbers:	F34, F02, G15
Keywords:	Market access; Spreads; Credit rationing; Machine Learning; Random Forest; Moral Hazard

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WORKING PAPERS

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Prepared by

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[1] The authors would like to thank Luis Cubeddu, Vitor Gaspar, Yasemin Bal Gunduz, Eduardo Levy Yeyati, Aiko Mineshima, Andrea Presbitero, Christoph Trebesch, Renato Vassallo, Rodrigo Valdés and participants of the IMF's Western Hemisphere Department and Strategy, Policy, and Review Department seminars and Surveillance Meeting for their comments.

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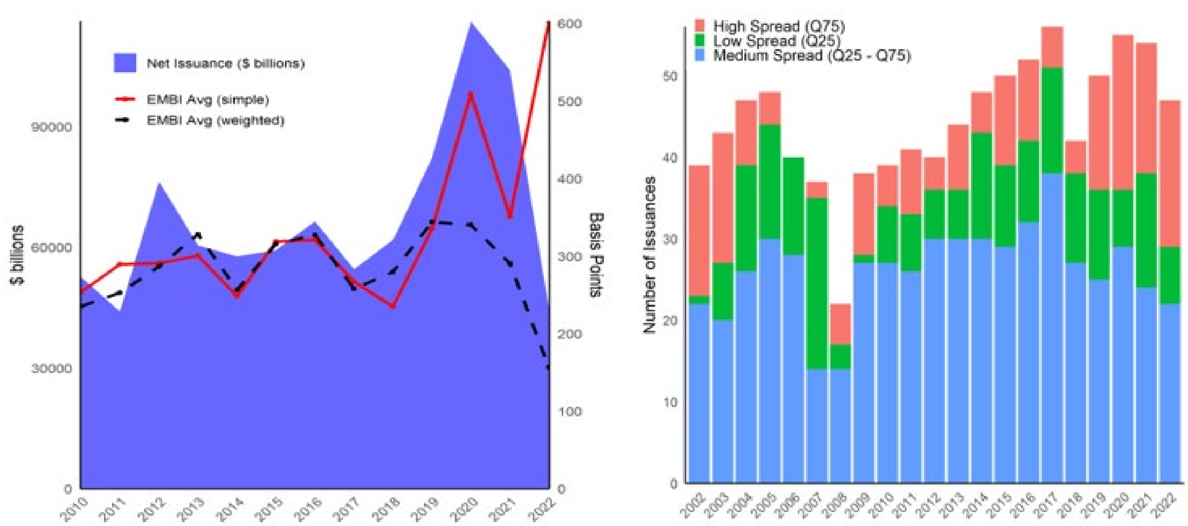
1. Introduction

Access to international capital markets for emerging market and developing economies (EMDEs) grew substantially during the pre-pandemic period. As illustrated in Figure 1, net international issuances by EMDE sovereigns surged, leading to a threefold increase in the nominal value of outstanding international securities. At the same time, the average cost of debt has remained elevated and has increased further since 2019. Notably, the share of issuances with spreads above 500 bps reached a record of 20 percent in 2020 and has remained above 25 percent thereafter. That said, the weighted EMBIG spread, calculated using net issuances, has declined, as high spread issuances focused on refinancing operations, reducing net issuance volumes for countries with high spreads. This pattern suggests that constraints to market access may have become more binding recently.

Figure 1. Emerging Market Sovereign Issuances under International Law



Note: Net debt issuances (area, left panel) show the annual sum of debt-securities inflows (in $ billions) for all bonds with a positive issuance event. The lines (right axis) plot the average EMBI spread (red solid) and the EMBI spread weighted by net issuance (black dashed).
Source: BIS and IMF staff calculations.

To better understand these developments, it is important to examine what determines EMDE's likelihood to issue bonds and maintain regular access to international capital markets. In a frictionless market, price adjustments would balance supply and demand. However, as shown by Jaffee and Russell (1976), Keeton (1997), and Stiglitz and Weiss (1981), credit rationing can persist as an equilibrium phenomenon due to asymmetric information. Higher interest rates can lead to adverse selection (countries willing to borrow at high rates are those more likely to default) or to moral hazard (high rates reduce borrowers' incentives to repay by lowering their payoff in the case of repayment). These mechanisms can explain why markets would shut down for countries where risk premia are beyond a certain threshold.

In this study, we aim to deepen the understanding of what drives countries' access to international bond markets, leveraging earlier studies on the determinants of EMBI spreads (e.g. Eichengreen and Mody, 2000) and of sovereign borrowing (Gelos, Sahay, and Sandleris 2011; Bassanetti, Cottarelli and Presbitero, 2019). For this purpose, we first outline a stylized theoretical framework based on moral hazard to develop the key intuition on how spreads and credit rationing arise and what factors determine them. We then compile a comprehensive dataset including all indicators highlighted by a broad range of previous studies in the literature, covering all EMDEs with available EMBIG spreads. Based on this dataset, we contribute to the literature along two main dimensions. First, we estimate a non-parametric machine learning model (random forest) to forecast issuances and identify key factors, including non-linear effects and interactions. We also compare these findings to a traditional logit model to assess the relevance of non-linear feature interactions. Second, we assess the characteristics of issuances under high spreads using detailed information we collect on individual issuances at spreads higher than 440bps.

Based on the theoretical model elaborated in section III, we highlight two key results. First, the model emphasizes that credit rationing is a function of the cost of borrowing (directly related to the likelihood of default), but also of other factors such as the borrower's net worth as well as effort incentives and the strength of the signal lenders receive about that effort (e.g., credit rating)—a classic moral hazard mechanism. Spreads alone, therefore, are not sufficient to summarize market access. Second, in cases when traditional bonds cannot be sold, instruments like guarantees or collateral can provide lenders with insurance and allow borrowers to re-access markets. Reverse macro-contingent instruments offer another solution, where borrowers agree to higher rates in case of policy slippage (bad signal), serving as a commitment mechanism against moral hazard. In April 2024, El Salvador used such a commitment mechanism to re-access capital markets, where the coupon rate would rise from 0.25 percent to 4.0 percent starting in October 2025, unless (i) an IMF arrangement is approved with regular reviews, or (ii) the credit ratings from at least two agencies improve from its initial level.

Next, we empirically assess the key determinants of debt issuances. A major challenge in the empirical literature is distinguishing between supply and demand factors. Intuitively, countries may refrain from issuing debt due to a lack of supply for financing, or they may not need to issue because financing needs are small or other sources of financing are available. Papers on the determinants of EMBI spreads are not able to separate these effects, and the research that has studied the drivers of issuances has not resolved this difficulty. Although we do not identify supply and demand shocks, we progress in that direction thanks to a nonparametric machine learning model (a random forest), which predicts the issuances conditioning on variables capturing demand and supply factors as well as their non-linear interactions. This approach offers the advantage of incorporating a wide range of features (explanatory variables). Additionally, we think the non-linear interaction effects obtained with our empirical approach are useful to interpret the role of demand and supply factors in predicting market issuance, as they allow us to estimate the effect of, say, a demand factor, holding a supply factor constant, on the likelihood of future issuance. Importantly, however, our empirical findings reflect predictive associations rather than causal relationships.

Finally, building on the theory, we document some of the unconventional features like contingencies or guarantees that have been used by countries to issue bonds at high spreads. We examine issuances from small EMDEs at high spreads (above 440 basis points). Consistent with the model's intuition, we find that 36 percent of these issuances include special features such as guarantees, contingencies, or collateral. When the threshold is increased to 600 basis points, the share of unconventional issuances rises to 42 percent. The results also indicate that unconventional issuances are typically larger.

The rest of the paper is organized as follows. Section 2 provides a literature review and Section 3 elaborates the theoretical model of credit rationing. Section 4 describes the empirical strategy (random forest), Section 5 provides an overview of the empirical results, and Section 6 discusses briefly model fit. The characteristics of high-spread issuances are studied in Section 7. Section 8 provides some concluding remarks.

2. Literature

Our analysis builds on three main strands of literature. We are closest to the empirical literature assessing countries' likelihood to issue sovereign international debt and the broader determinants of international capital flows.[1] Using traditional econometric methods, these studies emphasize the importance of country-specific fundamentals, as well as external variables such as global liquidity (Fostel and Kaminsky, 2007), domestic debt dynamics (Bassanetti, Cottarelli and Presbitero, 2019), institutional quality (Gelos et al., 2011; da Silva et al., 2021), sovereign credit ratings (Guscina et al., 2017) as well as conditions in primary and secondary markets (Zigraiova and Erce, 2024). We extend this literature by applying a non-parametric, random forest model. The usefulness of machine learning techniques has recently been underscored in the context of economic early warning indicators, where they have shown significant improvements in out-of-sample prediction accuracy compared to standard econometric approaches (e.g., Fouliard et al., 2021). A closely related study by Belly et al. (2024) examines the ability of machine learning techniques to predict sovereign risk in the Euro Area. In contrast, our analysis adopts a broader perspective by focusing on sovereign issuances in emerging market and developing economies and provides an in-depth examination of issuances under high spreads—i.e., high borrowing costs—a crucial issue for frontier economies.

Second, our analysis is related to the extensive literature on the pricing of sovereign debt and the determinants of sovereign spreads or credit ratings.[2] This literature's findings are fairly heterogeneous, with different variables identified as the primary drivers of spreads. This may be due to differences in econometric models, country samples, observation periods, and the variables considered. More recent studies, such as Balduzzi et al. (2023), have employed machine learning techniques, highlighting the significance of non-linear, time-varying relationships and contagion effects. Our analysis deviates from this literature by utilizing a quantity-based measure of market access, which allows us to assess the importance of sovereign spreads as an independent variable beyond the typical focus on country fundamentals and global factors.

Finally, our paper relates to the literature on sovereign default and state-contingent debt. Quantitative models of strategic sovereign default find that default is costly due to higher subsequent borrowing costs or full market exclusion,[3] although empirically, exclusion effects tend to diminish rapidly once defaults are resolved (e.g., Gelos, Sahay, and Sandleris 2011; Cruces and Trebesch 2013).[4] In this study, we aim to address sovereign access to capital markets more generally. To establish core intuition, we start our paper with a theoretical

[1] Seminal contributions on the determinants of international capital flows include Krugman (1979), Obstfeld (1994) and Kaminsky and Reinhart (1999), Calvo, Leiderman and Reinhart (1996); Caballero and Krishnamurthy (2002), Calvo (1999), Calvo, Izquierdo, and Mejía (2004).

[2] Important contributions include Edwards (1986), Cantor and Packer (1996), Eichengreen and Mody (1998), Francis et al. (2011), Aizenman et al. (2013).

[3] Important contributions include, but are not limited to, Eaton and Gersovitz (1981), Aguiar and Gopinath (2006) and Arellano (2008). Other studies suggested that sovereign defaults have costly spillovers beyond sovereign credit markets (see Cole and Kehoe 1998), with adverse effects on trade (Rose 2005), on private sector access to credit (Arteta and Hale 2008), or for the financial sector (Acharya and Rajan 2011).

[4] For surveys, see Panizza et al. (2009), Aguiar and Amador (2014) and Mitchener and Trebesch (2023).

model based on moral hazard, following the tradition of Stiglitz and Weiss (1981). In that framework, we also explore the role of state-contingent and GDP-indexed bonds, demonstrating how reverse contingent instruments can help restore access by providing a commitment device.[5]

3. Stylized Model of Credit Rationing Based on Moral Hazard

We start with a presentation of a theoretical model of credit rationing that provides hypotheses on the factors driving credit rationing as well as an explanation for how state-contingent debt can improve or worsen market access. The analysis focuses on moral hazard, though a similar logic applies under adverse selection, where state-contingent debt can serve as a screening device that facilitates or hinders access depending on how repayment terms affect borrower self-selection. Readers interested in the empirical analysis can jump to Section 4 directly.[6]

Set-up

Consider a two-period model economy with t = 0 and 1, two representative agents, a borrower (the sovereign) and an international lender, and two states of the world (good and bad), denoted by $\theta \in \{G,B\}$. The borrower is risk averse and aims to maximize expected utility given by the concave function $u(c_1)$. In period 0, it faces an investment opportunity $\overline{K}$ that yields a return R^{θ}, where $R^G > R^B$. For simplicity, we assume that the project's return is linear and $R^B=0$ such that the borrower always defaults in the bad state of the world.[7] The borrower finances its investment by using its endowment A or issuing debt D to international foreign lenders at the costs $(1+r)$.[8] In period 1, returns are realized, and—depending on the state of nature—the borrower repays its outstanding debt or defaults. Investment $\overline{K}$ fully depreciates in period 1 such that the sovereign consumes whatever output is left following debt repayments or default. Hence, the two budget constraints read:

$$\overline{K} = A + D,$$
$$C_1(G) = R^G - D(1+r)$$
$$C_1(B) = 0$$

The probability of the good state G, $\pi(e_i)$, is a function of the amount of effort e_i that the borrower exerts, which can take two values: $e_i \in \{e_H, e_L\}$. Exerting effort e_H comes with a cost $B>0$, but increases the probability of the good state such that $(e_H) > \pi(e_L)$. Low effort, on the other hand is not costly but implies a lower probability of success. In our international macroeconomics context, e_i may represent the effort a country undertakes to raise

[5] Important contributions studying the design of state-contingent instruments include Borensztein et al. (2004); Hatchondo and Martinez (2012), Cohen et al. (2020) and Roch and Roldan (2023). Pina (2022) also provides a database of sovereign state-contingent debt issuances. Krugman (1988) argues that GDP indexed bonds could create moral hazard problems by disincentivizing the government to conduct growth-friendly policies or misreport GDP statistics.

[6] The model is static and abstracts from repeated interactions. Allowing for repeated interactions would introduce dynamic mechanisms—such as reputation effects, threat of future punishment, or intertemporal incentive schemes—that could also influence credit allocation and market access.

[7] This is a simplifying assumption and implies that, in the bad state, borrowers always default , and lenders receive nothing (zero-recovery), independent of the interest rate. To ensure the problem is well defined in the bad state we assume $u(0)=0$.

[8] Note that, if borrowers have existing debt at the start of period zero, A may assume a negative value.

taxes or cut expenditure (see e.g. Ghosh et al. 2013), or undertake structural reforms that boost growth and thus the fiscal balance. It is associated with some cost (*B*), but it is assumed to increase the probability of the good state in which the return on investment (the fiscal balance in our context) is higher.[9]

We assume that the net present value (NPV) of the investment project with cost $\bar{K}$ is positive if borrowers exert effort but negative otherwise, a standard assumption in the literature[10]:

$$\pi(e_H)R^H + \big(1-\pi(e_H)\big)R^L - B - \bar{K} \geq 0, \qquad (A1)$$
$$\pi(e_L)R^H + \big(1-\pi(e_L)\big)R^L - \bar{K} < 0$$

The lender cannot observe the amount of effort that borrowers exert which implies that effort is not contractible. However, the lender receives a signal $s_i, \in \{H,L\}$ —say, a credit rating[11] — which reveals some information about the amount of effort that was exerted such that the probability of observing the good signal is indeed higher after the borrower exerted a high amount of effort and is lower vice versa, i.e., $q_H > q_L$ and $(1-q_H) < (1-q_L)$, where q_H denotes the probability of a good signal and $(1-q_H)$ the probability of the bad signal, conditional on the borrower exerting high effort. For the rest of the analysis, we also assume that the probability of observing a bad signal in the good state is lower if the borrower exerts a high amount of effort, i.e.,

$$\pi(e_H)\,(1-q_H) < \pi(e_L)(1-q_L). \qquad (A2)$$

Since the signal is observed by everyone, interest rates can be conditioned on the signal. Lenders are risk neutral and are willing to purchase bonds if the return compensates them for risk, i.e., the following participation constraint (PC) holds:[12]

$$\pi(e_H)\left\{q_H\, D\big(1+r(s_H)\big) + (1-q_H)D\,\big(1+r(s_L)\big)\right\} \geq D, \qquad (1)$$

where $r(s_H)$ and $r(s_L)$ denote the contracted interest rate after the good or the bad signal has been observed. Since the lender does not have any bargaining power, the participation constraint always holds with strict equality. The borrower's expected utility is given by:

$$U = \mathrm{E\,u(c_1)} = \pi(\mathrm{e_H})\,\{q_H\, u\big(R^H - (K-A)\big(1+r(s_H)\big) - B\big) + (1-q_H)u\big(R^H - (K-A)\big(1+r(s_L)\big) - B\big)\}.$$

[9] Possible structural reforms include labor and product market deregulation and the strengthening of fiscal capacity for efficient revenue mobilization (Ilzkovitz and Dierx 2011). As shown by Blanchard and Giavazzi (2003), such reforms deliver long-term gains but impose short-run costs for citizens at large, governments, or special-interest groups. An alternative modeling framework would let the sovereign allocate borrowed funds between consumption and productive investment, while lenders remain unable to directly observe how those funds are deployed (see e.g. Liu et al. 2025, Dovis 2019 and Mueller et al 2019).

[10] See, e.g, Tirole (2006).

[11] Credit rating agencies usually take into account various quantitative and qualitative factors. A large body of literature tries to identify the determinants of sovereign credit ratings, as well as the proxies for qualitative factors, i.e. the credit rating committee's opinion (see e.g. Slapnik and Loncarski, 2021). In the past, credit rating agencies have been accused of being procyclical (Forest et al., 2015) and of lagging financial markets (e.g. Mora, 2006).

[12] The assumption of risk-neutral lenders is standard in sovereign debt models aiming for tractability (e.g., Eaton and Gersovitz, 1981; Aguiar and Gopinath, 2006), as it allows expected returns to be equated directly with the face value of debt. This places the framework within the canonical literature on sovereign credit rationing, where bond pricing reflects default probabilities rather than risk premia. Recent work has examined the role of lender preferences in shaping sovereign borrowing outcomes, including models with risk-averse or robust international lenders (see, e.g., Roch and Roldan, 2023, 2024; Pounzo and Presno, 2016; Pina, 2024).

In the good state, borrowers receive the high investment return and repay the signal-dependent interest rate *r(q)*. Given our assumption of zero return in the bad state, borrowers consume nothing in that state.

Importantly, because of their risk aversion, borrowers would like to fully insure against risk. Full insurance would be feasible if interest rates could be conditioned directly on the actual state of the economy, which would involve a positive transfer from lenders to borrowers in the bad state. For simplicity, we assume in the baseline model that rates can only be conditioned on the signal and must be strictly positive. Note that this is in line with empirical evidence showing that state-contingent sovereign debt instruments are used only infrequently and—when implemented—they rarely provide transfers to borrowers in bad states.[13]

The borrower maximizes utility by choosing the signal-dependent interest rates subject to the lender's participation constraint and the incentive compatibility (ICC) constraint given by

$$\begin{aligned}\pi(\mathrm{e_H})\left\{\mathrm{q_H}\left(R^H-(\bar{K}-A)\left(1+r(s_H)\right)-B\right)+(1-\mathrm{q_H})\left(R^H-(\bar{K}-A)\left(1+r(s_L)\right)-B\right)\right\}\\ \geq \pi(\mathrm{e_L})\left\{\mathrm{q_L}\left(R^H-(\bar{K}-A)\left(1+r(s_H)\right)\right)+(1-\mathrm{q_L})\left(R^H-(\bar{K}-A)\left(1+r(s_L)\right)\right)\right\},\end{aligned}$$

which can be re-arranged to:

$$\Delta\pi\, R^H \geq \pi(e_H)B + (\bar{K}-A)\left\{\left(1+r(s_H)\right)\left(\pi(e_H)q_H-\pi(e_L)q_L\right)+\left(1+r(s_L)\right)\left(\pi(e_H)(1-q_H)-\pi(e_L)(1-q_L)\right)\right\} \quad (1)$$

Equilibrium

The first order conditions with respect to the two choice variables $\{r_H, r_L\}$ are given by:

$$\pi(\mathrm{e_H})q_H\, u'(.)(\bar{K}-A) = \mu_{PC}\,(\bar{K}-A)\pi(\mathrm{e_H})q_H + \mu_{ICC}\,(K-A)\,[\pi(\mathrm{e_L})\,\mathrm{q_L} - \pi(\mathrm{e_H})\,q_H] \quad (2)$$

$$\pi(\mathrm{e_H})(1-q_H)u'(.)(\bar{K}-A) = \mu_{PC}\,\pi(\mathrm{e_H})(1-q_H)\,(\bar{K}-A) + \mu_{ICC}\,(K-A)[\pi(\mathrm{e_L})(1-q_L)-\pi(\mathrm{e_H})(1-q_H)] \quad (3)$$

These conditions reflect that an increase in the interest rates lowers the borrower's return but relaxes the PC in both states. Further note that while an increase in r_H tightens the incentive compatibility constraint, an increase in r_L relaxes the constraint given the assumptions $\pi(e_H) > \pi(e_L)$ and $q_H > q_L$. This is intuitive as an increase in r_H lowers the borrower's incentive to exert effort, while a higher r_L increases the cost of shirking. Note that this effect increases with the quality of the signal.

Definition

A competitive equilibrium is defined by a set of prices $\{r_H, r_L\}$, Lagrange multipliers $\{\mu_{ICC}, \mu_{PC}\}$ for a given realization of the exogenous state θ∈{G, B} and parameters $\{\pi(e_H), \pi(e_L), q(s_H), q(s_L), A, K, B\}$ that satisfy:

1. The participation constraint (1)
2. The incentive compatibility constraint (2) and

[13] For instance, GDP-linked warrants—such as those issued by Argentina or Greece—trigger payments to creditors in good states rather than offering relief in downturns. Even in cases where state-contingent features have been implemented—such as natural disaster clauses in Grenada or Barbados—they typically involve temporary debt service suspension rather than explicit transfers to the borrower. These mechanisms provide relief but do not involve net positive transfers to the borrower in bad states and repayments in good states

3. The first order condition (3) and (4)

We now turn to the possible equilibrium outcomes, which depend on whether the incentive compatibility constraint (ICC) binds or not. First, consider the case where the ICC is non-binding, i.e., $\mu_{ICC} = 0$.

Proposition 1 (Non-binding ICC)

If the return of effort is sufficiently high, i.e., the probability of success after effort is sufficiently high, such that the following condition holds:

$$\Delta\pi\ (R^H - (\bar{K} - A)\,(1 + r^{**})) > B\ \pi(e_H),$$

borrowers don't choose to set signal-dependent interest rates and set the unique interest rate equal to the minimum value that satisfies the PC, $r^{**} = \frac{1}{\pi(e_H)}$.

Note that besides the cost of borrowing (i.e. the probability of default), there are two additional central parameters: borrowers net worth and borrowers return of exerting effort. An increase in the borrower's net worth *A* relaxes the ICC by increasing her stake in the project. This implies that balance sheet strength (such as international reserves, the level of debt, or the net international position) should be an important factor for a country's ability to access international markets for a given sovereign spread. In a similar vein, an increase in returns (summarizing factors such as higher expected growth/higher expected fiscal revenues), a decline in the cost of effort B (proxying for the economic or political costs of fiscal consolidation) or an increase in $\Delta\pi$ (i.e. a stronger effect of effort on the probability of a good state) all relax the ICC for a given spread.[14]

Although gross financing needs (GFN) and official debt are not explicitly modeled as separate variables, they can be interpreted within this framework as factors that effectively reduce the borrower's net worth A. High GFNs reflect imminent liquidity pressures and repayment obligations, which diminish the borrower's financial buffer and thus are analogous to a lower net worth in the model. Likewise, while the model does not explicitly incorporate official debt, its seniority could introduce crowding-out effects: senior official debt increases repayment priority, potentially reducing the resources available to other creditors and effectively lowering net worth A in the eyes of market participants. On the other hand, official credit may improve the quality of the signal investors receive, indicating stronger oversight or commitment, which could mitigate concerns and even foster crowding-in effects.

Next, we consider the case where the ICC is binding such that $\mu_{ICC} > 0$. The result is summarized by proposition 2. When the constraint binds, credit rationing may arise, consistent with Tirole (2006) and others. However, lenders remain willing to extend credit if repayment is guaranteed by a credible third party or if borrowers can pledge sufficient collateral. Moreover, as shown in Proposition 2, access to credit can also be restored through the use of state-contingent interest rates.

This is a simplifying assumption and implies that borrowers always default in the bad state of the world, independent of the level of the interest rate. To ensure the problem is well defined in the bad state we assume *u(0)=0*.

[14] Note that, if borrowers have existing debt at the start of period zero, A may assume a negative value.

Proposition 2 (Binding ICC)

If the collateral constraint is binding, borrowers offer signal dependent interest rates and pay a higher interest rate after the bad signal, i.e., $r_L^{**} > r_H^{**}$. *This is an equilibrium if the probability of default is sufficiently high, i.e.,*

$$\Delta\pi \left(R^H - \frac{K - A}{\pi(e_H)}\right) \geq B\,\pi(e_H),$$

This result is intuitive. By committing to repaying the higher interest rates after the bad signal, the borrower's return after the bad signal is even lower, making "shirking" (choosing low effort e_L) less attractive. This loosens the incentive compatibility constraints. As a result, this form of "reverse"-macro contingent debt instrument can allow borrowers to re-access markets in credit constrained states.

Having described the theoretical foundation in this section, we are now turning to the empirical framework the relevance of the theoretical model's key concepts—such as borrower's net worth, exerted effort, and signal quality—through an analysis of observable indicators. In particular, we investigate the importance of balance sheet strength (with variables such as debt ratios, FX reserves) and expected performance (with variables such as projections of the fiscal balance and growth projections). Indicators for having an IMF program in place, and a broad set of institutional indicators employed in this empirical analysis can also be traced to the theoretical model's concepts of effort exerted by the borrower and borrower's signal quality.

4. Empirical Methodology

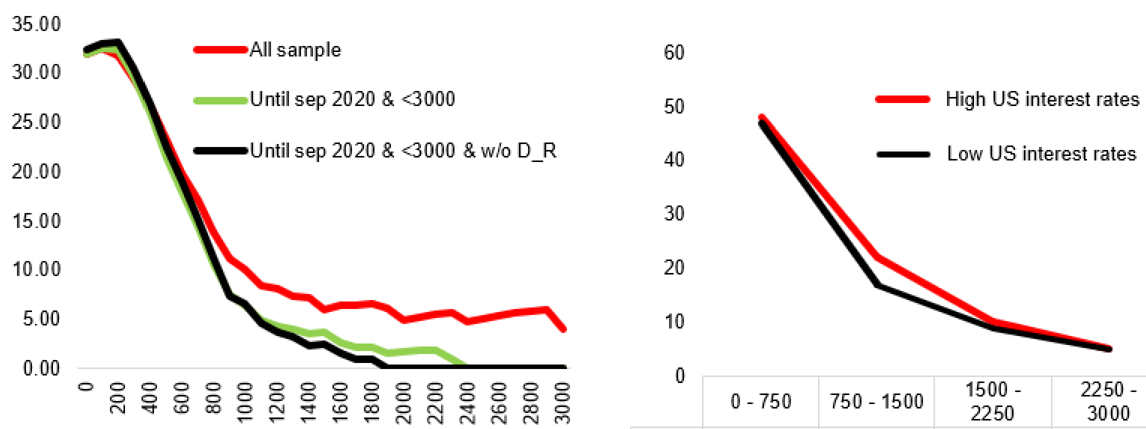
This section outlines the empirical framework used to investigate key determinants of market access. We begin by defining the concept of market access as it applies to our analysis, highlighting its theoretical relevance and practical measurement. We then present the model specification and detail the estimation strategy employed to identify the effects of interest. Finally, this section describes the data sources, construction of key variables, and any relevant sample restrictions.

Definition of Market Access

Two broad measures of market access have been used in the literature: price- and quantity-based measures. The idea of price-based measures goes back to the concept of asymmetric information of Stiglitz and Weiss (1981). The key argument is that higher interest rates reduce borrowers' stake in a project because borrowers receive lower returns in states where they repay the debt (limited liability). As a result, higher rates attract lower quality borrowers and lenders are unwilling to lend at a certain level of rates and credit rationing occurs. As shown by Figure 2, the frequency of issuances indeed declines as spreads increase, and the sharpest decline seems to occur when spreads are between 300 and 800 basis points. Importantly, however, some countries continue to access markets even under relatively high spreads and in the absence of debt restructuring and default. Although yields might intuitively seem to better capture market access than spreads, the evidence suggests that risk-free rates have a comparatively limited impact. Specifically, the right panel of Figure 2 illustrates that U.S. interest rates, as a proxy for the risk-free rate, play a minimal role in explaining issuance decisions. This finding implies that country-specific risk factors and pecking-order considerations are more influential than global financial conditions in determining market access.

Quantity-based measures, on the other hand, address market access directly based on the frequency of actual issuances (e.g. Gelos et al. 2011) or the primary gross issuances (e.g. Fostel and Kaminsky 2007). For our analysis, we focus on the frequency of actual issuances for the following reasons: First, as shown by the figure above, some countries continue to issue debt under relatively high spreads, a phenomenon which is of particular importance for frontier economies and a main interest for this paper. Second, quantity-based measures allow us to assess the importance of factors such as balance sheet strength or the macro-fiscal outlook in addition to spreads, as emphasized by theory. Third, this approach allows us to assess potential non-linear patterns in feature importance for varying levels of spreads.[15]

Figure 2. Frequency of Issuance at Different Levels of Spreads



	0 - 750	750 - 1500	1500 - 2250	2250 - 3000
	48	22	10	5
	47	17	9	5

Note: The left panel shows the cumulative probability of issuing international debt securities when EMBI spreads are greater than certain level for all sample (2000-2022) The series "until sep 2020 & < 3000" does not incorporate issuances after September 2020 (date to which the Trebesch default database was last updated) nor the issuances made with a EMBI spread above 3,000. The series "until sep 2020 & <3000 & w/o D_R" does excludes periods of debt restructuring or default. The right panel shows absolute numbers.

More specifically, our dependent variable is a binary variable, reported at the quarterly frequency, equal to one if a country issued in either quarter t+3 or t+4, and 0 otherwise. In the baseline specification, we forecast issuances three to four quarters in advance as this is the horizon at which the model could be applied in real-time, given data publication lags. However, the results are robust to alternative forecasting horizons. Classes are broadly balanced, with our dependent variable equal to one in 58 percent of the observations and, as a result, we do not use sampling methods in the baseline specification.

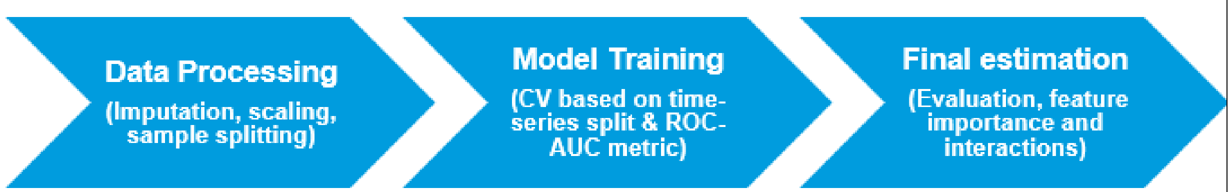
[15] By capturing purely the *number* of issuances, our dependent variable abstracts from complexities such as the desirability or quality of those issuances. In particular, it does not account for variation in terms—such as maturity, pricing, covenants, or other potentially costlier contractual features—that may accompany the issuance decision. In countries with high spreads, which are a focus of the paper, these features are likely to reflect primarily market restrictions. Moreover, some sovereign borrowing is undertaken on behalf of state-owned firms, whereas in other cases these firms issue abroad directly. Countries in the latter group will therefore appear to issue less at the sovereign level, mechanically penalizing them relative to countries where such financing is centralized through the sovereign.

Model Specification and Estimation Procedure

Studies aiming to discern factors enabling countries to access international markets inevitably face an identification challenge (see e.g. Gelos et al. (2011) among others). Generally, a government's decision not to borrow during a particular period could result from either creditors' reluctance to lend (the supply side) or the sovereign's choice not to borrow (the demand side). While an ideal strategy would estimate demand and supply separately, this has proven challenging given data gaps, the need to rely on strong assumptions to help isolate demand from supply components amid incomplete information, and non-intersecting demand and supply curves in the presence of credit rationing. Nevertheless, we think the non-linear interaction effects obtained with our empirical approach are useful to interpret the role of demand and supply factors in predicting market issuance, as they allow us to estimate the effect of, say, a demand factor, holding a supply factor constant, on the likelihood of future issuance.

Our empirical framework is based on a non-parametric machine learning model. Specifically, we estimate a random forest based on Breiman (2001).[16] The outline of the algorithm is the following: First, each decision tree in the forest is trained on a random subset of the data; and second, when building each tree, a random subset of features (explanatory variables) is considered at each decision point. This randomness helps ensure that the individual trees are diverse and not overly correlated. For the outputs depending on regressions, the final prediction is the average of all tree predictions, while for outputs depending on classification, it is based on the majority vote from the trees. This ensemble approach enhances the model's accuracy and reduces the risk of overfitting, providing a more robust and reliable prediction compared to using a single decision tree. For comparison, we also apply the same procedure to estimate a Logit model,[17] incorporating three different regularization techniques (lasso, ridge, or no regularization).[18]

Figure 3. Estimation Procedure



The estimation procedure is well-established (Hyndman and Athanasopoulos, 2021) and outlined in Figure 3. In the first stage, we combine source datasets, and missing values are imputed using K-nearest neighbors' imputation. After imputation, we add variable transformations including percentages of GDP,[19] growth rates,

[16] The term 'random' refers to these two key steps of the algorithm. The term 'forest' reflects the fact that the model uses many decision trees, each making its own prediction.

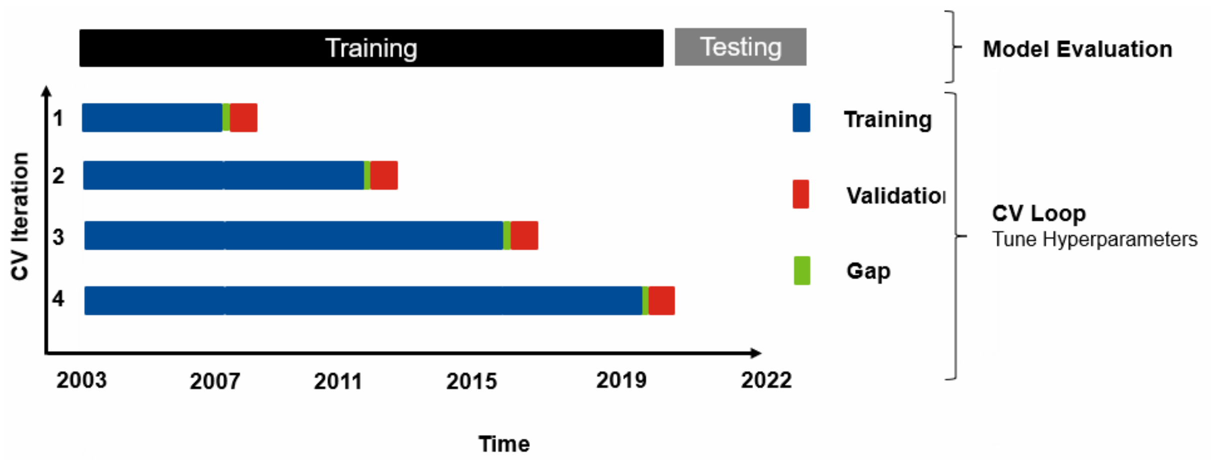
[17] The Logit model is used to estimate the probability of a binary outcome (0 or 1) based on a set of predictor variables, using a logistic function to model the relationship between the inputs and the outcome. Logit models are non-linear in the dependent variable but linear in parameters.

[18] Specifically, lasso regularization adds an L1 penalty (i.e., the sum of the absolute values of the model coefficients) to the log-likelihood function, and optimizing over this function can yield several coefficients estimates to be exactly zero, effectively selecting a subset of features that are most predictive. Ridge regularization, on the other hand, applies an L2 penalty, shrinking coefficients but not setting them to zero, which can help mitigate multicollinearity and improve stability in the estimates.

[19] Converting variables that are in units of national currency to ratios (i.e., as a proportion of GDP) helps avoiding inconsistencies due to currency units and the impact of changing price levels due to imputation.

average growth rates and variances of growth rates. Finally, the sample is split into a training set (2001Q1-2021Q4) and a testing set (2022Q1-2023Q2).[20]

Figure 4. Expanding Window Approach Here



To train the hyperparameters of the model, we implement a cross-validation procedure based on an expanding-window time-split approach, designed to account for the temporal structure of the data and avoid look-ahead bias. To further prevent data leakage, we introduce a one-period gap between the end of the training set and the beginning of the validation set (see Figure 4). Specifically, the training data is partitioned into four folds, each consisting of an in-sample training subset and an out-of-sample validation subset defined by an expanding time window. In each fold, the training period is iteratively extended by a fixed number of quarters, while the validation period remains constant, covering the four quarters following the training window plus the one-quarter gap. This setup closely mirrors the model's intended real-time use, where only information available at the time of prediction is used. As a performance metric, we use the area under the Receiver Operating Characteristic curve (ROC-AUC), averaged across the four validation sets in the cross-validation procedure, to identify the optimal hyperparameter configuration for each model type.
In parallel, we apply a recursive feature elimination (RFE) procedure to systematically reduce the dimensionality of the feature space (see Weston et al. 2002). At each iteration, the model is trained using the current feature set, and the best-performing hyperparameter combination is selected based on the average ROC-AUC across all validation splits. Feature importance metrics from the model are then used to identify and remove the least informative predictors. This process is repeated until a predefined minimum number of features (80 in the baseline model) is reached.[21]

Finally, the model is re-estimated on the full training set using the selected hyperparameters and reduced feature set, and performance is evaluated on the out-of-sample test data. A summary of the best performing hyperparameters is provided in Annex IV.

[20] This implies a 90/10 percent split between the training and the testing sample.

[21] The recursive feature elimination process was stopped at 50 features because the model's cross-validated mean AUC stabilizes around this point (see Annex III).

Data

We use quarterly data for all EMDEs with available EMBIG spreads over the period from 2000Q1 until 2023Q2. The date selection is based on a trade-off between sufficient historical coverage and data availability while countries are included if EMBIG spread data is available. Data for international issuances is based on the BIS debt security statistics which covers all sovereign issuances under international law.[22]

Our set of explanatory variables (see Annex II for details) comprises 99 base variables, including all key predictors identified in the existing literature, along with a few novel additions—most notably, forward-looking variables from the IMF's World Economic Outlook (WEO) forecasts. These series, obtained from sources including the WEO, IMF IFS, World Bank IDS and Bloomberg, span a broad range of domains, covering macroeconomic fundamentals, fiscal and external indicators, global conditions, and financial market dynamics. For analytical clarity, they can be grouped into three main categories: macroeconomic variables, global factors, and primary market data. Macroeconomic variables encompass standard indicators such as GDP, fiscal balances, public debt (both in gross and net terms),[23] real GDP growth, inflation, exchange rates, trade and current account balances and gross financing needs. Global factors capture the external environment affecting sovereign issuance, including measures of global risk sentiment (e.g., the VIX), U.S. interest rates, and global growth trends. Finally, primary and secondary market data reflects past activity in sovereign debt markets, such as gross and net bond issuances, CDS and EMBIG spreads. Collectively, these variables offer a comprehensive representation of the domestic and international factors that influence sovereign issuance decisions. In total, our dataset covers 94 quarters and 46 countries.

5. Empirical Results

We first present the results of the random forest showing feature importance, assessed using Shapley values, as well as Partial Dependence Plots (PDP), to show how individual features influence predictions (model fit is discussed in the next section). Shapley values attribute the model's predictions to individual features by considering all possible combinations of inputs. This method offers consistent and locally accurate explanations of feature contributions and is widespread in machine learning. The mean absolute Shapely values for the top 15 base features are summarized in Figure 5.24 Since these figures reflect the absolute importance of features in explaining model predictions, but do not indicate the direction of their effects, we also present partial dependence plots for the top 15 features (see Figures 6 and 7).25 These plots show how the predicted outcome varies with a single feature, averaging over the distribution of all other covariates. This approach isolates the relationship between the feature of interest and the prediction, smoothing out the influence of all other covariates.26 Because PDPs show changes due to a variable averaging over the other covariates, the

[22] Note that these issuances can be denominated in various foreign currencies, not only USD, but excludes local currencies

[23] For the relevance of gross and net public debt in explaining emerging market sovereign spreads, see Hadzi-Vaskov and Ricci (2022).

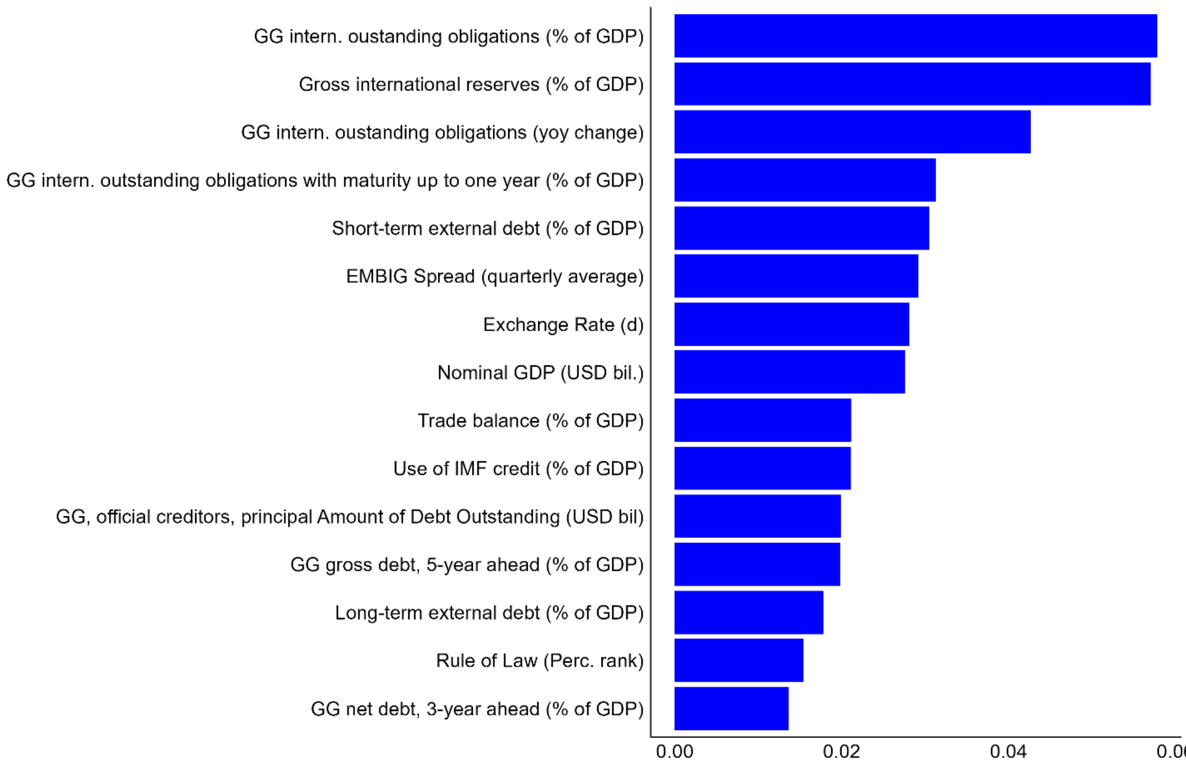
[24] Annex IV also provides a summary of the top features in the Logit model.

[25] For this exercise we selected features individually and do not aggregate by base variable.

[26] Importantly, PDPs are different from marginal effects in a regression as they show the average predicted change in the outcome as a single feature varies, averaging over the distribution of all other covariates, rather than the conditional effect holding other variables fixed. Even when a predictor is influential in a model such as a random forest, the average change in predicted probabilities is often modest, because nonlinearities and interactions with other features are averaged out. In other words, the partial dependence isolates the ceteris paribus effect of a single feature, which naturally smooths the variation observed across individual observations (Friedman, 2001).

results may seem smaller than what would be found for parametric models' marginal effects, but this doesn't imply that effects are small.

Figure 5. Random Forest Shapley Feature Importance



Note: Mean absolute shapely values of top-15 predictors in the random forest model, aggregated by base variables (third to sixth lag).

Balance sheet-related features. Four of the five most important features in the model relate to external debt. These include the total and short-term general government (GG) international outstanding obligations (with short-term defined as residual maturity of up to one year), the year-over-year change in GG international obligations (i.e., net issuances), and the total short-term external debt. The partial dependence plots show that sovereigns with larger stocks of outstanding obligations (and thus greater financing needs) are more likely to issue international bonds: increases in total and short-term outstanding sovereign international debt securities are both associated with a higher predicted probability of issuance. The relationships appear to be nonlinear: the effect is strongest at moderate levels of outstanding debt but tends to plateau as debt levels become elevated. This flattening may indicate supply-side constraints or limits to market access when debt burdens reach high levels. The partial dependence plot for changes in general government outstanding international securities shows that countries are most likely to issue following modest increases in outstanding debt, while larger increases actually reduce the likelihood of issuance.

The last top-five variable is gross international reserves, another feature capturing balance sheet strength. Although in theory reserves may act as a signal of creditworthiness or policy strength, helping countries maintain or regain access to international markets (see, e.g., Alfaro & Kanczuk, 2009; Bianchi, Hatchondo & Martinez, 2018), the partial dependence plot implies that countries with higher reserve levels tend to issue less frequently, most likely because reserves can be used and substitute for external financing. [27] Finally, the importance of long-term external debt further suggests that not only the level but also the composition and maturity profile of debt plays a critical role in determining market access.

Forward-looking features. The model identifies several forward-looking debt variables as relevant predictors—most notably WEO projections for the fiscal balance and for public debt. This result underscores the importance of expectations about a country's future fiscal trajectory, in line with theory. Projections that debt will be high as a share of GDP tend to lower the probability of issuance, reflecting the intuitive concern that increased debt raises credit risk and borrowing costs. A similar result holds for projections of the fiscal balance, with a sharp change in the predicted probability of issuance occurring around the zero threshold. Specifically, countries with projected fiscal balances that are positive three years ahead are significantly more likely to issue than countries with expected deficits, suggesting that fiscal discipline enhances market access—see also IMF (2021) and End and Hong (2022).

External sector-related features. External sector characteristics play a significant role in the model. Countries with a more positive trade balance are found to be less likely to issue debt on international markets. This likely reflects the fact that trade surpluses reduce the need for external financing by generating sufficient foreign exchange earnings to meet balance of payments and fiscal needs. The exchange rate regime also influences market issuance, with issuance less likely for fixed exchange rate regimes, possibly because under these regimes, the sovereign's options to capture FX resources to repay external debt are limited. The Nominal Effective Exchange Rate (NEER) also appears to matter, with a substantial non-linearity around 0: countries experiencing currency appreciations have a higher likelihood of issuance, whereas the effect is less clear for countries whose currency is depreciating.

Official debt. The impact of official debt—including both total outstanding obligations to official creditors and IMF credit outstanding—on market access is expected to be complex: while official financing may crowd out private capital by signaling distress or generating concerns around the seniority of debt, official support can have a catalytic effect, helping to restore market confidence by addressing liquidity issues and signaling macroeconomic discipline. Shapley values indicate that official debt and IMF financing are indeed important, and partial dependence plots show substantial non-linearities. Higher outstanding amounts of official creditor debt are associated with a lower likelihood of market issuance, but this relationship flattens at higher debt levels, indicating diminishing marginal effects of official debt on issuance probability. Similarly, the probability of market issuances increases when official outstanding debt has previously declined, whereas positive changes in official debt correspond to a significantly lower but relatively flat issuance probability.[28]

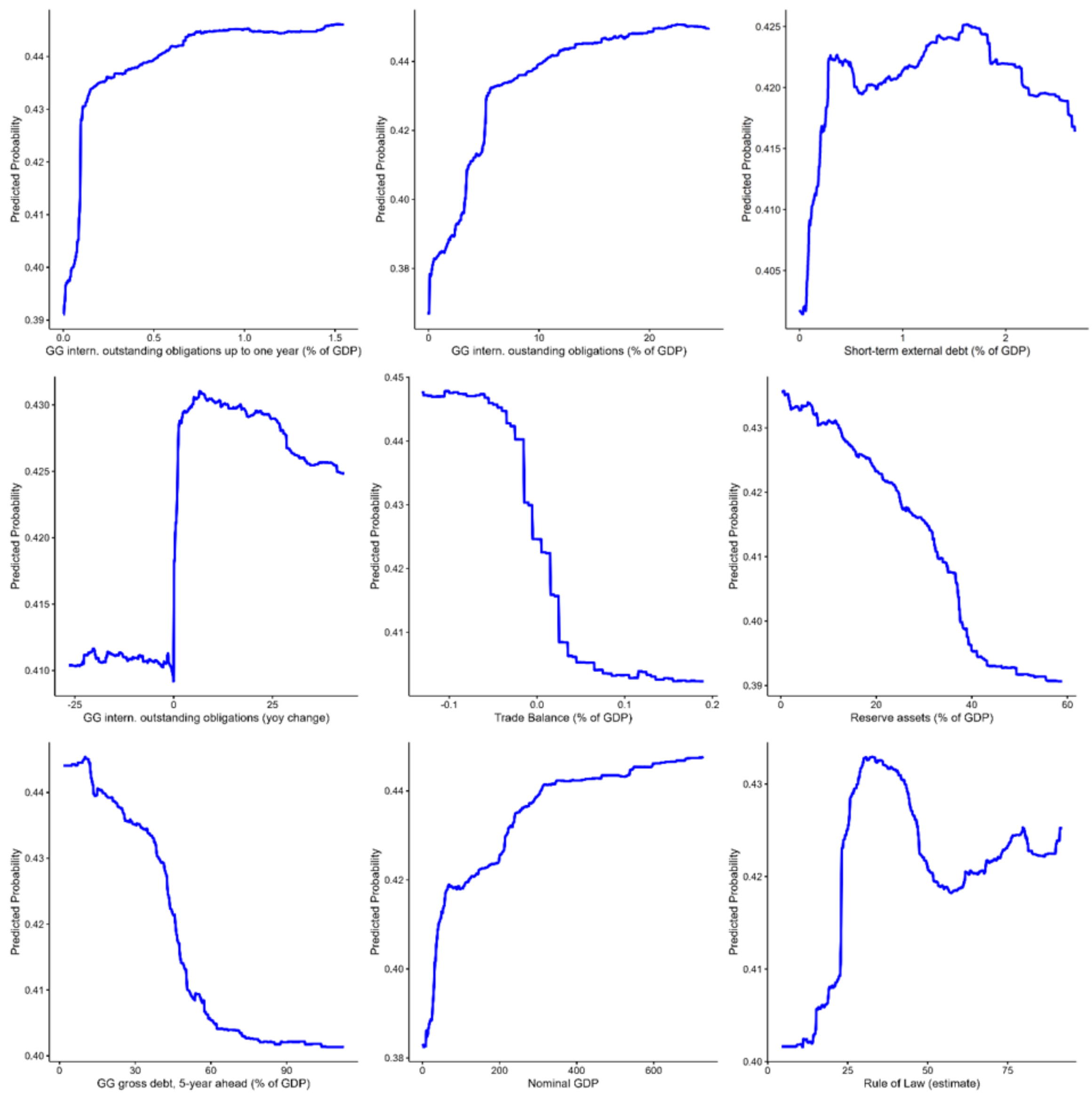
These patterns likely reflect both demand- and supply-side dynamics: on the demand side, countries may shift toward market financing as official support wanes and vice versa; on the supply side, official creditor debt can crowd out market financing due to its seniority in the debt structure. These findings align with Krahnke (2023) and others who argue that official lending can either catalyze or displace private capital depending on market

[27] This relationship likely reflects a demand effect—countries with lower reserves need to borrow more externally due to weaker self-insurance. However, a supply-side channel may also be present, as low reserves can reduce investor willingness to lend. The partial dependence plot averages over the entire data set, indicating that the demand channel dominates in the model's predictions. Interestingly, this negative relationship is also present in various sub-samples (grouped by EMBIG spreads of IG vs. non-IG countries).

[28] Note that the PDP for IMF credit is not included as it does not appear among the top 25 individual features.

conditions, the overall size of official loans and concerns about debt sustainability.[29] Finally, the interest rate on new official credit is also among the top predictors, showing a clear negative relationship: lower official rates are associated with a higher likelihood of market issuance.

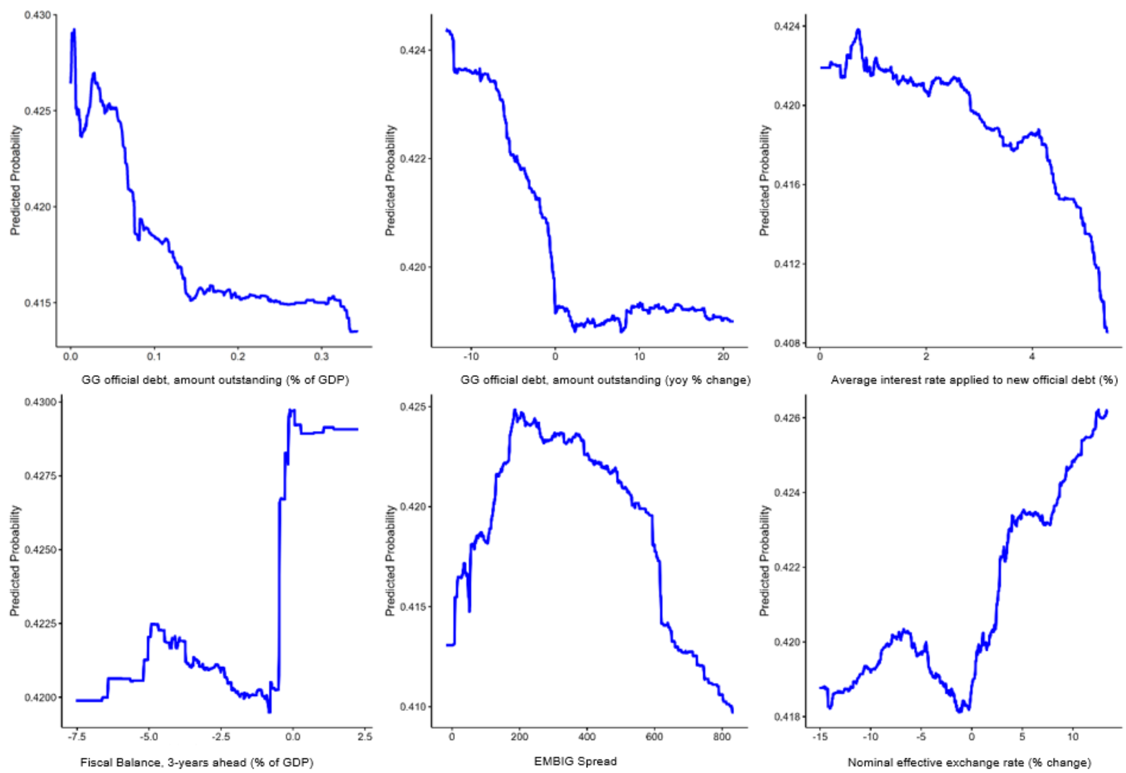
Figure 6. Partial Dependence Plots - Top Features



Note: Partial dependence plots for the top 15 individual predictors identified by the random forest model using mean absolute Shapley values, excluding binary variables. When a variable appeared in multiple transformed versions, only the most important transformation was included.

[29] Note that the x-axis of the PDP is cut at approximately 3.5% of GDP for outstanding official debt, as the partial dependence function cannot be calculated for extreme values with very few observations. A sharper decline in issuance probability could occur for higher levels of official debt, consistent with the findings of Krahnke (2023).

Figure 7. Partial Dependence Plots - Additional Features



Note: The partial dependence plots include additional features ranked up to the top 25 individually, beyond the top 15 shown earlier. This is because Shapley values are aggregated by baseline contributions, and not all features reflected in the Shapley importance are included among the top 15 in the PDP analysis.

Structural factors. Finally, institutional and structural factors emerge as significant predictors.

- Nominal GDP, a proxy for economic size, is among the most important predictors. This is consistent with prior research (e.g., Gelos et al., 2011), which shows that larger economies are more likely to access international markets, possibly due to deeper financial systems, greater visibility among investors, and a perception of lower rollover risk.

- Stronger governance, particularly improvements in the rule of law, is positively associated with sovereign debt issuance, as shown in the corresponding partial dependence plot, and consistent with the literature. Notably, this relationship is nonlinear, with the strongest marginal effects occurring between the 15th and 40th percentiles of the rule of law indicator. Similar nonlinear patterns emerge for other governance indicators, such as regulatory quality and political stability. One interpretation for this non-linear pattern is that there are diminishing returns to credibility once institutional quality exceeds a certain threshold, beyond which other factors—such as market size, global financial conditions, or policy space—become more influential. However, it is worth noting that the economic magnitude of these effects is relatively modest, as indicated by the small differences in predicted probabilities.

Annex IV shows that feature importance remains broadly stable across sub-periods (2002-2007, 2008–2014, and 2015–2021), suggesting that the main determinants of international debt issuance are robust to changes in the global environment. However, a few exceptions stand out. Indicators of IMF financing and exchange rate regimes are more influential in earlier periods, likely reflecting greater reliance on multilateral support and more varied exchange rate frameworks prior to the global financial crisis. In contrast, forward-looking fiscal indicators—such as projected debt ratios—gain prominence in more recent years, potentially indicating a shift in investor focus towards medium-term debt sustainability and fiscal outlooks in a post-crisis environment characterized by elevated debt levels and tighter market scrutiny.

EMBI Spreads and Supply vs. Demand Factors

In line with previous findings (see, e.g., Kogan et al., 2023), EMBIG spreads emerge as a key factor influencing a country's likelihood to issue debt on the international market, as they reflect global investor sentiment and perceived sovereign risk. However, spreads are not the most important feature, and, as we argue below, they seem to matter especially when interacting with other features.

First, one can note that the partial dependence plot displays a non-linearity: there is a clear inverted U-shaped relationship, with the predicted probability of issuance increasing with the EMBIG spread at low levels, and peaking around 200 basis points (bps). Beyond this point, the probability of issuance begins to decline, with the sharpest drop occurring around 600 bps. This pattern suggests that at moderate spread levels, countries may still access international markets, possibly taking advantage of favorable conditions or responding to moderate financing needs. However, once spreads rise above a certain threshold, elevated borrowing costs appear to deter issuance, likely reflecting reduced market access.

This finding is consistent with supply vs. demand factors dominating at different levels of spreads: in particular, at low spreads, market issuance is likely to be more common when there are larger financing needs, whereas at high spreads, market issuance would depend on supply of funds, i.e. on the willingness of investors to purchase bonds and thus on the capacity of the sovereign to credibility commit not to default.
Since a key strength of the random forest model is its ability to capture nonlinear interactions between features, we next divide the data into three samples based on EMBI spreads: low, medium, and high. We think this strategy also helps us disentangle demand vs supply factors. The cut-off values are defined as follows: low spreads are those below the 40th percentile (approx. 200 basis points), medium spreads fall between the 40th and 80th percentiles (approx. 200–500 basis points), and high spread correspond to EMBI spreads above the 80th percentile (500 basis points).[30] We use this classification to (i) assess whether the top 15 most important features differ across the three spread groups, and (ii) examine whether the influence of these features on a country's likelihood to issue international debt varies depending on the level of market stress, as proxied by its EMBI spread.

Figure 8 shows the top 15-features for the three subsamples, again aggregated by base variables while Figure 9 presents partial dependence plots for the three subgroups.[31] Overall, variables are largely consistent across the low, medium, and high spread groups. For example, the amount of outstanding sovereign international obligations—both long-term and short-term—international reserves, and sovereign spreads are among the top predictors in all groups. Additionally, nominal GDP, the use of IMF resources, and long-term debt also rank

[30] Note that the grouping based on EMBI spread percentiles allows for a dynamic classification over time. While this approach captures nonlinear effects more flexibly, it may introduce sample composition changes across periods, which could affect comparability and interpretation of feature importance.

[31] Note that the range of predicted probabilities in the partial dependence plots is relatively narrow because these plots average over the distribution of all other features. As a result, they reflect the *average marginal effect* of each variable rather than the full variation captured by the model.

highly. In fact, 9 of the top 15 predictors are common across all three spread groups, indicating strong overlap in key drivers.

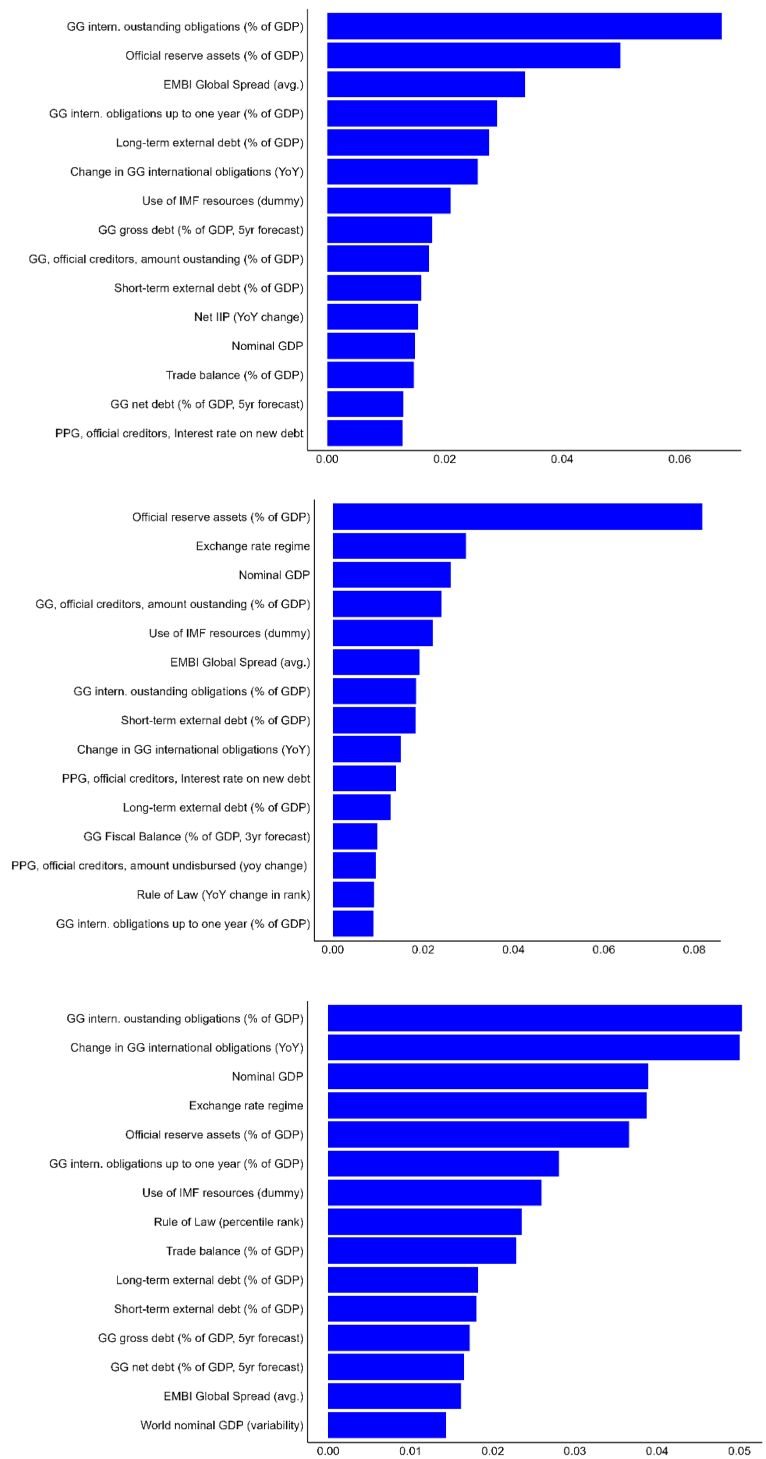
However, there are some notable differences. Issuances at high spreads are less frequent, which aligns with expectations. Second, there are interesting differences that provide evidence that countries with higher spreads face tighter supply constraints.

- ***Outstanding debt and maturity structure.*** An increase in the amount of outstanding international sovereign obligations in percent of GDP has little effect on issuance probability at low spreads. In contrast, the probability initially rises—but then declines—at medium- and high-spread levels as obligations increase further. Similarly, high-spread cases see a decline in issuance probability at very high levels of short-term international debt securities, whereas low- and medium-spread cases remain largely unaffected. Most notably, low-spread countries with higher levels of long-term external debt are the most likely to issue, while the opposite holds for medium- and high-spread countries. Theoretically, the effect of long-term external debt on sovereign issuance could go in either direction: On the one hand, higher long-term debt may signal market credibility, reduce near-term rollover risk, from the investor perspective, it could also benefit from strong appetite for long-term instruments, facilitating additional issuance. On the other hand, long-term debt can increase perceived default risk via debt dilution channels (see e.g. Hatchondo et. al, 2016) and increased exposure to currency and debt composition constraints. The results suggest that, for low-spread countries, the positive signaling and investor appetite effects appear to dominate, whereas for medium and high-spread countries, the observed negative relationship could reflect both lower demand (e.g., reduced short-term rollover needs) or constrained supply of funds (e.g., due to debt dilution).

- ***Official debt.*** High-spread countries are less likely to issue when they have larger volumes of outstanding official debt, suggesting a potential crowding-out effect from concessional or bilateral lending. Interestingly, the opposite pattern emerges with IMF credit, where a higher amount outstanding is associated with a greater likelihood to issue. This may reflect the signaling effect of IMF programs, which can restore market confidence and unlock market access (see e.g., Mody and Saravia 2006, Krahnke 2023, Chahine et al. 2015). In contrast, at low and medium spreads levels, issuance is largely insensitive to the levels of either official debt or IMF credit. Committed but undisbursed official credit also appears among the top predictors in the high spread group. This suggests that even off-balance-sheet commitments can crowd out private funding or raise concerns about future debt service obligations, influencing sovereign risk.

- ***Global conditions.*** It is also notable that under high spreads, issuances are more likely during periods of strong global economic growth, providing further evidence for supply-side constraints: these cases may only be able to access markets under favorable global conditions—likely driven by heightened investor risk appetite and a search-for-yield environment during global upswings. In contrast, low-spread countries are more likely to issue during periods of weaker global growth, suggesting a counter-cyclical issuance pattern that aligns with fiscal policy needs rather than market timing.

Figure 8. Feature Importance for Low, Medium vs. High Spread Observations



- ***Fiscal projections***. Based on Shapley values, debt projections are less important for the high spread group, where projected fiscal balances become more prominent among the top predictors. This may reflect that, for countries facing higher spreads, investors focus more on the fiscal adjustment and financing needs rather than long-term debt trajectories. The PDP, however, still suggests the a strong negative relationship between projected debt levels and likelihood of issuance for the high spread group.

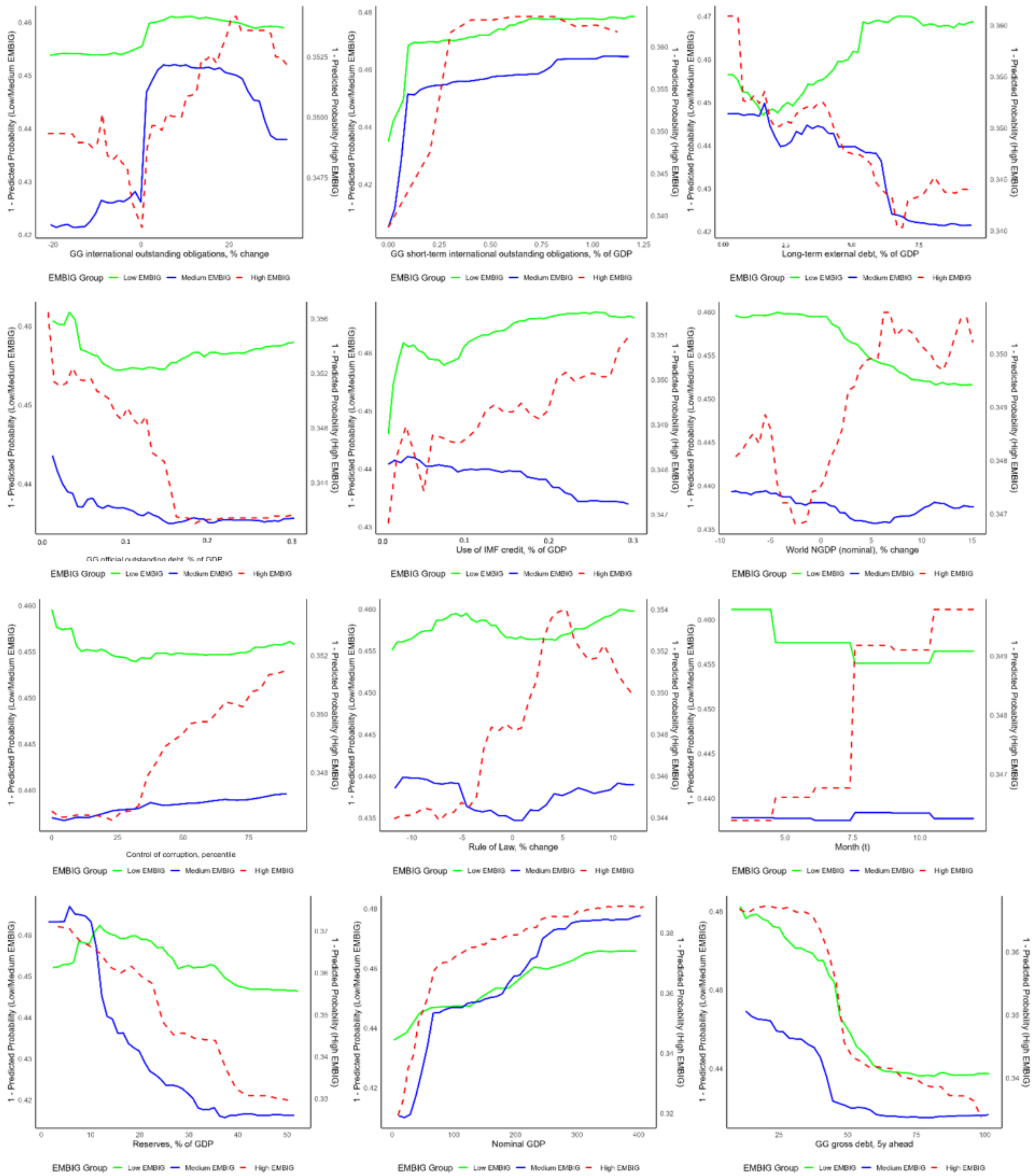
- ***Reserves.*** It is also interesting to note that gross international reserves emerge as the most important predictor for the high spread group. While the probability of issuance declines notably as reserves rise for high and medium spread countries, the relationship between reserves and issuance probability is flatter, for lower spread countries, indicating that reserves are less important. This pattern underscores the role of reserves as a form of self-insurance that is particularly relevant for riskier sovereigns.

- ***Exchange rate regime.*** The exchange rate regime is significantly more important for medium and high-spread situations, ranking even as the second most important predictor for the high-spread group. One possible intuition is that rigid exchange rate regimes in high-spread countries may signal vulnerability to external shocks and limited capacity to adjust to generate foreign exchange. thus

- ***Governance.*** Market access appears more sensitive to governance indicators in high-spread situations. Improvements in the control of corruption and in the rule of law are both associated with a significantly higher probability of issuance for these cases. Meanwhile, issuance in medium- and low-spread situations show little sensitivity to governance, possibly because governance is less critical to repayment prospects when the fiscal situation is strong.

- ***Timing.*** Finally, timing patterns suggest that high-spread countries tend to issue later in the year, particularly in the third and fourth quarters, whereas low- and medium-spread countries are more likely to issue early in the year. This could indicate that high-spread countries issue reactively, possibly once other funding options are exhausted, or budget pressures become acute.

Figure 9. Partial Dependence Plot for Low, Medium vs High Spread Observations



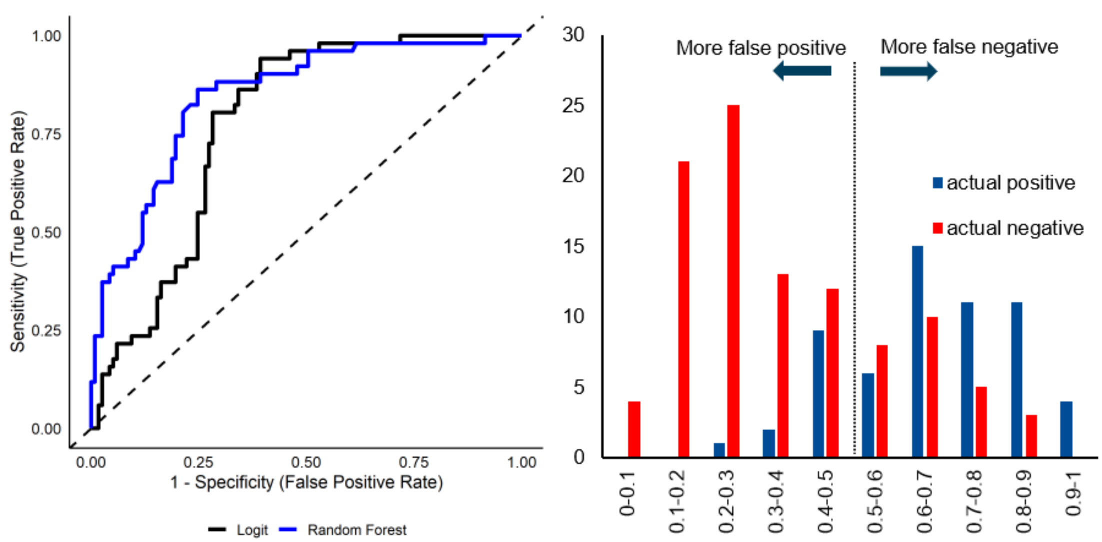
Note: Partial dependence plots for observations grouped by EMBIG spread level: Low EMBIG <200bps, Medium EMBIG>200 & <500bps and high EMBIG >500bps. The model was estimated for each subsample separately, and then used to calculate partial dependencies. Excludes episodes of debt restructuring and default.

6. Model Performance

The model described in the previous section works well according to standard metrics and is an improvement over a traditional parametric model such as the logit model. The ROC-AUC (Receiver Operating Characteristic – Area Under the Curve), which measures the model's ability to discriminate between the positive and negative classes across all possible classification thresholds,[32] is particularly useful in classification problems, as it evaluates performance independent of any specific threshold and accounts for both sensitivity (true positive rate) and specificity (false positive rate). The ROC curves of the random forest model and the logit model are plotted in the left panel of Figure 10. In our case, the random forest model achieves an ROC-AUC of 0.84, which indicates strong predictive performance and suggests that the model is highly effective at distinguishing between future issuers and non-issuers. The best performing logit model, on the other hand, achieves a notably lower ROC-AUC score of 0.77.

As an additional evaluation tool, we examine a plot that displays the distribution of actual positives and negatives across predicted probabilities, represented by the right panel in Figure 10. In this plot, the x-axis represents the model's predicted probabilities, while the y-axis shows the number of observations. Separate bars are used to indicate the counts of actual positives and negatives within each probability bin. This visualization allows us to assess how well the model distinguishes between the two classes: a well-performing model should assign higher predicted probabilities predominantly to positive cases and lower probabilities to negative cases, resulting in a clear separation. The vertical dashed line in the figure marks the threshold that maximizes the F1 score. As can be seen, adjusting this threshold involves a tradeoff: for example, while a high threshold reduces the number of false positive predictions (improving precision), it risks missing actual positives (lowering recall).

Figure 10. ROC Curve and Actual Positive vs Actual Negative Predictions



Note: ROC curves (left) and predicted probabilities of the RF model for the actual positive and negative observations (right).

[32] A score of 0.5 indicates no discriminative power (equivalent to random guessing), while a score of 1.0 reflects perfect classification.

7. High Spread Issuances

We finally provide an in-depth analysis of issuances at high spreads, to understand better their characteristics. For this purpose, we construct a database of the issuances of small, frontier EMDEs (economies with nominal GDP below US$300 billion) that took place since 2012Q1 at spreads above 437 bps (the sample mean in this restricted subsample).[33] We identify 84 issuances of 16 different economies with EMBI spreads ranging from 437bps to 3206 bps. Given the theoretical finding that unconventional features like contingencies or guarantees can restore market access, we also seek to identify potentially unconventional features of these international issuances. For this purpose, we rely on five main sources: Bloomberg, Bond Radar, Cbonds, Perfect Information (LEG) as well as news articles one week prior and after the issuing date.[34]

Figure 11 summarizes the main patterns we observe in the data. First, we find that most high-spread issuances occur in Latin American countries, regardless of the specific spread threshold used. On average, these issuances are also the largest—measured as gross issuance in percent of GDP—in Latin America. Second, the number of high-spread issuances has increased over time, with roughly one-third of all such cases in our sample occurring between 2019 and 2022. During this period, the average size of high-spread issuances was also larger compared to earlier years. Third, most high-spread issuances take place in the absence of debt restructuring or default, although they tend to be smaller than those issued during restructuring episodes. Fourth, while the majority of high-spread issuances occur without an active IMF arrangement, countries are approximately five times more likely to have an ongoing IMF program when issuing at high spreads compared to the full sample.

Finally, in line with the intuition derived in the model, we find that a significant share of the issuances (36 percent) include special features such as guarantees or collateral, mostly in the form of sinkable bonds (see Figure 12). When we increase the threshold further to 600bps (grey bars) the share of unconventional issuances increases even further to 42 percent. We further find that unconventional issuances tend to be larger compared to conventional issuances at high spreads, again well in line with intuition. At the same time, it is interesting to note that some countries continue to issue conventional bonds without enhancements even under elevated spreads. Several factors could explain this pattern. First, speculative investor demand or favorable market sentiment may allow borrowers to access markets without additional safeguards. Second, credible policy reforms or institutional improvements may signal lower default risk, reducing the need for enhancements. Finally, legal or institutional constraints may limit the ability to structure complex instruments, forcing borrowers to rely on conventional debt even in high-spread environments. These factors suggest that, while state-contingent or enhanced instruments are more common at high spreads, the choice of debt instrument also depends on broader market, policy, and institutional conditions.

[33] Note that we focus on the period starting in 2012 because as we rely on additional data sources with limited data availability in earlier periods. The results are robust to increasing the threshold spread.

[34] New based information is based on Factiva; Bloomberg data is accessed via the Sovereign Debt Metrics.

Figure 11. High Spread Issuances

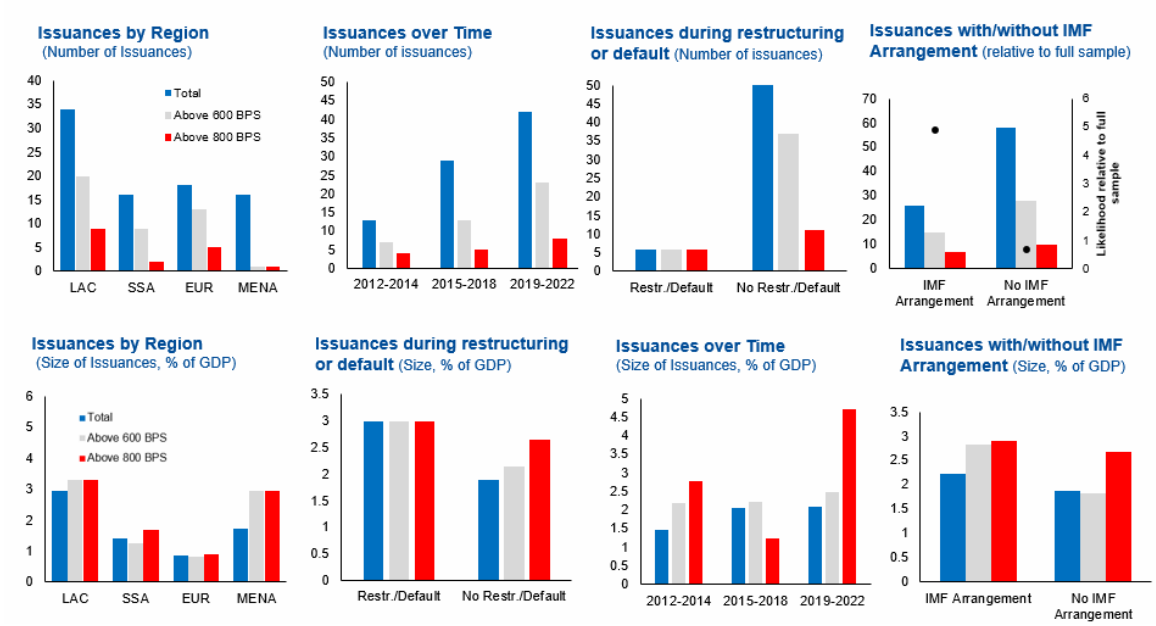
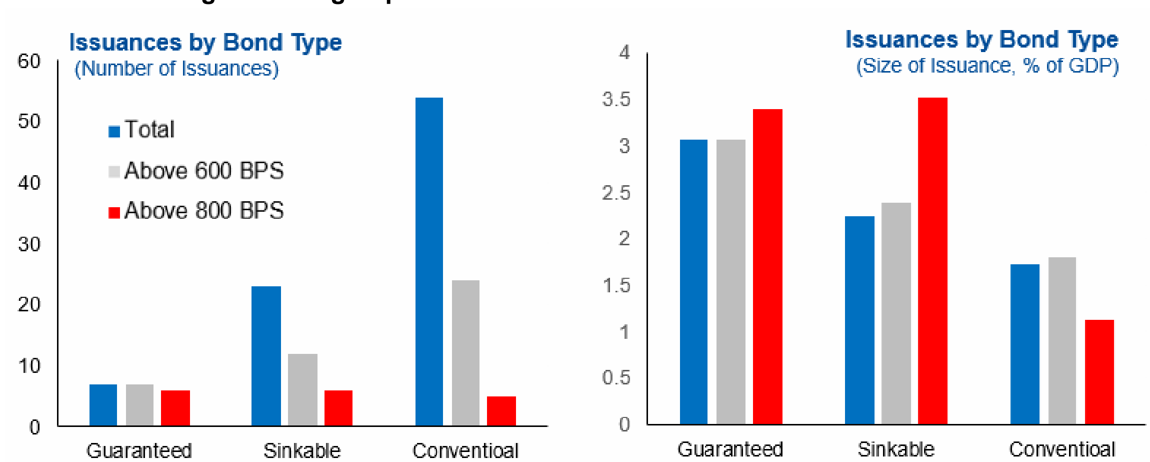


Figure 12. High Spread Issuances with Unconventional Features



8. Conclusion

This paper explores the determinants of emerging markets' access to international capital markets, combining theoretical insights with empirical analysis. A simple theoretical model illustrates the central role of risk, borrower's net worth, exerted effort, signal quality and repayment costs in shaping market access, while also highlighting the trade-offs between risk sharing and moral hazard. Empirically, we apply a random forest model to identify key predictors of market access, captured by the likelihood of issuance, and find that outstanding international obligations, international reserves, short-term debt, sovereign spreads, and the size of the economy consistently rank as the most important factors. We uncover significant non-linear interactions, indicating that market access is shaped by the interplay of multiple variables rather than any single factor.

Notably, the impact of some variables changes with the EMBIG spread level. For example, countries with high spreads are more sensitive to factors such as exchange rate regimes, official credit, global financial conditions, governance quality, and international reserves—suggesting that investor concerns shift under heightened risk. Partial dependence plots segmented by spread levels offer insights into supply and demand dynamics. In particular, for high-spread countries, the probability of issuance declines even as refinancing needs (i.e., short-term debt) increase, pointing toward more stringent supply constraints. Finally, a novel dataset on high-spread issuances reveals that these are often structured through non-traditional mechanisms, in line with theoretical predictions. Together, the findings emphasize the importance of both sound fundamentals and tailored financial instruments to secure market access under stress.

Overall, our findings provide insights that could help inform discussions centered on gaining or regaining market access. Our empirical analysis emphasizes the broad set of factors that matter when assessing market access, the value of looking beyond sovereign spreads as its determinant, for instance with the inclusion of comprehensive forward-looking aspects, and the importance of non-linearities in the determinants of the likelihood of bond issuance.

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Annex I. Proofs Omitted in the Main Text

Proposition 1: Nonbinding ICC

First, consider the case where the incentive compatibility constraint is non-binding, i.e., $\mu_{ICC}=0$. Combining equations (3) and (4) then implies $u'(\theta=G, s=H) = u'(\theta=G, s=L)$ and thus $r_H=r_L$. Hence, if the ICC is non-binding, the borrower equalizes the two signal-dependent interest rates given its preference for smooth consumption. Note that this result is partly driven by the assumption discussed above that interest rates can only be signal-dependent but not state-dependent. The equilibrium interest rate is then given by the PC which implies:

$r_H = r_L = r^{**} = \frac{1}{\pi(e_H)}$.

Hence, the equilibrium interest rate exactly compensates lenders for the riskiness of their investment such that their expected net return is zero. There is no credit rationing in the market, and all borrowers can issue the desired amount of debt in the market. Note that this is also the first-best allocation in the model.

This is an equilibrium if the ICC is indeed nonbinding, i.e.,

$$\Delta\pi\, R^H > \pi(e_H)\, B + (K - A)\,(1 + r^{**})\Delta\pi \quad (4)$$

Proposition 2: Binding ICC

Now consider the case where the ICC is binging such that $\mu_{ICC}>0.$ In this case, the signal dependent interest rates are determined by the PC and the ICC which imply:

$$(1 + r_L^*) = \frac{\left(\pi(e_H)B + (K - A)\,\dfrac{(\pi(e_H)q_H - \pi(e_L)q_L)}{\pi(e_H)q_H} - \Delta\pi R^H\right)}{\dfrac{(K - A)\pi(e_L)\,[q_H - q_L]}{q_H}}$$

$$(1 + r_H^*) = \frac{\dfrac{1}{\pi(e_H)} - (1 - q_H)(1 + r_L^*)}{q_H}$$

The Lagrange multipliers are then determined by the FOCs, which imply,

$$\mu_{ICC}^* = \frac{[\pi(e_H)\,(1 - q_H)u'(g, L) - u'(g, H)]}{\pi(e_L)\left[\,(1 - q_L) - \dfrac{q_L}{q_H}(1 - q_H)\right]}$$

$$\mu_{PC}^* = u'(g, H)\,(K - A) - \mu_{ICC}^*\,(K - A)\left[\frac{\pi(e_L)q_L}{\pi(e_H)q_H} - 1\right]$$

This is an equilibrium if and only if $\mu_{PC}^{*} > 0$ and $\mu_{ICC}^{*} > 0$ as well as $R^{H} - (A\text{-}K^{*})(1+r(s)) \geq 0.$

Now, to show that $r_L > r_H$, note that this is true if

$$\frac{\left(\frac{1}{\pi(e_H)} - (1-q_H)(1+r_L)\right)}{q_H} < (1+r_L)q_H,$$

which implies

$$(1+r_L) > (1+r^{**}).$$

As shown by proposition 1, this always holds if the collateral constraint binds.

Annex II. Data

Table 1. Features Included in the RFE Process			
Description	**Frequency**	**Source**	**Transformations Included**
Nominal GDP, USD billion	Quarterly	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
EMBIG, J.P.Morgan EMBI Global, Index, quarterly average	Quarterly	Bloomberg	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
International sovereign debt securities, gross issuance, USD million	Quarterly	BIS Debt Statistics	% of GDP
International sovereign debt securities, net issuance, USD million	Quarterly	BIS Debt Statistics	% of GDP
International sovereign debt securities, amount outstanding, USD million	Quarterly	BIS Debt Statistics	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
International sovereign debt securities, amount outstanding with maturity up to one year, USD million	Quarterly	BIS Debt Statistics	% of GDP
Period of Restructuring or default, dummy	Quarterly	Asonuma & Trebesch	Dummy
Total external debt, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, total arrears, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, banks external debt, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, official debt, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, official debt, short-term, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, long-term, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, short-term, USD billion	Quarterly	WB IDS	% of GDP
Total external debt, short-term, remaining maturity basis, USD billion	Quarterly	WB IDS	% of GDP
External debt stock, public and publicly guaranteed, USD billion	Quarterly	WB IDS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance

Table 1 *(continued)*			
Description	**Frequency**	**Source**	**Transformations Included**
Use of IMF credit, USD billion	Quarterly	MONA database	% of GDP
Gross financing needs, USD million	Annual	IMF Fiscal Monitor	% of GDP
Low-income country, dummy	Quarterly	WEO	Dummy
Asia Pacific, dummy	Quarterly	WEO	Dummy
Euro area, dummy	Quarterly	WEO	Dummy
Latin American countries, dummy	Quarterly	WEO	Dummy
Middle East and North Africa, dummy	Quarterly	WEO	Dummy
Sub-Saharan Africa, dummy	Quarterly	WEO	Dummy
Control of corruption, estimate	Annual	WB WGI	Index
Control of corruption, percentile rank	Annual	WB WGI	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Political stability and absence of violence, estimate	Annual	WB WGI	Index
Political stability and absence of violence, percentile rank	Annual	WB WGI	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Regulatory quality, estimate	Annual	WB WGI	Index
Regulatory quality, percentile rank	Annual	WB WGI	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Rule of law, estimate	Annual	WB WGI	Index
Rule of law, percentile rank	Annual	WB WGI	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Net international investment position, USD million	Quarterly	IMF IFS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Official reserve assets, USD million	Quarterly	IMF IFS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Exchange rate regime, dummy	Quarterly	IMF AREAER	Dummy
US 10-year treasury yield, quarterly average	Quarterly	Bloomberg	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Ongoing IMF supported arrangement	Quarterly	MONA database	Dummy

Table 1 *(continued)*			
Description	**Frequency**	**Source**	**Transformations Included**
Quarter	Quarterly	NA	Categorial
Total debt service paid, USD billion	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Terms of trade, index	Annual	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
GDP, current price, per capita, USD	Annual	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government fiscal balance, end of period, % of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government cyclical adjusted balance, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government net debt, % of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government gross debt, % of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Total population, Billion	Annual	WEO	Level
World nominal GDP, USD billion	Annual	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
World real GDP, Index (2005=100)	Annual	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Credit to the private sector, percent of GDP	Quarterly	IMF IFS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Consumer price index, period average	Quarterly	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Nominal effective exchange rate, Index, period average	Quarterly	IMF IFS	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Real effective exchange rate, Index, period average	Quarterly	IMF IFS	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Foreign direct investment, USD billion	Quarterly	IMF IFS	% of GDP

Table 1 *(continued)*			
Description	**Frequency**	**Source**	**Transformations Included**
Current account, USD billion	Quarterly	WEO	% of GDP
VIX, index, period average, Index	Quarterly	Bloomberg	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
US federal funds rate, period average	Quarterly	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Credit default swap, period average	Quarterly	Bloomberg	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Exports plus Imports, percent of GDP	Quarterly	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Exports, percent of total debt service	Quarterly	WEO	Level, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Trade balance, percent of GDP	Quarterly	WEO	% of GDP
General government fiscal balance, 1-year ahead, percent of Fiscal year GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government fiscal balance, 3-year ahead, percent of Fiscal year GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government fiscal balance, 5-years ahead, percent of Fiscal year GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government gross debt, 1-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government gross debt, 3-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government gross debt, 5-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government net debt, 1-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
General government net debt, 3-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance

Table 1 *(continued)*			
Description	**Frequency**	**Source**	**Transformations Included**
General government net debt, 5-year ahead, percent of GDP	Annual	WEO	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Real GDP growth, 3-years ahead, percent change	Annual	WEO	Percent change
Real GDP growth, 5-years ahead, percent change	Annual	WEO	Percent change
Real GDP growth, 1-years ahead, percent change	Annual	WEO	Percent change
Investment grade, S&P, dummy	Quarterly	WEO	Dummy
Public and publicly guaranteed debt, official debt creditors, principal Amount of Debt Outstanding, USD billions	Annual	WB IDS	% of GDP
Public and publicly guaranteed debt, official debt creditors, Disbursements, USD billions	Annual	WB IDS	% of GDP
Public and publicly guaranteed debt, official debt creditors, Debt Outstanding and Disbursed, USD billions	Annual	WB IDS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance
Public and publicly guaranteed debt, official debt creditors, Interest Payments, USD billions	Annual	WB IDS	% of GDP
Public and publicly guaranteed debt, official debt creditors, Net Flows, USD billions	Annual	WB IDS	% of GDP
Public and publicly guaranteed debt, official debt creditors, Net Transfers, USD billions	Annual	WB IDS	% of GDP
Public and publicly guaranteed debt, official debt creditors, Total Debt Service, USD billions	Annual	WB IDS	% of GDP
General government, official debt creditors, principal Amount of Debt Outstanding, USD billions	Annual	WB IDS	% of GDP
General government, official debt creditors, Disbursements, USD billions	Annual	WB IDS	% of GDP
General government, official debt creditors, Debt Outstanding and Disbursed, USD billions	Annual	WB IDS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance

Table 1. *(concluded)*			
Description	**Frequency**	**Source**	**Transformations Included**
General government, official debt creditors, Interest Payments, USD billions	**Annual**	**WB IDS**	**Level, % of GDP**
General government, official debt creditors, Net Flows, USD billions	Annual	WB IDS	% of GDP
General government, official debt creditors, Net Transfers, USD billions	Annual	WB IDS	% of GDP
General government, official debt creditors, Total Debt Service, USD billions	Annual	WB IDS	% of GDP
New external loan amounts committed by bilateral creditors, USD billions	Annual	WB IDS	% of GDP
New external loan amounts committed by multilateral institutions, USD billions	Annual	WB IDS	% of GDP
Average total time from disbursement to final repayment of new external official debt, years	Annual	WB IDS	Years
Average interest rate applied to new external loans from official creditors, percent	Annual	WB IDS	Level
The degree of concessionality; calculated as the difference between the loan's present value and face value, expressed as a % of the face value.	Annual	WB IDS	Percent
The average time before a country starts repaying principal on new loans, years	Annual	WB IDS	Years
Overdue interest payments on loans from official creditors, USD billions	Annual	WB IDS	% of GDP
Interest payments that have been renegotiated and deferred, USD billions	Annual	WB IDS	% of GDP
Overdue repayments of loan principal from official creditors, USD billions	Annual	WB IDS	% of GDP
Principal amounts that have been renegotiated and rescheduled, USD billions	Annual	WB IDS	% of GDP
Amount of committed debt from official creditors that has not yet been disbursed, USD billions	Annual	WB IDS	% of GDP, yoy growth, five-quarter average yoy growth, 5-quarter growth variance

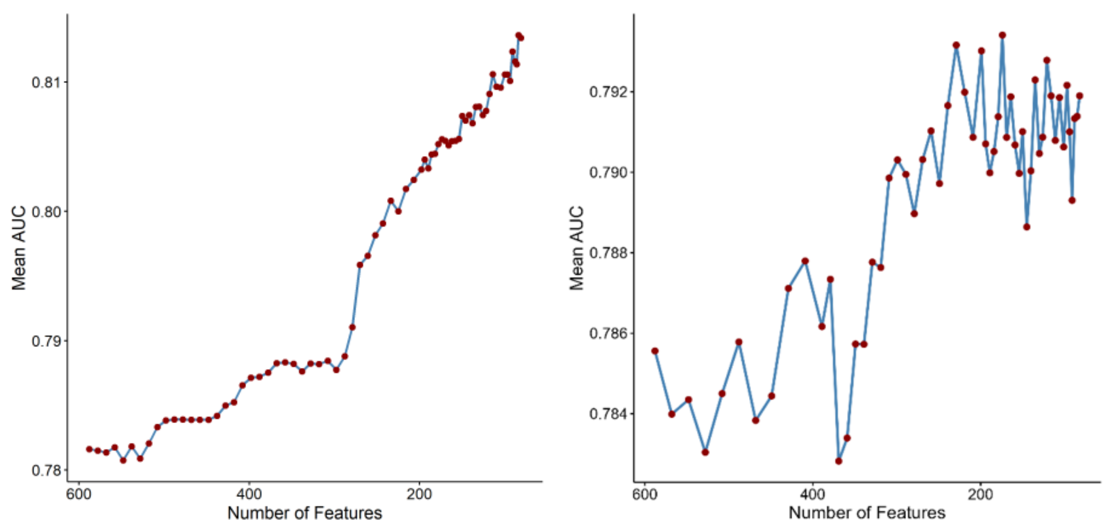
Table 2. Countries Included in the Sample and Number of Issuances

Bulgaria	59	China	27	Guatemala	10
Mexico	56	Ecuador	25	Morocco	9
Poland	53	Dominican Republic	23	Cote d'Ivoire	8
Indonesia	52	Chile	21	Malaysia	8
Brazil	44	Ghana	21	Costa Rica	7
Lebanon	43	Ukraine	21	Thailand	5
Türkiye	43	Argentina	17	Bolivia	4
Colombia	42	South Africa	17	Honduras	4
Philippines	42	Jamaica	16	Tunisia	4
Hungary	34	Russia	16	Trinidad and Tobago	3
Egypt	32	Pakistan	14	Barbados	2
Panama	30	El Salvador	13	Belize	2
Kazakhstan	29	Czech Republic	12	Suriname	2
Uruguay	29	Jordan	12	India	1
Latvia	28	Slovak Republic	12		
Peru	28	Paraguay	11		

Annex III. Estimation and Training Process

Figure III.1 illustrates the relationship between the number of features used in a model and its corresponding mean ROC-AUC on the validation sets, as derived from a recursive feature elimination (RFE) process. Each point on the plot represents a model trained with a specific subset of features. Overall, the plot shows a clear upward trend in AUC for the random forest and the logit model as the number of features decreases, suggesting that reducing the feature set—by removing less informative or redundant variables—can improve model performance. The variability in AUC values along the curve reflects the randomness inherent in the training and selection process.

Figure III.1. RFE, Number of Features vs Mean ROC-AUC, Random Forest vs Logit



Note: The figure illustrates the mean ROC-AUC score across varying numbers of features during recursive feature elimination for the random forest model (left panel) and the logit model (right panel).

Annex IV. Estimation Results

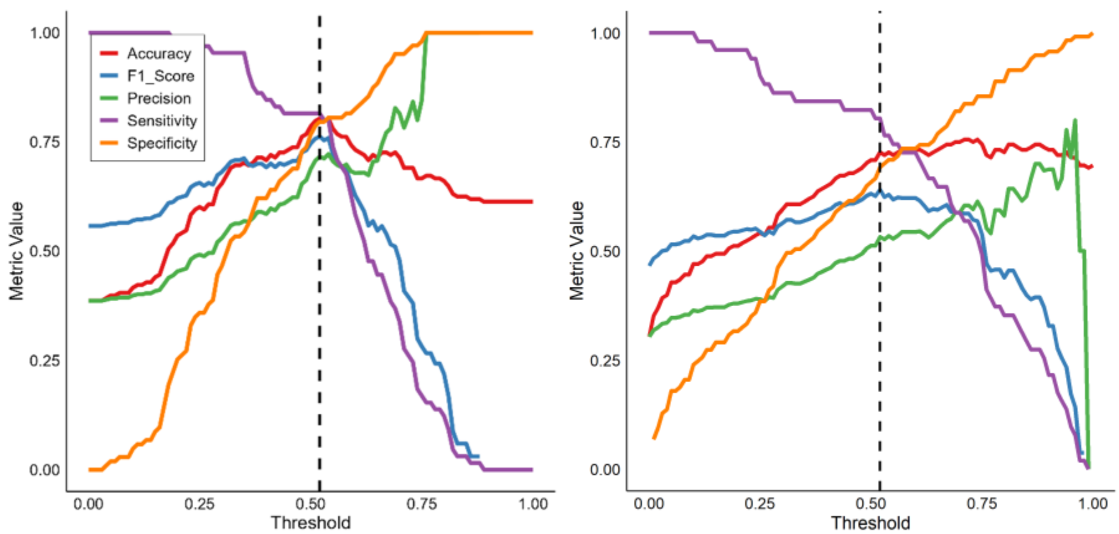
The best-performing hyperparameters for both models are summarized in Table 2. For the Random Forest model, cross-validation revealed that the most effective configuration involves 500 decision trees, providing a strong ensemble through aggregation. 5 variables are randomly selected at each split, encouraging tree diversity and reducing correlation among trees. The minimum terminal node size was set to 1, while the maximum depth was restricted to 15 levels, constraining the complexity of individual trees to enhance generalization. The model was trained using bootstrap sampling, introducing randomness into each tree's construction by drawing samples with replacement from the training data. For the regularized logistic regression model, determined through the expanding window cross-validation approach described earlier, the selected hyperparameters correspond to a penalty strength (lambda) of 0.06 and a mixing parameter (alpha) of 0. This specification implies pure Ridge-type (L2) regularization, which uniformly shrinks all coefficient estimates to mitigate overfitting without enforcing sparsity. This approach is particularly suited to high-dimensional settings where retaining all predictors is desirable, promoting model stability and improved generalization performance.

Table 2. Best Performing Hyperparameters

Random Forest		**Logit Model**	
Number of trees	500	Regularization type (α)	0
Number of variables considered at each split	5	Regularization strength (λ)	0.06
Minimum number of observations in a terminal node	1		
Maximum tree depth	15		
Resampling method	Bootstrap		

Figure IV.1 illustrates how key classification metrics vary with the decision threshold for both, the random forest model (left panel) and the logit model (right panel). For the random forest, as the threshold increases, precision and specificity steadily rise, while sensitivity declines. The F1 Score, which balances Precision and Sensitivity, peaks at an intermediate threshold of 0.52 (marked by the dashed line), reflecting the best trade-off between false positives and false negatives. Accuracy peaks around the same threshold as F1 score because both metrics benefit from a balanced trade-off between correctly identifying positives and correctly rejecting negatives. Similar patterns are evident for the evaluation metrics in the logit model, although the threshold at which the F1-score is maximized is slightly lower (at 0.51).

Figure IV.1. Model Performance Random Forest and Logit Model



Note: The figure performance metrics for random forest model (left panel) and the logit model (right panel).

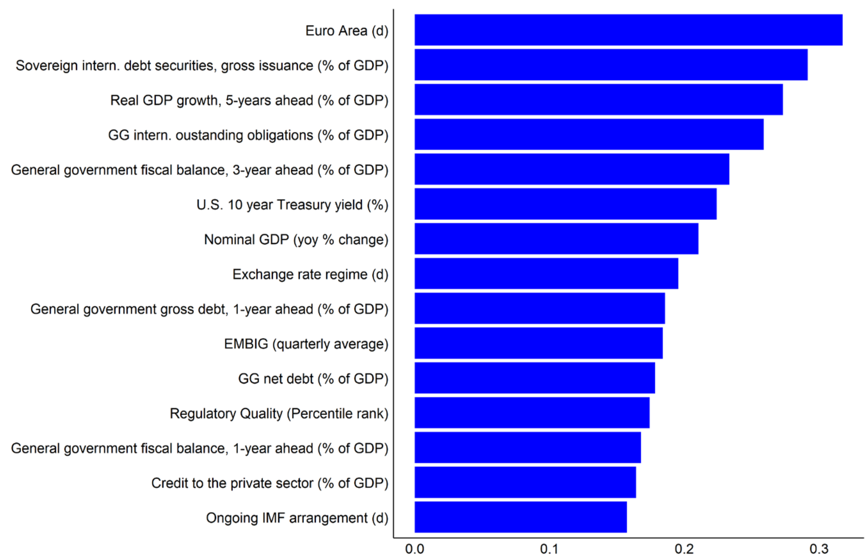
Logit Model—Feature Importance

The bar charts in Figure IV.2 presents the top 15 predictors of sovereign debt issuance in international markets, evaluated based on Shapley values. The comparison of the top 15 features from the logit model and the random forest model reveals a high degree of consistency in the key determinants of sovereign debt issuance. Both models identify similar macro-financial fundamentals as important, including the stock of international debt obligations, fiscal forecasts, GDP measures, and sovereign risk indicators such as the EMBIG spread. In both approaches, general government international outstanding obligations (% of GDP) and fiscal balance forecasts (particularly 3 years ahead) feature prominently, underscoring their importance across model types. Likewise, Nominal GDP, exchange rate regime, EMBIG spreads and net debt metrics are included in both rankings, reflecting their predictive value in explaining issuance decisions.

Where differences emerge, they largely reflect the underlying model structures. The logit model tends to highlight high-level categorical and forward-looking indicators—such as the Euro Area dummy, U.S. 10-year

Treasury yield, or real GDP growth forecasts—capturing average marginal effects effectively. This is partly because logistic regression approximates non-linearities through categorical splits, whereas tree-based models handle interactions more flexibly. In contrast, the random forest prioritizes variables with high interaction potential or inherent non-linearity, such as debt composition, international reserves, and IMF credit usage. These differences are not contradictory but complementary, offering a more nuanced view of market access drivers. Importantly, the strong alignment in top features across both models reinforces the robustness of the results, underscoring the central role of previous market access, fiscal space, external conditions, and investor risk perceptions in shaping sovereign issuance decisions.

Figure IV.2. Logit Shapley Feature Importance

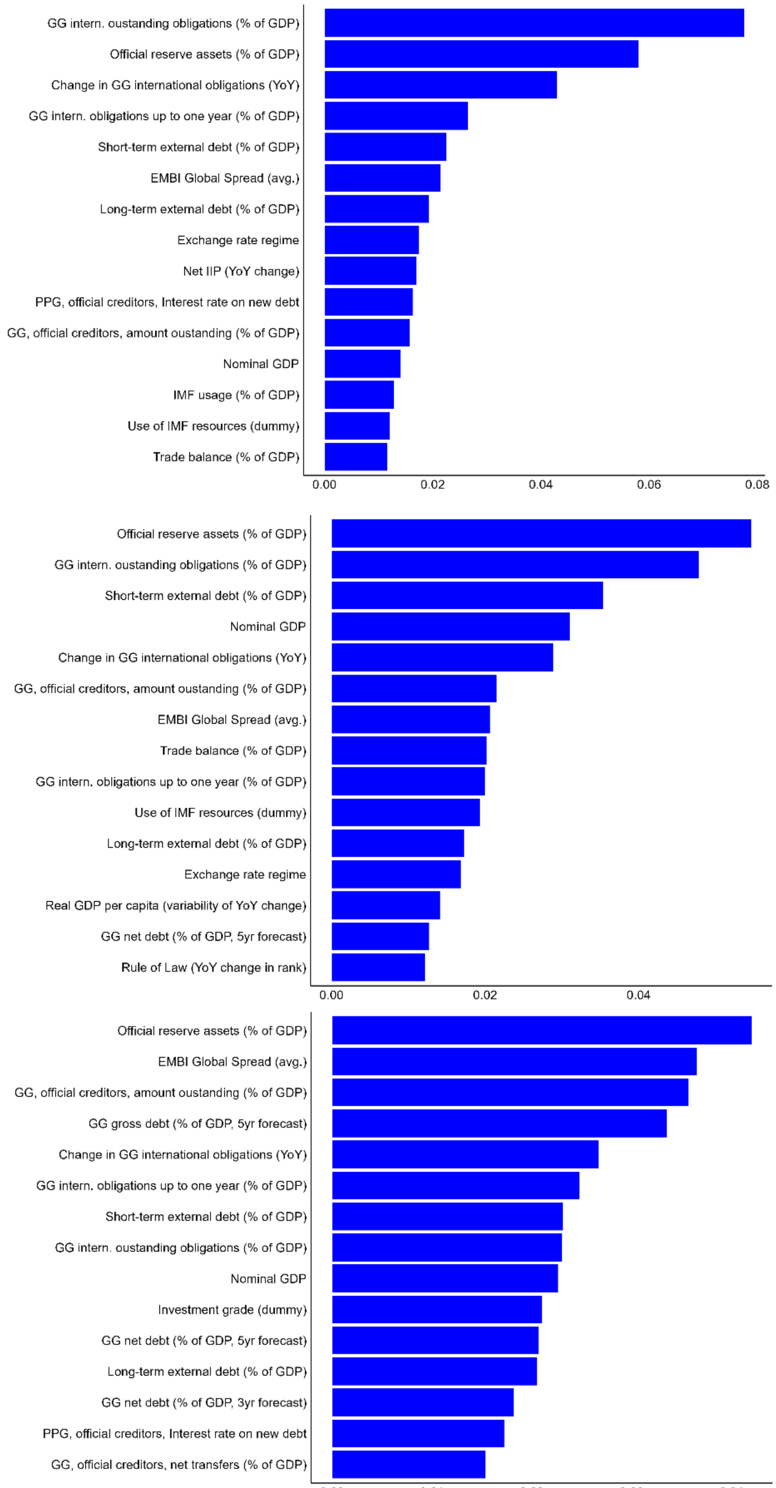


Note: Mean absolute shapely values of top-15 predictors in the logit model, aggregated by base variables (3rd lag to 6th lag).

Feature Importance Over Time

To assess whether feature importance changes over time, we split the sample into three sub-periods: 2002–2007, 2008–2014, and 2015–2021. Feature importance appears largely stable across these periods, suggesting that the main drivers of international sovereign debt issuance remain consistent over time (see Figure IV. 3). Core variables—such as international reserves, outstanding international obligations, short-term external debt, and global risk indicators (e.g., EMBIG spreads)—consistently rank among the most influential features. However, some variables show time-specific relevance. For instance, the exchange rate regime dummy and the IMF usage indicator were among the top predictors in the earlier subperiods but dropped in importance in the most recent period. This shift may reflect institutional or structural changes following the global financial crisis, during which exchange rate frameworks and multilateral engagement became less central to investor assessments. Conversely, forward-looking indicators—such as projected debt ratios over 3- or 5-year horizons—gain prominence in the most recent period, possibly reflecting improved forecasting quality or a shift in investor focus toward long-term sustainability. EMBIG spreads also rise in relative importance in the latest subsample, suggesting that global risk perceptions have become more influential in recent years.

Figure IV.3. Performance Feature Importance by Sub-Periods



Note: Shapley feature importance for three estimation subperiods. The first panel shows results for 2002-2007, 2008–2014, and 2015–2021. For each period, the model was re-estimated on the corresponding subsample, using the same hyperparameters as the base model.

PUBLICATIONS

Market Access and High Spread Issuances

Working Paper No. WP/2026/010