Inelastic Markets: The Demand and Supply of Risky Sovereign Bonds*

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Abstract

We present new evidence of downward-sloping demand curves in international sovereign-debt markets and analyze their macroeconomic implications. Our methodology exploits high-frequency bond price movements around index rebalancings to identify exogenous shifts in the supply of sovereign bonds. We find that bond prices significantly respond to these rebalancings. For risky bonds, part of this response may be explained by changes in default risk and we cannot directly map these estimates into a demand elasticity. We use these price reactions to discipline a sovereign-debt model and we use the model to back out a demand elasticity that isolates the effects of default risk. Using the calibrated model, we show that a downward-sloping demand acts as a commitment device that reduces debt issuances and default risk.

Keywords: inelastic financial markets, sovereign debt, international capital markets, small open economies, index rebalancings.

JEL Codes: F34; F41; G11; G15; G32.

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1 Introduction

Governments in emerging and developing economies heavily depend on foreign funding for bond financing, with approximately two thirds of this financing consisting of bonds denominated in US dollars and issued in international capital markets.[1] As such, the behavior of investors in these markets is crucial to understanding a government's borrowing costs, its default risk, and its optimal debt management. Standard sovereign-debt models generally assume that international investors' demand is perfectly elastic. This implies that they are willing to lend to a government any amount it desires at the risk-free rate plus a default-risk premium. This assumption on investor behavior contrasts with a body of recent work that allows for a richer investor demand structure, typically involving inelastic (downward-sloping) demand, in different asset markets (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 international sovereign-debt markets and analyze its macroeconomic implications. In the context of risky bonds, estimating a demand elasticity is challenging because the demand itself is intrinsically tied to a bond's default risk, which is influenced by its debt supply. To isolate the role of default risk, we combine a structural sovereign-debt model with high-frequency bond-level price reactions to investor demand shocks. We use the model to back out a demand elasticity and to explore the consequences of downward-sloping demand curves on a government's optimal debt and default policies.

To guide the empirical analysis, we start by formulating a simple portfolio problem for heterogeneous investors that differ on how they are compensated. The model features both active and passive investors, whose compensation is tied to the return of their portfolios and also to their performance relative to an index. We use this simple framework to illustrate how, under some assumptions, one can use shifts in the demand of certain investor types to estimate a demand elasticity for risky assets. The underlying mechanism is as follows: since the demand of (purely) passive funds is perfectly inelastic, we can view an exogenous increase in their demand as a leftward shift in the available supply of bonds for active investors (effective supply). We can then use such shift as an instrument to estimate a price demand elasticity (given a fixed level of default risk). This type of identification strategy has been widely used in the literature (Pandolfi and Williams, 2019 and Pavlova and Sikorskaya, 2022 are recent examples).

[1] Appendix Figures B1 and B2 describe issuances of emerging government debt in international markets.

To identify exogenous shifts in a country's effective supply of sovereign bonds, we exploit monthly rebalancings in the largest benchmark index for emerging market (EM) international dollar debt, the J.P. Morgan Emerging Markets Bond Index (EMBI) Global Diversified. The EMBI Global Diversified is the most widely tracked index by institutional investors that invest in dollar-denominated sovereign debt issued by emerging countries. Many of these investors tend not to deviate from the composition of this index given potential tracking error costs and end up passively tracking the index. As a result, index rebalancings lead to similar rebalancings in the portfolio of institutional investors.

We derive a measure of flows implied by index rebalancings (FIR) by combining the assets passively tracking the EMBI with the monthly rebalancings. We then combine our FIR measure and the timing of the rebalancings to quantify the impact of changes in investor demand on sovereign-bond prices. In particular, we develop an instrumental-variable strategy that allows us to exploit the variation in flows to a country's sovereign bonds that is driven by changes in the face amount of bonds issued by other countries. That is, we exploit the variation in FIR that is only attributable to the inclusion or exclusion from the index of bonds issued by other emerging countries.

Our analysis reveals that a higher FIR leads to an increase in bond prices. On average, a 1-percentage-point increase in the FIR corresponds to a 65-basis-point increase in bond prices. Assuming that default risk remains unchanged due to the index rebalancings, we can directly map these estimates to a demand elasticity. Our findings imply a price demand elasticity of -1.5, indicating a significant degree of inelasticity. Moreover, our estimates vary across countries with different levels of default risk. Specifically, for countries with higher default risk, a 1-pp-FIR inflow results in a 100-basis-point increase in bond prices, whereas for safer countries, the effect is close to zero and statistically non-significant. Overall, these findings suggest that investors' downward-sloping demand may be attributed to their reluctance to hold an additional unit of a risky asset. This behavior may be explained by factors such as their risk aversion or constraints on the amount of risk they are allowed to bear, such as regulatory limitations.

Although our FIR measure is orthogonal to a country's current fundamentals, high-frequency changes in the FIR may still impact bond prices through changes in default risk. This is because the index rebalancings lead to changes in the composition of investors, potentially influencing the government's *future* bond issuances and default policy. Even if the *current* bond supply is fixed, investors may be pricing in such effects today.

We then develop a structural model to formally decompose the different mechanisms underpinning our empirical estimates and to back out a demand elasticity that isolates the effects of changes in default risk. We then use the model to examine the implications of a downward-sloping demand on a government's optimal debt and default policies.

We adopt a rather canonical sovereign-debt model where the government has limited commitment and can endogenously default on its debt obligations. Traditional 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 with a richer demand structure that allows us to capture different investor types (active and passive) and a downward-sloping demand for active investors. In our model, an exogenous increase in the demand of passive investors influences the bond price through two interconnected mechanisms: (i) a reduction in the supply of bonds available to active investors, and (ii) a decrease in default risk. As the demand of active investors is downward sloping, both mechanisms contribute to an increase in the price that investors are willing to pay for the bond.

We discipline the model based on our empirical estimates. In particular, we calibrate the model to match the overall effect of an exogenous change in the demand of passive funds (i.e., the FIR) on bond prices. We then use the calibrated model to back out the demand elasticity, isolating changes in default risk. To this end, we create a counterfactual scenario in which we maintain the default risk at a constant level and examine how an exogenous shift in the demand of passive funds (i.e., the effective supply) influences the price that active investors are willing to pay. Our findings reveal that changes in default risk can explain nearly a third of the overall price effect. Failing to account for movements in default risk can thus significantly amplify the estimated demand elasticity.

Finally, our model allows us to examine the impact of a downward-sloping demand on a government's optimal debt and default policies. In the presence of an inelastic demand, we observe *lower* default risk and *higher* average debt compared to a scenario with a perfectly elastic demand. The rationale behind this outcome is rooted in the inelastic demand serving as a commitment device, restricting the government from extensive debt issuance. The logic is as follows: A negative demand elasticity limits the maximum amount of debt that a government is willing to issue, resulting in a lower default risk.

Related Literature. Our findings contribute to different strands of literature. First, our results relate to a long-standing literature that uses index rebalancings to estimate demand elasticities across different asset classes (see, for example, 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).[2] We contribute to this literature by showing that demand curves slope downward in one of the most important funding markets for governments in emerging economies, the international dollar-bond market. More broadly, we show that for risky bonds part of the price reaction to an index rebalancing is attributable to changes in default risk rather than the inelastic component of demand. We provide a structural model to isolate and quantify this effect.

Second, there is a growing literature on inelastic financial markets that emphasizes the role of demand in explaining asset prices across various financial markets. Koijen and Yogo (2019) formulate a demand-based asset-pricing model with flexible heterogeneity in asset demand across investors.[3] Gabaix and Koijen (2021) use their granular instrumental variable approach to estimate a macro-level demand elasticity for the US equity market. Vayanos and Vila (2021) explore the role of investor demand in explaining the term structure of interest rates. Krishnamurthy and Vissing-Jorgensen (2012), Greenwood et al. (2015), Mian et al. (2022), Jiang et al. (2021), and Choi, Kirpalani, and Perez (2022) analyze how an inelastic demand affect the pricing, term-structure, and issuances of riskless US Treasuries.[4] Koijen and Yogo (2020), Gourinchas et al. (2022), and Greenwood et al. (2023) investigate the impact of inelastic investors on the pricing of international financial assets. Among these studies, the one most closely related to ours is Choi, Kirpalani, and Perez (2022), which analyzes the implications of a downward-sloping demand on the optimal issuance of safe government bonds. In contrast, our focus is on the interplay between a downward-sloping demand curve and the provision of risky sovereign bonds. We show that demand elasticity interacts with default risk and distorts a government's supply of risky bonds.

Third, our paper also connects to a literature on the determination of government bond yields, particularly in relation to a recent body of work that examines how changes in the investor base of government debt impact bond yields.[5] A closely related paper is Fang, Hardy, and Lewis (2022), which develops a demand system to quantify how alterations in the composition of investors (domestic versus foreign, banks versus non-banks) affect government bond yields. In this paper, we utilize exogenous changes in the composition of the investor base (passive versus active funds) to provide evidence of downward-sloping demand curves

[2]Beyond index rebalancings, Droste, Gorodnichenko, and Ray (2023) use US treasury auctions to relate demand shocks to US treasury yields, utilizing micro-data and high-frequency identification.

[3]In recent work, Bretscher et al. (2021) and Eren et al. (2023) use this setup to study the US corporate bond and Treasury markets.

[4]Dathan and Davydenko (2020), Kubitza (2022), and Calomiris et al. (2022) analyze empirically how institutional investors and their institutional constraints affect issuance decisions in corporate bond markets.

[5]See, for example, Arslanalp and Poghosyan (2016), Peiris (2013), and Dell'Erba et al. (2013). Warnock and Warnock (2009) and Ahmed and Rebucci (2022) present evidence for the US.

for risky sovereign bonds.

Lastly, our paper is closely related to a large literature on quantitative sovereign-debt models. Our framework extends standard sovereign-default models (Arellano, 2008; Chatterjee and Eyigungor, 2012) in two ways: we incorporate different investor types (active and passive investors) and introduce a downward-sloping demand. This richer structure, allows us to discipline the model using our micro-level estimates. We then use the model to isolate the role of default risk behind those estimates and to back out a demand elasticity. In our baseline model, we microfound a downward-sloping demand by introducing risk-averse investors. In this regard, our framework extends previous work by Borri and Verdelhan (2010), Lizarazo (2013), and Pouzo and Presno (2016). Such investors' behavior, however, can also be captured in a setup with risk-neutral investors that are subject to regulatory limitations, such as a Value-at-Risk constraint (as in Miranda-Agrippino and Rey, 2020) or in which investors follow a mandate that specifies how they should allocate their funds across risky assets (as in Gabaix and Koijen, 2021). Our focus, thus, is not to quantify the effects of risk aversion per se, but to focus more broadly on the aggregate implications of a downward-sloping demand in the market for risky sovereign bonds.

The paper is structured as follows. In Section 2, we introduce a simple model featuring investors with a downward-sloping demand. Section 3 presents the empirical analysis, including details on the institutional setup of EMBI indexes, data sources, empirical strategy, and results. Sections 4 and 5 formulate a sovereign default model where investors are inelastic, exploring the impact of a downward-sloping demand curve on a government's optimal debt issuances. Section 6 concludes.

2 A Model of Heterogeneous Inelastic Investors

In this section, we formulate a simple portfolio problem for risk-averse heterogeneous investors that differ on how they are compensated. The model shares many features with the one presented in Pavlova and Sikorskaya (2022), and we employ it as a guide for our empirical analysis. In particular, we use this simple framework to illustrate how, under some assumptions, one can use exogenous movements in the demand of certain investor types to estimate a demand elasticity for risky assets.

2.1 The Model

Investors are risk averse and have mean-var preferences. They care about the total return of their portfolio and also about their return relative to a benchmark index $\mathcal{I}$ they track. Investors are heterogeneous and they differ on their degree of risk aversion and on how their compensation depends on their total and relative return. 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). Lastly, let $\boldsymbol{B}_t = \left\{B_t^1, ..., B_t^N\right\}$ denote the supply of bonds. For now, we assume that the supply of bonds is fixed. In Section 4 we relax this assumption.

We assume that international markets are competitive and each investor type takes prices as given. For an investor of type j, its total compensation is a convex combination between the return of its 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. Its compensation is

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

where α_j captures the weight that relative returns have on the compensation of the investor. This sort of heterogeneity allows us to decompose the demand for risky bonds into an active and a passive component.

The problem of an investor of type j is to chose 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 the investor's risk aversion. In matrix form, we can write this problem as follows:

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

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

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

The first term in the right-hand side of Equation (1) captures the usual mean-variance portfolio. This expression is analogous to the optimal portfolio under CARA preferences (as in Pavlova and Sikorskaya, 2022). An identical expression can be also derived for investors that are risk neutral and subject to a Value-at-Risk (VaR) constraint (see, for instance, Miranda-Agrippino and Rey, 2020).[6]

The second term of Equation (1) accounts for the fact that some investors do not want to deviate from the benchmark portfolio, $\boldsymbol{w}$. Such demand is inherently inelastic. 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 funds (i.e., those with $\alpha_j = 0$ and $\sigma_j \to \infty$) never deviate from the benchmark portfolio and exhibit a perfectly inelastic demand.[7]

Let $W_{j,t}$ denote the wealth of each type of investor j. Then $B^i_{j,t} = \frac{W_{j,t} x^i_{j,t}}{q^i_t}$ are the purchases of bond i made by investor j, where q^i_t denotes the bond price. For each bond i, its market clearing condition is $q^i_t B^i_t = \sum_j W_{j,t} x^i_{j,t}$. We assume that investors' total wealth is fixed, $\sum_j W_{j,t} = \bar{W}$. Let $\omega_{j,t} \equiv W_{j,t}/\bar{W}$ denote the relative wealth of each type of investor. After we replace with investors' optimal portfolio weights, the market clearing conditions are given by

$$\begin{aligned}\begin{bmatrix} q^1_t B^1_t \\ \vdots \\ q^N_t B^N_t \end{bmatrix} &= \sum_j \bar{W} \omega_{j,t} \left[\frac{1}{\sigma_j} \boldsymbol{\Sigma}^{-1}_t \boldsymbol{\mu}_t + (1 - \alpha_j)\, \boldsymbol{w}_t \right] \\ &= \tilde{\boldsymbol{\mathcal{A}}}_t + \tilde{\boldsymbol{\mathcal{T}}}_t, \end{aligned} \tag{2}$$

where $\tilde{\boldsymbol{\mathcal{A}}}_t \equiv \sum_j \bar{W} \omega_{j,t} \frac{1}{\sigma_j} \boldsymbol{\Sigma}^{-1}_t \boldsymbol{\mu}_t$ denotes the "active" component of investors' demand (at market value). Since investors are risk averse, $\tilde{\mathcal{A}}^i_t$ is downward sloping and it is a function of the expected return of bond i and of its variance-covariance matrix. We will usually refer to this component as the demand of active investors or active demand. The term $\tilde{\boldsymbol{\mathcal{T}}}_t \equiv \boldsymbol{w}_t \sum_j \bar{W} \omega_{j,t} (1 - \alpha_j)$ denotes the "passive demand" (at market value). It includes all the purchases made by passive investors to track the index $\mathcal{I}$. It is useful to rewrite this as $\tilde{\boldsymbol{\mathcal{T}}}_t = \boldsymbol{w}_t A_t$, where $A_t \equiv \sum_j \bar{W} \omega_{j,t} (1 - \alpha_j)$ accounts for all the assets under management that passively track the index $\mathcal{I}$. More importantly, notice that $\tilde{\boldsymbol{\mathcal{T}}}_t$ is perfectly inelastic since it is not a function of the expected return or variance of the bonds.

[6] Adrian and Shin (2014) provide a microfoundation for VaR constraints. Gabaix and Maggiori (2015) use a similar constraint, in which the outside option of a financier is increasing in the size and variance of its balance sheet. Gabaix and Koijen (2021) directly impose a reduced-form mandate that specifies how active investors should allocate their funds across risky assets.

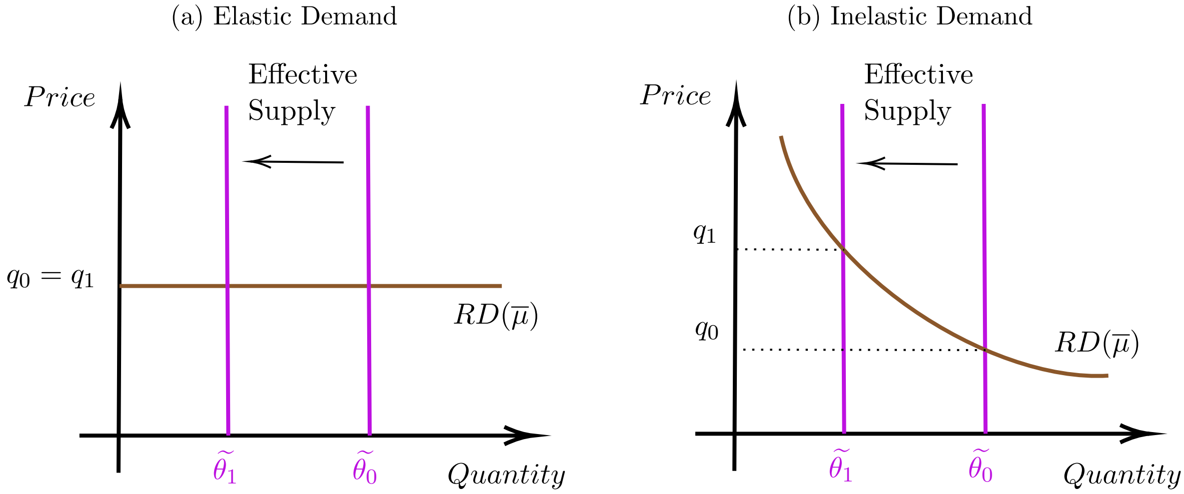
[7] This is consistent with a preferred-habitat specification, in which investors have a higher demand for those assets which are part of the benchmark they track.

2.2 Changes in Passive Demand Under Constant Expected Returns

For any bond i that is in fixed supply, an increase in $\tilde{\mathcal{T}}_t^i$ implies a reduction in the supply of bonds available to active investors (a leftward shift in the "effective" or "residual" supply), which can be exploited to analyze the demand of active investors. If the increase in $\tilde{\mathcal{T}}_t^i$ is exogenous (i.e., orthogonal to a country's fundamentals), one can potentially use that variation to analyze whether demand curves for active investors slope downward, and can try to infer the specific elasticity of demand.

Figure 1 illustrates this point. If the demand of active investors is fully elastic, then the change in $\tilde{\mathcal{T}}_t^i$ should have no effect on prices (Panel a). If the active demand is downward sloping and the expected excess return μ_t^i is unaffected by movements in $\tilde{\mathcal{T}}_t^i$, changes in passive demand allow us to identify the demand elasticity of active investors (as shown in Panel b).

Figure 1
Index Rebalancing and the Demand Elasticity



Note: The figure depicts a reduction in the effective supply of an asset upon an index rebalancing and its effect on its price. Panel (a) considers the case when the residual demand is fully elastic and panel (b) when it is price sensitive. $RD(\mu)$ denotes the residual demand under a certain expected return $\bar{\mu}$.

More formally, let η^i denote the inverse demand elasticity of bond i. Given an exogenous change in the tracking intensity, $\Delta\tilde{\mathcal{T}}_t^i$, we can estimate this elasticity as follows:

$$\eta^i \equiv \frac{\partial q_t^i}{\partial \tilde{\mathcal{A}}_t^i} \times \frac{\tilde{\mathcal{A}}_t^i}{q_t^i} \approx (-)\frac{\Delta q_t^i}{\Delta \tilde{\mathcal{T}}_t^i} \times \frac{q_{t-1}^i B^i - \tilde{\mathcal{T}}_{t-1}^i}{q_{t-1}^i}. \quad (3)$$

This view has been the standard or conventional practice in the literature since Shleifer (1986), who uses index additions to the S&P 500 as an exogenous instrument for $\Delta\tilde{\mathcal{T}}_t^i$ to analyze whether demand curves for equities slope downward. In recent work, Pavlova and

Sikorskaya (2022) use a similar strategy and a regression discontinuity design (RDD) on Russell indexes to estimate the price demand elasticity of active investors.

2.3 Changes in Passive Demand Under Varying Expected Returns

Underlying Equation (3) is the assumption that μ_t^i is unaffected by changes in $\tilde{\mathcal{T}}_t^i$. If instead changes in passive demand affect expected returns, it is no longer possible to use this type of approach to estimate the demand elasticity for active investors. This is an important concern for risky assets since their default risk may be intrinsically related to the composition of underlying investors. To see this clearly, take the market clearing condition of Equation (2) and assume for simplicity only two assets. For easiness of exposure consider that bond i is risky and that bond $-i$ is not. It is straightforward to show that the price for bond i is given by

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

where $\mathcal{R}_{t+1}^i$ denotes the next-period repayment per unit of the bond and Ψ_t^i captures the downward-sloping nature of the demand and is given by

$$\Psi_t^i \equiv 1 - \frac{\sigma}{\bar{W}} \frac{\mathbb{V}_t\left(\mathcal{R}_{t+1}^i\right)}{\mathbb{E}_t\left[\mathcal{R}_{t+1}^i\right]} \left(B_t^i - \mathcal{T}_t^i\right), \tag{5}$$

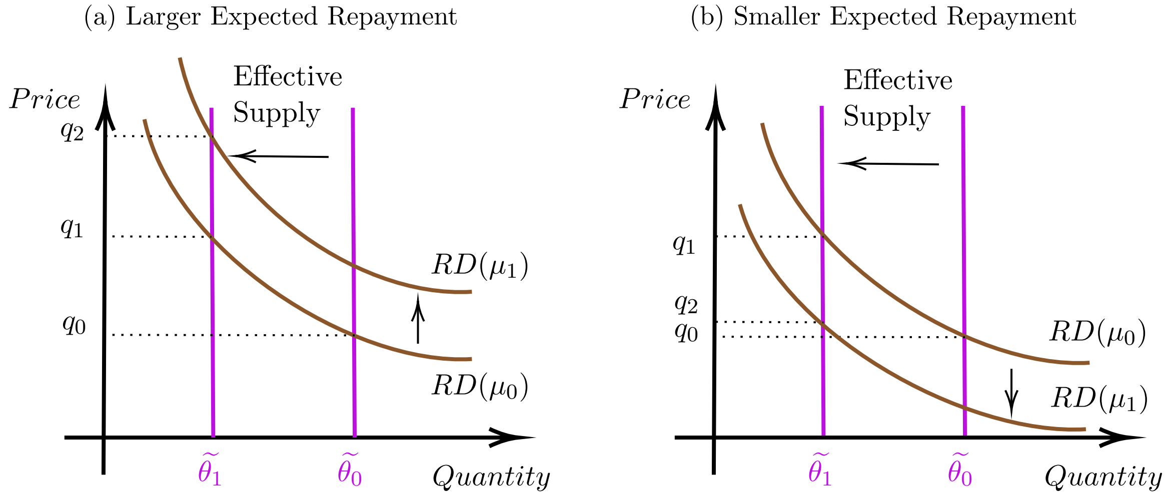
where $\mathcal{T}_t^i \equiv \tilde{\mathcal{T}}_t^i / q_t^i$ denotes the face value of bond i's purchases of passive funds that track the index. In this case, the price response given a change in passive demand contains two components: (i) the true demand elasticity and (ii) the effect of the change in passive demand on the expected repayment. More formally,

$$(-)\frac{\Delta q_t^i}{\Delta \tilde{\mathcal{T}}_t^i} \times \frac{q_{t-1}^i B^i - \tilde{\mathcal{T}}_{t-1}^i}{q_{t-1}^i} = \underbrace{(-)\frac{\Delta \Psi_t^i}{\Delta \mathcal{T}_t^i} \frac{B_t^i - \mathcal{T}_t^i}{\Psi_t^i}}_{\equiv \eta^i < 0} + \underbrace{(-)\frac{\Delta \mathbb{E}_t\left[\mathcal{R}_{t+1}^i\right]}{\Delta \mathcal{T}_t^i} \frac{B_t^i - \mathcal{T}_t^i}{\mathbb{E}_t\left[\mathcal{R}_{t+1}^i\right]}}_{\equiv \alpha^i}. \tag{6}$$

Figure 2 provides a graphical illustration. If an increase in passive demand raises the next-period expected repayment (i.e., $\alpha^i < 0$), then for any given B_t^i, investors are willing to pay a higher price for that bond. This results in an upward adjustment in the demand from active investors, causing the "conventional" estimates of elasticity derived from index rebalancings to overstate the demand elasticity, as illustrated in Panel (a). On the other hand, if $\alpha^i > 0$, an exogenous increase in passive demand triggers a downward adjustment in the demand from active investors. Consequently, this downward shift results in an underestimation of the demand elasticity, as depicted in Panel (b).

The strength and direction of these biases are unclear. One could argue that changes in $\tilde{\mathcal{T}}_t^i$ that are more persistent will likely have a more substantial impact on expected returns,

Figure 2
Index Rebalancing and the Demand Elasticity: Changes in μ



Note: The figure depicts a reduction in the effective supply of an asset upon an index rebalancing and its effect on its price. Both panels show the case in which the demand is price sensitive. Panel (a) considers a case in which the expected repayment increases due to the rebalancing (i.e., $\alpha^i < 0$). Panel (b) shows the case with $\alpha^i > 0$.

potentially strengthening the effect of α^i. Conversely, more temporary changes in passive demand may have more muted effects on shifting the residual demand, resulting in a lower strength of α^i.

The previous analysis applies to any asset whose expected return, μ_t^i, is affected by (exogenous) movements in $\mathcal{T}_t^i$. As such, it applies to a wide literature in different asset markets (sovereign and corporate bonds and equities) that uses index rebalancings as an instrument to estimate demand elasticities. For risky bonds for instance, α_t^i may be capturing changes in default risk that are driven by exogenous changes in $\mathcal{T}_t^i$. Since bond prices and default risk are jointly determined, even for an exogenous $\Delta\mathcal{T}_t^i$, it is hard to disentangle the effect on bond prices that is driven by a downward-sloping demand versus the effect that is coming from changes in default risk. To quantify each mechanism separately, one would need a structural model in which both bond prices and default are endogenous.

In the next section, we construct an instrument for $\Delta\tilde{\mathcal{T}}_t^i$ based on monthly index rebalancings in a major sovereign-bond index for emerging economies. We use that instrument to estimate changes in bond prices around these rebalancings and informally discuss (using CDS data) how much of those estimates can be explained by the demand elasticity and expected-returns channels. In Section 4, we formulate a structural model to formally separate these two channels.

3 Empirical Analysis

3.1 Index Rebalancings as Passive Demand Shocks

In this section, we exploit monthly rebalancings in the EMBI Global Diversified index to identify exogenous shifts in the demand of passive investors for sovereign bonds in emerging economies.

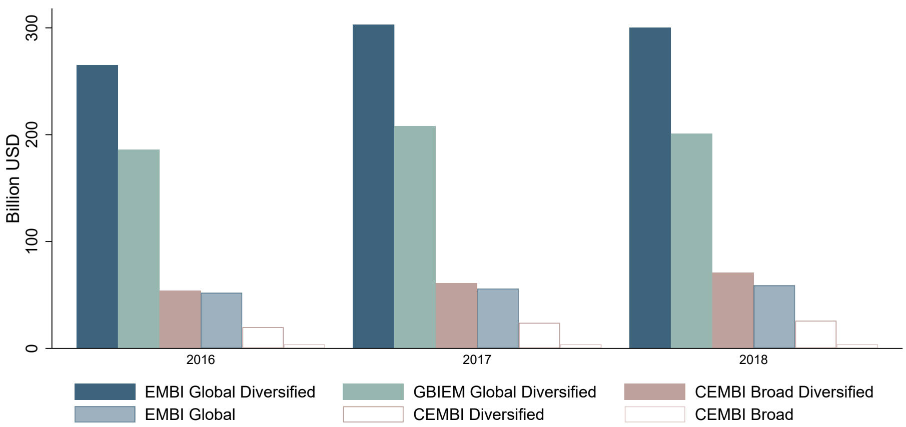
The J.P. Morgan EMBI Global Diversified is one of the most popular indexes for emerging sovereign-debt instruments. It includes sovereign and quasi-sovereign USD-denominated bonds issued by emerging countries with a maturity of at least 2.5 years and a face amount outstanding of at least US$500 million.[8] Among emerging-markets bond indexes, the EMBI Global Diversified is the the most widely tracked, with a combined assets under management (AUM) tracking the index of around US$300 billion in 2018 (Figure 3). Unlike other indexes that adopt a traditional market capitalization-based weighting scheme, the EMBI Global Diversified limits the weights of countries with larger amounts of debt outstanding by only including a fraction of these countries' face amount of debt oustanding.[9]

Rebalancings in the EMBI Global Diversified index, such as inclusions and exclusions, take place on the last business day of each month, when J.P. Morgan releases a report with

[8]To be classified as an emerging market, a country's GNI per capita must be below an Index Income Ceiling (IIC) – 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 – for three consecutive years. Bonds included in the index must settle internationally and have accessible and verifiable bid and ask prices. Once included, the bond may remain in the index until 12 months before maturity. Local law instruments are not eligible.

[9]Appendix Figure B3 plots the EMBI Global country weights of both the diversified and non-diversified versions for December 2018.

Figure 3
Assets under management (AUM) benchmarked to EM bond indexes



Note: Billion USD assets under management (AUM) benchmarked to EM bond indexes.
Sources: JPMorgan Markets, and authors' calculations.

the updated index composition. These rebalancings lead to changes in the composition of the portfolios of passive investors tracking the index, who need to buy and sell bonds to replicate the index's weights.

Following Pandolfi and Williams (2019), one can measure the Flows Implied by the Rebalancings (FIR) for each country at each rebalancing date as follows:

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

where $\Delta\tilde{\mathcal{T}}_{c,t} \equiv (w_{c,t} - w_{c,t}^{BH})A_t$. The first term in the numerator, $w_{c,t} \equiv \frac{q_{c,t}f_{c,t}B_{c,t}}{q_t I_t}$, is the benchmark weight for country c at time t in the index $\mathcal{I}$. It depends on the relative market capitalization of country c's sovereign bonds included in $\mathcal{I}$. The term $q_{c,t}B_{c,t}$ denotes the market value of bonds from country c at time t, and $f_{c,t}$ is the face-value share of country c bonds tracked by the index, which only depends on a country's amount outstanding of debt and not on a country's bond prices.[10] The term $q_t I_t \equiv \sum_{c\in\mathcal{I}} q_{c,t}f_{c,t}B_{c,t}$ denotes the market value of the index $\mathcal{I}$ (the product of the unit price of the index, q_t, and the number of index units that are available, I_t). The second element of $\Delta\tilde{\mathcal{T}}_{c,t}$, $w_{c,t}^{BH}$ captures a "buy-and-hold weight", which is defined as the weight country c would have had at time t if the composition of the index had remained unchanged.[11] That is, $w_{c,t}^{BH} \equiv w_{c,t-1}\frac{q_{c,t}/q_{c,t-1}}{q_t/q_{t-1}}$. Lastly, A_t represents the assets under the management of investors passively tracking the EMBI Global Diversified. To sum up, the numerator on Equation (7) is the amount of money that, on a given rebalancing date, enters or leaves a country because of the rebalancing in the portfolio of passive investors tracking the $\mathcal{I}$ index. For convenience, we normalize those flows by the market value of the bonds that are available for active investors, $q_{c,t-1}B_{c,t-1} - w_{c,t-1}A_{t-1}$.

Quantitatively, the FIR is a measure of the relative change in the purely passive demand for a country's sovereign bonds due to the rebalancing of the index: a 1% FIR can be therefore interpreted as a 1% reduction in the available supply of bonds in the market. These flows, however, may not be entirely exogenous to a country's fundamentals. First, the FIR is affected by countries' sovereign-bond issuances. If a country issues new bonds that are included in the index, that increases the country's weight in the index, which in turn leads to

[10]In a purely market capitalization-weighted index (such as the EMBI Global), $f_{c,t} = 1, \forall_{c,t}$. To preserve diversification, the weighting scheme of the EMBI Global Diversified 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. That is, $f_{c,t} < 1$. Appendix A describes the rules of the EMBI Global Diversified to compute the weights of the instruments included in the index.

[11]Notice 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 the other countries in the index, the weight of that country in the index increases but investors do not need to make any rebalancing to their portfolios as the "buy-and-hold weight" coincides with the new weight in the index, $w_{c,t}$.

higher FIR. Second, even for countries whose face amount $B_{c,t}$ and share $f_{c,t}$ remain constant over time, the FIR may be mechanically correlated to present or past bond price changes.

Given that our goal is to isolate the impact of passive demand shocks on bond prices, these two issues can potentially bias our estimates. We tackle these challenges in two ways. First, for each rebalancing event, we only consider countries whose amount outstanding of bonds $B_{c,t}$ does not change relative to the previous period. In other words, we only consider countries with no new issuances, repurchases of bonds, or with bonds that drop out of the index because of their maturity. Additionally, we exploit the fact that the weighting scheme of the EMBI Global Diversified is based on the face amount outstanding of bonds. This is important because it allows us to net out the variation that is potentially correlated with current or past bond price changes.

In particular, we construct an instrument for the FIR based on a theoretical index in which country weights are only a function of the diversified amount outstanding of bonds included in the index: $w^{FA}_{c,t} \equiv \frac{f_{c,t}B_{c,t}}{\sum_c f_{c,t}B_{c,t}}$. Then, we compute the fractional change in theoretical weights:

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

which, given our focus on countries whose debt outstanding in the index remains unchanged, reduces to

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

Given that $f_{c,t}$ is not a function of bond prices and because we only consider countries where $B_{c,t}$ is fixed, then $\frac{\partial Z_{c,t}}{\partial q_{c,t}} = \frac{\partial Z_{c,t}}{\partial q_{c,t-1}} = 0$. By instrumenting the FIR with $Z_{c,t}$ we can thus isolate the variation in FIR that is coming exclusively from changes in the amount outstanding of bonds of other countries, either because of changes in the relative size of the country's sovereign-bond market or because of changes in the diversification coefficient, $f_{c,t}$.

In what follows, we use the $Z_{c,t}$ instrument to estimate how exogenous demand changes induced by passive flows affect sovereign-bond prices. For this, we take advantage of the specific timing of the rebalancings: index changes always occur on the last business day of each month, which is when passive funds will rebalance their portfolios. For each rebalancing date, we can therefore identify pre- and post-rebalancing periods, and estimate the effect of the $FIR_{c,t}$ (instrumented by $Z_{c,t}$) on bond prices.

We adopt an instrumented difference-in-differences design (DDIV) and estimate, in our main specification:

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

where $p_{i,t,h}$ is the price of bond i at rebalancing date t, h trading days before or after the rebalancing. For each rebalancing date, t, we consider a 10-day window around it, so that $h \in [-5, 5]$. $\theta_{c(i),t}$ are country-by-month fixed effects, and $\theta_{b(i),t}$ are bond characteristics-by-month fixed effects, where we include characteristics such as maturity, rating, and bond type (sovereign or quasi-sovereign). $F\hat{I}R_{c(i),t}$ is our FIR measure instrumented with the percentage change in the theoretical index weights, $Z_{c,t}$, obtained by regressing $FIR_{c,t}$ on $Z_{c,t}$ (first stage). The term $\mathbb{1}_{h \in Post}$ is an indicator function that is equal to one in the 5 days after the rebalancing and 0 in the 5 days before it. $\mathbf{X}_{i,t}$ is a vector of monthly bond controls including the bond's face amount and the (beginning-of-month) spread. Our coefficient of interest is β, which captures the effect of the FIR on bond prices.

Additionally, we also estimate a specification with leads and lags, in which the instrumented FIR is interacted with trading-day dummies. This analysis allows us to explore the dynamic effect of the FIR. It also allows us to test for parallel trends in the period prior to rebalancing.

3.2 Data and Summary Statistics

To compute both the FIR and our instrument, we collect data from different sources. Most of the variables used in the analysis are retreived directly from J.P. Morgan. There is one variable that is not straightforward to measure: the assets under management of funds that passively track the EMBI Global Diversified, 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 such information were available, many active funds may 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 EMBI Global Diversified and re-scale it by an estimate of the share of passive funds. To estimate the share of passive funds, we perform the following steps. We retrieve from Morningstar data on the returns of funds benchmarked against the EMBI Global Diversified and EMBI Global Core.[12] For each fund, we estimate a regression of its returns on the returns of the index and compute the corresponding R^2, that is, the share of the variance in the fund's return that is explained by variation in index returns (see Appendix Figure B4). We categorize as passive all funds whose R^2 is higher than 0.96. We choose 0.96 as a threshold because it is the average R^2 of

[12]The criteria for inclusion of bonds in the EMBI Global Core is the same as the EMBI Global and EMBI Global Diversified, except that 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. As the EMBI Global Diversified, it utilizes the diversification methodology described in Appendix A to calculate the bond weights.

ETFs in our sample.[13] Nonetheless results are robust to considering different thresholds.[14] Using this classification rule, the share in terms of market capital of 'passive' funds tracking the EMBI Global Diversified in the Morningstar database is 30%.[15] We calculate A_t by adjusting the assets under management tracking the EMBI Global Diversified index, using a rescaling factor of 30%.

We gather data on individual bond prices from Datastream. We also retrieve several bond characteristics (maturity, duration, among others) directly from J.P. Morgan data. We clean our dataset by dropping extreme values in terms of daily returns, stripped spreads, and $Z_{c,t}$. We drop daily returns that are in absolute value larger than 50%, and stripped spreads that are below 0 or above 5000 basis points. We also drop the three largest and smallest $Z_{c,t}$. In general, extreme values of $Z_{c,t}$ could be potentially driven by large changes in the EMBI Global Diversified that are pre-announced during the month and thus are not appropiate for our identification strategy, which relies on the assumption that most information is known in the last business day of the month.[16]

Our final dataset consists of 247,826 bond-time observations for 702 bonds in 67 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 371 basis points, an average maturity of 10 years, and an average face amount of US$1.3 billion.

Figure 4 displays results regarding our first stage. It shows a scatter plot of the FIR and our $Z_{c,t}$ instrument after both variables have been residualized with rebalancing-month and country fixed effects. There is a clear positive relation between the two variables and the R-squared is 71%. Figure 5 presents the distribution of our instrumented FIR measure. The values range from -0.5% to around 0.2%, with more negative than positive observations. This is consistent with the fact that over time the number of bonds included in the EMBI Global Diversified increased. Since we restrict our analysis to countries whose face amount remains constant, the inclusion of bonds from other countries typically leads to a reduction in the weight of sample countries (i.e., a negative FIR).

[13]For this calculation we only include ETFs that are passive and whose base currency is the USD.

[14]Appendix Table B1 provides results using alternative shares of passive funds used to construct the FIR measure. While our quantitative estimates do change slightly, the qualitative implications remain the same.

[15]The share of market capital of these funds is first computed for every month of the period under analysis in the paper (2016-2018), and then is averaged across all months in the period. This produces the value of 30%.

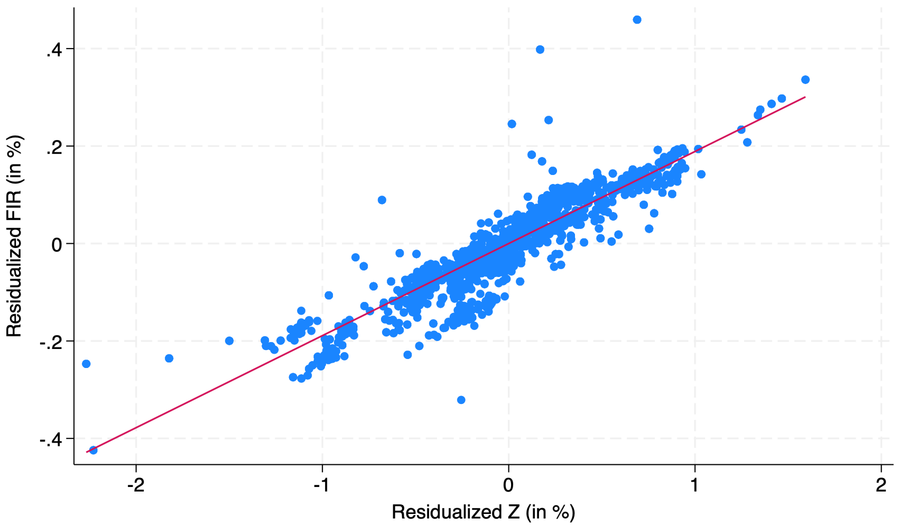
[16]For our baseline analysis, we exclude Argentina and Turkey, since these countries exhibited large spreads during our sample period. In Appendix Tables B2, B3, and B4 we present robustness tests with respect to this winsorizing. We show that our results are qualitatively similar when dropping different extreme values in terms of Z, when keeping Argentina and Turkey, and when we keep only sovereign bonds excluding quasi-sovereign bonds.

Table 1
Summary statistics

Variable	Mean	Std. Dev.	25th Ptile	75th Ptile	Min	Max
log(Price)	4.604	.229	4.579	4.683	2.708	5.192
Instrumented FIR (in bps)	-.095	.144	-.204	.022	-.462	.212
Stripped Spread	371.172	555.982	134.00	396.00	0.00	4993.00
EIR duration	6.436	3.961	3.525	7.833	-.037	19.081
Average Life	10.082	8.949	4.224	11.208	1.075	94.519
Face Amount (USD billion)	1.320	.812	.75	1.619	.5	7.00
CDS	495.650	1247.065	105.599	311.790	42.450	13956.959

Note: The table displays summary statistics for the main variables utilized in the empirical analysis. Instrumented FIR values are in basis points, and face amount values are in billion USD. The Effective Interest Rate (EIR) duration is a measure of sensitivity of dirty price with respect to the US interest rates parallel shift. It approximately shows the percentage change of dirty price if all US interest rates change by 100bp (JPMorgan). Sources: Morningstar Direct, JPMorgan Markets, DataStream, and authors' calculations.

Figure 4
Relationship between FIR and Z



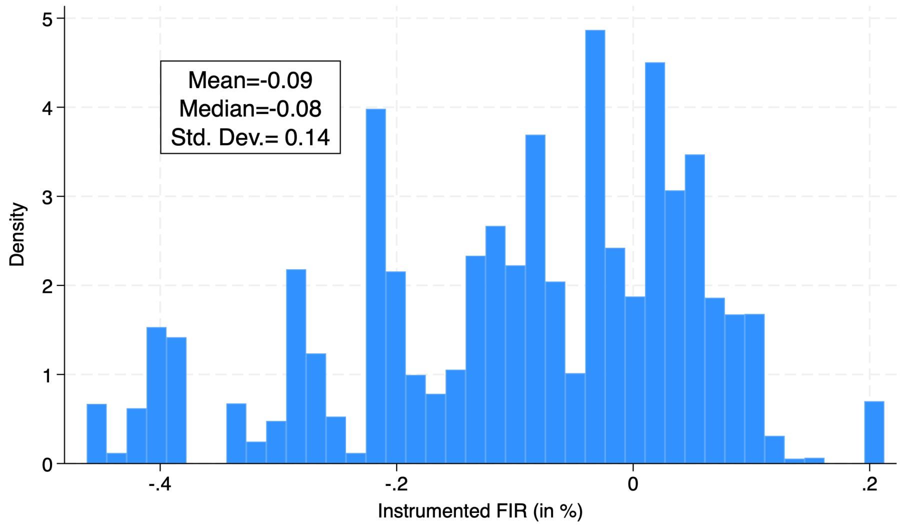
Note: This figure presents a scatter plot of the FIR and the Z instrument. Both variables are residualized based on a regression with rebalancing-month and country fixed effects. FIR is computed as in Equation (7) and Z as in Equation (9). Sample period is 2016-2018.

3.3 Results

We present results for our baseline estimation from Equation (10) in Table 2. Our coefficient of interest, β, is always positive and statistically significant in the different specifications. The estimate in our preferred specification —the one with bond controls, country-by-time and bond-type-by-time fixed effects— is 0.65. This implies that a 1-percentage-point increase in FIR increases bond returns by 0.65 percentage points.

One potential concern with these results is that bonds receiving larger or smaller FIR on the rebalancings are on different price trends even before the rebalancing date. To show that this is not the case, we estimate a leads-and-lags specification, where we interact the

Figure 5
Distribution of instrumented FIR values



Note: This figure shows a histogram of the instrumented FIR. Sample period is 2016-2018.

instrumented FIR with a dummy for each of the trading days around the rebalancing event. The estimated coefficients are reported in Figure 6. On the days prior to the rebalancing date, from -5 to -1, changes in FIR are not associated with systematic differences in bond prices. On the rebalancing day, instead, the estimated coefficient becomes positive and significant, and remains so until the end of our estimation window. This is consistent with the patterns of rebalancings from different institutional investors highlighted in Escobar et al. (2021), where most investors rebalance their portfolio on the effective date of the rebalancing but not before that. Additionally, this finding is not consistent with prior leakage of information regarding the rebalancing changes.

The previous effects are heterogeneous across countries' with varying levels of default risk. To see this, 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. We find that the price of high-spread bonds react more to rebalancing-driven demand shocks. For bonds issued by riskier countries, a 1-percentage-point increase in FIR is associated with a 1.05-percentage-point increase in bond returns. Instead, the effect is quantitatively close to zero for low-spread countries and not statistically significant.[17]

[17]In Appendix Table B5 we re-estimate this dividing bonds into 3 groups and find that bond prices are positively associated with FIR for both high (above 328 bps) and medium spread bonds (between 166 and 328 bps), while they are not for bonds with low spreads (below 166 bps). The estimated coefficient is increasing in the risk profile of bonds.

Table 2
Log Price and FIR

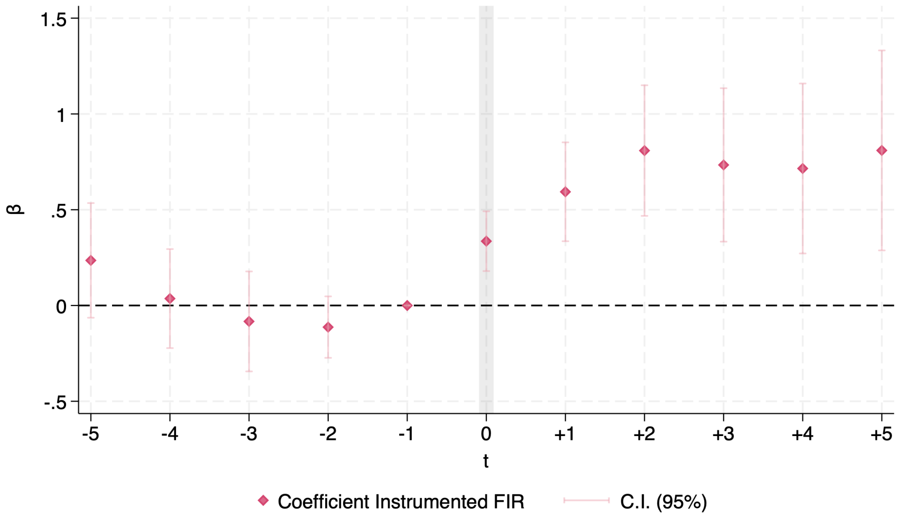
Dependent Variable: Log Price					
FIR Instrumented	-8.732***	-1.901	1.575		
	(1.384)	(2.677)	(1.386)		
FIR Instrumented*Post	0.653***	0.652***	0.651***	0.651***	0.651***
	(0.190)	(0.190)	(0.192)	(0.192)	(0.192)
Post	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No
Maturity-Rating-Bond Type-Time FE	No	No	Yes	Yes	Yes
Country-Time FE	No	No	No	Yes	Yes
Bond Controls	No	No	No	No	Yes
Observations	130,151	130,151	130,151	130,151	130,107
N. of Bonds	706	706	706	706	706
N. of Countries	67	67	67	67	67
N. of Clusters	1,783	1,783	1,783	1,783	1,782
R^2	0.014	-0.001	0.002	0.002	0.002

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in Equation (10). The sample period is 2016-2018 and contains a window of 10 trading days around each end-of-the-month rebalancing date. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from Equation (7) instrumented with Z in (9). Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

3.4 Interpretation of the Estimates as Demand Elasticities

As we explained in Section 2.2, the standard assumption in the literature is that exogenous movements in the composition of indexes (i.e., our FIR measure) do not affect the fundamental value of the assets (hence, default risk in the case of risky bonds). If we assume that default risk does not change as a consequence of index rebalancings, we can directly map the previous estimates to a demand elasticity for risky sovereign bonds. To see this, notice that we can rewrite the elasticity in Equation (3) in terms of our FIR measure as $\eta \approx (-)\frac{\Delta log(q_t^i)}{FIR_{c,t}}$. This is exactly what our β coefficient in Equation (10) captures. Based on the results in Table 2, one can infer that the inverse demand elasticity for this market is around -0.65 (the demand elasticity is -1.53). These estimates are in the ballpark of other estimates in the literature for other financial markets and assets (see Appendix Figure B5).

Figure 6
Leads and Lags Coefficients



Note: This figure presents leads and lags coefficients from a 2SLS estimation of the log price of bonds on a set of trading-day dummies around the rebalancing date. The 2SLS procedure is identical to the one described in Table 2. The estimation includes both bond and month-of-rebalancing-maturity-rating-bond-type fixed effects. $t = 0$ indicates the day of the rebalancing. The vertical red lines show a 95% confidence interval for each horizon. Standard errors are clustered at the country by month of rebalancing level.

Table 3
Log Price and FIR - Spread Heterogeneity

Dependent Variable: Log Price	High Spread		Low Spread	
FIR Instrumented	-11.993***		-4.005***	
	(2.270)		(0.873)	
FIR Instrumented*Post	1.051***	1.048***	0.141	0.141
	(0.302)	(0.306)	(0.133)	(0.135)
Post	0.003***	0.003***	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes
Maturity-Rating-Bond Type-Time FE	No	Yes	No	Yes
Country-Time FE	No	Yes	No	Yes
Bond Controls	No	Yes	No	Yes
Observations	64,789	64,789	65,362	65,318
N. of Bonds	463	463	498	498
N. of Countries	61	61	50	50
N. of Clusters	1,357	1,357	966	965
R^2	0.021	0.036	-0.000	0.003

Note: This table presents results from 2SLS estimations of log bond prices on different explanatory variables around rebalancing dates. The 2SLS procedure is identical to the one described in Table 2. We divide the sample into bonds with high spreads (Columns 1 and 2) and low spreads (Columns 3 and 4). High (low) spread bonds are those above (below) the median stripped spread in our sample. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

If default risk does change with exogenous movements in $\tilde{\mathcal{T}}$, we can no longer interpret our β estimate as a demand elasticity. This is because, in that case, β also captures the effects that $\Delta\tilde{\mathcal{T}}$ has on the expected next-period repayment, as shown in Equation (6) (the α^i term). The question, thus, is how sensitive is default risk to exogenous changes in the composition of indexes?

One way to assess the magnitude of α^i is to quantify how a country's default risk is affected with changes in the FIR. To this end, we use credit default swaps (CDS) as a proxy for default risk. In Appendix Table B6 we find that the FIR tends to decrease the spreads of CDS. The estimates imply that for the median CDS spread in the sample (of about 190 basis points) a 1-percentage-point increase in FIR decreases CDS spreads by 2.9 basis points. Given a median duration for bonds of 5.5, a simple back-of-the-envelope calculation suggests that the lower CDS spread increases bond prices by almost 16 basis points. This effect accounts for about 25% of our baseline estimate in Table 2. One may argue that a larger and more permanent shock should exert a more substantial impact on the fundamental value of the asset (hence, on default risk). Our FIR measure, thus, holds an advantage over the common index additions and deletions that are frequently used in other studies, since it exhibits a more temporary nature.

Although informative, the previous estimates should be taken with caution because bond prices and the price of CDS are determined jointly. If demand shocks are correlated across markets, it might be the case that the fall in CDS spreads (i.e., a higher price) is not really capturing a lower default risk. In the next section we build a quantitative model that allows us to quantify the role of changes in default risk in our estimated demand elasticity.

4 The Supply of Risky Sovereign Bonds

We formulate a quantitative sovereign-debt model to disentangle the mechanisms behind our empirical elasticity and to back out a demand elasticity that isolates the effects of default risk. The model features a risk-averse government that issues long-term debt in international debt market. It has limited commitment and can endogenously default on its debt obligations. We introduce a rich demand structure that allows us to capture different investor types (active and passive) and a downward-sloping demand for active investors.

4.1 The 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 $f_y(y' \mid y)$. We assume that the preferences of the representative consumer are given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t), \tag{11}$$

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 debt in international markets to smooth consumption. Let B denote the beggining-of-period stock of government debt.

Government bonds are long term. Debt contracts mature probabilistically. Each unit of B matures in the next period with probability λ. If the bond does not mature (and the government does not default), it pays a coupon ν. Let $d = \{0, 1\}$ denote the default policy, where $d = 1$ denotes a default. Default leads to a temporary exclusion from international debt markets and an exogenous output loss, $\phi(y)$. We assume that it regains access to debt markets with probability θ and there is no recovery value.

We assume that international markets are competitive and populated by two types of investors: active and passive. Active investors have a downward-sloping demand curve. Motivated by the analysis of Section 2, we assume that this demand is a function of the expected returns and the volatility of such returns. Passive investors, on the other hand, have a perfectly inelastic demand: They buy the government's bonds to not deviate from their benchmark portfolio index $\mathcal{I}$. Let $\mathcal{A}'(.)$ and $\mathcal{T}'(.)$ denote the demand functions (at face value) for active and passive investors, respectively. For the demand of passive investors, we assume that $\mathcal{T}' = \mathcal{T}(\tau, B')$. That is, passive funds adjust their purchases based on the end-of-period supply of bonds, B', and based on some time-varying index weight, τ. For tractability, we assume that τ is exogenous and follows a continuous Markov process with transition function $f_\tau(\tau' \mid \tau)$. Given an end-of-period supply of bonds B', by market clearing, the residual demand of active investors is $\mathcal{A}'(\tau, B') = B' - \mathcal{T}'$.

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

$$c(h=0,B,y,\tau;B') = y + q\left(y,\tau,B'\right)\left(B'-(1-\lambda)B\right) - \left(\lambda+(1-\lambda)\nu\right)B \tag{12}$$
$$c(h=1) = y - \phi_j(y),$$

where $q\left(y,\tau,B'\right)$ denotes the price of a unit of debt. As is standard in these models, this pricing function is an endogenous object that depends on the default risk of the bond. Moreover, since the demand of active investors is downward sloping, it also depends on the share of bonds that are purchased by passive funds.

4.2 Government's Recursive Problem

The government is benevolent and chooses $\{d,c,B'\}$ to maximize Equation (11) subject to the resource constraint in (12). If the government is not currently in default, its value function is given by

$$V\left(y,\tau,B\right) = Max_{d=\{0,1\}}\left\{V^r\left(y,\tau,B\right), V^d\left(y\right)\right\}, \tag{13}$$

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

$$V^r\left(y,\tau,B\right) = Max_{B'}u(c) + \tilde{\beta}\mathbb{E}_{s'|s}V\left(y',\tau',B'\right), \tag{14}$$

subject to

$$c = y + q(y,\tau,B')\left(B'-(1-\lambda)B\right) - \left(\lambda+(1-\lambda)\nu\right)B.$$

If the government defaults, it is excluded from debt markets and it cannot issue new debt. The government exits the default with probability θ and there is no recovery value. We also assume that the demand of passive funds is zero while the government is in default (i.e., the share in the index $\mathcal{I}$ is zero). Under these assumptions, the government's value function is given by

$$V^d\left(y\right) = u\left(y-\phi(y)\right) + \tilde{\beta}\mathbb{E}_{s'|s}\left[\theta V\left(y',\tau',0\right) + (1-\theta)V^d\left(y'\right)\right]. \tag{15}$$

4.3 Bond-pricing Kernel

Foreign lenders are competitive and discount payoffs at the risk-free rate. Given the government's current choice of B' and given the passive investors' demand, the bond-price function faced by the government is given by

$$q\left(y,\tau,B'\right)=\beta^{\star}\,\mathbb{E}_{s'|s}\left[\mathcal{R}\left(y',\tau',B'\right)\right]\;\Psi\left(y,\tau,B'\right), \tag{16}$$

where $\beta^{\star}\equiv 1/(1+r_f)$, $\mathcal{R}'(.)\equiv\mathcal{R}\left(y',\tau',B'\right)$ denotes the next-period repayment function, and the $\Psi(y,\tau,B')$ term captures the downward-sloping component of the residual demand (i.e., the inelastic behavior of active investors).[18] The next-period repayment function, in turn, is given by

$$\mathcal{R}\left(y',\tau',B'\right)=\left[1-d\left(y',\tau',B'\right)\right](1-\lambda)\left(\nu+q(y',\tau',B'')\right), \tag{17}$$

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 the next-period debt policy and passive investors' demand.

From Equations (16) and (17), it is easy to see that the bond price decreases with the expected default probability. Since a larger B' increases the risk of default (conditional on a level of output), $q(y,\tau,B')$ is thus typically decreasing in B'. As for $\Psi\left(y,\tau,B'\right)$, we assume 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

In the same fashion to what we did in the empirical analysis, we can exploit exogenous movements in τ and analyze its effects on bond prices. This is straightforward to do in the model because we can directly construct counterfactuals in which we change τ and at the same time, we keep the country's fundamentals, $\{y,B'\}$, fixed. Let $\Delta\mathcal{T}'\equiv\mathcal{T}(\tau_1,B')-\mathcal{T}(\tau_0,B')$ denote an exogenous change in the demand of passive investors, in which we keep the bond supply fixed. We can derive an analogous expression than the one in Equation (6):

$$(-)\frac{\Delta q(.)}{\Delta\mathcal{T}'}\times\frac{B'-\mathcal{T}'}{q(.)}=\underbrace{(-)\frac{\Delta\Psi\left(.\right)}{\Delta\mathcal{T}'}\frac{B'-\mathcal{T}'}{\Psi\left(.\right)}}_{\equiv\eta<0}+\underbrace{(-)\frac{\Delta\mathbb{E}_{s'|s}\mathcal{R}'\left(.\right)}{\Delta\mathcal{T}'}\frac{B'-\mathcal{T}'}{\mathbb{E}_{s'|s}\mathcal{R}'\left(.\right)}}_{\equiv\alpha}. \tag{18}$$

Using the model, we can easily isolate the price effect that is coming from a downward-sloping demand. By keeping $\Delta\mathbb{E}_{s'|s}\mathcal{R}'(.)$ fixed, we can disentangle the effects of an exogenous change in the composition of an index into an elasticity channel (η) and a return or risk channel (α).

Apart from being able to recover the price elasticity, the model has important implications regarding the optimal supply of risky assets when the demand for those assets is downward sloping. To see this clearly, notice that when the government chooses its debt policy it

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

internalizes not only the effects of a larger B' on $q(.)$ through changes in its default probability, but also its effects through the downward-sloping demand component. Let $\varepsilon \equiv \frac{\Delta q(.)}{\Delta B'} \frac{B'}{q(.)}$ denote the elasticity of the bond-pricing kernel with respect to the supply of the bond. It is easy to show the following:

$$\varepsilon = \underbrace{\frac{\Delta \mathbb{E}_{s'|s} \mathcal{R}'(.)}{\Delta B'} \frac{B'}{\mathbb{E}_{s'|s} \mathcal{R}'(.)}}_{\text{Default Risk}(\leq 0)} + \underbrace{\frac{\Delta \Psi(.)}{\Delta B'} \frac{B'}{\Psi(.)}}_{\text{Inelastic Demand}(<0)} - \underbrace{[\eta + \alpha] \frac{\Delta \mathcal{T}'}{\Delta B'} \frac{B'}{B' - \mathcal{T}'}}_{\text{Index Composition}}. \tag{19}$$

The first term on the right-hand side captures the elasticity of the expected repayment function. This elasticity is typically negative, as a larger B' increases default risk and reduces the expected repayment. The second term captures the decline in the bond price due to the downward-sloping demand. The third term accounts for the effect of a larger B' on the relative weight in the index $\mathcal{I}$ (and thus in the purchases of passive investors), influencing the bond-pricing kernel through the elasticity (η) and risk (α) channels.

From Equation (19), it is thus clear that an increased B' not only lowers the bond price due to heightened default risk but also due to the downward-sloping demand of active investors. Given that the government internalizes both effects, a more inelastic demand affects its supply of bonds. In the next section, we use a calibrated version of the model to quantify the implications of an inelastic demand on the optimal supply of risky bonds.

5 Quantitative Analysis

5.1 Calibration

The model is calibrated at quarterly frequency based on Argentine data. 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, following Morelli and Moretti (2023). We internally calibrate the remaining parameters to match relevant moments for Argentine spreads and other business-cycle statistics. Table 4 describes the model calibration.

In terms of functional forms and stochastic processes, we assume that the government has CRRA preferences: $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, where γ denotes the risk aversion. Output follows an AR(1) process given by $\log(y') = \rho_y \log(y) + \epsilon'_y$, with $\epsilon'_y \sim N(0, \sigma_y)$. If the government defaults, output costs are governed by a quadratic loss function $\phi(y) = \max\left\{d_0 y + d_1 y^2, 0\right\}$. 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 type of loss function is identical to the one used in Chatterjee and Eyigungor (2012) and allows to match reasonably well the sovereign spreads

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	0.947
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	Downward sloping demand	50.0
θ	Reentry probability	0.0385	κ_1	Downward sloping demand	0.54
ρ_{y}	Output, autocorrelation	0.93			
σ_{y}	Output, shock volatility	0.02			

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. That is, $\mathcal{T}' = \mathcal{T}(\tau, B') = \tau \times B'$. 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 $\epsilon'_\tau \sim N(0, \sigma_\tau)$. We calibrate $\tau^\star$ to match the share of Argentina's external debt that is on average tracked by passive funds. We then calibrate ρ_τ and σ_τ to match the persistence and volatility of our FIR measure.

Panel (A) of Table 4 lists the parameters we fix in the calibration. We set the risk aversion $\gamma = 2$, which is a standard value in the literature. We set $r_f = 1\%$, in line with the observed average real risk-free rate in the United States. We set the re-entry parameter to $\theta = 0.0385$, which implies an average exclusion from international markets of 6.5 years. We set $\lambda = 0.05$ to target a maturity of 5 years and $\nu = 0.03$ to match Argentina's average debt services. Parameters for the endowment process, ρ_y and σ_y, are estimated based on log-linearly detrended quarterly real GDP data for Argentina.

The remaining parameters (Panel B of Table 4) are internally calibrated to match key moments of the Argentine economy (described in Table 5). We jointly calibrate $\{d_0, d_1\}$ together with the government's discount factor β to target Argentina's average ratio of (external) debt to GDP, average spread, and volatility of spreads.[19] For the other three moments, we target an average external-debt-to-GDP ratio of 72%, an average spread of 624 basis points (bps), and a standard deviation of spreads of 288 bps.

Based on the analysis in Section 2.3, we consider the following functional form for the $\Psi(.)$ function:

$$\Psi\left(y,\tau,B'\right) = exp\left\{-\kappa_0 \frac{\mathbb{V}_{s'|s}\left(\mathcal{R}'(.)\right)}{\mathbb{E}_{s'|s}\left(\mathcal{R}'(.)\right)} \times \left(B' - \mathcal{T}' - \kappa_1\right)\right\}, \tag{20}$$

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

Table 5
Targeted Moments

Target	Description	Data	Model
$\mathbb{E}[SP]$	Average bond spreads	630bp	514bp
$\sigma(SP)$	Volatility spreads	253bp	166bp
$\mathbb{E}[D/Y]$	Average debt	72%	62%
η	Demand Elasticity	-0.35	-0.32
Ψ	Average Premium	1.0	1.005

which is a function of the residual demand $(B' - \mathcal{T}')$ and the relative variance of the next-period repayment function.[20] This specification introduces a wedge only for risky bonds (i.e., those with $\mathbb{V}_{s'|s}(\mathcal{R}'(.)) > 0$) and, as we show next, it allows us to capture the two key features of our empirical analysis: (i) a downward-sloping demand for active investors; (ii) an elasticity that is larger (in magnitude) for riskier countries (i.e., countries with a larger return variance). We have microfounded such expression based on risk-averse investors with mean-variance preferences. However, as we explained in Section 2, we can obtain a similar functional form in the case of risk-neutral agents that are subject to a Value-at-Risk constraint.

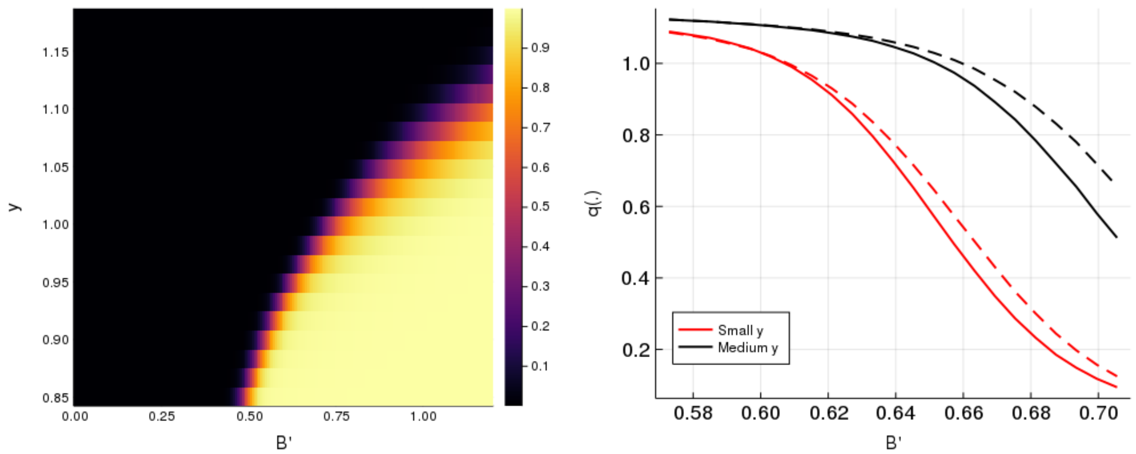
We calibrate κ_0 to match our empirical estimates. In particular, we target the on-impact effect of an exogenous index rebalancing on the price of sovereign bonds (as reported in Figure 6). We set κ_1 such that, on average, $\Psi(.)$ is equal to one. That is, $\mathbb{E}(\Psi(y, \tau, B')) = 1$. The only effect of introducing $\Psi(.)$ is thus to affect the sensitivity of changes in B' in the pricing of the sovereign bonds. We do this to avoid distorting the level of the bond-pricing kernel, conditional on a $\mathcal{R}'(.)$ function. Our goal is to analyze the implications of a downward-sloping demand; not the direct implications of a "risk-premium" per se.

Figure 7 shows the default set and the bond-price function $q(.)$ for different values of B' and y. Panel (a) shows that the government defults in states with high debt and low output. The bond price is thus decreasing in B' and increasing in y (Panel (b), solid lines). The dashed lines in Panel (b) show the bond price in a counterfactual in which we take the baseline $B'(.)$ policy but we assume that the demand is perfectly elastic (i.e., it shows the $q(.)/\Psi(.)$ function). For low levels of B', when the default risk is small, bond prices are almost unaffected by the downward-sloping demand. As B' increases, the volatility of returns rises and investors demand a premium for holding the bonds, which ends up reducing q.

[20] We use an exponential specification (rather than Equation (5)) purely for computational reasons: to avoid having a negative price.

Figure 7
Default Set and Bond Prices

(a) Default Set (b) Bond Price



Note: Panel A: The figure shows the default policy for different combinations of B' and y. 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., $q(.)/\Psi(.)$).

5.2 Decomposing the Demand Elasticity

In this section, we formally disentangle the different channels through which changes in $\mathcal{T}$ affect bond prices. As explained in Section 2 and as shown in Equation (18), index rebalancing affects bond prices through two channels: (i) the demand elasticity of active investors, η, (ii) changes in default risk and in the expected repayment function, α. Using the calibrated model, we can easily shut down the effect of changes in default risk on bond prices, which allows us to properly identify the demand elasticity.

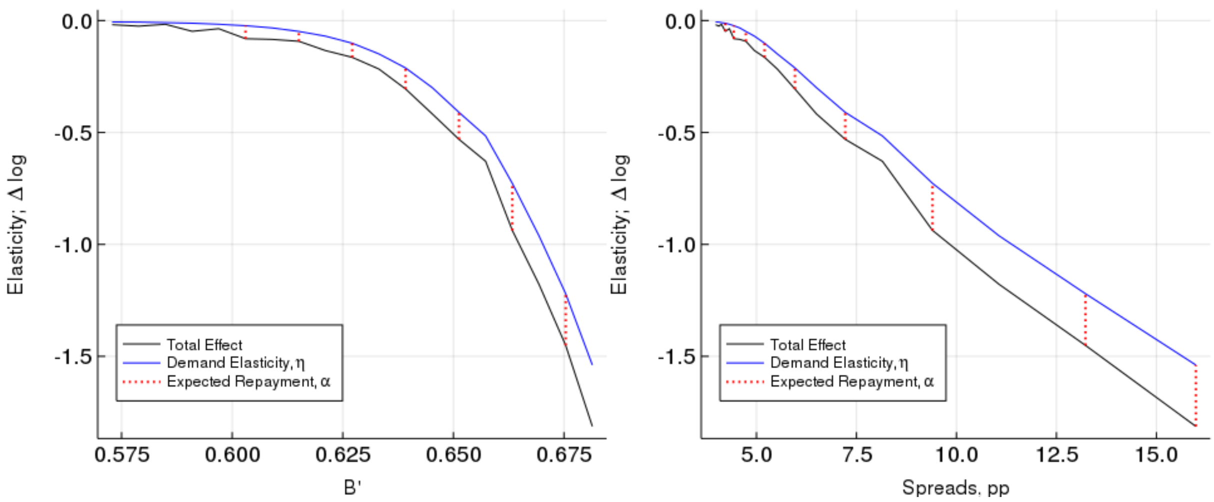
Figure 8 decomposes the different elements behind Equation (18). The black line shows the relative change in bond prices driven by an exogenous index rebalancing (the $(-)\frac{\Delta q(.)}{\Delta \mathcal{T}'} \times \frac{B'-\mathcal{T}'}{q(.)}$ term). The blue line shows the demand elasticity η. The vertical difference between the two lines captures the α channel (dotted red lines).

Consistent with our empirical analysis based on CDS spreads, we find that the index rebalancings lead to changes in the expected repayment that amplify the response of bond prices. The relative bias can be substantial, particularly for small values of B' and when default risk is small. In Table 6, we simulate the model and report the unconditional average for η, α, and for the total effect. On average, the repayment channel α explains about a third of the total change in price.

To sum up, even if the fundamentals of the economy (y, B') are fixed, changes in the composition of the index (our FIR measure) affect a country's default risk, which ends up affecting bond prices. Failing to account for these effects, thus, introduces a bias in the

Figure 8
Dissentangling the Demand Elasticity

(a) As a function of B' (b) As a function of spreads



Note: The figure decomposes the different channels through which index rebalancings affect bond prices. The black lines show the total effect: $(-)\frac{\Delta q(.)}{\Delta \mathcal{T}'} \times \frac{B'-\mathcal{T}'}{q(.)}$. The blue lines show the demand elasticity η. The vertical difference between the two lines captures the α channel (dotted red lines). Panel (a) shows the results as a function of B'. Panel (b) shows the results as a function of annualized bond spreads.

empirical estimates of the price demand elasticity.

Table 6
The Demand Elasticity

Moment	Demand Elasticity, η			Repayment Effect, α	Total Effect
	Slope	Rel. Var	Total		
Average	-0.235	0.029	-0.206	-0.108	-0.315
Standard Deviation	0.499	0.158	0.402	0.214	0.591

Given our specification for $\Psi(.)$, we can further decompose the demand elasticity as follows:

$$\eta = -\kappa_0 \frac{\mathbb{V}\left(\mathcal{R}'(.)\right)}{\mathbb{E}\left(\mathcal{R}'(.)\right)}\left(B' - \mathcal{T}'\right) + \kappa_0 \frac{\Delta\left(\frac{\mathbb{V}(\mathcal{R}'(.))}{\mathbb{E}(\mathcal{R}'(.))}\right)}{\Delta \mathcal{T}'}(B' - \mathcal{T}') \times (B' - \mathcal{T}' - \kappa_1). \tag{21}$$

The first term on the right hand side captures the "slope" of the demand of active investors when keeping the (relative) variance of the repayment function fixed. By design, the slope is higher (in magnitude) the larger the variance of the repayment function, which captures our empirical finding that the demand elasticity is higher for riskier countries. The second term captures changes in the relative variance of the repayment function with respect to $\mathcal{T}'$. Table 6 shows that the latter mechanism is small (given our calibration strategy) and most of the demand elasticity is explained by the "slope" term.

5.3 Implications of a Downward-sloping Demand

We analyze next how a downward-sloping demand affects a government's optimal policy functions, and its implications on bond prices. When the government solves for its optimal debt policy, it internalizes not only the effects of a higher B' on $q(.)$ through changes in its default probability, but also its effects through the downward-sloping demand component (as shown in Equation (19)). In this section, we show that this can lead to large changes in the optimal bond policy function and in the pricing of sovereign debt.

Table 7 reports the set of targeted moments as well as other untargeted moments for our baseline model and a model with a perfectly elastic demand (with $\kappa_0 = \kappa_1 = 0$). Under an inelastic demand, the default frequency and average spreads are *lower* and average debt is *higher* relative to the perfectly elastic case. Why is this the case? As we explain next, the inelastic demand acts as a commitment device that precludes the government from issuing large amounts of debt.

Table 7
Comparison with Perfectly Elastic Case

Moment	Description	Baseline	Perfectly Elastic
$\mathbb{E}\,(SP)$	Average bond spreads	514bp	880bp
$\sigma\,(SP)$	Volatility spreads	166bp	509bp
$\mathbb{E}\,(B/y)$	Average debt	62%	59%
$\mathbb{E}\,(d)$	Default Frequency	3.88%	4.82%
$\sigma(B)/\sigma(y)$	Standard deviation of debt, relative to output	1.925	2.404
$\rho\,(SP, y)$	Correlation between spreads and output	-0.723	-0.469

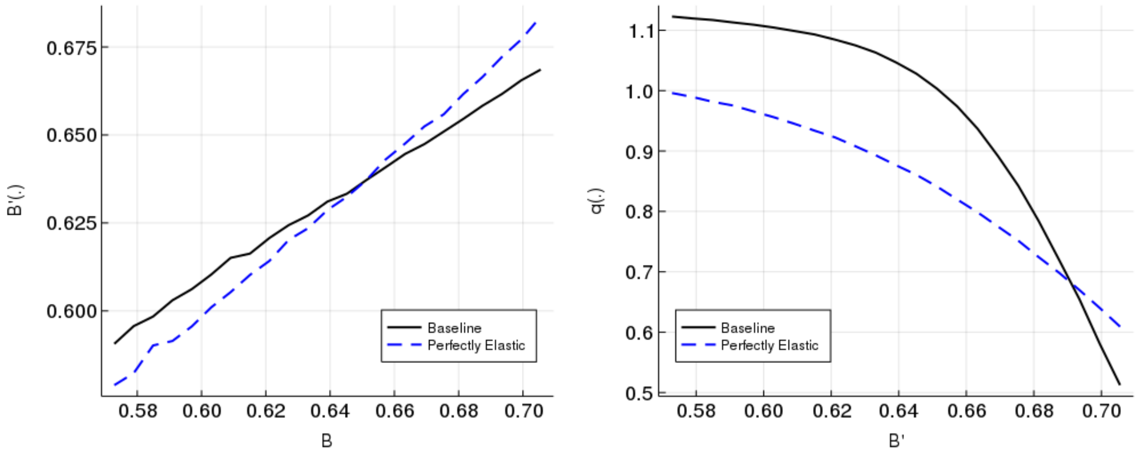
The government's bond policy is significantly affected by a downward-sloping demand. Panel A of Figure 9 shows the optimal debt policy in our baseline model and in the perfectly elastic case. For large values of B (in states where $\mathbb{V}\,(\mathcal{R}'(.))$ is high), an additional unit of B' reduces the bond price $q(.)$ not only due to a higher default risk, but also due to investors' inelastic behavior. The government, thus, finds it optimal to issue a smaller amount compared to the perfectly elastic case.

The previous changes in the optimal bond policy have important effects on the pricing of bonds (Panel B of Figure 9). For small values of B' (low default risk), $q(.)$ is actually *higher* than under the perfectly elastic case. As shown in Figure 10 (Panel A), this larger bond price is not driven by a "convenience yield" (i.e., $\Psi(.) > 1$), since $\Psi(.)$ is close to one for low levels of B'. Instead, what is being affected is the default risk of the government (Panel B).

Overall, for the case of risky bonds, a downward-sloping demand acts as a commitment

Figure 9
Implications on Policies and Prices

(a) Bond Policy (b) Bond Price

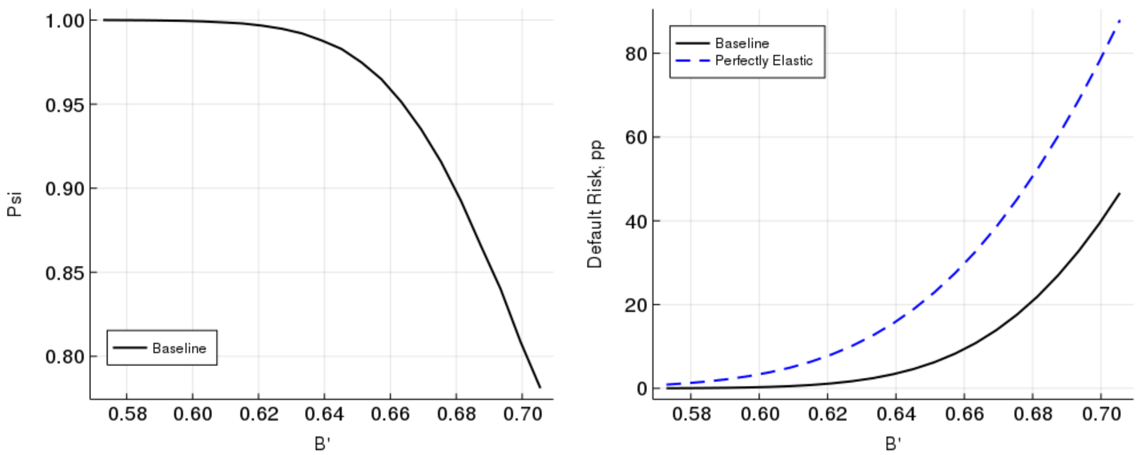


Note: The figure shows bond policies and prices for our baseline model with inelastic investors (black solid lines) and in an alternative model in which investors are perfectly elastic (blue dotted lines).

device. That is, the government does not find it optimal to issue a large B' because it leads to a large reduction in bond prices through η. Lenders internalize the government's lower incentives to issue a large B' and this, in turn, ends up decreasing the government's spreads and its default risk.

Figure 10
Premium and Default Risk

(a) $\Psi(y, \tau, B')$ (b) Default Risk, Annualized



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

6 Conclusion

We present novel evidence of downward-sloping demand curves in international sovereign-debt markets and analyze its implications on the optimal supply of risky sovereign bonds.

Estimating a demand elasticity for risky bonds poses additional challenges (relative to a safe bond) because the demand itself depends on a bond's default risk. To address this, we combine a structural model with high-frequency bond-level price reactions to exogenous shifts in the effective supply of bonds. This combination allows us to isolate the role of default risk and back out a demand elasticity.

Overall, we find that global investors in sovereign-debt markets are inelastic. An exogenous 1% reduction in the effective supply of sovereign bonds leads to a 65 basis point increase in bond prices. Our structural model reveals that two thirds of this effect can be attributed to a demand elasticity component (the rest is captured by changes in default risk). We use the model to analyze the implications of downward-sloping demand curves for governments' optimal debt and default policies. We show that by diminishing a government's incentives to issue additional units of debt, a downward-sloping demand acts as a commitment device that reduces default risk.

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A Diversification Methodology

The diversification methodology anchors on the average size (debt stock) of countries in the index and the debt stock of the largest country in the index.

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

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

1. The largest country based on face amount will be capped at double the average country debt stock in the index (ICA*2). This is the maximum threshold and sets the scale to determine the diversified face amounts of other countries in the index.

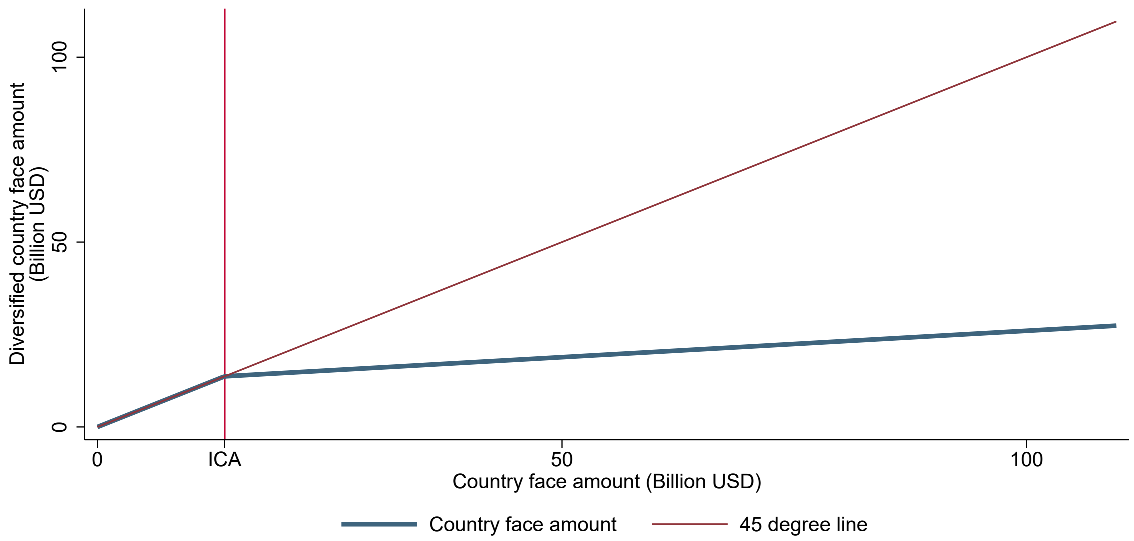
2. If a county's debt stock is below the index country average (ICA), the entire amount will be eligible for inclusion.

3. Countries whose debt stock falls between the index country average (ICA) and double the average (ICA * 2) will be linearly interpolated.

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

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

Figure A1
Effect of the diversification methodology on the amount of the bonds' face values used to compute the weights

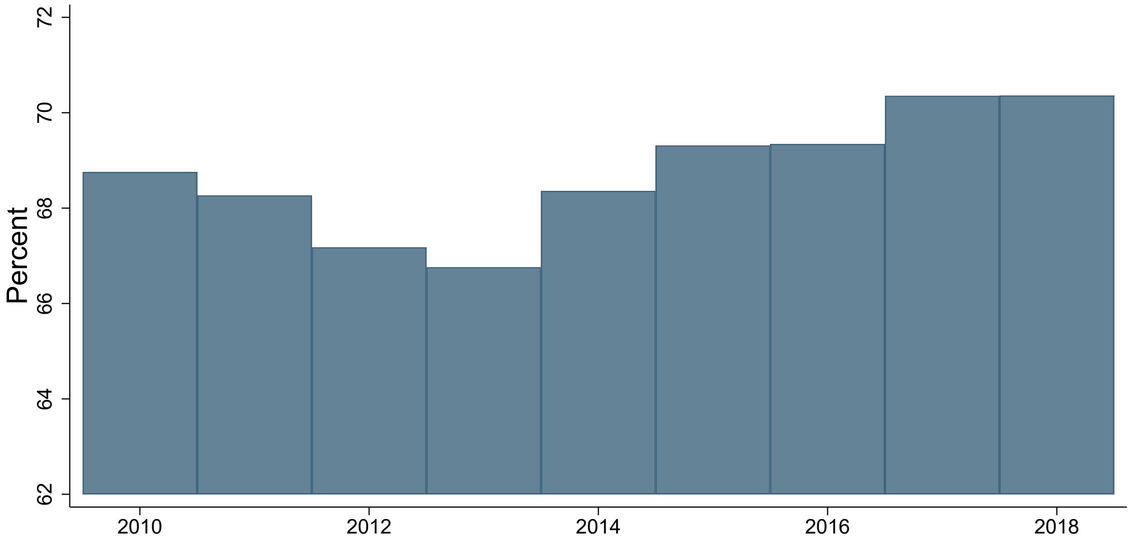


Note: The figure illustrates the differences between the country-level face values and their diversified versions, which the index uses to generate bond weights. The data used is from December 2018.
Sources: JPMorgan Markets, and authors' calculations.

Subsequently, the same proportional reduction or increase that the country-level face amount suffered is applied to each bond from that country. The diversified market value is then computed by multiplying the diversified face amount by the price of the bond. The diversified weight of each bond is its share of the index diversified market capital. In addition, country weights will be capped at 10%. Any excess weight above the cap will be redistributed to smaller countries that are below the cap in a pro rata form across all bonds of countries not capped at 10%. Figure A1 compares the country-level diversified vs non-diversified face amounts.

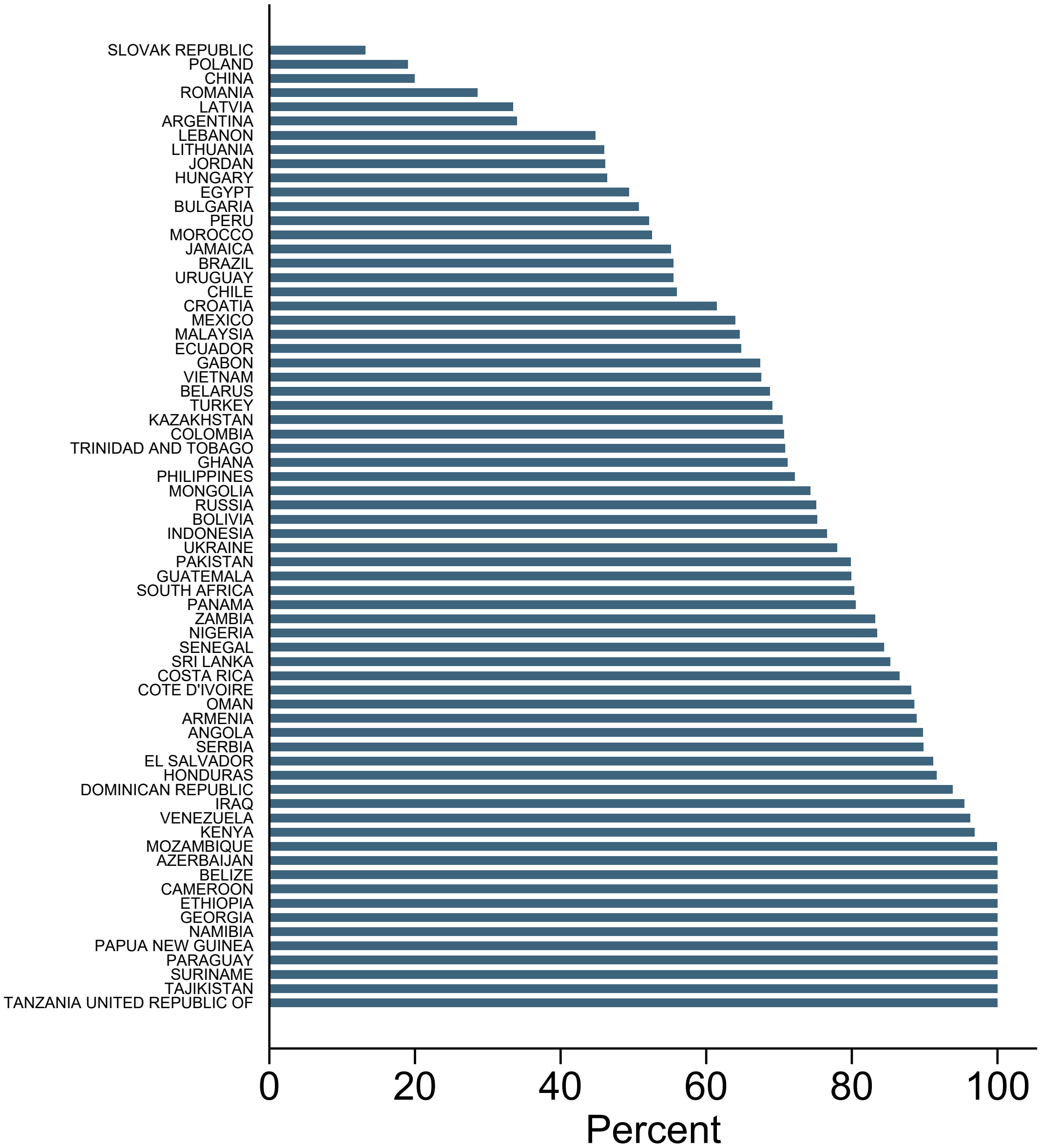
B Additional Tables and Figures

Figure B1
USD-denominated emerging-market sovereign debt as a share of emerging-market general government international debt securities



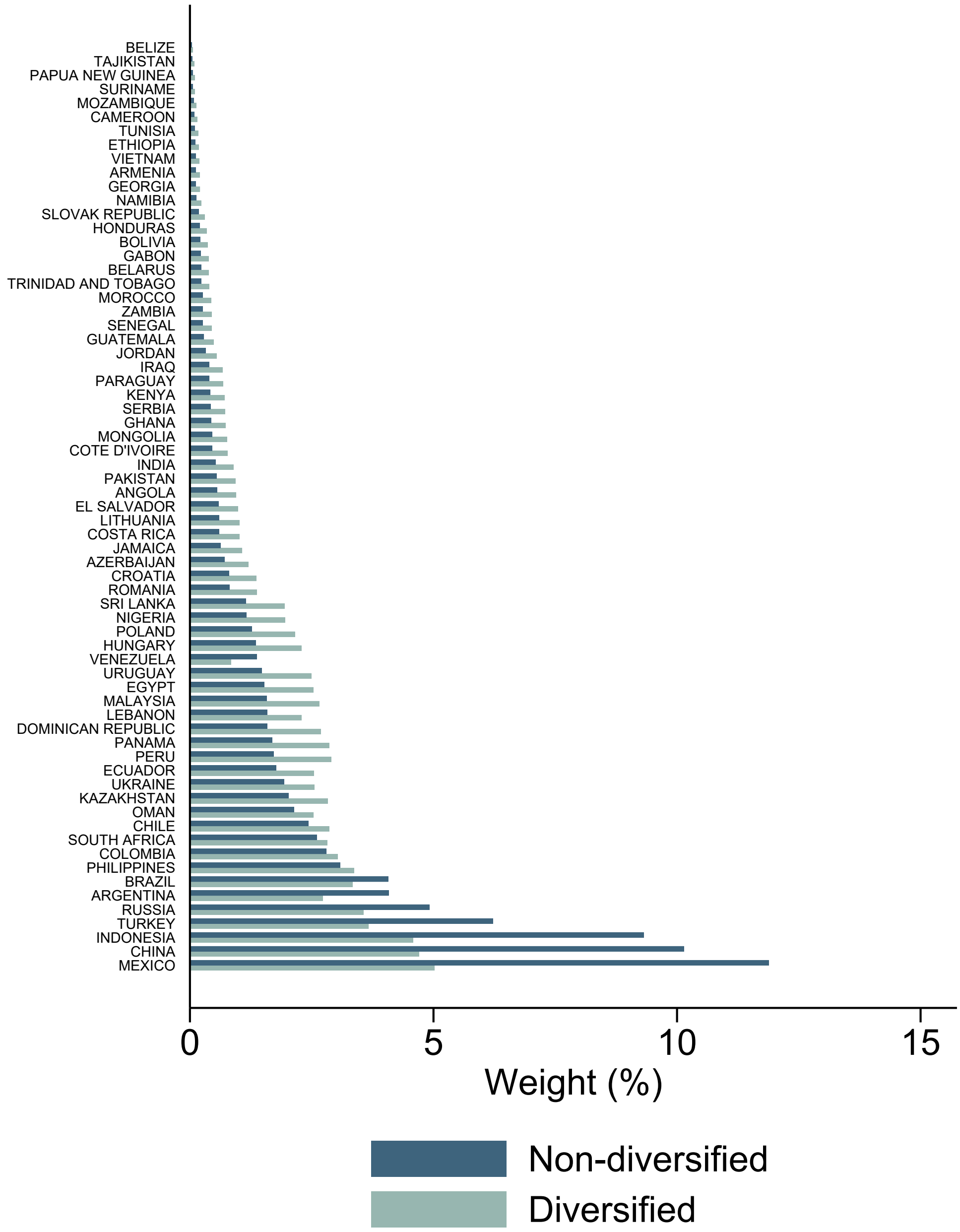
Note: The bars represent the value of USD-denominated sovereign debt included in the EMBI Global index as a percentage of general government international debt securities of the corresponding countries. The averages are created by computing the percentage for each country and year and then averaging across countries in each year. Each country's percentage is weighted by its debt amount outstanding included in the EMBI indexes.
Sources: BIS, JPMorgan Markets, and authors' calculations.

Figure B2
USD-denominated emerging-market sovereign debt as a share of emerging-market general government international debt securities



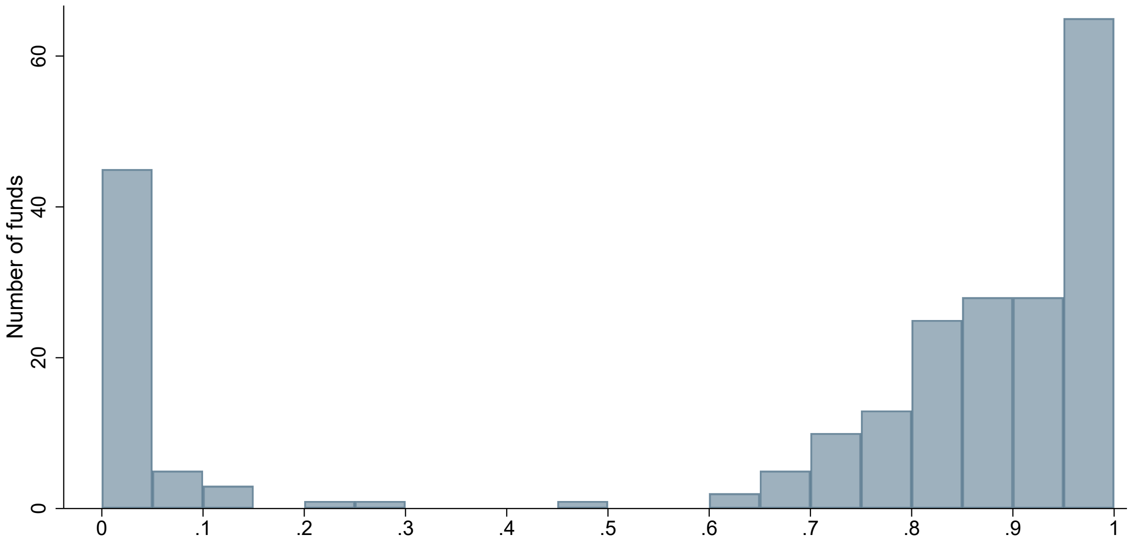
Note: The bars represent the value of USD-denominated sovereign debt included in the EMBI Global index as a percentage of general government international debt securities of the corresponding countries. The averages are created by computing the percentage for each country and year and then averaging across years 2010-2018 for each country.
Sources: BIS, JPMorgan Markets, and authors' calculations.

Figure B3
Country-level weights in December 2018



Note: The figure illustrates the 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 the country included in the index.
Sources: JPMorgan Markets, and authors' calculations.

Figure B4
Distribution of R^2 from linear regressions of returns of funds benchmarked to the EMBI Global Diversified versus EMBI Global Diversified returns



Note: Distribution of the R^2 values from fund-by-fund regressions of fund returns against EMBI Global Diversified returns. Only funds benchmarked to the CEMBI Global Diversified and Core indexes are included. Returns expressed in USD are utilized.
Sources: Morningstar Direct, JPMorgan Markets, and authors' calculations.

Table B1
Log Price and FIR

Dependent Variable: Log Price				
	20%	25%	30%	35%
FIR Instrumented*Post	1.039***	0.806***	0.651***	0.599***
	(0.307)	(0.238)	(0.192)	(0.177)
Post	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes
Maturity-Rating-Bond Type-Time FE	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes
Bond Controls	Yes	Yes	Yes	Yes
Observations	130,107	130,107	130,107	130,107
N. of Bonds	706	706	706	706
N. of Countries	67	67	67	67
N. of Clusters	1,782	1,782	1,782	1,782
R^2	0.002	0.002	0.002	0.002

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end of the month rebalancing date. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Each different column indicates the share of passive funds used to construct the FIR face amount measure. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

Table B2
Log Price and FIR - Dropping Different Extreme Values for Z

Dependent Variable: Log Price				
	4 Extreme Values		2 Extreme Values	
FIR Instrumented	-8.791***		-7.484***	
	(1.485)		(1.298)	
FIR Instrumented*Post	0.496**	0.494**	0.555***	0.554***
	(0.199)	(0.201)	(0.177)	(0.178)
Post	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes
Maturity-Rating-Bond Type-Time FE	No	Yes	No	Yes
Country-Time FE	No	Yes	No	Yes
Bond Controls	No	Yes	No	Yes
Observations	128,644	128,600	131,581	131,537
N. of Bonds	706	706	706	706
N. of Countries	67	67	67	67
N. of Clusters	1,742	1,741	1,824	1,823
R^2	0.012	0.002	0.010	0.002

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end of the month rebalancing date. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Each different column indicates the share of passive funds used to construct the FIR face amount measure. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

Table B3
Log Price and FIR - Keeping Crises Countries (Argentina and Turkey)

Dependent Variable: Log Price					
FIR Instrumented	-9.765***	-1.758	1.654		
	(1.414)	(2.446)	(1.219)		
FIR Instrumented*Post	0.564***	0.564***	0.563***	0.563***	0.563***
	(0.197)	(0.197)	(0.199)	(0.199)	(0.199)
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	Yes
Time FE	No	Yes	Yes	No	No
Maturity-Rating-Bond Type-Time FE	No	No	Yes	Yes	Yes
Country-Time FE	No	No	No	Yes	Yes
Bond Controls	No	No	No	No	Yes
Observations	138,258	138,258	138,258	138,258	138,214
N. of Bonds	766	766	766	766	766
N. of Countries	69	69	69	69	69
N. of Clusters	1,829	1,829	1,829	1,829	1,828
R^2	0.006	-0.002	0.002	0.001	0.001

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end of the month rebalancing date. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Each different column indicates the share of passive funds used to construct the FIR face amount measure. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B4

Log Price and FIR - Dropping Quasi-Sovereign Bonds

Dependent Variable: Log Price					
FIR Instrumented	-8.736***	-0.805	1.196		
	(1.215)	(3.025)	(1.282)		
FIR Instrumented*Post	0.770***	0.769***	0.768***	0.768***	0.768***
	(0.191)	(0.191)	(0.193)	(0.193)	(0.193)
Post	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No
Maturity-Rating-Bond Type-Time FE	No	No	Yes	Yes	Yes
Country-Time FE	No	No	No	Yes	Yes
Bond Controls	No	No	No	No	Yes
Observations	89,726	89,726	89,726	89,726	89,682
N. of Bonds	396	396	396	396	396
N. of Countries	64	64	64	64	64
N. of Clusters	1,715	1,715	1,715	1,715	1,714
R^2	0.016	-0.000	0.002	0.002	0.005

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end of the month rebalancing date. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Each different column indicates the share of passive funds used to construct the FIR face amount measure. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

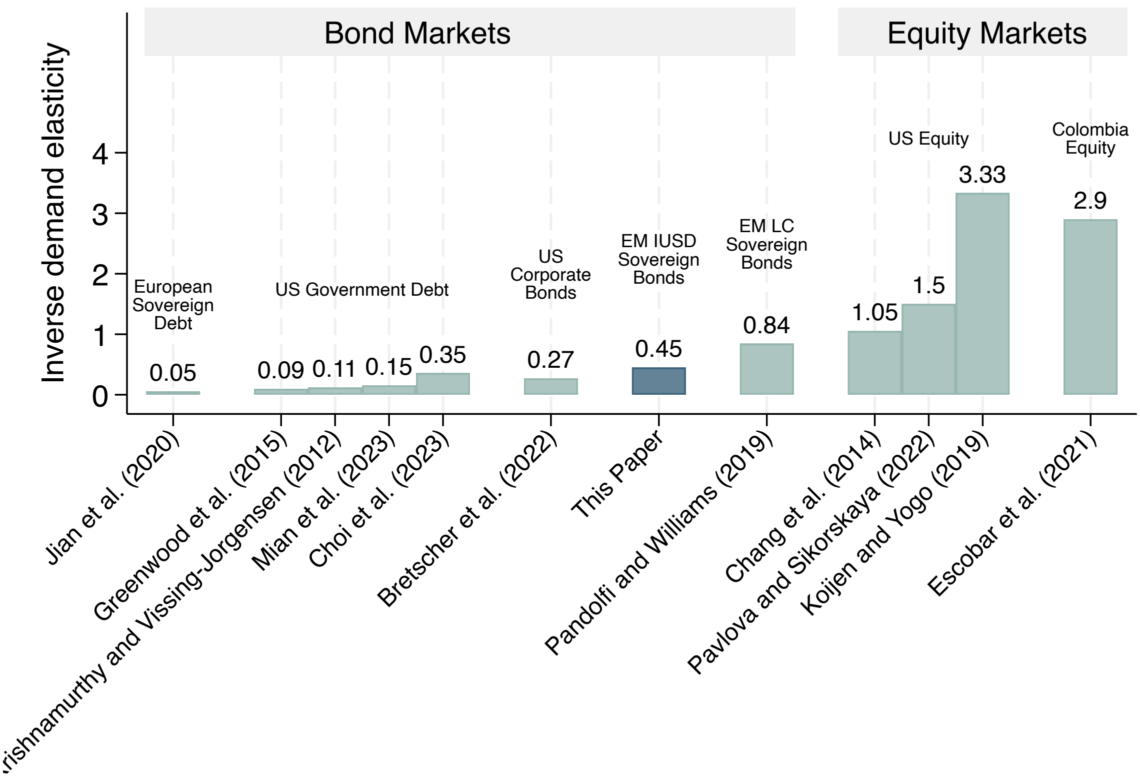
Table B5
Log Price and FIR - Spread Heterogeneity (3 Groups)

Dependent Variable: Log Price

	High Spread		Median Spread		Low Spread	
FIR Instrumented	-14.165***		-5.225***		-4.119***	
	(3.174)		(0.815)		(1.066)	
FIR Instrumented*Post	1.196***	1.192***	0.499***	0.499***	0.104	0.103
	(0.415)	(0.420)	(0.186)	(0.189)	(0.139)	(0.141)
Post	0.003***	0.003***	0.002***	0.002***	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Maturity-Rating-Bond Type-Time FE	No	Yes	No	Yes	No	Yes
Country-Time FE	No	Yes	No	Yes	No	Yes
Bond Controls	No	Yes	No	Yes	No	Yes
Observations	43,438	43,438	42,966	42,966	43,747	43,703
N. of Bonds	338	338	443	443	389	389
N. of Countries	56	56	51	51	41	41
N. of Clusters	1,062	1,062	935	935	705	704
R^2	0.023	0.043	0.016	0.074	0.001	0.005

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end of the month rebalancing date. We divide the sample into bonds with high spreads (Columns 1 and 2), median spreads (Columns 3 and 4), and low spread (Columns 5 and 6). Spreads are divided according to their 33.3 and 66.6 percentile into the three different buckets. The dependent variable is the log price of a bond. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Time fixed effects are dummy variables for each month of rebalancing. Maturity fixed effects are constructed by dividing the time to maturity of a bond into four different categories: short (less than 5 years), medium (between 5 and years), long (10 to 20 years) and very long (more than 20 years). Ratings from each bond are from Moody's. Bond Type indicates whether a bond is sovereign or quasi-sovereign. Bond controls indicates whether the estimation includes the log face amount and log stripped spread of the bond. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.

Figure B5
Estimated inverse demand elasticities for financial markets



Sources: EM IUSD Sovereign Bonds stands for emerging-market sovereign bonds issued internationally in US dollars. EM LC Sovereign Bonds stands for emerging-market sovereign bonds issued in local currency. The elasticities in Jiang et al. (2021), Krishnamurthy and Vissing-Jorgensen (2012), and Greenwood et al. (2015) are taken from the review Table 2 in 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. For this paper, we compute the midpoint in elasticity from Table 2. For the EM local currency sovereign bonds we take the estimated number in Table 15 in Pandolfi and Williams (2019) for GBI bonds (Panel D). We adjust that number by the share of AUM (23.6%) that behave de facto in a passive way. For that, we compute the share of assets in EPFR tracking the GBI-EM Global Diversified that have an R^2 higher than that of ETFs tracking the GBI-EM Global Diversified. We compute the average R^2 of ETFs using a weighted average (weighted by assets) of the R^2 of the different ETFs.

Table B6
Log CDS and FIR

Dependent Variable: Log CDS			
FIR Instrumented	12.850**	-15.733*	
	(5.154)	(8.026)	
FIR Instrumented*Post	-1.518**	-1.518**	-1.518**
	(0.605)	(0.606)	(0.604)
Post	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)
Country FE	Yes	Yes	No
Time FE	No	Yes	No
Country-Time FE	No	No	Yes
Observations	11,836	11,836	11,836
N. of Countries	42	42	42
N. of Clusters	1,076	1,076	1,076
R^2	0.000	0.005	0.007

Note: This table presents results from 2SLS estimations of log price on different explanatory variables around rebalancing dates. The first stage and second stage equations are described in 10. The sample period is 2016-2018 and contains a window of 10 trading days around each end-of-the-month rebalancing date. The dependent variable is the log CDS (5-year) of country. FIR Instrumented is the FIR from 7 instrumented with Z in 9. Post is an indicator variable that is 1 for the day of the rebalancing and 5 trading days after it, and 0 otherwise. Time fixed effects are dummy variables for each month of rebalancing. Standard errors are clustered at the country by month of rebalancing level. *** p<0.01, **p<0.05, * p<0.1.