Inelastic Demand Meets Optimal Supply of Risky Sovereign Bonds*

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March 21, 2024

Abstract

We present evidence of inelastic demand in the market for risky sovereign bonds and examine its interplay with government policies. Our methodology combines bond-level evidence with a structural model featuring endogenous bond issuances and default risk. Empirically, we exploit monthly changes in the composition of a major bond index to identify flow shocks that shift the available bond supply and are unrelated to country fundamentals. We find that a 1 percentage point reduction in the available supply increases bond prices by 33 basis points. Although exogenous, these shocks might influence government policies and expected bond payoffs. We identify a structural demand elasticity by feeding the estimated price reactions into a sovereign debt model that allows us to isolate endogenous government responses. We find that these responses account for a third of the estimated price reactions. By penalizing additional borrowing, inelastic demand acts as a commitment device that reduces default risk.

Keywords: emerging markets bond index, inelastic financial markets, institutional investors, international capital markets, small open economies, sovereign debt

JEL Codes: F34, F41, G11, G15

*We thank Walker Ray and the participants at a presentation held at the ASSA Annual Meetings for helpful feedback. We are grateful to Patricio Yunis for research assistance and Antonn Park for copy editing. The World Bank Chile Research and Development Center and Knowledge for Change Program (KCP) and George Washington University Facilitating Fund (GWU UFF) provided financial support for this paper. Lorenzo Pandolfi gratefully acknowledges financial support from the Unicredit Foundation. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the IMF or the World Bank, those of their Executive Directors, or the governments they represent. Moretti: matias.moretti@rochester.edu. Pandolfi: lorenzo.pandolfi@unina.it. Schmukler: sschmukler@worldbank.org. Villegas Bauer: gvillegasbauer@imf.org. Williams: tomaswilliams@email.gwu.edu.

1 Introduction

Governments in emerging economies heavily depend on bonds issued in liquid international capital markets for their overall financing. The behavior of investors in these markets is thus crucial to understanding governments' borrowing costs, default risk, and optimal debt management. Standard sovereign debt models often assume that investor demand is perfectly elastic, implying that investors are willing to lend any amount governments request at the risk-free rate plus a default risk premium. This assumption on investor behavior contrasts with a body of recent work for other asset markets that allows for a richer investor demand structure, typically involving an inelastic or downward-sloping demand (Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Vayanos and Vila, 2021; Gourinchas et al., 2022; Greenwood et al., 2023).

In this paper, we present novel evidence of downward-sloping demand curves in risky sovereign bond markets, and analyze its impact on governments' optimal debt policies. In the context of risky sovereign bonds, estimating a demand elasticity is challenging for two main reasons. Ideally, one would like to identify shocks to the available bond supply that are unrelated to country fundamentals, estimate price reactions around them, and map those effects into an elasticity. However, such exogenous shocks are rare for sovereign bonds. Moreover, even if one were able to identify those shocks, governments could respond to them by adjusting future issuances or their default likelihood. Thus, part of the estimated price reaction might not fully capture a downward-sloping demand curve but rather changes in bonds' expected payoffs.

We overcome these challenges by combining a novel identification strategy with a structural model, which allows us to isolate the endogenous responses of governments. We first estimate price reactions to well-identified shocks to the available bond supply, using monthly changes in the composition of the largest index for emerging economies bonds. To avoid endogeneity concerns, we exploit only the variation generated by the issuance or retirement of bonds from *other* countries in the index. We find that bond prices significantly react to these shocks in the high frequency, even when they are orthogonal to country fundamentals. Our estimates imply an inverse price demand elasticity of -0.33, which we refer to as a reduced-form elasticity, since it does not account for endogenous government responses to the identified shocks. We identify the structural elasticity by indirect inference. We formulate a quantitative sovereign debt model that characterizes governments' optimal debt and default policies as a function of observables, and we discipline it based on our reduced-form estimates. Through counterfactuals, we can isolate the endogenous responses of governments to shocks and identify the structural elasticity. Our findings show that over one-third of our reduced-form elasticity is explained by endogenous government responses that decrease default risk. Last, we use our calibrated model to analyze the implications of facing an inelastic bond demand. We find that downward-sloping demand curves act as a commitment device that limits governments' debt issuances and reduces default risk.

We start our analysis with a simple framework to guide our identification strategy. This setup features heterogeneous investors who differ in how they allocate their funds across risky assets. Specifically, they exhibit differences in their levels of activism and passivism. We define the passive demand as the portion of investors' holdings aimed at replicating the composition of the index they follow. This demand is perfectly inelastic and shifts with changes in the index. For any asset in fixed supply, an increase in the passive demand implies a leftward shift in the "effective supply," namely the quantity available to active investors. If this shift is exogenous one can use that variation to examine whether demand curves for active investors slope downward (Pandolfi and Williams, 2019; Pavlova and Sikorskaya, 2022). However, we show that if the issuer endogenously responds to this shift (e.g., by adjusting its future issuances), it might alter asset payoffs. In such cases, any observed price variation resulting from the shift in the effective supply may not necessarily reflect an inelastic demand.

On the empirical front, we identify exogenous shifts in a country's effective supply of sovereign bonds by using monthly rebalancings in the J.P. Morgan Emerging Markets Bond Index Global Diversified (EMBIGD), the most widely tracked index by institutional investors for U.S. dollar-denominated sovereign bonds issued by emerging economies. Changes in the composition of this index affect the effective bond supply because it leads to similar rebalancings in the portfolios of passive investors who, due to potential tracking error costs, tend not to deviate from the index. Given the EMBIGD's popularity, these rebalancings can have market-wide effects.

We derive a measure of flows implied by rebalancings (FIR) by combining the assets passively tracking the EMBIGD with the index's monthly rebalancings. Qualifying new bond issuances are incorporated into the EMBIGD each month, while maturing bonds are removed. These frequent adjustments lead to changes in country weights within the index, generating passive funds flows. To avoid endogeneity issues, we construct an instrument that exploits changes in the FIR generated by the issuance or retirement of bonds from other countries in the index. As such, these changes are orthogonal to a country's own fundamentals. In addition, we focus on changes in the face amount of the FIR (as opposed to market value) to exclude changes in index composition triggered by endogenous changes in bond prices.

Our analysis reveals that a higher FIR leads to higher bond prices. On average, a 1 percentage point (p.p.) increase in the FIR corresponds to a 33 basis point increase in bond prices. These estimates imply a reduced-form inverse demand elasticity of -0.33. We find that these price reactions vary across countries with different levels of default risk. Specifically, for countries with higher default risk, a 1 p.p. FIR inflow can result in up to a 46 basis point increase in bond prices. In contrast, for safer countries, the estimates are close to zero and statistically not significant.

On the quantitative front, we formulate a sovereign debt model where the government has limited commitment and can endogenously default on its debt obligations. Standard models of this nature typically assume a perfectly elastic demand for sovereign bonds, with changes in bond prices driven solely by variations in default risk (Arellano, 2008; Chatterjee and Eyigungor, 2012). We extend these models using a richer demand structure that includes both active and passive investors and a downward-sloping demand curve for active investors. In our model, an exogenous increase in the passive demand that reduces the effective supply affects the bond price through two interconnected mechanisms. First, because the active demand is downward sloping, the implied reduction in the effective supply leads to a higher bond price. Second, this higher bond price lowers financing costs, reducing the government's incentives to default. This in turn increases the expected bond repayment and further raises the price investors are willing to pay for it.

We discipline the model using our empirical estimates. Introducing passive and active investors allows us to replicate our empirical exercise, and we calibrate the model to match the estimated reduced-form elasticity. We then use the model to back out a structural elasticity, isolating changes in governments' policies and default risk. To this end, we fix the expected bond payoffs and examine how an exogenous shift in the effective supply affects the price that active investors are willing to pay. Our findings reveal that endogenous changes in default risk account for nearly a third of the reduced-form elasticity. Moreover, we find that the larger the persistence of the supply-shifting shock, the greater the impact of changes in default risk on the overall price response.

More broadly, these results underscore the importance of accounting for issuers' endogenous responses and the resulting changes in the expected repayment of assets. These factors must be considered to avoid significant biases in estimating demand elasticities. While our supply-shifting shock instrument is inherently more temporary than other instruments used in the literature, such as index additions or deletions or index methodological recompositions, we still find that the bias can represent about one-third of the total price response.

Our model allows us to examine the impact of a downward-sloping demand on the optimal debt and default policies of governments. In the presence of an inelastic demand, we observe lower default risk and higher bond prices compared to a scenario with a perfectly elastic demand and similar debt levels. This outcome is not driven by investors' preferences for holding the debt (which could lead to a convenience yield) but rather by the inelastic demand serving as a commitment device for the government. The mechanism behind it is as follows: With a downward-sloping demand, issuing an additional unit of debt decreases bond prices even if the default risk remains fixed. As a result, the government finds issuing large amounts of debt too costly and opts not to do so. An inelastic demand thus limits the maximum amount of debt the government is willing to issue. We find that this limit leads to a quantitative reduction in default risk and an increase in bond prices.

Related Literature. Our findings contribute to several strands of literature. First, we contribute to a long-standing literature using index rebalancings to estimate asset price reactions, demand elasticities, and changes in investors' portfolios across different asset classes (Harris and Gurel, 1986; Shleifer, 1986; Greenwood, 2005; Hau et al., 2010; Chang et al., 2014; Raddatz et al., 2017; Pandolfi and Williams, 2019; Pavlova and Sikorskaya, 2022).[1] Our contribution lies in showing that demand curves slope downward in one of the most relevant markets for government financing in emerging economies: the international U.S. dollar bond market.

Another key contribution of our work is showing that, even in response to exogenous supply-shifting shocks, part of the price reaction is attributable to changes in the asset's expected repayment and the rest to the inelastic component of demand. Our analysis can be applied to any asset whose future cash flows or payoffs are affected by movements in the effective supply, extending beyond sovereign bonds. As such, it can be extended to a vast literature in different markets that use exogenous shifts in the effective supply as an instrument to estimate demand elasticities. Typical examples are sovereign and corporate bonds and equities from both developed and emerging economies.

Second, a growing literature on inelastic financial markets emphasizes the role of the demand side in explaining asset prices across various financial markets (Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Vayanos and Vila, 2021). Taking as given expected asset payoffs, this literature analyzes how an inelastic demand affects the pricing of risk-free U.S. Treasuries

[1] Beyond index rebalancings, Droste et al. (2023) use high-frequency U.S. Treasury auctions to estimate the effect of demand shocks on Treasury yields.

(Krishnamurthy and Vissing-Jorgensen, 2012; Greenwood et al., 2015; Mian et al., 2022; Jiang et al., 2021b) and international financial assets (Koijen and Yogo, 2020; Gourinchas et al., 2022; Greenwood et al., 2023).[2] A paper closely related to our work, by Choi et al. (2022), analyzes the effects of a downward-sloping demand on the optimal issuance of safe government bonds. In contrast, we focus on the interplay between a downward-sloping demand curve, default risk, and the provision of risky bonds. We show that the demand elasticity interacts with default risk and influences a government's supply of risky bonds. Failing to account for this endogenous link can lead to biases when estimating demand elasticities.

Third, our paper also connects to a body of work examining how changes in the investor base of government debt impact bond yields (Warnock and Warnock, 2009; Dell'Erba et al., 2013; Peiris, 2013; Arslanalp and Poghosyan, 2016; Ahmed and Rebucci, 2022). A closely related paper, by Fang et al. (2022), develops a demand system to quantify how changes in the composition of investors (domestic versus foreign, banks versus non-banks) affect government bond yields in international markets. In this paper, we exploit exogenous changes in the composition of the investor base (passive versus active funds) to provide evidence of downward-sloping demand curves for risky sovereign bonds.

Fourth, our paper relates to a large literature on quantitative sovereign debt models. Our framework extends standard models (Aguiar and Gopinath, 2006; Arellano, 2008; Chatterjee and Eyigungor, 2012) by incorporating two different investor types (active and passive) and introducing a downward-sloping demand. This richer structure allows us to discipline the model using our reduced-form estimates.[3] We then use the model to isolate the role of default risk behind those estimates and to back out the structural demand elasticity.

In our analysis, we are agnostic about the mechanisms behind the downward-sloping demand. Previous work by Borri and Verdelhan (2010), Lizarazo (2013), Pouzo and Presno (2016), and Arellano et al. (2017) analyze sovereign debt models with risk-averse investors. In their models, investors' downward-sloping demand is a by-product of their risk aversion. In other words, investors are inelastic only because they must be compensated for each additional unit of risky debt they hold. However, several different mechanisms can generate a downward-sloping demand. For example, it can be explained by regulatory limitations, such as a value-at-risk (VaR) constraint (as in Miranda-Agrippino and Rey, 2020), by investors'

[2]A related literature focuses on U.S. and international corporate bond markets (Dathan and Davydenko, 2020; Bretscher et al., 2022; Calomiris et al., 2022; Kubitza, 2023).

[3]In this regard, our paper connects with recent work by Costain et al. (2022), who introduce endogenous default risk into a Vayanos-Vila preferred habitat model to analyze the term structure of interest rates in the European Monetary Union.

buy-and-hold strategies (which can be rationalized by a taste for simplicity or agency frictions), or by fixed-share mandates specifying how investors should allocate their funds across assets (as in Gabaix and Koijen, 2021). Our setup relies on a flexible demand structure that can accommodate any of these potential drivers. Our aim is not to uncover the causes of investors' inelastic behavior but rather to examine its aggregate implications.

The rest of the paper is structured as follows. Section 2 introduces a simple framework to guide our analysis. Section 3 presents the empirical analysis, including details on the institutional setup of EMBI indexes, data sources, the identification strategy, and results. Section 4 formulates a sovereign debt model with endogenous default and inelastic investors. Section 5 presents the quantitative analysis, and Section 6 concludes.

2 Demand Elasticity for Risky Bonds

To guide our analysis, we introduce a simple framework featuring heterogeneous investors who differ in how they allocate their funds across risky assets. This stylized framework illustrates how, under some assumptions, exogenous shifts in the demand of certain investors can be used to estimate a reduced-form price demand elasticity. In doing that, we show how endogenous changes in assets' expected repayment can influence the estimated elasticity. Although we focus on the case of risky bonds, our framework can be applied to any risky asset (e.g., equities).

2.1 Model

Investors are heterogeneous in how they allocate their funds across risky assets. Let $j = \{1, ..., J\}$ denote the investor. As in Gabaix and Koijen (2021), we assume that each investor j has a mandate or rule that specifies how they should allocate their funds across $i = \{1, ..., N\}$ risky bonds. To tightly link the model with our empirical analysis, we further assume that investors track the composition of a benchmark index $\mathcal{I}$ and differ in how actively or passively they do so. Let $\boldsymbol{w}_t = \left\{w_t^1, ..., w_t^N\right\}$ denote the vector of time-varying index weights for each constituent bond of index $\mathcal{I}$. Markets are competitive, and investors take asset prices as given.

We define $x_{jt}^i = \frac{q_t^i B_{jt}^i}{W_{jt}}$ as the share of wealth that investor j invests in bond i at time t. The term q_t^i denotes the unit price of bond i, $B_{j,t}^i$ denotes the end-of-period holdings of investor j in bond i, and $W_{j,t}$ denotes their wealth. The share x_{jt}^i is given by the following exogenous mandate:

$$x^i_{jt} = \theta_j \left(\xi^i_j e^{\Lambda_j \hat{\pi}_{i,t}\left(r^i_{t+1}\right))} \right) + (1-\theta_j)\, w^i_t. \tag{1}$$

The term θ_j parameterizes the degree of activeness or passiveness of investor j. Purely passive investors can be characterized by $\theta_j = 0$, indicating that their portfolio simply replicates the benchmark index $\mathcal{I}$. Conversely, active and semi-active investors are those with $\theta_j \in (0, 1]$, which captures the fraction of their portfolio that is not linked to index $\mathcal{I}$. Within their active allocation, investors apportion a fixed fraction, ξ^i_j, of their wealth to bond i and a varying component determined by $\Lambda_j \hat{\pi}_{i,t}\left(r^i_{t+1}\right)$, where $\Lambda_j > 0$ parameterizes their demand elasticity and $\hat{\pi}_{i,t}$ is an arbitrary function of the next-period excess return of bond i, r^i_{t+1}. For instance, if $\hat{\pi}_{i,t}\left(r^i_{t+1}\right) = \mathbb{E}_t\left(r^i_{t+1}\right)$, investors allocate a higher share of their wealth to bonds with higher expected excess returns.

As we show next, the reduced-form mandate in Equation (1) allows us to introduce an aggregate demand elasticity that can be parameterized by $\mathbf{\Lambda} \equiv \{\Lambda_1, .., \Lambda_J\}$. While this mandate can have different microfoundations (as shown in Appendix), we take it as given for our analysis. Our goal is not to explain the reasons behind the inelastic demand for risky bonds but rather to examine its implications.[4]

After adding up all the individual demands, we can write the market-clearing condition as follows:

$$q^i_t B^i_t = \tilde{\mathcal{A}}^i_t + \tilde{\mathcal{T}}^i_t(w^i_t), \tag{2}$$

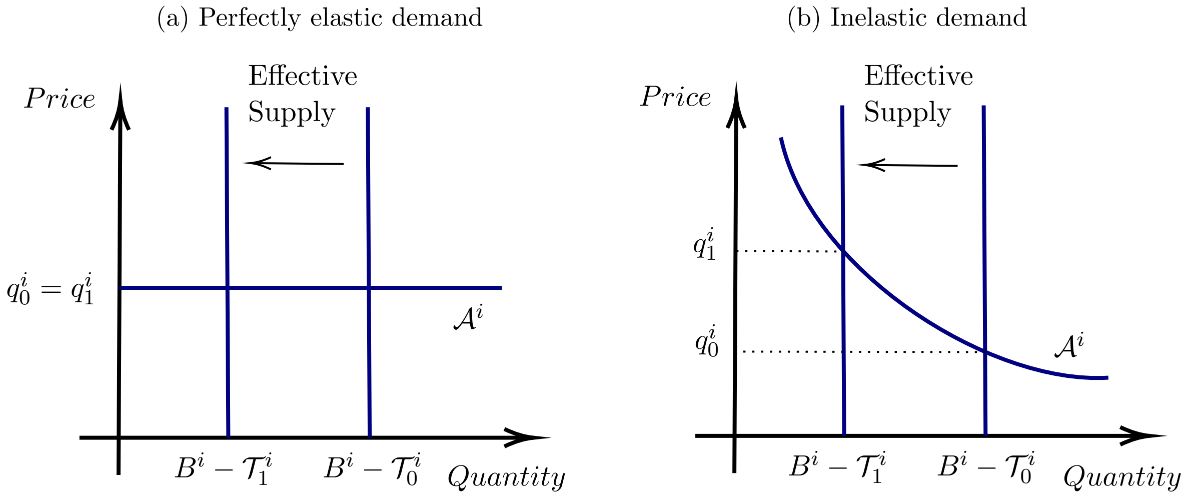
where B^i_t is the bond supply, and $\tilde{\mathcal{A}}^i_t \equiv \sum_j W_{j,t}\theta_j \left(\xi^i_j e^{\Lambda_j \hat{\pi}_{i,t}}\right)$ and $\tilde{\mathcal{T}}^i_t(w^i_t) \equiv \sum_j W_{j,t}\left(1-\theta_j\right) w^i_t$ denote the market-value active and passive demands, respectively. The passive demand, $\tilde{\mathcal{T}}^i_t(w^i_t)$, is the portion of investors' holdings aimed at replicating the index composition they follow. It captures the holdings of both semi- and fully passive investors. We explicitly write $\tilde{\mathcal{T}}^i_t(w^i_t)$ as a function of w^i_t to emphasize its dependence on the index weights. For the rest of the analysis, it is useful to rewrite this market-clearing condition as $B^i_t = \mathcal{A}^i_t + \mathcal{T}^i_t\left(w^i_t\right)$, where $\mathcal{A}^i_t$ and $\mathcal{T}^i_t\left(w^i_t\right)$ denotes the face-value active and passive demands.[5]

For any bond i in fixed supply, an increase in the passive demand implies a decrease in the supply of bonds available to active investors (i.e., a leftward shift in the effective or residual supply). If this increase is exogenous, one can use that variation to analyze whether the demand curves for active investors slope downward. Figure 1 illustrates this point. If

[4] As argued by Gabaix and Koijen (2021): "While identifying the exact reasons for low market elasticity is interesting, this question has a large number of plausible answers. Fortunately, it is possible to write a framework in a way that is relatively independent to the exact source of low elasticity [...]."

[5] In Section 2.2, we impose additional structure to obtain closed-form expressions for $\mathcal{A}^i_t$ and $\mathcal{T}^i_t\left(w^i_t\right)$.

Figure 1
Index rebalancing and the demand elasticity



Note: The figure depicts a decrease in the effective supply driven by an increase in $\mathcal{T}^i$. Panel (a) considers the case when the residual demand is fully elastic and Panel (b) when it is price sensitive.

the active demand is fully elastic, then an exogenous shift in $\mathcal{T}_t^i(w_t^i)$ should not affect bond prices (Panel (a)). Conversely, bond prices should react to this shift if the active demand slopes downward (Panel (b)).

Based on this graphical intuition, one could exploit exogenous changes in index weights w_t^i to compute an instrument for shifts in the passive demand, $\Delta\mathcal{T}_t^i \equiv \mathcal{T}_{t+1}^i(w_{t+1}^i) - \mathcal{T}_t^i(w_t^i)$, and estimate high-frequency bond price responses around those shifts. For a given $\Delta\mathcal{T}_t^i$, we can then estimate the following reduced-form inverse demand elasticity:

$$\hat{\eta}^i = (-)\frac{\Delta q_t^i}{\Delta\mathcal{T}_t^i}\frac{B_t^i - \mathcal{T}_t^i}{q_t^i}. \tag{3}$$

Equation (3) and the use of changes in index composition as a supply-shifting instrument is a standard practice in the literature to estimate demand elasticities in equity markets. Shleifer (1986) was the first to use index additions to the S&P 500 as an exogenous instrument for $\Delta\mathcal{T}_t^i$ to analyze whether demand curves for equities slope downward. More recently, Pavlova and Sikorskaya (2022) employ a similar strategy and a regression discontinuity design on Russell equity indexes. For the case of bonds (sovereign or corporate), exploiting index changes to construct $\Delta\mathcal{T}_t^i$ has additional challenges. In many cases, changes in index weights coincide with large bond issuances that tend to reflect information about the issuer's own fundamentals. We address this issue using a novel instrument in Section 3.

2.2 Endogenous Issuer Responses and Bond Payoffs

To directly map Equation (3) into a structural elasticity, η^i, we need to assume that the intrinsic value of the asset is unaffected by $\Delta\mathcal{T}_t^i$. However, exogenous shifts in the effective supply might influence issuers' policies and expected asset payoffs. For example, in the case of risky bonds, a positive $\Delta\mathcal{T}_t^i$ that leads to a higher bond price implies a lower borrowing cost, potentially affecting the issuer's default likelihood or her (future) bond issuances. Even if the current supply B_t^i remains fixed, these endogenous responses can affect the expected payoff from holding the bond and therefore its price.

Price responses to exogenous shifts in the effective supply can thus capture both an inelastic demand component and endogenous changes in expected payoffs. To decompose these effects, we put more structure behind investor demand, allowing us to derive a closed-form solution for the price. We assume that $\hat{\pi}_{i,t}(r_{t+1}^i) = \frac{\mathbb{E}_t\left(r_{t+1}^i\right)}{\mathbb{V}_t\left(r_{t+1}^i\right)}$ so that the active demand is a function of the bond's expected excess return and its variance (the Sharpe ratio).[6] We define $\mathcal{R}_{t+1}^i$ as the next-period repayment per unit of the bond so that $r_{t+1}^i \equiv \frac{\mathcal{R}_{t+1}^i}{q_t^i} - r_f$, where r_f denotes the risk-free rate.[7] Based on these definitions and the market-clearing condition in Equation (2), we can write the equilibrium bond price as

$$q_t^i = \frac{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{r^f}\,\Psi_t^i. \tag{4}$$

The term $\frac{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{r^f}$ captures the price under perfectly elastic investors, which is a function of the expected next-period repayment. On the other hand, the Ψ_t^i function captures the demand's downward-sloping nature and is given by

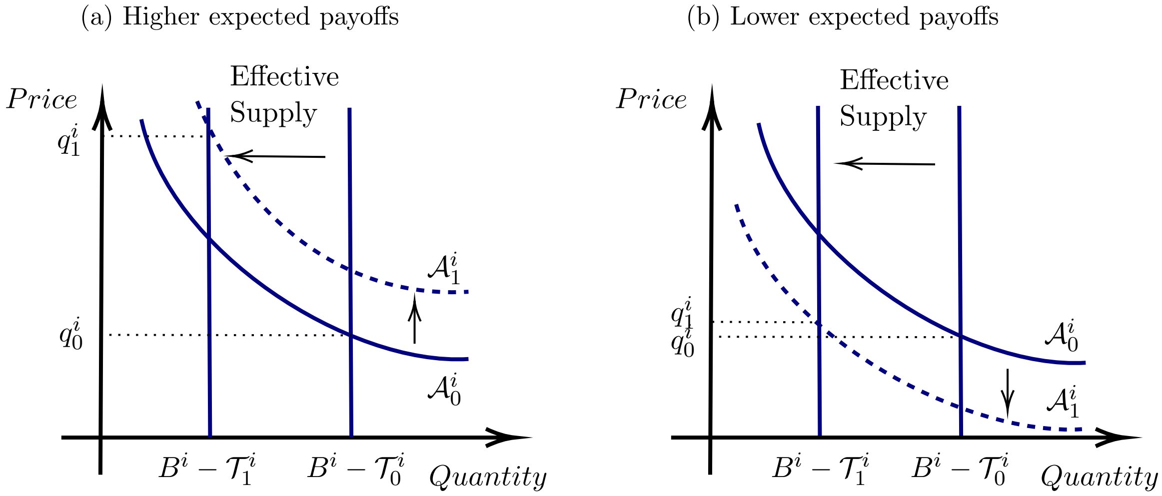
$$\Psi_t^i \equiv 1 - \kappa_t^i\left(\mathbf{\Lambda}\right)\frac{\mathbb{V}_t\left(\mathcal{R}_{t+1}^i\right)}{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}\left(B_t^i - \mathcal{T}_t^i - \bar{\mathcal{A}}_t^i\right). \tag{5}$$

The term $\kappa_t^i\left(\mathbf{\Lambda}\right) \equiv \frac{1}{\sum_j \Lambda_j W_{j,t}\theta_j \xi_j^i}$ characterizes the degree of inelasticity in the market for bond i. When $\kappa_t^i\left(\mathbf{\Lambda}\right) = 0$, the demand is perfectly elastic and the price only depends on the expected repayment. The $B_t^i - \mathcal{T}_t^i$ component is what we have referred to as the residual supply, and $\bar{\mathcal{A}}_t^i$ captures the inelastic portion of the active demand, which depends on the fixed component of investors' mandates, ξ_j^i. See Appendix for the details and derivations.

[6] This is a similar specification to the one in Gabaix and Koijen (2021), which is a function of expected excess returns and a shock to tastes or perceptions of risk. As shown in our quantitative analysis, this specification allows us to capture a demand elasticity that differs across countries with different levels of default risk, which is consistent with our empirical findings.

[7] The repayment function depends on the expected default and next-period issuances. For a short-term (one-period) risky bond, it is given by $\mathcal{R}_{t+1}^i = 1 - d_{t+1}^i$, where $d = 1$ denotes a default. For long-term bonds, it also depends on next-period issuances as they affect the next-period bond price. In Section 4, we analyze this function in detail.

Figure 2
Endogenous changes in expected payoffs



Note: The figure depicts a reduction in the effective supply driven by an increase in $\mathcal{T}^i$. Panel (a) considers a case in which the expected asset payoffs increase after the effective supply decreases, while Panel (b) shows the opposite case.

From Equation (5), one can decompose the reduced-form elasticity into two components: the structural elasticity, η^i, and endogenous changes in expected repayment, α^i. In particular, we can extend Equation (3) as follows:

$$\underbrace{(-)\frac{\Delta q_t^i}{\Delta \mathcal{T}_t^i}\frac{q_t^i B_t^i - \mathcal{T}_t^i}{q_t^i}}_{\equiv\hat{\eta}^i} = \underbrace{(-)\frac{\Delta \Psi_t^i}{\Delta \mathcal{T}_t^i}\frac{B_t^i - \mathcal{T}_t^i}{\Psi_t^i}}_{\equiv\eta^i} + \underbrace{(-)\frac{\Delta \mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{\Delta \mathcal{T}_t^i}\frac{B_t^i - \mathcal{T}_t^i}{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}}_{\equiv\alpha^i}. \tag{6}$$

Figure 2 provides a graphical illustration. If a positive $\Delta\mathcal{T}_t^i$ raises the next-period expected repayment (i.e., $\alpha^i < 0$), investors will be willing to pay a higher price for any given B_t^i, leading to an upward shift in the active demand (Panel (a)). Failing to account for this effect might result in the false conclusion that the demand curve is steeper (more inelastic) than it truly is. Conversely, if a positive $\Delta\mathcal{T}_t^i$ lowers the next-period expected repayment (i.e., $\alpha^i > 0$), it would cause the active demand to shift downward shift (Panel (b)). This shift might lead to the demand curve being estimated as flatter (more elastic) than it truly is.

Since bond prices and payoffs are jointly determined, it is challenging to disentangle the effects on bond prices due to the downward-sloping demand from those resulting from changes in expected payoffs. To formally quantify each mechanism separately, one would need a structural model in which bond prices, the supply of the bond, and its payoffs are endogenous outcomes. Put differently, in order to quantify α^i, we must first understand how $\Delta\mathcal{T}_t^i$ affects issuers' policies (debt issuances and default). One could argue that more persistent changes in $\mathcal{T}_t^i$ would likely have a larger impact on the issuers' policies, potentially making the absolute value of α^i larger. Conversely, a more transitory shock could lead to a smaller α^i in absolute terms. In any case, one must consider both effects.

In the next section, we construct a novel instrument for $\Delta\mathcal{T}_t^i$, based on monthly index rebalancings for a major sovereign bond index for emerging economies. We estimate bond price reactions to these rebalancings and map the reactions into a reduced-form elasticity. In Section 4, we formulate a structural model to back out the structural elasticity.

3 Empirical Analysis

3.1 Index Rebalancings as Passive Demand Shocks

In this section, we exploit monthly rebalancings in the EMBIGD to identify exogenous shifts in the available bond supply for active investors (the effective supply). The EMBIGD tracks the performance of emerging market sovereign and quasi-sovereign bonds in U.S. dollars issued in international markets.[8] Unlike other indexes that use a traditional market capitalization-based weighting scheme, the EMBIGD restricts the weights of countries with above-average debt outstanding by including only a fraction of their face amount of debt outstanding.[9] Among bond indexes for emerging economies, the EMBIGD is the most widely tracked, followed by funds with combined assets under management (AUM) of around US$300 billion in 2018 (Appendix Figure C1).[10]

Rebalancings in the EMBIGD index, triggered by bond inclusions and exclusions, occur on the last U.S. business day of each month. J.P. Morgan announces these updates through a report detailing the updated index composition. Consequently, passive investors tracking the index adjust their portfolios by buying or selling bonds to match the new index weights.

Following Pandolfi and Williams (2019), we construct the flows implied by the rebalancings (FIR) measure for each country at each rebalancing date. The FIR quantitatively measures the relative change in passive demand for a country's sovereign bonds resulting from index

[8]The index includes bonds with a maturity of at least 2.5 years and a face amount outstanding of at least US$500 million. To be classified as an emerging economy, a country's gross national income (GNI) per capita must be below an Index Income Ceiling (IIC) for three consecutive years. The IIC is defined by J.P. Morgan and adjusted every year by the growth rate of the World GNI per capita, Atlas method (current US$), provided by the World Bank. Bonds in the index must settle internationally and have accessible and verifiable bid and ask prices. Once included, they can remain in the index until 12 months before maturity. Local law instruments are not eligible.

[9]The J.P. Morgan Emerging Markets Bond Index Global (EMBIG) has the same bond inclusion criteria as the EMBIGD. The only difference between them is that while the EMBIG uses a market capitalization weighting scheme, the EMBIGD modifies this scheme to limit the weights of countries with above-average debt outstanding. Appendix Figure C4 plots the EMBIG country weights of both the EMBIG (a more traditional market-based index) and EMBIGD versions for December 2018. Appendix describes the rules that the EMBIGD uses to compute the weights of the instruments included in the index.

[10]Appendix Figures C2 and C3 show the high preponderance of U.S. dollar-denominated sovereign debt issued by emerging economies in international markets.

rebalancing. A 1% FIR can be interpreted as a 1% reduction in the available bond supply in the market. More precisely, the FIR measure is constructed as follows:

$$FIR_{c,t} \equiv \frac{\Delta\tilde{\mathcal{T}}_{c,t}}{q_{c,t-1}B_{c,t-1} - w_{c,t-1}A_{t-1}}. \tag{7}$$

The numerator captures the change in passive demand implied by the index rebalancing, and is defined as $\Delta\tilde{\mathcal{T}}_{c,t} \equiv (w_{c,t} - w_{c,t}^{BH})A_t$. It measures the amount of funds that, on a given rebalancing date, enter or leave a country due to the rebalancing in the portfolio of passive investors tracking index $\mathcal{I}$. For convenience, we normalize $\Delta\tilde{\mathcal{T}}_{c,t}$ by the market value of the bonds available to active investors, $q_{c,t-1}B_{c,t-1} - w_{c,t-1}A_{t-1}$.

The first term in the parentheses, $w_{c,t}$, is the benchmark weight for country c, at time t, in index $\mathcal{I}$. It is defined as $w_{c,t} \equiv \frac{q_{c,t}B_{c,t}f_{c,t}}{q_t I_t}$, where $q_{c,t}B_{c,t}$ denotes the market value of bonds from country c at time t. $q_{c,t}$ denotes the price and $B_{c,t}$ denotes the face amount outstanding. $f_{c,t}$ is the face amount share of country c's bonds in the index, which depends on the country's amount of outstanding debt rather than on market values.[11] The denominator of $w_{c,t}$ denotes the market value of index $\mathcal{I}$, calculated as q_t times I_t, where q_t is the unit price of the index and I_t is the number of available index units. That is, it captures the relative market capitalization of country c's sovereign bonds included in $\mathcal{I}$. The second term in the parentheses, $w_{c,t}^{BH}$, is defined as $w_{c,t}^{BH} \equiv w_{c,t-1}\frac{q_{c,t}/q_{c,t-1}}{q_t/q_{t-1}}$.[12] It captures the "buy-and-hold weight," defined as the weight country c would have had at time t if the index composition had remained unchanged.[13] A_t in $\Delta\tilde{\mathcal{T}}_{c,t}$ represents the AUM of investors passively tracking the EMBIGD.

Although index changes drive the FIR, this measure might not be entirely exogenous to a country's fundamentals, for two reasons. First, the FIR is affected by countries' sovereign bond issuances. When a country issues new bonds that become part of the index, its weight increases, leading to a higher FIR. Second, even for countries whose $B_{c,t}$ and share $f_{c,t}$ remain constant, the FIR can be mechanically correlated to present or past bond price changes. Note that, generally, $\frac{\partial FIR}{\partial q_{c,t}} \neq 0$ and $\frac{\partial FIR_{c,t}}{\partial q_{c,t-1}} \neq 0$. This can be seen from Equation (7), where the former derivative will not be equal to zero given the effect of current prices through the

[11] To preserve diversification, J.P. Morgan applies a scheme that entails a cap to the weight of countries with greater-than-average sovereign bond markets, for whom the diversification coefficient is therefore smaller than one, $f_{c,t} < 1$. In contrast to the EMBIGD, for purely market capitalization-weighted indexes (such as the EMBI Global), $f_{c,t} = 1, \forall_{c,t}$.

[12] This buy-and-hold weight is computed as if no bonds had entered or exited the index at time t.

[13] Note that $w_{c,t}^{BH} = \frac{q_{c,t}f_{c,t-1}B_{c,t-1}}{q_t I_{t-1}}$. Absent any change in the index composition (i.e., inclusions or exclusions of new bonds or countries), if the price of a country's sovereign bonds increases more than that of other countries in the index, the weight of that country in the index increases. Nevertheless, investors do not need to rebalance their portfolios as the "buy-and-hold weight" coincides with the new weight in the index, $w_{c,t}$.

numerator. In turn, the latter derivative might not be equal to zero due to the effects of past prices through the denominator. Given that we aim to isolate the impact of passive demand shocks on bond prices, the potential endogeneity of the FIR could bias our estimates.

We address the potential challenge of the FIR endogeneity in two ways. First, for each rebalancing event, we consider only countries whose amount outstanding of bonds, $B_{c,t}$, does not change relative to the previous period. In other words, we focus only on countries that experience no new issuances, bond repurchases, or the removal of bonds from the index due to maturity on the given date. The rationale behind this approach is, for each country, to isolate and examine the impact of index changes driven by changes in other countries' standings within the index at each specific point in time. Second, we exploit the fact that the EMBIGD's weighting scheme is based on the face amount of outstanding bonds. This is important as it allows us to net out the variation potentially correlated with current or past bond price changes.

In particular, we construct an instrument for the FIR based on a synthetic index in which country weights are only a function of the diversified face amount outstanding of bonds included in the index, not on market values, $w_{c,t}^{FA} \equiv \frac{f_{c,t}B_{c,t}}{\sum_c f_{c,t}B_{c,t}}$. We then compute the fractional change in the synthetic index:

$$\frac{\Delta w_{c,t}^{FA}}{w_{c,t-1}^{FA}} = \left(\frac{f_{c,t}B_{c,t}}{\sum_c f_{c,t}B_{c,t}} - \frac{f_{c,t-1}B_{c,t-1}}{\sum_c f_{c,t-1}B_{c,t-1}} \right) / \left[\frac{f_{c,t-1}B_{c,t-1}}{\sum_c f_{c,t-1}B_{c,t-1}} \right]. \tag{8}$$

Focusing on countries whose debt outstanding in the index remains unchanged ($B_{c,t} = B_{c,t-1}$), the instrument becomes

$$Z_{c,t} \equiv \left(\frac{f_{c,t}}{\sum_c f_{c,t}B_{c,t}} - \frac{f_{c,t-1}}{\sum_c f_{c,t-1}B_{c,t-1}} \right) \; / \left[\frac{f_{c,t-1}}{\sum_c f_{c,t-1}B_{c,t-1}} \right]. \tag{9}$$

By instrumenting the FIR with $Z_{c,t}$, we can isolate the variation in the FIR that is solely attributable to changes in the outstanding amount of bonds from other countries. These changes are a result of fluctuations in the relative size of other countries' sovereign bond markets or alterations in the diversification coefficient, $f_{c,t}$. Because $f_{c,t}$ is not a function of bond prices, and because we only consider countries where $B_{c,t}$ is fixed, $\frac{\partial Z_{c,t}}{\partial q_{c,t}} = \frac{\partial Z_{c,t}}{\partial q_{c,t-1}} = 0$.

We then use the $Z_{c,t}$ instrument to estimate the effect of exogenous demand changes induced by passive flows on sovereign bond prices. We take advantage of the specific timing of the rebalancings: index changes always occur on the last business day of each month. For each rebalancing date, we can therefore identify pre- and post-rebalancing periods and estimate the FIR's effect (instrumented by $Z_{c,t}$) on bond prices.

We adopt an instrumented difference-in-differences (DDIV) design and estimate the following main specification using two-stage least squares (2SLS):

$$\log(q_{i,t,h}) = \theta_{c(i),t} + \theta_{b(i),t} + \gamma \mathbb{1}_{h\in Post} + \beta(F\hat{I}R_{c(i),t} \times \mathbb{1}_{h\in Post}) + \mathbf{X}_{i,t} + \varepsilon_{i,t,h}, \qquad (10)$$

where $q_{i,t,h}$ is the price of bond i at rebalancing date t, h trading days before or after the rebalancing information is confirmed. For example, $h = 1$ indicates the first trading after J.P. Morgan releases the EMBIGD's new composition. This happens during the trading hours on the last business day of each month, meaning that $h = 1$ falls on this day. For each rebalancing date t, we consider a symmetric h-day window around it. $\theta_{c(i),t}$ are country-month fixed effects, and $\theta_{b(i),t}$ are bond characteristics-month fixed effects, including maturity, rating, and bond type (sovereign or quasi-sovereign). $F\hat{I}R_{c(i),t}$ represents the flows implied by the rebalancing, instrumented with the percentage change in the theoretical index weights, $Z_{c,t}$. We obtain $F\hat{I}R_{c(i),t}$ by regressing $FIR_{c,t}$ on $Z_{c,t}$ (first stage). $\mathbb{1}_{h\in Post}$ is an indicator function equal to 1 in the h days after the rebalancing and equal to 0 in the h days before. $\mathbf{X}_{i,t}$ is a vector of monthly bond controls, including the bond's face amount and (beginning-of-month) spread. Our coefficient of interest is β, which captures the FIR's effect on bond prices. In particular, how much the average log price change (or percentage change) around the rebalancing day varies with a 1 p.p. exogenous increase in $FIR_{c(i),t}$. Our main specification replaces the country-month fixed effects, bond characteristics-month fixed effects, and bond controls with bond-month fixed effects.

We also estimate a leads and lags regression in which the instrumented FIR is interacted with trading-day dummies. This analysis allows us to both explore the dynamic effect of the FIR and test for parallel trends before the rebalancing.

3.2 Data and Summary Statistics

We collect data from different sources to compute the FIR and our instrument. Most of the variables used in the analysis come directly from J.P. Morgan. However, one variable is not straightforward to measure: the AUM of funds that passively track the EMBIGD, A_t. While J.P. Morgan provides data on the amount of assets benchmarked against their indexes, it does not distinguish between passive and active funds. Additionally, even if these data were available, many active funds might passively manage a significant share of their portfolios, as highlighted by Pavlova and Sikorskaya (2022).

To compute A_t, we start with J.P. Morgan data on assets tracking the EMBIGD, which we then adjust based on an estimate of the share of passive funds. The estimation of this share involves the following steps. We retrieve data from Morningstar on the asset holdings

Table 1
Summary statistics

Variable	Mean	Std. Dev.	25th Pctl	75th Pctl	Min	Max
log(Price)	4.64	0.13	4.59	4.68	3.07	5.19
Instrumented FIR (%)	-0.16	0.22	-0.34	0.00	-0.70	0.25
Stripped Spread (bps)	278	286	129	357	0	4904
EIR Duration (%)	6.35	3.91	3.48	7.71	-0.03	19.08
Average Life (years)	9.6	8.9	4.0	9.9	1.0	99.8
Face Amount (billion U.S. dollars)	1.3	0.8	0.7	1.6	0.5	7.0
CDS (bps)	298	694	104	285	42	6171

Note: This table displays summary statistics for the main variables in the analysis. *Stripped Spread* is the difference between a bond yield-to-maturity and the corresponding point on the U.S. Treasury spot curve, where the value of collateralized flows are "stripped" from the bond. *EIR Duration* measures the sensitivity of dirty prices to parallel shifts of the U.S. interest rates, expressed as the percentage change of dirty price if all U.S. interest rates change by 100 basis points. *Average Life* is the weighted average period until principal repayment, and *CDS* denotes the five-year credit default swap spread of USD-denominated sovereign bonds. Sources: Bloomberg, Datastream, J.P. Morgan Markets, Morningstar Direct, and authors' calculations.

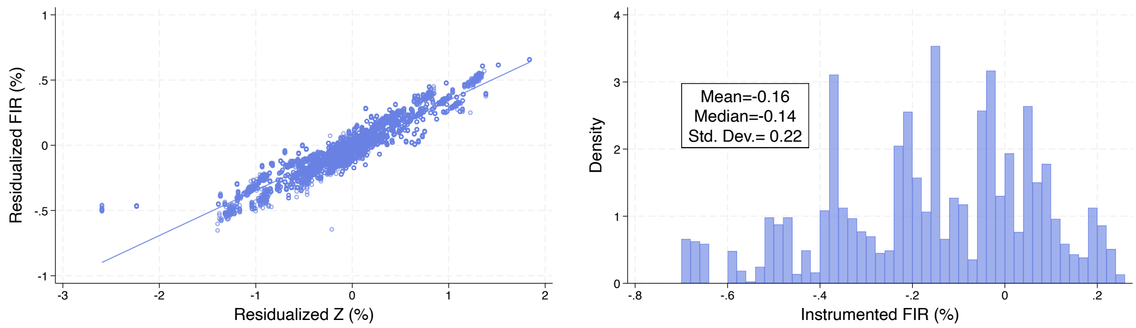
of funds benchmarked against the EMBIGD and EMBI Global Core for 2016–2017.[14,15] For each fund, we compute their $Passive\ Share = 100 - Active\ Share$, where *Active Share* is the measure developed by Cremers and Petajisto (2009). We first estimate this variable at the country level, which is the level of the FIR measure.[16] This allows us to separate, even for active funds, the fraction of a fund's portfolio that might be passive or active, consistent with the model in Section 2. We then compute the average *Passive Share* weighted by each fund's AUM. With this strategy, we obtain an estimated passive fund share of 50%.[17] We calculate A_t by adjusting the AUM tracking the EMBIGD index, using a rescaling factor of 50%, thus obtaining the estimated passive funds tracking the index we use to compute the FIR.[18]

We gather data on individual bond prices from Datastream and obtain several bond characteristics (maturity and duration, among others) directly from J.P. Morgan Markets.

[14]The EMBI Global Core uses the same diversification methodology as the EMBIGD to calculate the bond weights, as described in Appendix . The criteria for including bonds in the EMBI Global Core is the same as that for the EMBIGD (and the EMBI Global), except the minimum face amount of the bonds must be US$1 billion and the maturity required to be maintained in the index is of at least one year.
[15]The data sample periods utilized in the paper are determined by data access constraints.
[16]We compute the *Active Share* at the country level by using the country weights in the index and in the funds' portfolios rather than bond weights. For the portfolios, we only assign bonds to a given country if they are included in the EMBIGD. Specifically, a country's weight in a portfolio is determined by adding together the weights of all bonds from that country that are included in the EMBIGD.
[17]Appendix Table D1 provides results using alternative shares of passive funds used to construct the FIR measure. Although our quantitative estimates change slightly, the qualitative implications remain the same.
[18]For comparison, we construct *Active Share* at the bond level, obtaining a value-weighted average of 72%. Cremers and Petajisto (2009) show an average value-weighted *Active Share* that fluctuates between 55% and 80%.

Figure 3
Flows implied by rebalancing (FIR)

(a) Relationship between FIR and Z (b) Distribution of instrumented FIR values



Notes: Panel (a) presents a scatter plot of the FIR and the Z instrument. Both variables are residualized based on a regression with rebalancing-month and country fixed effects. The FIR is computed as in Equation (7) and Z as in Equation (9). Panel (b) shows a histogram of the FIR instrumented with Z. For both panels, the sample period is 2016–2018.

To clean our dataset, we drop extreme values of daily returns, stripped spreads, and $Z_{c,t}$.[19] We drop stripped spreads below 0 or above $5,000$ basis points as well as observations below the 5th or above the 95th percentiles in terms of the distribution of $Z_{c,t}$. The reason for the latter is that extreme values of $Z_{c,t}$ could be driven by large, pre-announced changes in the EMBIGD and thus are not appropriate for our identification strategy, which relies on the assumption that most information is known on the last business day of the month. Finally, we exclude bond-month observations that experience daily returns below (above) the 1st (99th) percentile in terms of the daily return distribution.

Our final dataset comprises 107,350 bond-time observations for 738 bonds in 68 countries. Table 1 displays summary statistics for our main measure of the instrumented flows implied by the rebalancing, $F\hat{I}R_{ct}$, as well as for the other key variables in our database. Bonds in our sample have an average stripped spread of 278 basis points, an average maturity of 10 years, and an average face amount of US\$1.3 billion.

Panel (a) of Figure 3 presents results regarding our first stage. It shows a scatter plot of the FIR and the $Z_{c,t}$ instrument after both variables have been residualized with rebalancing-month and country fixed effects. The two variables have a clear positive relationship, and the R-squared is 86%. Panel (b) presents the distribution of our instrumented FIR measure. The values range from -0.7% to around 0.25%, with more negative than positive observations. This is consistent with the fact that over time, the number of bonds included in the EMBIGD increased. Given that we restrict our analysis to countries whose face amount remains constant, including bonds from other countries typically reduces the weight of sample countries (i.e., a

[19]Stripped spread is defined in the notes of Table 1.

negative FIR).[20]

3.3 Results

Table 2 reports the results of our baseline estimation using a five-day window around each rebalancing event (i.e., $h \in [-5, 5]$).[21] Our coefficient of interest, β, is always positive and statistically significant in the different specifications. The estimate in our preferred specification, with bond-rebalancing month fixed effects, implies that a 1 p.p. increase in the FIR increases bond returns by 0.29 p.p.

One potential concern with these results is that bonds receiving a larger or smaller FIR during the rebalancings are on different price trends even before the rebalancing date. To show that this is not the case, we estimate a specification with leads and lags, where the instrumented FIR is interacted with a dummy for each of the trading days around the rebalancing event:

$$\log(q_{i,t,h}) = \theta_{c(i),t} + \theta_{b(i),t} + \sum_{h \notin -2} \gamma_h \mathbb{1}_h + \sum_{h \notin -2} \beta_h (F\hat{I}R_{c(i),t} \times \mathbb{1}_h) + \mathbf{X}_{i,t} + \varepsilon_{i,t,h}, \tag{11}$$

where $\mathbb{1}_h$ are dummy variables equal to 1 for the h trading day in our $[-5 : +5]$ estimation window and 0 otherwise.

The estimated β_h coefficients are reported in Figure 4. On the initial four of the five trading days before the index rebalancing, changes in the FIR are not associated with systematic differences in bond prices. Instead, in the trading days after the event, the coefficient increases, becomes positive and significant, and eventually stabilizes below 0.4 by the end of our estimation window. We do observe a slight anticipation in the day before the index rebalancing, which is not uncommon in these setups. For example, this is consistent with the patterns of portfolio rebalancings by different institutional investors highlighted in Escobar et al. (2021), who show that institutional investors could move in the day before the actual index rebalancing event. In the last column of Table 2, we show the estimates based on our main specification of Equation (10) but after excluding the trading day before the index rebalancing. This leads to an estimate of 0.33, which we take as our baseline since it does not contain any anticipation effect in the pre-period.

One related concern is the potential for increased anticipation throughout the month. Between the middle and end of every month, J.P. Morgan releases preliminary estimates

[20] When a bond is added to the index, it generally reduces the weight of other bonds in terms of their total face amount. However, in certain situations, it could increase the weight of certain countries through a relaxation of face amount caps, as the EMBIGD sets limits on the included face amount of countries to maintain a diversified portfolio.

[21] Appendix Table D3 shows that our results are robust to alternative windows around the rebalancing events.

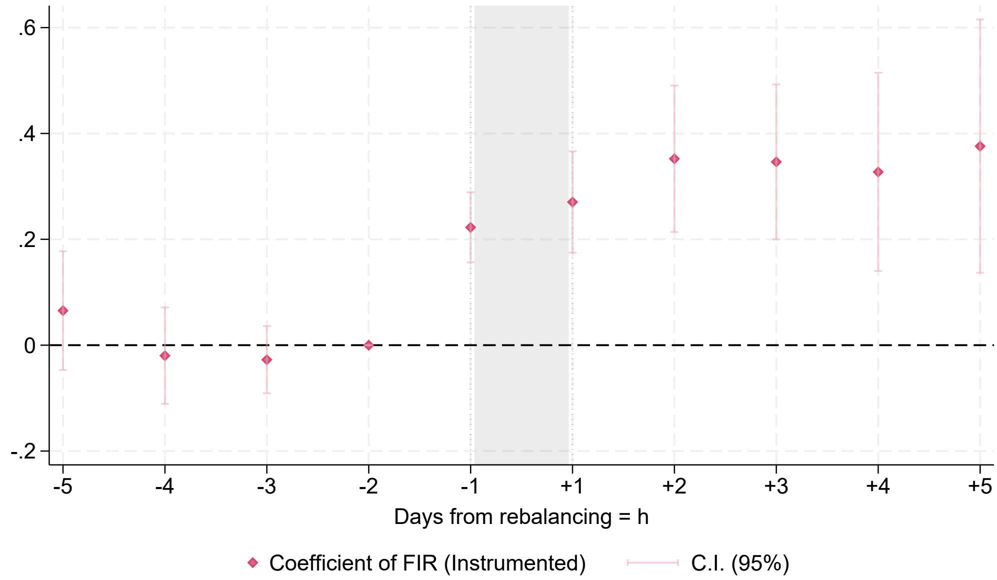
Table 2
Log price and FIR

Dependent Variable: Log Price						
			[-5:+5]			No h=-1
FIR	-4.014***	-0.170	1.252**			
	(0.583)	(0.740)	(0.572)			
FIR X Post	0.286***	0.286***	0.286***	0.287***	0.286***	0.330***
	(0.091)	(0.091)	(0.092)	(0.092)	(0.090)	(0.098)
Post	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes	No	No
Month FE	No	Yes	No	No	No	No
Bond Characteristics-Month FE	No	No	Yes	Yes	No	No
Country-Month FE	No	No	No	Yes	No	No
Bond-Month FE	No	No	No	No	Yes	Yes
Bond Controls	No	No	No	Yes	No	No
Observations	107,138	107,138	107,138	107,098	107,138	96,424
N. of Bonds	738	738	738	738	738	738
N. of Countries	68	68	68	68	68	68
N. of Clusters	1,618	1,618	1,618	1,617	1,618	1,618
F (FS)	1,000	693	1,008	1,958	2,017	2,023

Note: This table presents 2SLS estimates of log bond prices on the FIR measure (Equation (7)), instrumented by Z (Equation (9)), around rebalancing dates. The first- and second-stage equations are described in Equation (10). The estimations use a symmetric five-trading-day window, with *Post* as an indicator variable (equal to 1 for the five trading days after rebalancing, and 0 otherwise). Month fixed effects are dummy variables equal to 1 for each rebalancing month (0 otherwise), and bond characteristics are fixed effects that interact maturity, ratings, and bond type fixed effects. Maturity fixed effects are constructed by dividing a bond's time to maturity into four different categories: short (less than 5 years), medium (5–10 years), long (10–20 years), and very long (20+ years). Ratings from each bond are from Moody's. Bond type differentiates sovereign from quasi-sovereign bonds. Bond controls indicate whether the estimation includes the log face amount and log stripped spread of the bond. The last column's analysis drops the trading day before rebalancing. Standard errors are clustered at the country-month level, and the sample period is 2016–2018. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

about end-of-month face amounts, market values, and bond weights. While it is conceivable that active investors traded on this information before the actual index rebalancing date, our data do not support this behavior. Normally, if a significant number of investors were anticipating the index rebalancing, we would expect to observe pre-trends in bond prices before the actual event. However, our analysis reveals no correlation between the FIR and bond returns in the week leading up to the rebalancing (with the only exception being the day before the event). Finally, if part of the rebalancing-driven inflows were to occur before the event, our FIR measure would overestimate them at the index rebalancing date. This, in turn, implies that our estimates can be understood as a lower bound.[22]

Figure 4
Leads and lags coefficients



Note: This figure presents leads and lags coefficients from a 2SLS estimation of bond log prices on a set of trading-day dummies around each rebalancing event, using the same 2SLS procedure as in Table 2. The estimation includes bond characteristics-month fixed effects (maturity, rating, and bond type). The shaded area indicates the rebalancing on the month's last business day, with $h = +1$ for returns on that day and $h = -1$ for returns on the preceding business day. The vertical red lines show a 95% confidence interval for each horizon. Standard errors are clustered at the country-month level.

The documented effects are heterogeneous across bonds with varying levels of default risk. To show this heterogeneity, we divide our sample into high- and low-spread bonds, those above and below the median spread in our sample, respectively. We estimate Equation (10) for each of these subsamples and report the results in Table 3. The table shows that the price of high-spread bonds is more sensitive to rebalancing shocks, with a 1 p.p. increase in the FIR associated with a 0.46 p.p. increase in bond returns. In contrast, for low-spread bonds, the effect is quantitatively close to zero and not statistically significant.[23]

[22] Appendix Table D1 shows how our estimates change as we proportionally decrease the FIR measure (due to a lower share of passive funds). These results could serve as guidance for what might happen if the FIR measure were lower due to some investors' portfolio rebalancings being anticipated.

[23] Appendix Table D4 divides bonds into three groups according to their spreads. We find that bond prices are positively associated with the FIR for both high (above 302 basis points) and medium (between 158 and 302 basis points) spread bonds. Instead, for low spread bonds (below 158 basis points), the relationship is statistically insignificant. Additionally, the estimated coefficient increases with the risk profile of the bonds.

Table 3
Log price and FIR: Spread heterogeneity

Dependent Variable: Log Price						
	High Spread				Low Spread	
FIR X Post	0.461	***	0.462	***	0.100	0.100
	(0.136)		(0.135)		(0.088)	(0.088)
Bond FE	Yes		No		Yes	No
Month FE	Yes		No		Yes	No
Bond-Month FE	No		Yes		No	Yes
Observations	53,364		53,364		53,774	53,774
N. of Bonds	497		497		498	498
N. of Countries	62		62		51	51
N. of Clusters	1,249		1,249		895	895
F (FS)	594		2,333		451	963

Note: This table presents 2SLS estimates of bond log prices on the FIR measure, instrumented by Z, across rebalancing dates. The sample is divided into high-spread bonds in Columns 1 and 2, above the median stripped spread, and low-spread bonds in Columns 3 and 4, below the median. The sample period, the construction of five-day window, and the 2SLS procedure are identical to those described in Table 2. The estimation includes coefficients for $Post$ and FIR but are not reported for brevity. Standard errors are clustered at the country-month level. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

3.4 Reduced-Form Demand Elasticities

We can map the estimated reactions of bond prices to a reduced-form demand elasticity, as shown by rewriting Equation (3) to reflect our FIR measure: $\hat{\eta} = (-)\frac{\Delta \log(q_t^i)}{FIR_{c,t}}$. This aligns precisely with the role of our β coefficient in Equation (10). Based on the estimates in Table 2 (last column), the inverse demand elasticity is -0.33, implying a demand elasticity of -3. These estimates are in the ballpark of other estimates in the literature for other financial markets and assets (Appendix Figure C5).

As shown in Section 2, the previous estimates do not capture a structural elasticity because the default risk and expected payoffs of bonds may be affected by the shocks. Thus, part of the documented price reaction could be driven by these endogenous responses and not by a downward-sloping demand curve (as shown in Equation (6)). One way to assess the magnitude of these endogenous effects is to quantify how changes in the FIR affect a country's default risk. To this end, we use credit default swaps (CDS) as a proxy for default risk. We find that increases in the FIR tend to decrease CDS spreads (see Appendix Table D5). The estimates imply that, for the median CDS spread in the sample (about 190 basis points), a 1 p.p. increase in the FIR decreases CDS spreads by 1.5 basis points.

Using this estimate, and based on a simple back-of-the-envelope calculation, we can quantify the effects of changes in default risk on our reduced-form elasticity. For this, we first convert changes in CDS spreads into changes in bond prices by calculating the median duration of the bonds in our sample and then multiplying it by the estimated effect of the FIR on CDS spreads. Given a median duration for bonds of 5.5 years, the estimated decrease in CDS spreads increases bond prices by almost $1.5 \times 5.5 = 8.25$ basis points. This analysis thus suggests that changes in default risk could account for around 25% of our reduced-form elasticity (i.e., 8.25/33).

Although informative, these estimates should be taken with caution as bond prices and CDS spreads are determined jointly. Given that the FIR measure captures shocks to the demand of passive investors, it is possible that shocks are correlated across both bond and CDS markets. Thus, it might be the case that a fall in CDS spreads is not capturing a lower default risk but rather an increase in CDS demand. In the next section, we build a quantitative model that allows us to quantify the role of endogenous movements in default risk behind the documented price responses.

4 Optimal Supply of Risky Sovereign Bonds

We next formulate a quantitative sovereign debt model to study the impact of a downward-sloping demand on a government's supply of risky bonds. We use the model to disentangle the mechanisms behind our reduced-form demand elasticity and to back out a structural elasticity that isolates the endogenous response of default risk. The model features a risk-averse government that issues long-term debt in international debt markets. The government has limited commitment and can endogenously default on its debt obligations. To tightly link the model with our empirical analysis, we introduce two types of investors (active and passive) and a rich demand structure, allowing us to capture a downward-sloping demand for government bonds.

4.1 Issuer Problem

We consider a small open economy with incomplete markets and limited commitment. Output is exogenous and follows a continuous Markov process with a transition function $f_y(y' \mid y)$. Preferences of the representative consumer are given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t), \tag{12}$$

where β is the discount factor, c_t denotes consumption, and the function $u(.)$ is strictly increasing and concave.

An infinite-lived, risk-averse government issues long-term bonds in international markets to smooth consumption. Let B denote the beginning-of-period stock of government debt. Each unit of B matures in the next period with probability λ. If a bond does not mature (and the government does not default), it pays a coupon ν. Let $d = \{0, 1\}$ denote the default policy, where $d = 1$ indicates a default. Default leads to a temporary exclusion from international debt markets and an exogenous output loss, $\phi(y)$.

International markets are competitive and populated by heterogeneous investors who differ in their degree of activeness and passiveness. Let $\mathcal{A}'(.)$ and $\mathcal{T}'(.)$ denote the active and passive demand functions, respectively. As in Section 2, we assume that the active demand is a function of a bond's expected return and volatility. The passive demand is perfectly inelastic and given by $\mathcal{T}' = \mathcal{T}(\tau, B')$. That is, it depends on the end-of-period stock of bonds, B', and on some time-varying index weight, τ. For tractability, we assume that τ is exogenous and follows a continuous Markov process with a transition function $f_\tau(\tau' \mid \tau)$. Given an end-of-period bond supply B', the market-clearing condition can we written as $B' = \mathcal{A}'(\tau, B') + \mathcal{T}(\tau, B')$.

The state space can be summarized by the n-tuple (h, B, s), where h captures the government's current default status and $s = (y, \tau)$ the exogenous states. Under these assumptions, and for a given default status h and choice of B', the resource constraint of the economy can be written as

$$\begin{aligned} c(h=0, B, y, \tau; B') &= y + q\left(y, \tau, B'\right)\left(B' - (1-\lambda)B\right) - \left(\lambda + (1-\lambda)\nu\right)B, \\ c(h=1) &= y - \phi_j(y), \end{aligned} \tag{13}$$

where $q(y, \tau, B')$ denotes the price of a unit of debt, $B' - (1-\lambda)B$ are new bond issuances, and $(\lambda + (1-\lambda)\nu)B$ are current debt services.

4.2 The Government's Recursive Problem

The government is benevolent and chooses $\{d, B'\}$ to maximize Equation (12), subject to the resource constraint in Equation (13). If the government is not in default, its value function is given by

$$V(y,\tau,B) = \text{Max}_{d=\{0,1\}} \left\{ V^r(y,\tau,B), V^d(y) \right\}, \tag{14}$$

where $V^r(.)$ denotes the value function in case of repayment and $V^d(.)$ denotes the default value. If the government chooses to repay, then its value function is given by the following Bellman equation:

$$\begin{aligned} V^r(y,\tau,B) &= \text{Max}_{B'} \;\; u(c) + \beta\, \mathbb{E}_{s'|s} V\left(y',\tau',B'\right), \qquad (15) \\ \text{subject to} \quad c &= y + q(y,\tau,B')\left(B' - (1-\lambda)B\right) - \left(\lambda + (1-\lambda)\nu\right) B. \end{aligned}$$

If the government defaults, it is excluded from debt markets and cannot issue new debt. The government exits a default with probability θ, with no recovery value. We further assume that the demand from passive investors is zero while the government is in default. Under these assumptions, the value function in case of default is given by

$$V^d(y) = u\left(y - \phi(y)\right) + \beta\, \mathbb{E}_{s'|s} \left[\theta V\left(y',\tau',0\right) + (1-\theta)\, V^d\left(y'\right)\right]. \tag{16}$$

4.3 Bond Pricing Kernel

Foreign lenders are competitive and discount payoffs at the risk-free rate. Based on the analysis in Section 2, given an exogenous state $\{y, \tau\}$ and a choice of B', the bond price function faced by the government is given by

$$q\left(y,\tau,B'\right) = \beta^\star\, \mathbb{E}_{s'|s}\left[\mathcal{R}\left(y',\tau',B'\right)\right]\; \Psi\left(y,\tau,B'\right), \tag{17}$$

where $\beta^\star \equiv 1/(1+r_f)$, $\mathcal{R}'(.) \equiv \mathcal{R}(y',\tau',B')$ denotes the next-period repayment function, and $\Psi(y,\tau,B')$ captures the downward-sloping component of the active demand.[24] In turn, the next-period repayment function is given by

$$\mathcal{R}\left(y',\tau',B'\right) = \left[1 - d\left(y',\tau',B'\right)\right](1-\lambda)\left(\nu + q(y',\tau',B'')\right), \tag{18}$$

where $d(y',\tau',B')$ is the next-period default choice and $q(y',\tau',B'')$ denotes the next-period bond price, which is a function of next-period exogenous states, $\{y',\tau'\}$, and the next-period debt policy, $B'' \equiv B'(y',\tau',B')$.

[24] The case where $\Psi(y,\tau,B') = 1$ for all $\{y,\tau,B'\}$ captures the perfectly elastic case. In this instance, the bond price is only a function of the expected next-period repayment.

From Equations (17) and (18), it is clear that the bond price decreases with the expected default probability. Specifically, a larger B' (weakly) increases the default risk (conditional on a level of output), and thus $q(y, \tau, B')$ (weakly) decreases in B'. As for $\Psi(y, \tau, B')$, we only assume for now that $\frac{\partial \Psi(y,\tau,B')}{\partial \mathcal{A}'(\tau,B')} \leq 0$. Thus, this term introduces another mechanism for the bond price to be decreasing in B': the downward-sloping demand of active investors.

4.4 Demand and Supply Elasticities

Introducing passive and active investors allows us to replicate our empirical exercise. That is, we can exploit exogenous movements in τ, analyze their effects on bond prices, and estimate a demand elasticity. This is straightforward to do in the model as we can directly shock τ while keeping the country's fundamentals fixed. Let $\Delta\mathcal{T}' \equiv \mathcal{T}(\tau_1, B') - \mathcal{T}(\tau_0, B')$ denote an exogenous shift in the passive demand.[25] Given $\Delta\mathcal{T}'$, and by means of simulations, we can compute the same reduced-form elasticity within the model as in our empirical analysis. We denote this elasticity as $\hat{\eta} = (-)\frac{\Delta q(.)}{\Delta \mathcal{T}'}\frac{B'-\mathcal{T}'}{q(.)}$.

Through its effects on bond prices, changes in τ affect the government's value function $V^r(.)$ (as shown in Equation (15)) and thus influence its debt and default policies, $B'(.)$ and $d(.)$, respectively. Changes in these policies in turn impact the bond's expected payoff and its price (as shown in Equations (17) and (18)). Therefore, part of the price reaction captured in $\hat{\eta}$ is reflecting these endogenous responses and not a downward-sloping demand component.

We use the model to decompose $\hat{\eta}$ into a structural demand elasticity η and changes in expected risk and repayment α. Using the model formulas, we can derive an analogous expression to the one in Equation (6):

$$\underbrace{(-)\frac{\Delta q(.)}{\Delta \mathcal{T}'}\frac{B'-\mathcal{T}'}{q(.)}}_{\equiv \hat{\eta}} = \underbrace{(-)\frac{\Delta \Psi(.)}{\Delta \mathcal{T}'}\frac{B'-\mathcal{T}'}{\Psi(.)}}_{\equiv \eta} + \underbrace{(-)\frac{\Delta \mathbb{E}_{s'|s}\mathcal{R}'(.)}{\Delta \mathcal{T}'}\frac{B'-\mathcal{T}'}{\mathbb{E}_{s'|s}\mathcal{R}'(.)}}_{\equiv \alpha}. \tag{19}$$

By keeping the repayment function $\mathcal{R}'(.)$ fixed, we can isolate the part of the reduced-form elasticity that is explained by changes in default risk.

The model has important implications for the optimal supply of risky bonds. In our setup, the government internalizes the effects of changes in B' on $q(y, \tau, B')$ through both changes in its default probability and the downward-sloping demand component. More formally, let $\varepsilon \equiv \frac{\partial \log q(.)}{\partial \log B'}$ denote the (inverse) supply elasticity, which can be expressed as

$$\epsilon = \frac{\partial \log \mathbb{E}_{s'|s}\mathcal{R}'(.)}{\partial \log B'} + \frac{\partial \log \Psi(.)}{\partial \log B'}. \tag{20}$$

[25] Note that index weights change but the (end-of-period) bond supply remains fixed.

The first term on the right-hand side captures the elasticity of the expected repayment function with respect to the bond supply. This elasticity is typically negative because a larger B' increases default risk and reduces the expected bond payoff. The second term captures the additional decline in the bond price due to the downward-sloping demand. Given that the government internalizes both effects, a more inelastic demand affects its optimal bond supply. In the next section, we use a calibrated version of the model to quantify the effects of inelastic demand on both a government's bond supply and its default policy.

5 Quantitative Analysis

5.1 Calibration

We calibrate the model using data on Argentina at a quarterly frequency. The calibration follows a two-step procedure. We first fix a subset of parameters to standard values in the literature or based on historical Argentine data. We then internally calibrate the remaining parameters to match relevant moments for Argentine spreads and other business cycle statistics.

In terms of functional forms and stochastic processes, we assume that the government has CRRA preferences: $u\left(c\right)=\frac{c^{1-\gamma}}{1-\gamma}$, where γ denotes the risk aversion. Output follows an AR(1) process given by $\log\left(y'\right)=\rho_y\log\left(y\right)+\epsilon_y'$, with $\epsilon_y'\sim N(0,\sigma_y)$. If the government defaults, output costs are governed by a quadratic loss function $\phi\left(y\right)=\max\left\{d_0y+d_1y^2,0\right\}$. For $d_0<0$ and $d_1>0$, the output cost is zero whenever $0\leq y\leq-\frac{d_0}{d_1}$ and rises more than proportionally with y when $y>-\frac{d_0}{d_1}$. This loss function is identical to the one used in Chatterjee and Eyigungor (2012) and allows us to closely match the sovereign spreads observed in the data. As for the demand of passive investors, we assume that it is proportional to the (end-of-period) amount of bonds outstanding. Specifically, $\mathcal{T}'=\mathcal{T}\left(\tau,B'\right)=\tau\times B'$. We let τ follow an AR(1) process given by $\log(\tau')=(1-\rho_\tau)\log(\tau^\star)+\rho_\tau\log(\tau)+\epsilon_\tau'$, where $\epsilon_\tau'\sim N\left(0,\sigma_\tau\right)$.

Based on the analysis in Section 2, we consider the following functional form for the downward-slopping $\Psi(.)$ term:

$$\Psi\left(y,\tau,B'\right)=\exp\left\{-\kappa_0\frac{\mathbb{V}_{s'|s}\left(\mathcal{R}'(.)\right)}{\mathbb{E}_{s'|s}\left(\mathcal{R}'(.)\right)}\times\left(B'-\mathcal{T}'-\bar{\mathcal{A}}\right)\right\},\qquad(21)$$

where $\kappa_0\geq0$ captures the "slope" of the demand function and $\bar{\mathcal{A}}$ denotes the average holdings of active investors (as determined by the fixed component of their mandates, ξ_j^i).

Table 4
Calibration of the model

Panel a: Fixed Parameters			Panel b: Calibrated Parameters		
Param.	Description	Value	Param.	Description	Value
γ	Risk aversion	2.00	β	Discount rate	0.949
r	Risk-free interest rate	0.01	$\bar{d}_0$	Default cost—level	−0.24
λ	Debt maturity	0.05	$\bar{d}_1$	Default cost—curvature	0.29
z	Debt services	0.03	κ_0	Slope parameter	60.0
θ	Reentry probability	0.0385	$\bar{\mathcal{A}}$	Active investors demand	0.526
ρ_y	Output, autocorrelation	0.93			
σ_y	Output, shock volatility	0.02			
$\tau^\star$	Share of passive demand	0.123			
$\rho_\mathcal{T}$	FIR, autocorrelation	0.66			
$\eta_\mathcal{T}$	FIR, shock volatility	0.02			

For tractability, we assume time-invariant values for both κ_0 and $\bar{\mathcal{A}}$.[26] This specification introduces a wedge only for risky bonds (i.e., those with $\mathbb{V}_{s'|s}(\mathcal{R}'(.)) > 0$). As we show next, it allows us to capture the two key features of our empirical analysis: a downward-sloping demand for active investors and a demand elasticity that increases (in magnitude) with default risk (i.e., with a larger return variance). Note that when $B' - \mathcal{T}' - \bar{\mathcal{A}} \geq 0$, $\Psi(.) \leq 1$. We thus view $\Psi(.)$ as an "inconvenience" yield, that is, a premium demanded by investors as compensation for holding the bond, in excess of its default risk.[27]

Table 4 lists the calibrated parameters. For the subset of fixed parameters (Panel a), we set $\gamma = 2$, which is a standard value for risk aversion in the literature. We also set a quarterly risk-free rate of $r_f = 0.01$, in line with the average real risk-free rate observed in the United States. The probability of re-entering international markets is set to $\theta = 0.0385$, implying an average exclusion duration of 6.5 years. We set $\lambda = 0.05$ to target a debt maturity of 5 years and $\nu = 0.03$ to match Argentina's average debt services. The parameters for the endowment process, ρ_y and σ_y, are based on log-linearly detrended quarterly real GDP data of Argentina. All these parameters are taken from Morelli and Moretti (2023). Last, we set $\tau^\star$ to match the average share of Argentina's external debt tracked by passive investors, and calibrate $\rho_\mathcal{T}$ and $\sigma_\mathcal{T}$ to match the persistence and volatility of our FIR measure.

We internally calibrate the remaining parameters (Table 4, Panel b). We jointly calibrate the default cost level and curvature, $\{d_0, d_1\}$, together with the government's discount factor β, to target Argentina's average ratio of (external) debt to GDP, average spread, and volatility

[26] As shown in Section 2, these terms could be, in principle, time-varying functions. We also use an exponential specification purely for computational reasons: to avoid having a negative price.

[27] For low values of B', when $B' - \mathcal{T}' - \bar{\mathcal{A}} < 0$, $\Psi(.) \geq 1$. However, when B' is small, the variance of the repayment function tends to be small (due to the low default risk), and hence $\Psi(.)$ is typically close to one in these cases.

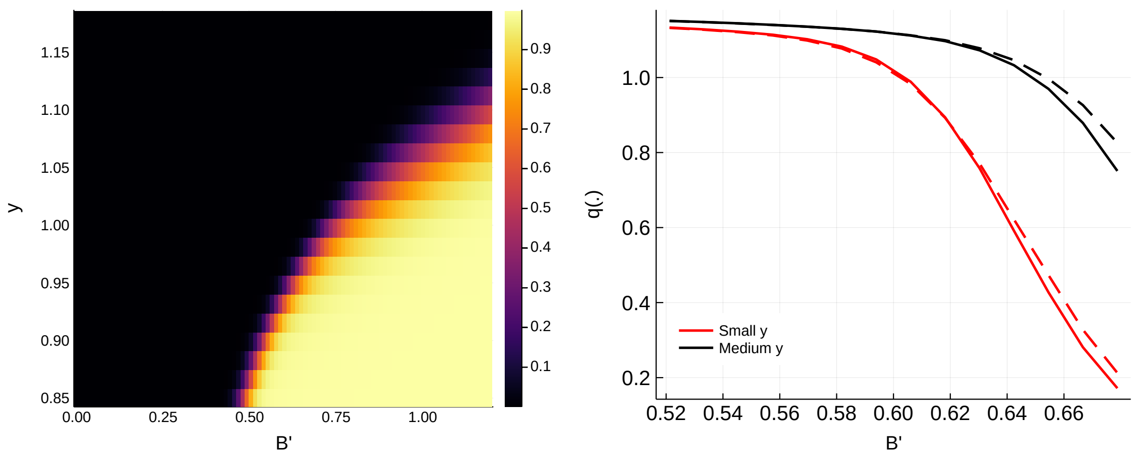
Table 5
Targeted moments

Target	Description	Data	Model
$\mathbb{E}[SP]$	Bond spreads	472bp	466bp
$\sigma(SP)$	Volatility of spreads	200bp	148bp
$\mathbb{E}[D/Y]$	Debt to output	72%	62%
$\mathbb{E}[\Psi]$	Inconvenience yield	1.0	1.006
$\hat{\eta}$	Reduced-form elasticity	-0.33	-0.31

Note: The table reports the moments targeted in the calibration and their model counterpart.

Figure 5
Default set and bond prices

(a) Default set (b) Bond price



Note: Panel (a) shows the default policy for different combinations of B' and y. The black area depicts combinations of B' and y such that default probability is zero. Lighter colors indicate a higher default probability. In Panel (b), the solid lines show the bond pricing kernel $q(y, \tau, B')$ for different values of B' and for two values of output. The dashed lines show the bond price under a perfectly elastic demand, taking as given the same bond and repayment policies as in our baseline model (i.e., $q(.)/\Psi(.)$).

of spreads.[28] Additionally, we calibrate κ_0 to match the estimated (inverse) reduced-form demand elasticity, $\hat{\eta} = -0.33$. Last, we set $\bar{\mathcal{A}}$ to match the average holdings of active investors. That is, $\bar{\mathcal{A}} = \bar{B} - \bar{\mathcal{T}}$, where $\bar{B}$ denotes the average debt stock and $\bar{\mathcal{T}}$ denotes passive investors' average holdings. Given Equation (21), this is equivalent to targeting an average $\Psi(.)$ of one. The introduction of $\Psi(.)$ thus only affects the sensitivity of the pricing kernel to changes in B' around the $\{\bar{B}, \bar{\mathcal{T}}, \bar{\mathcal{A}}\}$ point.

Figure 5 depicts the default set and the bond price function $q(.)$ for different values of B' and y. Panel (a) shows that the government defaults in states with high debt and low output. Panel (b) shows that, as a consequence, the bond price is decreasing in B' and increasing in y. The dashed lines in Panel (b) show the bond prices under a counterfactual in which we

[28] Annualized spreads are computed as $SP = \left(\frac{1+i(y,\tau,B')}{1+r_f}\right)^4 - 1$, where $i(y, \tau, B')$ is the internal quarterly return rate, which is the value of $i(.)$ that solves $q(y, \tau, B') = \frac{[\lambda+(1-\lambda)\nu]}{\lambda+i(y,\tau,B')}$.

Table 6
Persistence of shocks and demand elasticity

Moment	Baseline	Lower Persistence	Higher Persistence
Reduced-form Elasticity, $\hat{\eta}$	-0.306	-0.28	-0.331
Structural Elasticity, η	-0.188	-0.206	-0.166
Ratio, $\eta/\hat{\eta}$	61%	74%	50%

Note: The table compares the reduced-form inverse demand elasticity $\hat{\eta}$ with the structural one η. The "Baseline" column shows the elasticities under our baseline calibration. In the "Lower Persistence" case, we decrease the persistence of the $\{\tau\}$ process by setting $\rho_{\mathcal{T}} = 0.50$. The "Higher Persistence" column shows the results for $\rho_{\mathcal{T}} = 0.80$.

take the baseline $B'(.)$ policy but assume that the demand is perfectly elastic (i.e., it shows the $q(.)/\Psi(.)$ function). At lower B' levels, where default risk is minimal, bond prices remain largely unaffected by the downward-sloping demand. However, as B' increases, increased return volatility decreases Ψ, subsequently lowering the bond price q.

5.2 Decomposing the Reduced-form Demand Elasticity

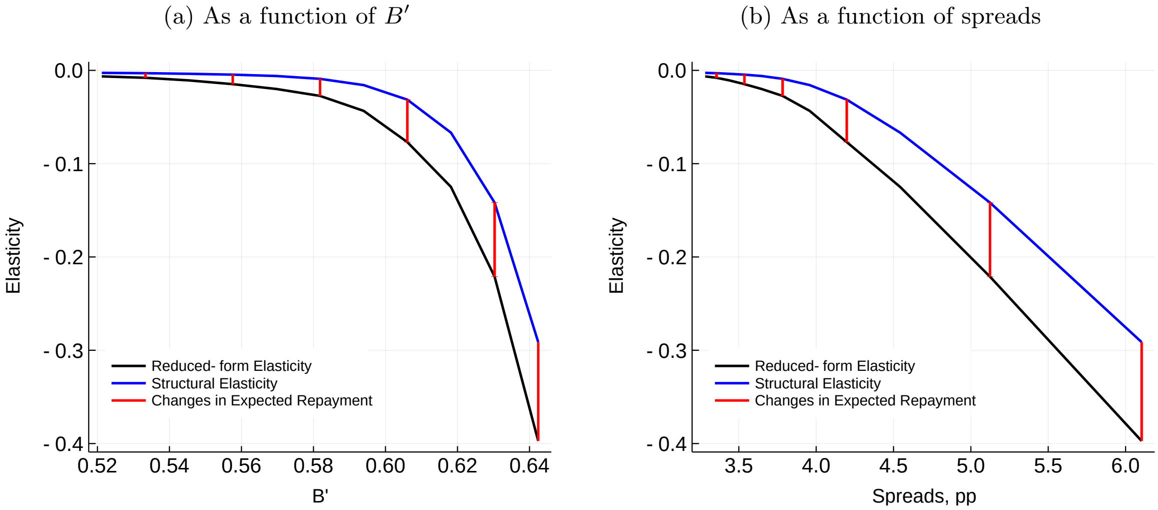
We formally disentangle the different channels through which changes in $\mathcal{T}$ affect bond prices. As shown in Equation (19), index rebalancing affects bond prices through two mechanisms: (i) the (inverse) structural demand elasticity of active investors, η, and (ii) changes in expected repayment, α. Using the calibrated model, we can isolate the effects driven by changes in expected repayment to properly identify the structural demand elasticity.

Figure 6 decomposes the channels outlined in Equation (19). The black line shows the reduced-form (inverse) demand elasticity $\hat{\eta}$, while the blue line depicts the model-implied structural elasticity, η. The vertical differences between these two curves (red lines) indicate the portion of the reduced-form elasticity attributable to endogenous changes in the repayment function, α. We find that the magnitude of $\hat{\eta}$ is always higher than that of η. This is consistent with our empirical analysis based on CDS spreads (described in Section 3). The difference can be substantial, particularly for larger values of B' and for higher bond spreads.

The first column of Table 6 shows the unconditional average for both the reduced-form elasticity, $\hat{\eta}$, and the structural elasticity, η. On average, the structural elasticity accounts for less than two-thirds of the reduced-form elasticity. The rest is explained by endogenous changes in the expected repayment, α. Despite the fundamentals (y, B') being fixed and the $\Delta\mathcal{T}'$ shocks being exogenous, the reduced-form elasticity significantly differs from the structural one.

The magnitudes of the documented biases critically depend on the persistence of the shock. The last two columns of Table 6 compare the reduced-form and structural elasticities

Figure 6
Disentangling the demand elasticity



Note: The figure shows the reduced-form inverse demand elasticity $\hat{\eta}$ (black lines) and the structural one η (blue lines). The vertical differences between the two lines (represented by the red lines) capture the endogenous changes in bonds' expected repayment, α. Panel (a) shows the results as a function of B', while Panel (b) shows the results as a function of annualized bond spreads.

for different persistence values for the $\{\tau\}$ process (i.e., ρ_τ). When the shock is more (less) persistent, a smaller (larger) share of the total price response is explained by the inelastic component of the investors' demand. This is because more permanent shocks lead to larger changes in government policies and thus in the bond's expected repayment function.

Overall, our analysis highlights the importance of accounting for issuers' endogenous responses to an exogenous (supply-shifting) shock and the resulting changes in assets' expected repayment. Neglecting these factors can introduce significant biases into the estimated demand elasticity, particularly if the shock is persistent. As argued in Section 3, our FIR measure is inherently more temporary than other supply-shifting instruments used in the literature, such as index additions or deletions. However, even in that case, the bias can represent over one-third of the reduced-form elasticity.

5.3 Implications of a Downward-sloping Demand

As shown in Equation (20), in determining its optimal debt policy, the government internalizes not only the effects of a higher B' on $q(.)$ through changes in its default probability but also its effects through the inelastic demand. This section quantifies the implications of a downward-sloping demand on government policies and their subsequent effects on bond prices. To this end, we compare our baseline model with a downward-sloping demand with an alternative scenario where investors are perfectly elastic.

Table 7 reports a set of targeted and untargeted moments for our baseline model (with

Table 7
Comparison with perfectly elastic case

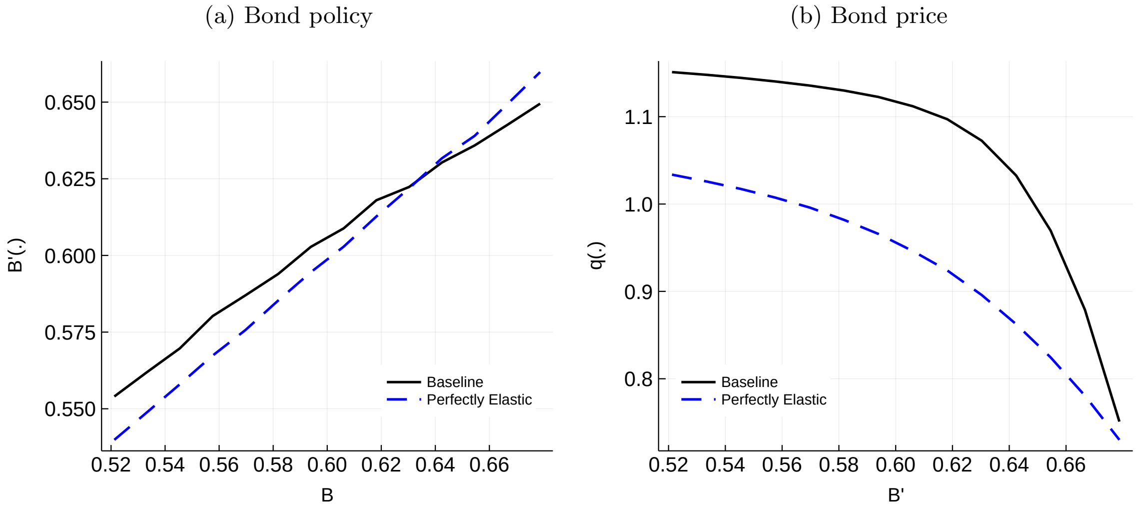
Moment	Description	Baseline	Perfectly Elastic
$\mathbb{E}\,(SP)$	Bond spreads	466bp	888bp
$\sigma\,(SP)$	Volatility of spreads	148bp	479bp
$\mathbb{E}\,(B/y)$	Debt to output	62%	59%
$\mathbb{E}\,(d)$	Default Frequency	3.896%	4.696%
$\sigma(B)/\sigma(y)$	Standard deviation of debt, relative to output	1.884	2.359
$\rho\,(SP, y)$	Correlation between spreads and output	-0.707	-0.496

Note: The table compares a set of key moments between our baseline model with inelastic investors and a counterfactual scenario in which investors are perfectly elastic ($\kappa_0 = 0$).

$\kappa_>$) and for an alternative case with a perfectly elastic demand (κ_0). All the other model parameters remain the same. Despite similar values of debt, we find that the default frequency and average spreads are *lower* relative to the perfectly elastic case when facing an inelastic demand.

Two factors explain the lower default rate and bond spreads. First, the government debt policy is significantly affected by a downward-sloping demand. Panel (a) of Figure 7 shows the optimal debt policy $B'(y, \tau, B)$ in our baseline model and in the perfectly elastic case. For large values of B (in states where $\mathbb{V}\,(\mathcal{R}'(.))$ is high), an additional unit of B' reduces the bond price $q(.)$ due to both higher default risk and investors' inelastic behavior. As a result, the government does not find it optimal to issue large amounts of debt because it is too costly to do so. An inelastic demand thus introduces a limit to the maximum amount of debt that a government is willing to issue.

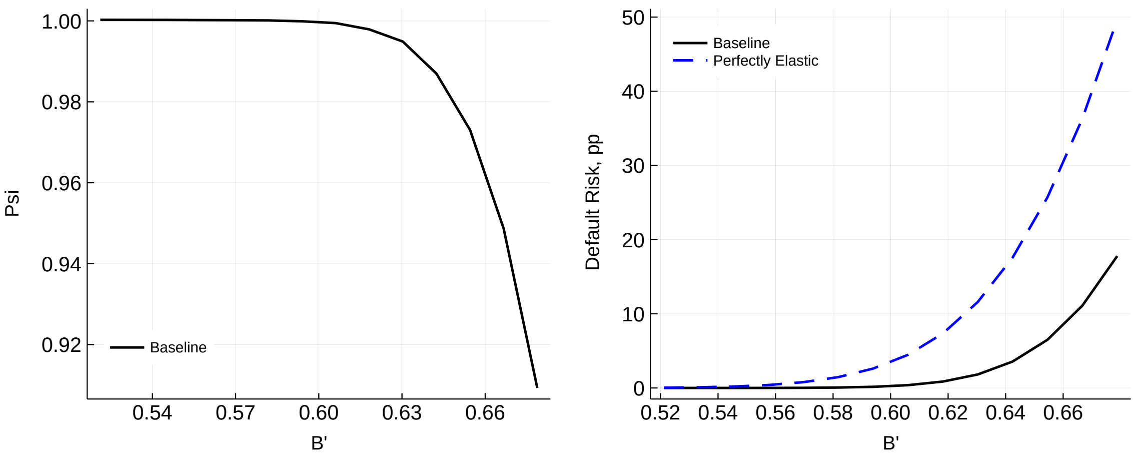
Figure 7
Implications on policies and prices



Note: The figure presents bond policies and prices for our baseline model with inelastic investors (black solid lines) and in an alternative model in which investors are perfectly elastic (blue dotted lines).

Figure 8
Inconvenience yield and default risk

(a) $\Psi(y, \tau, B')$ (b) Default risk, annualized



Note: Panel (a) depicts the $\Psi(y, \tau, B')$ function for different values of B'. Panel (b) shows the annualized default risk in our baseline model (black solid lines) and in a counterfactual in which investors are perfectly elastic (blue dotted lines).

Second, these changes in the optimal bond policy have important effects on the pricing of bonds (Figure 7, Panel (b)). For small values of B' (low default risk), $q(.)$ is actually *higher* than under the perfectly elastic case. As shown in Figure 8 (Panel (a)), this larger bond price is not driven by a convenience yield because, by construction, $\Psi(.)$ is typically smaller than one. Instead, the higher bond price is explained by a lower default risk (Panel (b)), which is a direct consequence of the government's lower incentives to issue large values of B'.

To summarize, an inelastic demand diminishes a government's incentives to issue additional units of debt, acting as a commitment device that reduces default risk and increases bond prices.

6 Conclusion

In this paper, we present evidence of downward-sloping demand curves in risky sovereign debt markets and analyze their implications for the optimal supply of sovereign bonds. Our approach combines evidence from high-frequency bond-level price reactions to well-identified shocks with a structural model featuring endogenous debt issuances and default risk. This methodology allows us to isolate endogenous changes in default risk behind the estimated price reactions and to back out a structural demand elasticity. Empirically, we find that a 1 p.p. exogenous reduction in the effective bond supply leads to a 33 basis point increase in bond prices. Our structural model reveals that over one-third of this response is due to endogenous changes in the expected repayment of bonds. Moreover, we find that the inelastic demand influences and shapes the governmental policies on optimal debt and default. By diminishing the government's incentives to issue additional units of debt, an inelastic demand acts as a commitment device that reduces default risk and borrowing costs.

Our results highlight the importance of considering issuers' endogenous responses and the resulting changes in expected asset payoffs. Failing to account for these responses can introduce significant biases when estimating demand elasticities, particularly for risky assets. Our paper can lead to further research along several dimensions. For example, given the model predictions, it would be interesting to empirically study the impact of inelastic demand on government debt issuances. More importantly, our framework can be extended to other assets and markets, notably equity and corporate bonds. The endogenous responses that we emphasize in this paper can be applied to other issuers' of risky assets, which we leave for future research.

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Appendix A: Model of Heterogeneous Inelastic Investors

In this appendix, we first provide additional material and derivations for the analysis in Section 2. We then describe microfoundations for the assumed demand structure, analyzing two related cases. In the first one, the inelasticity comes from investor risk aversion, while the second case is rooted in a VaR constraint to which investors are subject.

A.1 Additional Derivations

From Equation (1) in the main text, and based on a first-order approximation for the elastic component of the demand $e^{\kappa_j \hat{\pi}_{i,t}}$ around $\bar{\pi}_i$, we can write the market-value demand of active investors as follows:

$$\tilde{\mathcal{A}}_t^i = \sum_j \left(1 - \Lambda_j \bar{\pi}_i\right) W_{j,t} \theta_j \xi_j^i e^{\Lambda_j \bar{\pi}_i} + \hat{\pi}_{i,t} \sum_j \Lambda_j W_{j,t} \theta_j \xi_j^i e^{\Lambda_j \bar{\pi}_i}. \tag{A1}$$

The first term captures investors' average purchases of bond i, which are given by their exogenous mandates ξ_j^i. The second term captures deviations from those purchases (i.e., the elastic component of the demand), which is a function of $\hat{\pi}_{i,t}$.

For the remainder of the analysis, we focus on the case in which $\hat{\pi}_{i,t}\left(r_{t+1}^i\right) = \frac{\mathbb{E}_t\left(r_{t+1}^i\right)}{\mathbb{V}_t\left(r_{t+1}^i\right)}$. Define $\mathcal{R}_{t+1}^i$ as the next-period repayment per unit of the bond so that $r_{t+1}^i \equiv \frac{\mathcal{R}_{t+1}^i}{q_t^i} - r_f$, where r_f denotes the risk-free rate. We can then write $\hat{\pi}_{i,t}\left(r_{t+1}^i\right) = q_t^i \frac{\mathbb{E}_t \mathcal{R}_{t+1}^i - q_t^i r_f}{\mathbb{V}_t \mathcal{R}_{t+1}^i}$. Without loss of generality, consider a case where $\bar{\pi}_i$ is close to zero. After substituting these expressions into the equation, we can rewrite Equation (A1) as follows:

$$\tilde{\mathcal{A}}_t^i = q_t^i \bar{\mathcal{A}}_t^i + q_t^i \left(\frac{\mathbb{E}_t \mathcal{R}_{t+1}^i - q_t^i r_f}{\mathbb{V}_t \mathcal{R}_{t+1}^i}\right) \sum_j \Lambda_j W_{j,t} \theta_j \xi_j^i, \tag{A2}$$

where $\bar{\mathcal{A}}_t^i$ is defined such that $q_t^i \bar{\mathcal{A}}_{t+1}^i = \sum_j W_{j,t} \theta_j \xi_j^i$. We can interpret $\bar{\mathcal{A}}_t^i$ as active investors' holdings aimed at satisfying the fixed part of their mandates.

As for the demand of passive investors, let M_t denote the market value of the index $\mathcal{I}$ and define S_t^i as bond i's face amount included in this index. For simplicity, assume that bond i is only included in index $\mathcal{I}$. Then, $w_t^i = \frac{S_t^i q_t^i}{M_t}$, and we can write the market-value passive demand as

$$\tilde{\mathcal{T}}_t^i = q_t^i S_t^i \sum_j \frac{W_{j,t}\left(1 - \theta_j\right)}{M_t} = q_t^i \mathcal{T}_t^i, \tag{A3}$$

where $\mathcal{T}_t^i \equiv S_t^i \sum_j \frac{W_{j,t}(1-\theta_j)}{M_t}$ denotes the face amount of bond i's passive holdings.

After replacing Equations (A2) and (A3) in the market-clearing condition (Equation (2) in the main text), we obtain a closed-form solution for the bond price:

$$q_t^i = \frac{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{r_f}\left[1 - \kappa_t^i \frac{\mathbb{V}_t\left(\mathcal{R}_{t+1}^i\right)}{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}\left(B_{t+1}^i - \mathcal{T}_{t+1}^i - \bar{\mathcal{A}}_t^i\right)\right], \tag{A4}$$

where $\kappa_t^i\left(\mathbf{\Lambda}\right) \equiv \frac{1}{\sum_j \Lambda_j W_{j,t} \theta_j \xi_j^i}$ parameterizes the downward-slopping behavior of the demand. It is a weighted average of investors' $\{\Lambda_j\}$ parameters, where the weights are given by the amount that each investor allocates on bond i.

Next, we show that we can obtain an analogous pricing kernel under risk-averse investors or under risk-neutral investors subject to a standard variance-at-risk constraint.

A.2 Microfoundation Based on Risk-Averse Investors

Consider a case where investors are risk averse and have mean-var preferences. They care about both the total return of their portfolio and their return relative to a benchmark index $\mathcal{I}$ they track. Additionally, they are heterogeneous and differ in their degree of risk aversion and how their compensation depends on their total and relative return. Following the same notation as in the main text, let $j = \{1, ..., J\}$ denote the investor type. Let $i = \{1, ..., N\}$ denote the set of bonds that are part of the $\mathcal{I}$ index, and let $\boldsymbol{w}_t = \left\{w_t^1, ..., w_t^N\right\}$ be the vector of index weights for each constituent bond. The vector $\boldsymbol{r}_{t+1} = \left\{r_{t+1}^1, ..., r_{t+1}^N\right\}$ denotes the next-period (gross) returns (i.e., the bond gross return in excess of the risk-free rate, r^f). Last, let $\boldsymbol{B}_t = \left\{B_t^1, ..., B_t^N\right\}$ denote the bond supply.

For an investor j, their total compensation is a convex combination between the return of their portfolio and the relative return versus the index $\mathcal{I}$. Let $\boldsymbol{x}_{j,t} = \left\{x_{j,t}^1, ..., x_{j,t}^N\right\}$ be the vector of portfolio weights for investor j. The investor's compensation is

$$\begin{aligned} TC_{j,t} &= \theta_j \left(\boldsymbol{x}_{j,t}\right)' \cdot \boldsymbol{r}_{t+1} + \left(1-\theta_j\right) \left(\boldsymbol{x}_{j,t} - \boldsymbol{w}_t\right)' \cdot \boldsymbol{r}_{t+1} \\ &= \left[\boldsymbol{x}_{j,t} - \left(1-\theta_j\right) \boldsymbol{w}_t\right]' \cdot \boldsymbol{r}_{t+1}, \end{aligned}$$

where θ_j captures the weight of relative returns on the compensation.

Each investor chooses a combination of portfolio weights $\boldsymbol{x}_{j,t}$ to maximize $\mathbb{E}_t\left(TC_{j,t}\right) - \frac{\sigma_j}{2}\mathbb{V}_t\left(TC_{j,t}\right)$, where σ_j captures their risk aversion. In matrix form, we can write this problem as follows:

$$\text{Max}_{\boldsymbol{x}_j} \left[\boldsymbol{x}_{j,t} - \left(1-\theta_j\right) \boldsymbol{w}_t\right]' \boldsymbol{\mu}_t - \frac{\sigma_j}{2} \left[\boldsymbol{x}_{j,t} - \left(1-\theta_j\right) \boldsymbol{w}_t\right]' \boldsymbol{\Sigma}_t \left[\boldsymbol{x}_{j,t} - \left(1-\theta_j\right) \boldsymbol{w}_t\right],$$

where $\boldsymbol{\mu}_t \equiv \mathbb{E}_t\left(\boldsymbol{r}_{t+1}\right)$ denotes the expected excess return of the portfolio and $\boldsymbol{\Sigma}_t \equiv \mathbb{V}_t\left(\boldsymbol{r}_{t+1}\right)$ denotes the variance-covariance matrix of excess returns. It is straightforward to show that the optimal portfolio allocation for investor j is given by

$$\boldsymbol{x}_{j,t} = \frac{1}{\sigma_j}\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\mu}_t + \left(1-\theta_j\right)\boldsymbol{w}_t. \tag{A5}$$

The first term on the right-hand side of Equation (A5) captures the usual mean-variance portfolio. An analogous expression can also be derived for scenarios with CARA preferences (see, e.g., Pavlova and Sikorskaya, 2022). The second term reflects the reluctance of some investors to deviate from the benchmark portfolio, $\boldsymbol{w}$, indicating an inherently inelastic demand. It is not a function of the expected return or riskiness of the bonds and depends only on how much investors penalize deviations from the benchmark. Purely passive investors (i.e., those with $\theta_j = 0$ and $\sigma_j \to \infty$) never deviate from the benchmark portfolio and exhibit a perfectly inelastic demand.

Let $W_{j,t}$ denote the wealth of each type of investor j. Then $B_{j,t}^i = \frac{W_{j,t}x_{j,t}^i}{q_t^i}$ are the purchases of bond i made by investor j, where q_t^i denotes the bond price. For each bond i, its market-clearing condition is $q_t^i B_t^i = \sum_j W_{j,t}x_{j,t}^i$. After replacing these with the investors' optimal portfolio weights, the market-clearing conditions are given by

$$\begin{bmatrix} q_t^1 B_t^1 \\ \vdots \\ q_t^N B_t^N \end{bmatrix} = \sum_j W_{j,t} \left[\frac{1}{\sigma_j} \boldsymbol{\Sigma}_t^{-1} \boldsymbol{\mu}_t + (1-\theta_j)\, \boldsymbol{w}_t \right] \tag{A6}$$

$$= \tilde{\boldsymbol{\mathcal{A}}}_t + \tilde{\boldsymbol{\mathcal{T}}}_t,$$

where $\tilde{\boldsymbol{\mathcal{A}}}_t \equiv \sum_j W_{j,t} \frac{1}{\sigma_j} \boldsymbol{\Sigma}_t^{-1} \boldsymbol{\mu}_t$ denotes the active component of investors' demand (at market value). Since investors are risk averse, $\tilde{\mathcal{A}}_t^i$ is downward sloping and is a function of the expected return of bond i and its variance-covariance matrix. The term $\tilde{\boldsymbol{\mathcal{T}}}_t \equiv \boldsymbol{w}_t \sum_j W_{j,t} (1-\theta_j)$ denotes the passive demand (at market value).

Take the market-clearing condition of Equation (A6), and assume for simplicity only two assets. For ease of exposition, consider that bond i is risky and bond $-i$ is not. It is straightforward to show that the price for bond i is given by

$$q_t^i = \frac{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{r^f} \times \Psi_t^i, \tag{A7}$$

where $\mathcal{R}_{t+1}^i$ denotes the bond's next-period repayment per unit and Ψ_t^i captures the downward-sloping nature of the demand, and is given by

$$\Psi_t^i \equiv 1 - \kappa_t^{\mathrm{RA}} \frac{\mathbb{V}_t\left(\mathcal{R}_{t+1}^i\right)}{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)} \left(B_t^i - \mathcal{T}_t^i\right), \tag{A8}$$

where $1/\kappa_t^{\mathrm{RA}} \equiv \sum_j \frac{W_{j,t}}{\sigma_j}$ denotes the weighted-average risk aversion coefficient and $\mathcal{T}_t^i \equiv \tilde{\mathcal{T}}_t^i / q_t^i$ denotes the (face amount) holdings of passive investors.

Note that the bond price in Equation (A8) is analogous to the one in Equation (A4). The key difference is that with risk-averse lenders, the price elasticity is captured only by investors' risk aversion. In our main analysis, we do not specify the underlying mechanism driving this elasticity.

A.3 Microfoundation Based on a VaR Constraint

An identical expression can also be derived for investors who are risk neutral and subject to a VaR constraint. These constraints are common both in the literature and in the regulatory sphere (see, e.g., Miranda-Agrippino and Rey, 2020).[29]

Consider an analogous setup to the one in the previous subsection. Investors are heterogeneous and care about their absolute and relative return with respect to index $\mathcal{I}$. They are also risk neutral and subject to a VaR constraint that imposes an upper limit on the amount of risk they can take. In particular, the problem for investor j can be written as

$$\mathrm{Max}_{\{x_{j,t+1}^1, \ldots x_{j,t+1}^N\}} \; \mathbb{E}_t\Big(\left[\boldsymbol{x}_{j,t+1} - (1-\alpha_j)\, \boldsymbol{s}_{t+1}\right]' \cdot \boldsymbol{r}_{t+1} \Big)$$

$$\text{subject to } \; \Phi^2 \mathbb{V}_t\Big(\left[\boldsymbol{x}_{j,t+1} - (1-\alpha_j)\, \boldsymbol{s}_{t+1}\right]' \cdot \boldsymbol{r}_{t+1} \Big) - 1 \leq 0,$$

where the parameter Φ^2 captures the intensity of the risk constraint. We view Φ^2 as a

[29] Adrian and Shin (2014) provide a microfoundation for VaR constraints. Gabaix and Maggiori (2015) use a similar constraint, in which a financier's outside option is increasing in the size and variance of its balance sheet.

regulatory parameter that limits the amount of risk that an investor can take. Let ϱ_j denote the Lagrange multiplier associated with the VaR constraint. It is straightforward to show that the optimal portfolio is given by

$$\boldsymbol{x}_{j,t} = \frac{1}{\varrho_j \Phi^2} \boldsymbol{\Sigma}_t^{-1} \boldsymbol{\mu}_t + (1 - \theta_j)\, \boldsymbol{w}_t. \tag{A9}$$

The previous optimal portfolio is identical to that of Equation (A5), with the only difference being that the risk-aversion parameter σ has been replaced by the product of the Lagrange multiplier ϱ_j and the regulatory parameter Φ^2. Following the same steps as before, we can then derive an analogous pricing kernel to that of Equations (A7) and (A8). That is,

$$q_t^i = \frac{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)}{r^f} \left[1 - \kappa_t^{\mathrm{VaR}} \frac{\mathbb{V}_t\left(\mathcal{R}_{t+1}^i\right)}{\mathbb{E}_t\left(\mathcal{R}_{t+1}^i\right)} \left(B_t^i - \mathcal{T}_t^i\right)\right], \tag{A10}$$

where $1/\kappa_t^{\mathrm{VaR}} \equiv \sum_j \frac{W_{j,t}}{\lambda_j \Phi^2}$ denotes the (weighted-average) intensity for which the variance-at-risk constraint binds in the aggregate.

Appendix B: Diversification Methodology

The diversification methodology produces a more even distribution of country weights within the index relative to a market capitalization-weighted index. It does so by only partially including the debt stock from countries with above-average debt levels. The methodology is anchored on the average country face amount in the index (Index Country Average, ICA):

$$ICA \ = \ \frac{\sum(Country\ Face\ Amount)}{No.\ of\ Countries\ in\ the\ Index}.$$

Based on the ICA, the diversified face amount for any country in the index is derived according to the following rules:

1. The country with the largest face amount (FA_{max}) will be capped at twice the average country face amount in the index ($ICA * 2$). This is the maximum threshold and sets the scale to determine the diversified face amount of other countries in the index.

2. If a county's face amount is below the ICA, the entire face amount will be eligible for inclusion.

3. For countries with an face amount between the average (ICA) and twice the average (ICA * 2), their face amount will be linearly interpolated.

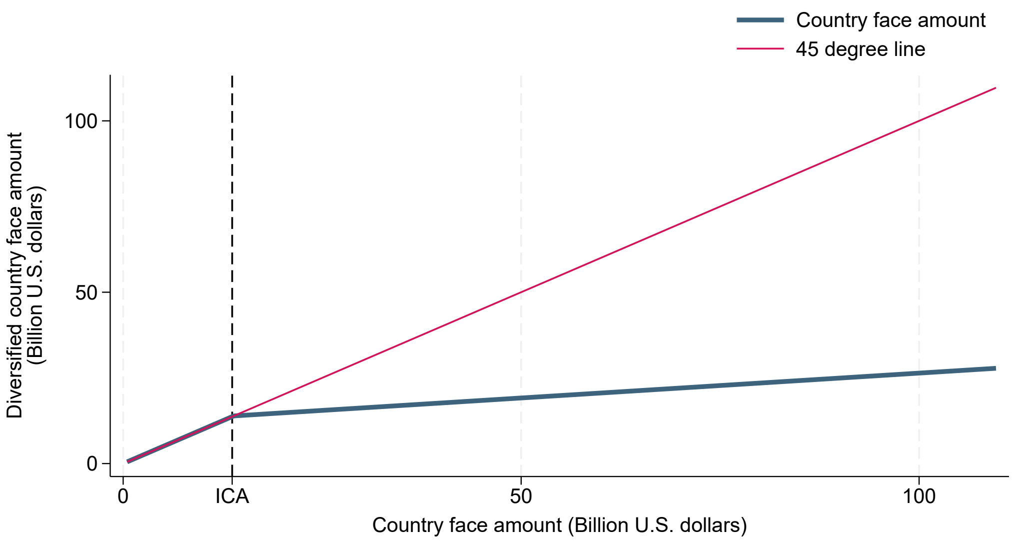
The formula below summarizes the calculation of the diversified country face amount (FA):

$$Diversified\, Country\ FA = \begin{cases} ICA * 2 & if \ \ Country\ FA \ = FA_{max} \\ ICA + \frac{ICA}{FA_{max} - ICA} * (Country\ FA \ - \ ICA) & if \ \ Country\ FA \ > \ ICA \\ Country\ FA & if \ \ Country\ FA \ \leq \ ICA. \end{cases}$$

Subsequently, the same proportional decrease or increase applied to the country-level face amount is also applied to each bond from that country. The diversified market value is then computed by multiplying the diversified face amount by the bond price. The diversified weight of each bond is determined by its share of the total diversified market capital in the index. In addition, country weights will be capped at 10%. Any excess weight above this cap will be redistributed pro rata to smaller countries below the cap, across all bonds from countries not capped at 10%. Figure B1 compares the country-level diversified and non-diversified face amount.

Figure B1

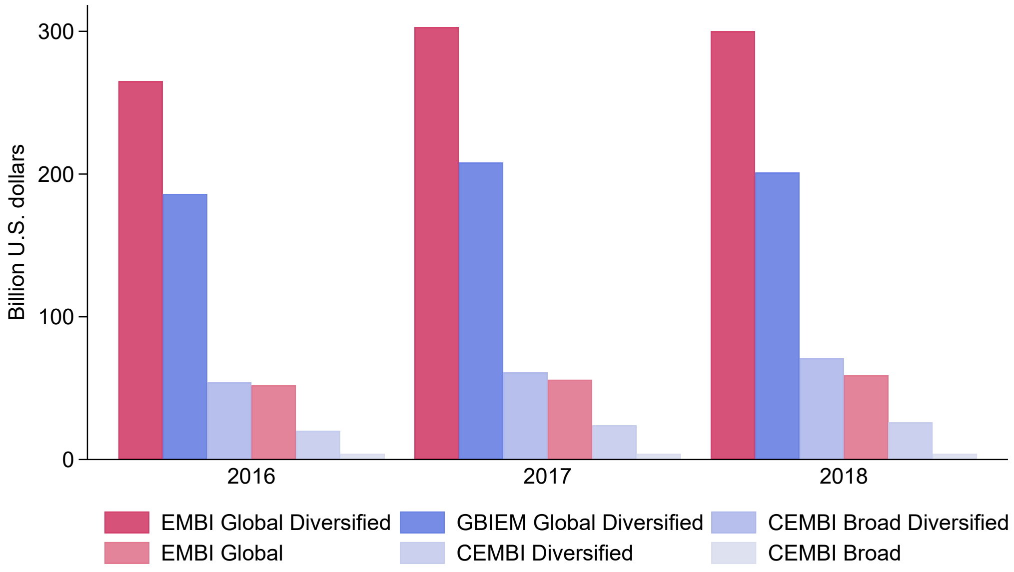
Effect of the diversification methodology on the face amount included in the EMBIGD



Note: The figure illustrates the differences between the country-level face amount and their diversified versions, which the EMBIGD uses to generate the diversified bond weights. The data used are from December 2018. Sources: J.P. Morgan Markets, and authors' calculations.

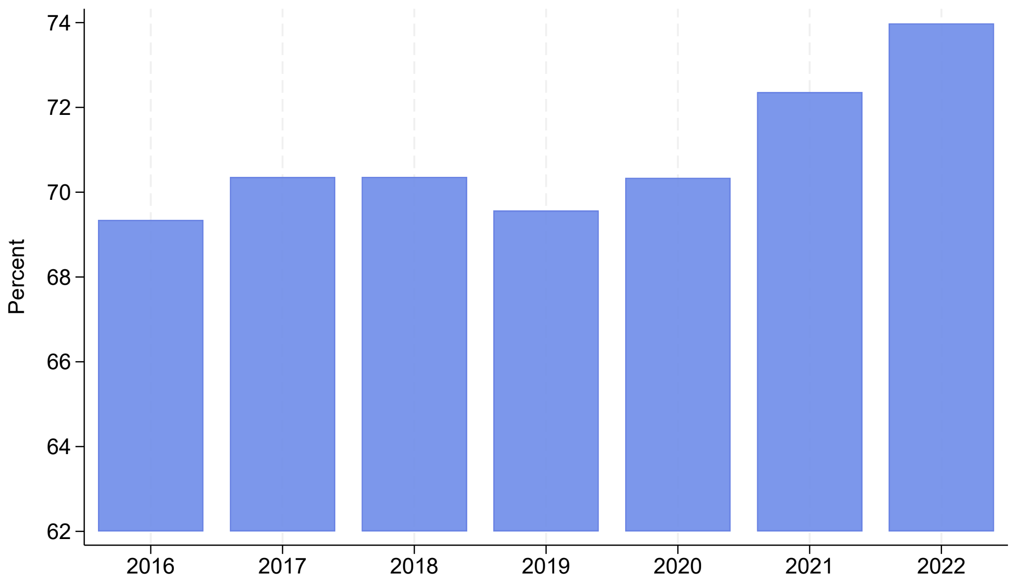
Appendix C: Figures

Figure C1
Assets under management benchmarked to emerging economies bond indexes



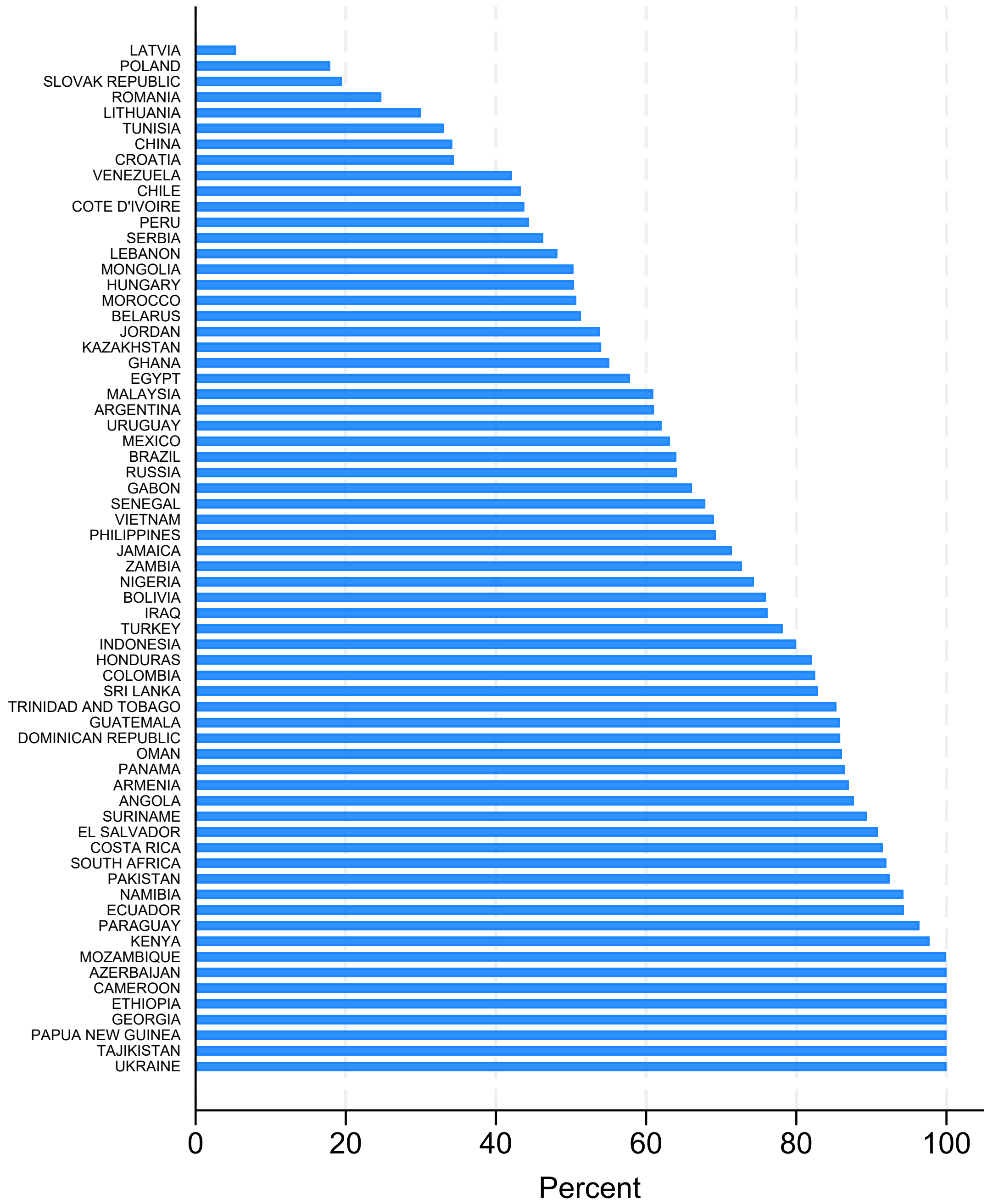
Note: The figure shows assets under management, in billions of U.S. dollars, benchmarked to emerging economies bond indexes. Sources: J.P. Morgan Markets, and authors' calculations.

Figure C2
Share of U.S. dollar-denominated emerging economies sovereign debt



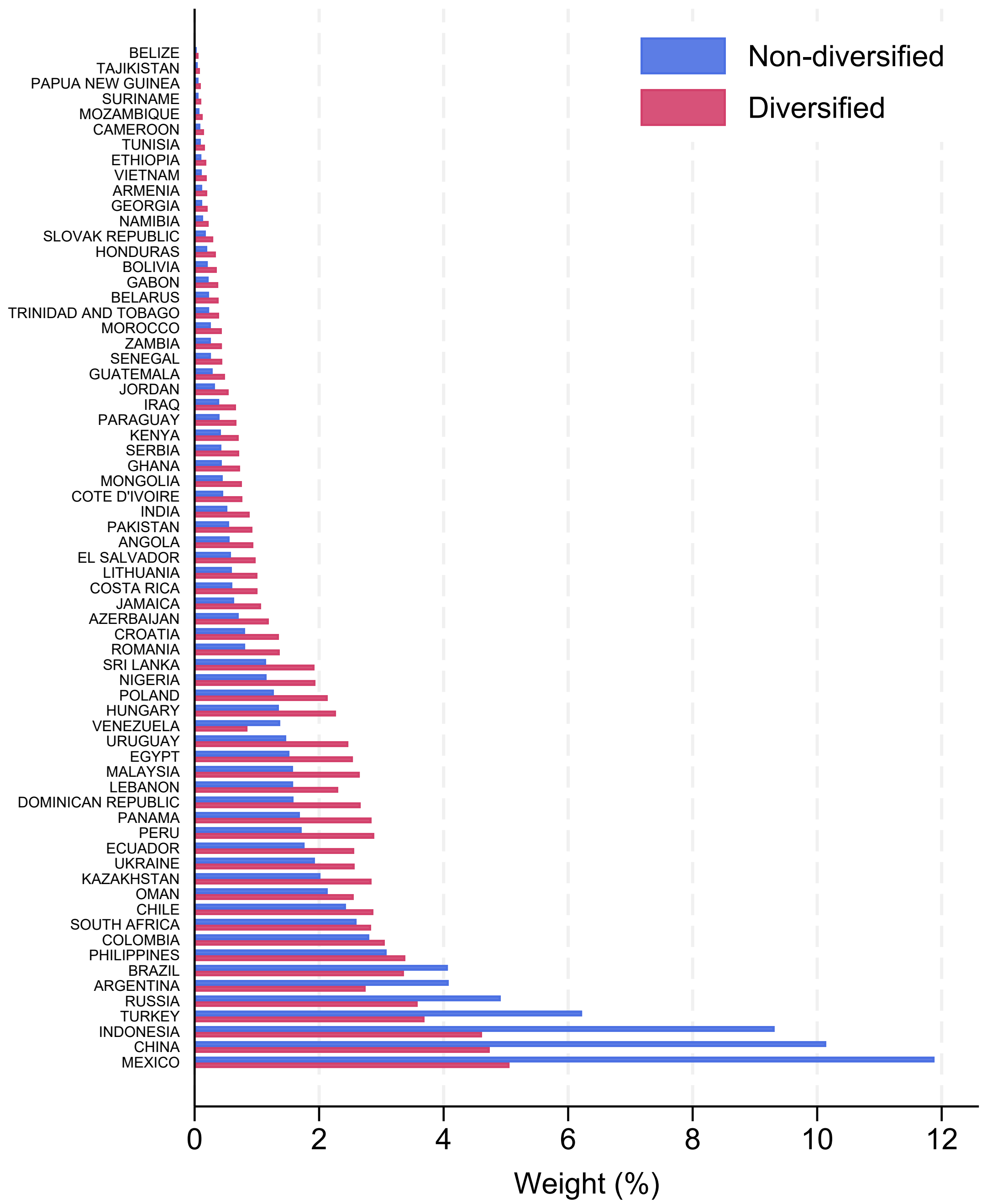
Note: The bars show the U.S. dollar-denominated sovereign debt in the EMBI Global index as a percentage of each country's general government debt securities issued in international markets. Averages are derived by calculating this percentage for each country and year, and then averaging these values annually across countries. Each country's percentage is weighted by its debt amount outstanding included in the EMBI Global indexes. Sources: BIS, J.P. Morgan Markets, and authors' calculations.

Figure C3
Share of U.S. dollar-denominated emerging economies sovereign debt, by country



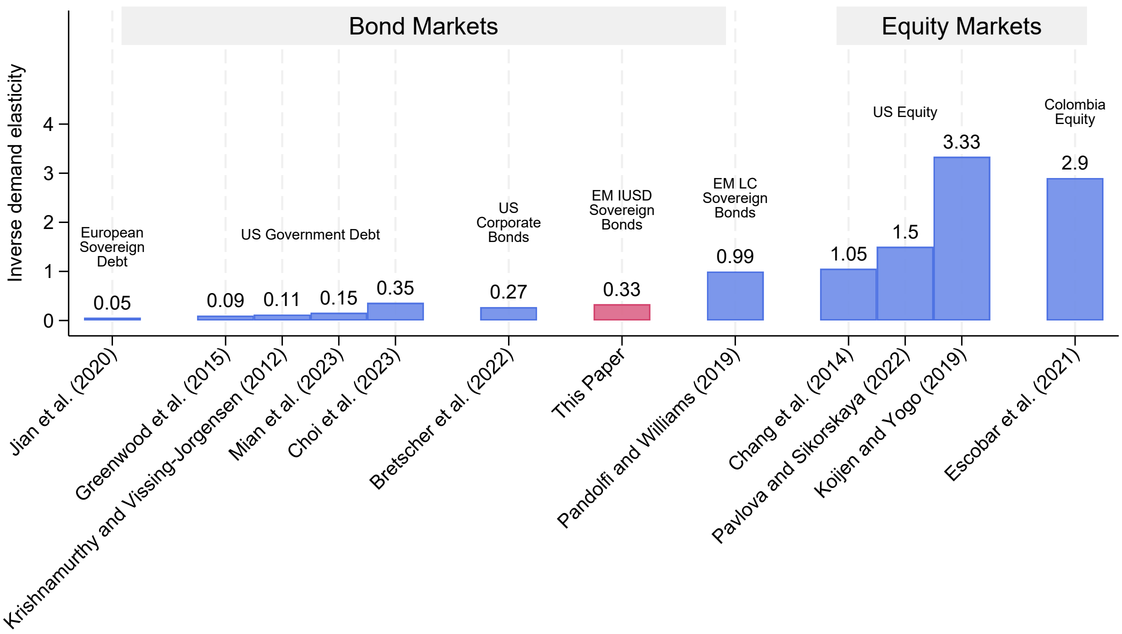
Note: The bars show the U.S. dollar-denominated sovereign debt in the EMBI Global index as a percentage of each country's general government debt securities issued in international markets. The averages are derived by calculating this percentage for each country and year, and then averaging these values across the years 2016–2022. Sources: BIS, J.P. Morgan Markets, and authors' calculations.

Figure C4
EMBI Global country-level weights in December 2018



Note: The figure illustrates the EMBI Global country-level diversified and non-diversified weights for December 2018. Country-level weights are computed as the sum of the weights of all bonds from each country included in the index. Sources: J.P. Morgan Markets, and authors' calculations.

Figure C5
Estimated inverse demand elasticities for financial markets



Note: EM IUSD Sovereign Bonds stands for emerging economies sovereign bonds issued internationally in U.S. dollars, while EM LC Sovereign Bonds stands for those issued in local currency. The elasticities in Jiang et al. (2021a), Krishnamurthy and Vissing-Jorgensen (2012), and Greenwood et al. (2015) are taken from the review Table 2 of Mian et al. (2022) and are converted into an inverse demand price elasticity, assuming a duration of 7 for the average bond. For Choi et al. (2022), we take the midpoint elasticity from the IV estimates, while for our paper, we compute the midpoint in elasticity from Table 2. For the emerging economies local currency sovereign bonds, we take the estimated number in Table 15, Panel D of Pandolfi and Williams (2019) for GBI bonds, which we adjust by the share of AUM (23.6%) that behave de facto in a passive way. For that, we compute the asset share in EPFR tracking the GBI-EM Global Diversified with an R^2 exceeding that of ETFs tracking the same index. We determine the average R^2 for ETFs by using a weighted average (based on assets) of the R^2 of the ETFs.

Appendix D: Tables

Table D1

Log price and FIR: Varying the share of passive funds to construct the FIR

Dependent Variable: Log Price					
	25%	30%	35%	40%	45%
FIR X Post	0.737 ***	0.596 ***	0.494 ***	0.418 ***	0.359 ***
	(0.179)	(0.168)	(0.139)	(0.118)	(0.101)
Bond-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	107,138	107,138	107,138	107,138	107,138
N. of Bonds	738	738	738	738	738
N. of Countries	68	68	68	68	68
N. of Clusters	1,618	1,618	1,618	1,618	1,618
F (FS)	511	2,261	2,201	2,141	2,082

Note: This table presents 2SLS estimates of log bond prices on the FIR measure (defined in Equation (7)), instrumented by Z (defined in Equation (9)), around rebalancing dates. The first- and second-stage equations are described in Equation (10). The estimations use a symmetric five-trading-day window, with *Post* as an indicator variable (equal to 1 for the five trading days after rebalancing, and 0 otherwise). Each different column indicates the share of passive funds used to construct the FIR FA measure. Month fixed effects are dummy variables equal to 1 for each rebalancing month, and 0 otherwise. Standard errors are clustered at the country-month level, and the sample period is 2016–2018. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

Table D2

Log price and FIR: Dropping quasi-sovereign bonds

Dependent Variable: Log Price										
FIR	-4.240	***	0.703		1.311	*				
	(0.604)		(0.846)		(0.725)					
FIR X Post	0.307	***	0.307	***	0.307	***	0.307	***	0.307	***
	(0.099)		(0.099)		(0.099)		(0.099)		(0.098)	
Post	0.001		0.001		0.001		0.001		0.001	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Bond FE	Yes		Yes		Yes		Yes		No	
Month FE	No		Yes		No		No		No	
Bond Characteristics-Month FE	No		No		Yes		Yes		No	
Country-Month FE	No		No		No		Yes		No	
Bond-Month FE	No		No		No		No		Yes	
Bond Controls	No		No		No		Yes		No	
Observations	74,430		74,430		74,430		74,390		74,430	
N. of Bonds	430		430		430		430		430	
N. of Countries	65		65		65		65		65	
N. of Clusters	1,553		1,553		1,553		1,552		1,553	
F (FS)	1,998		.		.		3,922		4,019	

Note: This table presents 2SLS estimates of log bond prices on the FIR measure (Equation (7)), instrumented by Z (Equation (9)), around rebalancing dates. The first- and second-stage equations are described in Equation (10). The estimations use a symmetric five-trading-day window, with *Post* as an indicator variable (equal to 1 for the five trading days after rebalancing, and 0 otherwise). Month fixed effects are dummy variables equal to 1 for each rebalancing month (0 otherwise), and bond characteristics are fixed effects that interact maturity and ratings fixed effects. Maturity fixed effects are constructed by dividing a bond's time to maturity into four different categories: short (less than 5 years), medium (5–10 years), long (10–20 years), and very long (20+ years). Ratings from each bond are from Moody's. Bond controls indicate whether the estimation includes the log FA and log stripped spread of the bond. Standard errors are clustered at the country-month level, and the sample period is 2016–2018. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

Table D3

Log price and FIR: Different windows

Panel A-Dependent Variable: Log Price				
	[-2:+2]	[-3:+3]	[-4:+4]	[-5:+5]
FIR X Post	0.200***	0.258***	0.280***	0.286***
	(0.049)	(0.066)	(0.079)	(0.090)
Post	0.000**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Bond-Month FE	Yes	Yes	Yes	Yes
Observations	42,853	64,281	85,707	107,138
N. of Bonds	738	738	738	738
N. of Countries	68	68	68	68
N. of Clusters	1,618	1,618	1,618	1,618
F (FS)	2,010	2,012	2,015	2,017

Panel B-Dependent Variable: Log Price (Excl. h=-1)				
	[-2:+2]	[-3:+3]	[-4:+4]	[-5:+5]
FIR X Post	0.311***	0.337***	0.340***	0.330***
	(0.060)	(0.077)	(0.088)	(0.098)
Post	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Bond-Month FE	Yes	Yes	Yes	Yes
Observations	32,138	53,567	74,993	96,424
N. of Bonds	738	738	738	738
N. of Countries	68	68	68	68
N. of Clusters	1,618	1,618	1,618	1,618
F (FS)	2,018	2,019	2,021	2,023

Note: This table presents 2SLS estimates of bond log prices on the FIR measure, with each column reporting estimates for different h-day symmetric windows before and after a rebalancing event. The sample period, the construction of $h-$day windows, and the 2SLS procedure are identical to those described in Table 2. Standard errors are clustered at the country-month level. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

Table D4

Log price and FIR: Spread heterogeneity (3 groups)

Dependent Variable: Log Price

	High Spread				Median Spread				Low Spread	
FIR	1.582				0.130				0.386	
	(1.619)				(0.461)				(0.332)	
FIR X Post	0.457	***	0.458	***	0.313	**	0.312	**	0.072	0.072
	(0.151)		(0.150)		(0.140)		(0.139)		(0.089)	(0.088)
Post	0.001	**	0.001	**	0.001	**	0.001	**	-0.000	-0.000
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	(0.000)
Bond FE	Yes		No		Yes		No		Yes	No
Month FE	Yes		No		Yes		No		Yes	No
Bond-Month FE	No		Yes		No		Yes		No	Yes
Observations	35,682		35,682		35,721		35,721		35,735	35,735
N. of Bonds	381		381		453		453		375	375
N. of Countries	58		58		51		51		43	43
N. of Clusters	1,001		1,001		861		861		647	647
F (FS)	560		2,953		482		865		.	1,022

Note: This table presents 2SLS estimates of log bond prices on the FIR measure (Equation (7)), instrumented by Z (Equation (9)), around rebalancing dates. The first- and second-stage equations are described in Equation (10). The estimations use a symmetric five-trading-day window, with *Post* as an indicator variable (equal to 1 for the five trading days after rebalancing, and 0 otherwise). The sample is divided into bonds with high spreads (Columns 1 and 2), median spreads (Columns 3 and 4), and low spread (Columns 5 and 6), with spreads divided according to their 33.3 and 66.6 percentile into the three different buckets. Month fixed effects are dummy variables equal to 1 for each rebalancing month, and 0 otherwise. Standard errors are clustered at the country-month level, and the sample period is 2016–2018. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

Table D5
Log CDS and FIR

Dependent Variable: Log CDS			
FIR	6.643 **	-7.013	
	(2.889)	(5.453)	
FIR X Post	-0.796 *	-0.796 *	-0.796 *
	(0.448)	(0.449)	(0.448)
Post	-0.006 ***	-0.006 ***	-0.006 ***
	(0.002)	(0.002)	(0.002)
Country FE	Yes	Yes	No
Month FE	No	Yes	No
Country-Month FE	No	No	Yes
Observations	10,160	10,160	10,160
N. of Countries	44	44	44
N. of Clusters	1,016	1,016	1,016
F (FS)	1,398	.	2,797

Note: This table shows 2SLS estimates of five-year log CDS of countries on the FIR measure (Equation (7)), instrumented by Z (Equation (9)), around rebalancing dates. The first- and second-stage equations are described in Equation (10). The estimations use a symmetric five-trading-day window, with *Post* as an indicator variable (equal to 1 for the five trading days after rebalancing, and 0 otherwise). Month fixed effects are dummy variables equal to 1 for each rebalancing month, and 0 otherwise. Standard errors are clustered at the country-month level, and the sample period is 2016–2018. *, **, and *** denote statistically significant at the 10%, 5%, and 1% level, respectively.