The fickle and the stable:

Global Financial Cycle transmission via heterogeneous investors

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Abstract

This paper shows that accounting for foreign investor base differences helps explain the heterogeneous influence of the Global Financial Cycle on the borrowing cost of emerging market governments. Using security-level holding data and a quantitative model featuring heterogeneous investors, debt default risk and global financial shocks, I investigate the role of investor demand and asset attributes in the transmission of global shocks. I document that facing global financial tightening, sovereign bonds with a higher institutional ownership by foreign investment funds suffer a larger price drop. By estimating the yield elasticity of demand for long-term foreign investors, such as banks, insurers and pension funds, I find that their shock-absorbing capacity is generally low and depends on bond characteristics such as currency denomination. My quantitative model featuring endogenous amplification of financial shocks is able to capture the empirical patterns. Counterfactual analyses suggest that encouraging the participation of long-term foreign investors or limiting the risk exposure of investment funds could substantially reduce the volatility of yields on emerging markets sovereign debt.

JEL classification: E32, F32, F34, G15.

Keywords: Global Financial Cycle, non-bank financial intermediation, sovereign risk.

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1 Introduction

Emerging market economies experience frequent surges and stops of capital inflow, channeled through an increasingly complex set of global intermediaries. Meanwhile, the prices of emerging market assets strongly comove with global risk factors, a phenomenon labelled the "Global Financial Cycle." (Rey, 2013)[1]

This paper connects these two observations through a new fact – the sensitivity of sovereign bond yield spreads to global risk factors is correlated with whether the liabilities are held primarily by foreign investment funds, insurance companies and pension funds (ICPFs), or banks, highlighting the potential role that investor composition plays in driving or amplifying the Global Financial Cycle. To understand the mechanism behind this pattern, I develop a quantitative equilibrium model of the sovereign debt market with heterogeneous investors, disciplined by a set of novel empirical facts obtained from a micro dataset of bond-level positions reported by global investment funds and Germany-based financial institutions. The model replicates the mapping between investor heterogeneity and sensitivity to global risk factors, and quantifies the interaction between asset attributes and investor composition. I also use the model to explore how policy measures, such as those that limit bank and investment fund exposure to sovereign risk, would impact the response of sovereign yield spreads to global shocks.

I start by documenting a strong correlation at the macro level. A country's sovereign yield spread is more sensitive to shifts in global risk factors when the share of its external liabilities or its government debt held by foreign non-banks increases relative to foreign banks. Among foreign holdings, the sensitivity is increasing in the share of investment funds, including mutual funds and exchange-traded funds (ETFs). Canonical frameworks with a single representative lender are unable to capture these salient facts or explore the implications of these correlations. Meanwhile, the role of foreign investor composition in the transmission of the Global Financial Cycle could depend on the interaction between investors' heterogeneity and the fundamental attributes of debtor countries' liabilities that attract a particular type of investor. I unpack this relationship through the lens of a quantitative framework informed by micro data.

Using a novel security-level, high-frequency dataset with substantial sectoral coverage of foreign investor base for more than 2400 emerging market long-term sovereign

[1] Longstaff et al. (2011) show that the first principal component of emerging market credit default swap spreads is closely related to indicators of global risk factors. Early contributions on the influence of global variables also include Calvo et al. (1996), Mauro et al. (2002), and González-Rozada and Levy Yeyati (2008).

debt securities, I establish a number of findings. First, even after controlling for time-varying issuer fundamentals through issuer×time fixed effects, I find that banks, insurers and pension funds are more likely to hold home currency (Euro-denominated) assets. Insurers and pension funds additionally tilt their emerging market portfolio towards securities with higher credit quality. Second, conditional on bond and issuer×time fixed effects that absorb the effect of investors' portfolio preferences and time-varying issuer characteristics on bond yields, emerging market sovereign bonds' yield sensitivity to shifts in the VIX index–a widely used proxy for global risk factors–increases when a larger fraction of the bond is held by investment funds prior to the shifts, and decreases with the ex ante share held by banks, insurers and pension funds. A 10 percentage point increase in the share held by investment funds correspond to a 29% increase in the bond yield sensitivity. I further show that this result is unlikely to be affected by concerns on imperfect data coverage, selection on important bond characteristics such as currency denomination and maturity, and reverse causality, such as investment funds' voluntary exposure to global volatility risks. On the quantity side, I show that during important episodes of heightened global financial risk, such as the Taper Tantrum and the COVID pandemic, banks, insurers and pension funds respond by buying emerging market sovereign debt, while investment funds, driven by strong capital redemption pressure, become net sellers.

The granular data also allows me to estimate the yield semi-elasticity of demand associated with stable, long-term investors such as banks, insurers and pension funds. This statistic is a barometer of the capacity of these investors to absorb adverse global financial shocks and is thus a key statistic governing the sensitivity of yields to shocks. For identification, I construct instrumental variables based on capital flows in and out of emerging market-focused mutual funds that move prices and shift the residual supply curve faced by long-term investors. The first instrument projects surprise fund flows onto each bond using past portfolio weights, in the spirit of Lou (2012) and van der Beck (2022). The second instrument exploits granularity of the fund size distribution and extracts idiosyncratic flows in and out of large mutual funds in the spirit of Gabaix and Koijen (2023). Using both approaches, I find that a one percentage point increase in the annualized yield of Euro-denominated sovereign bonds expands the demand of long-term investors by 29 percent, indicating a generally inelastic demand. I also find evidence that the demand for Euro-denominated bonds is more elastic than that for bonds denominated in other currencies, reflecting the close connection between favorable asset characteristics and the shock absorption capacity of long-term investors.

Informed by my empirical observations, I construct a quantitative model of the sovereign debt market featuring heterogeneous investors, stochastic debt default risk and global financial shocks to reproduce the empirical patterns and analyze the impact of foreign creditors' shifting demand structure on emerging market sovereign spreads. Two types of investors–investment funds and long-term investors–hold a risky perpetuity, whose value is subject to random arrivals of haircuts. Consistent with data, long-term investors have stable, downward sloping asset demand that limits their risk exposure to issuer default.[2] Meanwhile, motivated by my empirical findings and earlier work documenting the close relationship between open-ended investment fund flows and global risk (Jotikasthira et al., 2012), I assume that global financial tightening in my model induces capital redemption from investment funds. The outflows erode their risk-bearing capacity and endogenously depresses bond prices. The endogenous interaction between asset liquidation and wealth revaluation further amplifies the adverse impact of a tightening Global Financial Cycle. I calibrate the demand function of the long-term investors leveraging my empirical estimates, and other parameters to match key moments related to emerging market sovereign borrowing. To solve the model, I develop an algorithm based on finite differences that tackles multiple state variables, non-trivial boundary conditions and jump risk in continuous time.

The model matches empirical observations in three major ways. First, consistent with Longstaff et al.'s (2011), the financial factor explains 60 percent of the variation in the price of the risky bond in the model. Second, the model-implied relationship between investor composition and sovereign yield sensitivity to wealth shocks is in line with the data. When the share of the risky perpetuity held by investment funds expands by 10% relative to the average, the sensitivity of the bond yield to investment fund wealth shocks increases by 19%. Third, as long-term investors' demand elasticity vary according to default risk in the model, it can generate substantial cross-country differences in the sensitivity of sovereign yields to financial shocks. I am thus able to use the model as a laboratory to quantitatively evaluate the role of alternative configurations of investor base and derive policy implications. Among the takeaways, I highlight that financial regulations that make long-term investors more accommodative to fundamental risks, such as Solvency II, could reduce the volatility of sovereign borrowing costs and limit the endogenous amplification of the Global Financial Cycle particularly for countries more prone to default.

[2] The optimizing foundation of long-term investors, sketched in Appendix I.B.2, attributes this preference to risk-based capital requirements and risk management concerns.

Related literature My paper contributes to three strands of literature. First, this paper is among the few papers that provide a quantitative framework to analyze the transmission of the Global Financial Cycle. Since Miranda-Agrippino and Rey (2020), there have been several modeling attempts to study the underlying mechanisms contributing to global factors in asset prices (Kekre and Lenel, 2021) and capital flow (Davis and van Wincoop, 2022).[3] Bai et al. (2025) jointly study global and local prices of risk and the time-varying the influence of Global Financial Cycle on emerging market sovereign spreads. Akıncı et al. (2022), Gilchrist et al. (2022) and Morelli et al. (2022) highlight the role of intermediaries and financial frictions in propagating shocks across countries.[4] In comparison, I incorporate empirically identified moments into a model of inelastic asset markets and habitat investors (Vayanos and Vila, 2021). Like Xiong (2001) and Kekre et al. (2023), my model highlights the endogenous revaluation of financial intermediaries' wealth as an important shock amplification channel.

Second, my paper speaks to the empirical literature, starting from the seminal contribution of Calvo et al. (1993), that examines the relationship between emerging market sovereign risk and global financial risk, and the associated transmission channels.[5] Longstaff et al. (2011) and Tourre (2017) show that a single global factor can account for large variation in emerging market sovereign spreads. di Giovanni et al. (2022) provide direct causal evidence on the transmission of global financial shocks to Turkey's borrowing cost. My paper places these findings in the intermediary asset pricing literature through a model with a realistic asset demand structure informed by novel micro data, and use the model to conduct counterfactual analyses.[6]

My paper is also closely related to the emerging "macro-structure" literature (Haddad and Muir, 2025) dissecting the implications of investor base heterogeneity in a global context. Coppola (2022) analyzes investor base of corporate bond in advanced economies

[3]At a broader level, the literature studies the equilibrium asset pricing implication of investor heterogeneity in various contexts. Recent theoretical contributions include Pavlova and Rigobon (2008), Chabakauri (2013), Coimbra (2020), Coimbra and Rey (2024) and Kargar (2021). Cella et al. (2013) and Ben-David et al. (2021a) relate investor heterogeneity to the volatility of stocks. Siani (2023) focuses on the segmentation between primary and secondary markets, and Kremens (2024) connects currency risk to the positioning of hedge funds in the futures market.

[4]In related works, Oskolkov (2023) models the risk-bearing capacity of global banks through ambiguity aversion while Fu (2023) focuses on belief heterogeneity in generating risk-driven capital flow.

[5]Borri and Verdelhan (2011) and Lizarazo (2013) model the global factor in sovereign debt prices by introducing risk-averse investors to standard sovereign default problems. See Kalemli-Özcan (2019) and Gilchrist et al. (2022) for recent empirical attempts to identify this linkage via VAR or local projections.

[6]The estimation of long-term investors' demand elasticity in my paper echoes a fast-growing literature on demand system asset pricing (Koijen and Yogo, 2019; Koijen et al., 2021, among others, further reviewed in Section 4.) My innovation is to incorporate the demand elasticity estimate into the calibration of a fully-specified model to perform quantitative analysis.

and shows that corporate bonds held by insurance companies could fend off adverse financial shocks. Converse et al. (2023) show that exchange-traded funds (ETFs) amplify emerging markets' sensitivity to the Global Financial Cycle.[7] My empirical estimation and quantitative model, on the other hand, emphasize the importance of understanding the equilibrium determination of asset prices through the interaction of the entire investor base. In this way, my paper is closest to Fang et al. (2022), who analyze investor demand for sovereign debt using a demand system approach based on a low-frequency country-level database of sovereign debt ownership split between banks and non-banks, and Moretti et al. (2024), who exploits emerging market bond index rebalancing to identify market multipliers. By focusing on investment funds prone to risk-sensitive redemption, and banks, insurers and pension funds with a stable demand structure, my paper splits investors into more detailed and economically interpretable categories. Faia et al. (2022) and Bergant et al. (2023) analyze various investors' demand for emerging market securities and its association with bond characteristics. Relative to these papers, I estimate the demand equation of long-term investors and examine counterfactual demand structures in my model to derive the asset pricing implication of investor heterogeneity for emerging markets.[8]

The paper proceeds as follows. Section 2 motivates the paper with a set of aggregate stylized facts that highlight the potential role of foreign investor composition. Section 3 reports the results from my empirical analysis using micro data and discuss potential economic mechanisms. Section 4 provides estimates of the demand elasticity of long-term investors. I introduce the quantitative model in Section 5 and my counterfactual exercises in Section 6. Section 7 concludes. The Online Appendix contains a set of supplementary results and additional information.

[7] In the emerging market context, numerous contributions center around open-ended mutual funds and benchmark investors. Most focus on quantities instead of prices and do not provide an analytical framework. See International Monetary Fund (2014, 2021); Raddatz et al. (2017); Ng et al. (2019); Arslanalp et al. (2020); Chari et al. (2020, 2022) and Bush and Cañón (2025). Forbes et al. (2023) analyze the role of non-bank financial institutions in driving the dynamics of CDS spread during COVID-19.

[8] Cerutti et al. (2019) and Moro and Schiavone (2022) use aggregate data on portfolio investment of different investor sectors to study each investor type's sensitivity to the Global Financial Cycle (also see Faias and Ferreira (2017)). My analysis of the characteristics of investors' portfolio holding echoes recent work on home currency bias (Maggiori et al., 2020; Boermans and Burger, 2023) that belongs to the growing literature using granular data on security holdings to study international capital allocation (Boermans and Vermeulen, 2020; Beck et al., 2023) and frictions (Bacchetta et al., 2023).

2 Investor base and global risk sensitivity: Relationship at the aggregate level

My analysis is motivated by the following cross-country pattern from aggregate data spanning 2004 to 2019: sovereign yield spreads of emerging markets are more sensitive to shifts in global risk appetite when the share of foreign *non-bank* bond holders is high. For each major emerging market economy included in Arslanalp and Tsuda's (2014) dataset, I estimate its sovereign risk-global risk sensitivity, defined as the coefficient β_i from the following time-series regression for each country:

$$\Delta \text{Spread}_{i,t} = \alpha_i + \beta_i(100 \times \Delta \log \text{VIX}_t) + \gamma_i \Delta \text{FedFunds}_t + \varepsilon_{i,t} \tag{1}$$

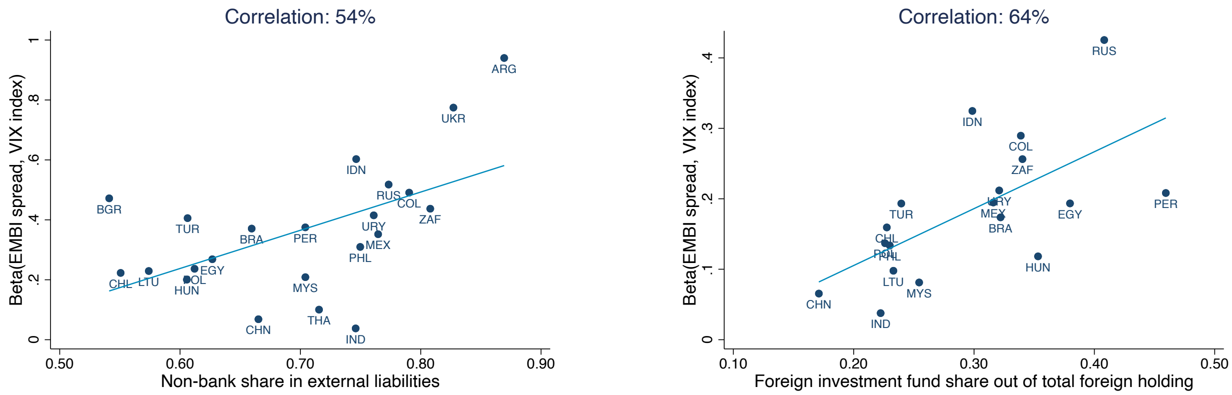
where $\text{Spread}_{i,t}$ corresponds to the yield spread of sovereign bonds issued by country i at month t over a risk-free benchmark. Measured in basis points, the sovereign spread for each country is calculated from U.S. dollar-denominated sovereign bonds included in the JPMorgan EMBI+ index. For my baseline analysis throughout the paper, I use the implied volatility of the S&P 500 (CBOE VIX Index) as the proxy for the global risk factor, following a large literature.[9] I include U.S. policy interest rate as a control to separate the impact of global risk from that of center-country monetary policy. Estimated from monthly data, the spread sensitivity in (1) captures the high-frequency comovement between secondary-market prices of country-i's sovereign debt and global financial conditions. This is a relevant metric, as the linkage between secondary-market yields and the actual borrowing cost is strong, given emerging markets' tendency to borrow short term and to face more frequent need for debt rollover than advanced economies (Broner et al., 2013).[10]

Emerging market economies are differentially exposed to the Global Financial Cycle, as the estimated country-specific β_i indicates. Both panels of Figure 1 plot the estimated sensitivity of sovereign yield spreads to log changes in the VIX index (y-axis). On average, a 1 percent increase in the VIX index corresponds to 0.4 basis point widening of the yield spread. From the most exposed country (Argentina) to the least exposed issuer

[9] See Kalemli-Özcan (2019), for instance. The pattern remains robust when I use alternative proxies for global risk, including the Bertaut et al. (2023) risk aversion index. The pattern remains robust when I extend the sample to small emerging and frontier economies included in the JPMorgan EMBI+ index.

[10] Disclosure of bond auction results from Indonesia shows that investor types in the primary market resemble those in my analysis. Meanwhile, yields from re-opening auctions closely track secondary market prices of the same bond the day before the auction, justifying the use of secondary market yields in my analysis.

(China), the estimated sensitivity differs by a factor of 13.4. Notably, country risk cannot fully explain these different sensitivities. Countries with similar credit standing, such as Indonesia and Egypt, differ widely in their estimated βs.



(a) Foreign non-bank share in external liabilities (04-19)

(b) Investment fund share in cross-border government bond holdings (13-19)

Figure 1: Sovereign spread-global risk β and investor composition: Aggregate patterns

Source: Arslanalp and Tsuda (2014); Lane and Milesi-Ferretti (2017); Coppola et al. (2021), BIS Locational Banking Statistics, IMF CPIS, World Bank Global Economic Monitor, FRED, and own calculations

Note: Figure 1 illustrates the cross-country pattern between foreign non-banks' presence through portfolio investment and emerging market economies' sensitivity to shifts in global risk factors. In both panels, the y-axis corresponds to time-series regression coefficients of monthly changes in sovereign bond spreads (proxied by JPMorgan EMBI spread) on monthly changes in the log of CBOE VIX index, controlling for changes in U.S. monetary policy (see (1)). In Panel (a), the x-axis corresponds to foreign non-banks' share in total non-FDI external liabilities averaged over 2004–2019. The x-axis of Panel (b) plots foreign investment fund holding as a share of total cross-border long-term debt holding of foreign investors, calculated using CPIS data, adjusted using the nationality-based measure based on the restatement matrix provided by Coppola et al. (2021), and averaged over 2013–2019. Panel (b) drops Argentina and Ukraine due to sovereign default dominating the post-2013 sample, and Bulgaria due to insufficient coverage of the EMBI data.

Figure 1 shows that the sensitivity of sovereign yield spreads to global risk is strongly correlated with foreign investor composition, measured in various ways. Panel (a) plots the β coefficients (y-axis) against the share of foreign *non-banks'* holdings relative to the total external liabilities of each country, obtained from subtracting total cross-border bank claims reported in the BIS Locational Banking Statistics from Lane and Milesi-Ferretti's (2017) international investment position.[11] This positive correlation cannot be fully explained by countries experiencing severe repayment issues or cherry-picking particular measures of investor composition or sovereign risk.[12] Using IMF's Coordinated Portfolio Investment Survey (CPIS) and the nationality-based restatement provided by Coppola et al. (2021) spanning 2013–2019, I further show in Panel (b) that a stronger

[11]For each country, the foreign investor composition in Panel (a) is an average measure over 2004–2019.

[12]The pattern remains robust if I use credit default swap spread as the measure for sovereign risk (see Figure I.A.1 in the Online Appendix,) or the foreign non-bank holding share in the sovereign bond market, calculated from Arslanalp and Tsuda's (2014) dataset, as the measure for foreign investor base.

presence of foreign *investment funds* relative to other foreign investors, such as banks, insurance companies and pension funds, corresponds to higher sensitivity of sovereign spread to changes in the VIX index. This finding motivates my subsequent grouping of investors in Section 3 and beyond when I investigate the role of investor base in the micro data.

Issuers' fundamental characteristics could exert a large influence on their investor composition, as institutions with varying degrees of risk appetite sort into different countries. Yet Table I.A.5 in the Online Appendix shows that the significant association between measures of investor base and yield sensitivity to VIX innovations remains robust after accounting for important borrower characteristics, such as the level of financial development, overall debt burden, country size and capital account openness, and above all, the country's credit standing. Measures of investor base by themselves could explain 22–30% of the cross-country variations in yield sensitivity.

3 The role of investor base: Evidence from granular data

Motivated by the findings in the previous section, I utilize micro-level data on securities holdings along with rich information on issuer fundamentals, sectors of bond holders and bond attributes, in an attempt to disentangle the two-way interaction between lenders and borrowers in shaping the impact of Global Financial Cycle on bond yields. The data's granular nature allows me to conduct a similar exercise at the bond level, and to introduce a rich set of fixed effects so as to isolate the role of investor demand in propagating global financial shocks.

3.1 Data

My main micro-level dataset comes from the Securities Holdings Statistics Base plus (SHS-Base plus) database (Blaschke et al., 2022) compiled by Deutsche Bundesbank.[13] The database is a security-level, full census of all financial institutions domiciled in Germany. Domestic banks report all assets held on their own balance sheets and those held in safe custody on behalf of their customers, regardless of the ultimate investors' countries of origin. For convenience, I call investors recorded in the SHS-Base plus data as "Germany-based" investors. For each security identified by its International Securi-

[13]DOI: 10.12757/SHSBaseplus.05122212.

ties Identification Number (ISIN), information is available on the face value and market value and the sector classification of its holders.

I expand my investor base coverage using portfolio holdings data from Morningstar on more than 1200 investment funds (mutual funds and ETFs) domiciled in important offshore financial centers (Luxembourg and Ireland) and United States, that invest primarily in emerging markets. The Morningstar sample of funds report a total asset under management exceeding \$600 billion as of June 2021. I merge the holdings data with the near-universe of emerging market sovereign bond issuances from 2005 to 2021, with information on bond characteristics sourced from Bloomberg and Refinitiv. My final, merged dataset contains 2499 bonds, of which over 900 are issued by emerging market governments in Eastern and Southern Europe and over 2000 have substantial data coverage on prices. My regression analysis uses monthly data available from the end of 2012 to June 2021, but I also report the aggregate data covering earlier years if possible.

Let $B_{i,s,t}(n)$ denote the total face value of bond n issued by country i held by sector s at time t. I measure the investor composition of a bond n by calculating

$$\theta_{i,s,t}(n) = \frac{B_{i,s,t}(n)}{\text{Amount Outstanding}_{i,t}(n)} \tag{2}$$

for each sector $s \in \mathcal{S} \equiv \{\text{Bank, ICPF, Investment Fund}\}$. I also calculate the aggregate share held by long-term investors. $\theta_{i,\text{Bank+ICPF},t}(n)$. Tables I.A.1 to I.A.3 of the Online Appendix report average investor composition covered in my dataset at the bond level, along with summary statistics on other important bond- and issuer-level characteristics. My dataset has a decent coverage of external issuances (an average of 15% of the amount outstanding), defined as bonds issued outside the domestic markets, and Euro-denominated bonds (18% on average).

Using this micro-level dataset comes with both advantages and challenges. The advantages include a wide security and sector coverage, high frequency (monthly), and the reporting of face values free from valuation effects. The major challenge, on the other hand, is that the data may not recover the entire investor base even after combining multiple data sources. While the issue is less relevant when analyzing the nature and determinants of investor demand, it could be more concerning when I relate investor composition to bond price variation. I provide a number of remedies to alleviate the concern over sample representativeness and measurement issues. First, in analyses connecting investor base to bond yield sensitivity (such as Table 1 in the following section), I focus on 27 EM European issuers, as Germany is among the largest creditors to these countries.[14] Second, I will show that my findings in Section 3.3 remain robust when I replace the denominator in (2) with the total *measured* amount held by the investor set $\mathcal{S}$, so that θ will have a "relative share" interpretation.

3.2 The variation of investor bases over time and across bonds

Before relating investor composition to bond price sensitivity to the Global Financial Cycle using the granular dataset, I delineate the drivers of investor bases to shed light on the variations in the data that I am going to exploit in the empirical exercise.

Cross-sectional determinants Figure 2 provides a snapshot of Germany-based investors' EM sovereign bond portfolio at the end of 2020. The breakdown by important bond characteristics reveals important heterogeneity. While mutual funds invest broadly in EM sovereign bond, with a sizable local-currency and dollar-denominated portfolio of various ratings and maturity, insurers and pension funds almost entirely specialize in Euro-denominated, investment-grade bonds. The share of long-term bonds with a residual maturity larger than 10 years is largest for insurers and pension funds. Banks also have a portfolio tilted towards safer, Euro-denominated bond, albeit to a lesser extent.

To augment Figure 2, I estimate a linear probability model on Germany-based investors' monthly holdings, regressing an indicator variable of whether a bond is held by a particular sector to a larger set of bond characteristics, while simultaneously controlling for time-varying issuer characteristics through the use of issuer$\times$time fixed effect. The universe of bonds included in the estimation are those that are held by at least one major sector in $\mathcal{S}$. With the issuer-time fixed effect, the comparison is among bonds issued by the same sovereign government and held by Germany investors.

Table I.A.6 in the Online Appendix reports the estimation results. Consistent with Figure 2, it shows that the propensity to hold bonds with a particular bond characteristic varies widely across investors, while being stable across specifications with different sets of fixed effects. For investment funds, maturity and currency denomination do

[14] The 27 countries classified as EM European countries comprise 950 bonds over my sample period matched to SHS-Base plus. These countries include Albania, Armenia, Azerbaijan, Belarus, Bulgaria, Bosnia and Herzegovina, Croatia, Czech Republic, Cyprus, Estonia, Georgia, Hungary, Lithuania, Latvia, Macedonia, Moldova, Montenegro, Malta, Poland, Romania, Serbia, Russia, Slovenia, Slovak Republic, Tajikistan, Turkey, and Uzbekistan. The rest of the country sample includes Argentina, Brazil, Chile, China, Colombia, Costa Rica, Dominican Republic, Egypt, Indonesia, India, Jamaica, Kazakhstan, Lebanon, Sri Lanka, Morocco, Mexico, Malaysia, Peru, Philippines, Pakistan, Thailand, Ukraine, Uruguay, Venezuela, Vietnam and South Africa.

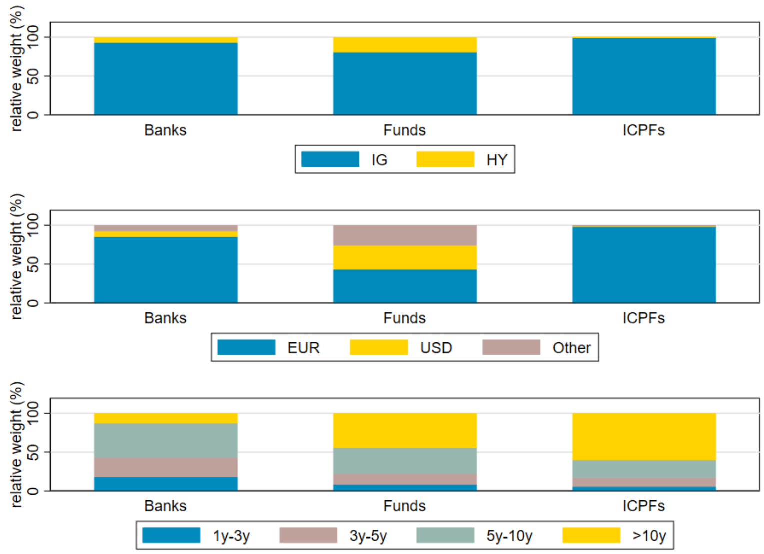


Figure 2: EM sovereign bond held by Germany-based investors (end-2020), face value in Euros, by sector of holders and bond characteristics

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), December 2020, own calculations.

Note: Figure 2 reports the breakdown of sector-specific EM sovereign bond holdings by bond characteristics (credit rating, currency denomination and residual maturity). "IG" refers to investment grade. "HY" corresponds to high-yield (non-IG) bonds.

not explain their portfolio holding patterns at the extensive margin. On the other hand, long-term investors exhibit strong propensities to hold bonds denominated in their home currency (Euro). Insurers and pension funds are 29 times more likely than investment funds to hold a Euro-denominated bond, and 3 times more likely than banks. Banks are more likely to hold bonds with a shorter duration. With less demanding fixed effects, I can also estimate the degree of sorting into time-varying issuer characteristics such as credit ratings. In particular, insurers and pension funds are 10 percent more likely to hold a bond if the issuer is rated at investment grade. Overall, the R^2 associated with investment funds are one half of that associated with insurers and pension funds, indicating that bond characteristics do less well in explaining investment funds' decision to hold a particular bond.

In Section I.A.1 of the Online Appendix, I report average measures of a larger set of bond characteristics held by each sector. Table I.A.2 shows that on average, bonds held by investment funds tend to have higher yield, larger amount outstanding, and pay higher coupons. Meanwhile, bonds held by insurers and pension funds have the lowest average yields among the three holder sectors, and have a lower bid-ask spread.

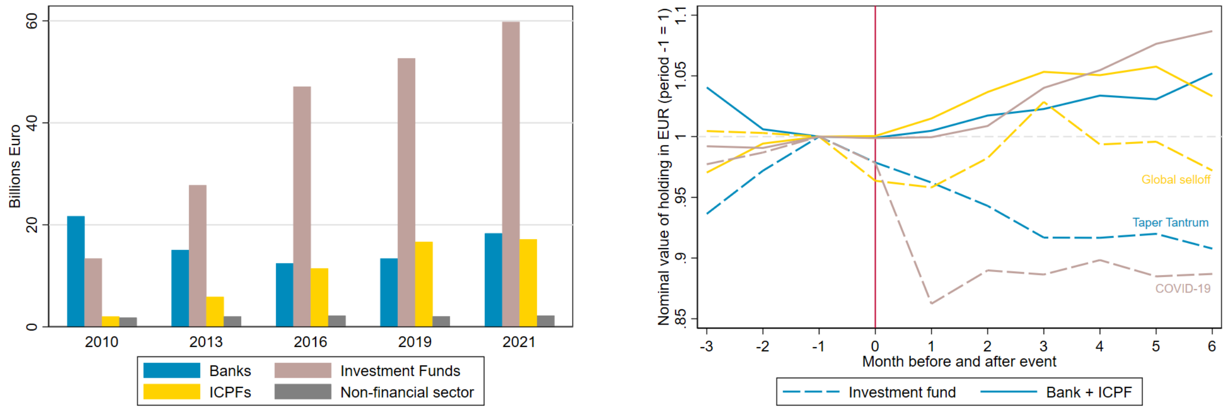
Time-series evolution Figure 3, Panel (a) traces the evolution of aggregate EM sovereign bond holdings by major Germany-based investor sectors since 2010. Throughout my sample period, bank holdings have been in decline until 2019, while investment funds, insurers and pension funds have been expanding their holdings. Given ICPFs' preference for high-grade bonds and the overall low interest rate environment over my sample period, this pattern likely reflects reach-for-yield motives and the overall improvement in issuer fundamentals over the past decade. Despite the underlying structural shifts, the overall investor base remains diverse.

The heterogeneity of investor base manifests its potential impact of the dynamics of sovereign borrowing costs during episodes of heightened global risk. Panel (b) of Figure 3 traces the quantities of EM sovereign bonds held by important sectors through three important global financial tightening ("risk-off") episodes. The episodes include the "Taper Tantrum" of May 2013, when the Federal Reserve surprised the market by unveiling plans to taper asset purchases, the August 2015 market selloff, when the VIX index jumped to its highest level between 2012 and 2019, and the initial phase of COVID-19 around February 2020. Prior to each event, investor holdings are relatively stable, displaying no clear pre-trends. Immediately following the shocks, investment funds (dashed lines) swiftly liquidate their holding of EM sovereign bonds, while other major investors as a whole steadily increase their holdings for months into each episode.

On top of Figure 1, the diverging portfolio holding dynamics across investor sectors constitutes another direct motivation for me to partition the EM sovereign bond investor base into investment funds and non-investment funds. They are also very different institutions on their own. With highly liquid liabilities subject to rapid redemption, open-ended investment funds may be forced to liquidate asset holding during downturns (Coval and Stafford, 2007; Jotikasthira et al., 2012). To support this mechanism, for the "risk-off" episodes studied in Figure 3(b), I document strong redemption pressure experienced by open-ended mutual funds from emerging market fixed income funds in Figure I.A.2 in the Online Appendix using Morningstar data. On the other hand, the stable liability structure of banks, insurers and pension funds and accounting conventions and regulations based on book values, enable these institutions to ride out transient fluctuations of market values of their portfolio holding (Hanson et al., 2015; Chodorow-Reich et al., 2020; Coppola, 2022).[15] In subsequent analyses, I call banks and ICPFs "long-term

[15] Ng et al. (2019) focus on Asia-Pacific bonds during the Taper Tantrum and, similarly, find that outflow-prone mutual funds sold bonds while insurers, annuities and pension funds served as net buyers. Ben-David et al. (2012) document redemption-driven outsized asset sales by hedge funds during the Global Financial Crisis. In related work, Brandao-Marques et al. (2022) show that the sensitivity of mutual

investors" to make the distinction from investment funds clear.



(a) Trend

(b) Risk-off episodes

Figure 3: Germany-based investors: Evolution of EM sovereign bond holdings

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2010M3–2021M6, Morningstar, own calculations.

Note: Panel (a) reports the total face value of emerging market sovereign bond with a tenor larger than one year held by each broad sector according to SHS-Base plus data from 2010 to 2021. Face values of non-EUR bond holding are converted to billions EUR using end-of-period exchange rates. "ICPFs" refer to insurance companies and pension funds. Panel (b) focuses on important episodes with adverse global risk factor movements. The dashed lines correspond to holding by investment funds, including holding recorded in both SHS-Base plus and Morningstar portfolio data. The solid lines correspond to holding by long-term investors (banks, insurers and pension funds (ICPFs)). Three episodes are covered. "Taper Tantrum" (in blue) refers to the surprise announcement of Federal Reserve's intention to taper asset purchases in May 2013. "Global selloff" refers to the August 2015 global stock market crash, during which the VIX index reached its highest point after the European debt crisis. "COVID-19" refers to the global outbreak of the COVID-pandemic in Febrary 2020. Each series is normalized by setting the amount of holding one month prior to the event start date to 1, and scaling the rest of the observations accordingly.

3.3 Propagation of global risk by different types of investors

Having shed light on the variations in investor bases in the micro data, I now examine its relation to the sensitivity of bond yields to global risk through the following regression:

$$\begin{aligned}\Delta y_{i,t}(n) = {} & \beta_0 \Delta \log \mathrm{VIX}_t + \beta_1 \Delta \log \mathrm{VIX}_t \times \theta_{i,\mathrm{Fund},t-1}(n) + \beta_2 \Delta \log \mathrm{VIX}_t \times \theta_{i,\mathrm{Bank+ICPF},t-1}(n) \\ & + \mathbf{X}_{i,t}(n)\delta + \mathbf{\Theta}_{i,t-1}(n)\gamma + \alpha(n) + \eta_{i,t} + \varepsilon_{i,t}(n)\end{aligned} \tag{3}$$

where $y_{i,t}(n)$ is the yield of bond n issued by country i; $\boldsymbol{X}_{i,t}(n)$ is a set of control variables at the issuer or bond level, including a benchmark risk-free interest rate, industrial production, credit qualities, amount outstanding, residual maturity bucket and bond

fund flows to global risk factors is higher when fund shares are easier to redeem. The net purchases of long-term investors I observe in the emerging market sovereign bond market is consistent with their role as buyers in other markets in these episodes, such as the U.S. corporate bond market during COVID-19 (O'Hara et al., 2023).

liquidity. Some of these controls drop out when issuer-time fixed effect is included. $\mathbf{\Theta}_{i,t-1}(n)$ denotes a vector of investor composition $(\theta_{i,\text{Bank+ICPF},t-1}(n), \theta_{i,\text{Fund},t-1}(n))'$ for each bond. $\alpha(n)$ and $\eta_{i,t}$ denote bond fixed effect and issuer$\times$time fixed effect, respectively. I focus on bonds issued by emerging market countries in Europe so that the investor base captured in my data likely includes important marginal investors such as Germany-based institutions and global mutual funds. I restrict the bonds to those that have not defaulted, with a fixed coupon and a non-amortized redemption schedule.[16]

Equation (3) builds on the standard "push-pull" regressions in the international finance literature to evaluate the global (push) and local (pull) correlates with capital flow and asset prices (see Calvo et al. (1993); Gilchrist et al. (2022), among others). The interaction coefficients β_1 and β_2 measure the dependence of sovereign spread sensitivity to global risk factors on ex-ante investor composition.

To control for bond-specific factors that affect bond yields and investors' ex-ante selection motives based on time-varying country characteristics, I exploit the granularity of the micro data by including bond and issuer-time fixed effects. Identification of the coefficients β_1 and β_2 is thus based on within-bond time variations in the investor composition that are unrelated to observed and unobserved global and issuer-specific factors. Examples of such variations include idiosyncratic outflows from EM sovereign bond funds (Chari et al., 2022), or randomness in the participation of insurers in the primary market (Coppola, 2022). Key confounding variations in the investor base driven by issuer fundamentals, such as current account balance or distance to default, are absorbed in the issuer-time fixed effect. In robustness checks, I restrict the comparison within narrower groups of bonds with common characteristics, such as currency denomination and residual maturity, to account for selection over observable key bond characteristics documented in Table I.A.6.

My estimates demonstrate that an investor base comprised of mostly long-term investors could dampen the impact of Global Financial Cycle, while investment funds tend to amplify the sensitivity to global risk factors. Column (1) of Table 1 reports the estimation result with bond fixed effect only. I first confirm the finding in the literature, but at the security level, that the borrowing cost of emerging market economies when global financial risk tightens. In terms of economic magnitudes, a one standard deviation increase in the VIX index is associated with a 5.4 basis point increase in sovereign

[16] I also drop bond-month observations in which $\theta_{i,s,t}(n)$ or the sum of $\theta_{i,s,t}(n)$ across sectors exceed 100% as they indicate potential measurement errors or doublecounting unaccounted for by my data cleaning procedure.

VARIABLES	(1) Δ yield	(2) large share Δ yield	(3) Δ yield	(4) large share Δ yield	(5) Δ yield
Δ log VIX	0.1949***	0.1720***			
	(0.0155)	(0.0352)			
Δ log VIX × lag bank+ICPF share	-0.0074***	-0.0052***	-0.0012**	-0.0013*	-0.0009*
	(0.0010)	(0.0012)	(0.0005)	(0.0007)	(0.0005)
Δ log VIX × lag fund share	0.0085***	0.0075***	0.0056***	0.0035***	0.0042***
	(0.0013)	(0.0017)	(0.0009)	(0.0008)	(0.0008)
lag bank+ICPF share	-0.0015***	-0.0014***	-0.0003	-0.0002	-0.0005*
	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
lag fund share	0.0018***	0.0000	0.0006*	-0.0000	0.0006
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)
Δ 10y Bund yield	0.4230***	0.5260***			
	(0.0153)	(0.0184)			
Δ log IP index	-0.2553***	-0.9771***			
	(0.0760)	(0.1012)			
Δ credit quality (issuance)	0.0912***	-0.0448	-0.0991***	-0.0472	-0.1879***
	(0.0225)	(0.0282)	(0.0365)	(0.0334)	(0.0440)
Δ log amount outstanding	-0.0364	0.0945	0.0029	0.0930***	0.0080
	(0.0322)	(0.0600)	(0.0204)	(0.0339)	(0.0194)
Switch maturity bucket	0.0167	0.0468**	0.0068	0.0273***	0.0145*
	(0.0132)	(0.0196)	(0.0091)	(0.0085)	(0.0083)
Δ bid-ask spread					0.1602***
					(0.0316)
Observations	33,071	10,671	32,938	10,388	30,500
R-squared	0.0722	0.1689	0.6118	0.7967	0.6806
Bond FE	✓	✓	✓	✓	✓
Issuer*Time FE	–	–	✓	✓	✓

Table 1: Bond yield sensitivity to global risk factors and the role of foreign investor base

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table 1 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (3). The sample runs from 2012M12 to 2021M6, including only sovereign bond issued by emerging market economies in Europe. The regressions are augmented with measures of lagged investor composition, including both investment fund share and total share of banks, insurance companies and pension funds, and interactions of lagged investor composition with log VIX. Credit quality is measured at the issuance level and refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. Maturity bucket is defined by separating bonds into bins according to residual maturity shorter than 1 year, between 1 and 3 years, 3 and 5 years, 5 and 10 years, and above 10 years. Each bucket is assigned a score from 0 to 4 with rising residual maturities. "Switch maturity bucket" takes on value 0 if the maturity bucket does not change from the previous month, and takes on value -1 if the maturity bucket switches from the previous month. Monthly changes in bond yield are winsorized at 1% and 99% tail. Bond-month observations with investor shares larger than 100% are dropped. Columns (1) to (2) report results with bond fixed effect only, while columns (3) to (5) add issuer×time fixed effect. Columns (1) and (3) use all EM European sovereign bonds while columns (2) and (4) focus on bonds with a large investor base (larger than 15%) coverage in my data. Column (5) further add bid-ask spread as an additional control. "ICPF" refers to insurance companies and pension funds. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

yield, controlling for other global and local factors. My estimate is quantitatively similar to Gilchrist et al. (2021), who find that a 8 basis point widening of bond yield for investment grade bonds.[17] The interaction with ex-ante investor composition shows that the sensitivity of sovereign yields to global risk factors depends on the ex-ante investor composition. A 10 percentage point higher long-term investor share is associated with a 38% reduction in the sensitivity in relative terms, while increasing the fraction held by investment funds by the same proportion corresponds to a 44% stronger effect of a rising VIX.

While investors' sorting according to issuer characteristics explain a substantial fraction of the observed relationship between investor base and bond yield sensitivity to VIX fluctuations, Adding issuer×time fixed effect, column (3) shows that the coefficients associated with interaction between VIX and investor composition shrink by 84% and 34% respectively for long-term investors and investment funds. Both interaction coefficients nevertheless remain statistically significant. A 10 percentage point higher share held by investment fund now corresponds to a 29% larger yield sensitivity to VIX. In addition, column (5) shows that controlling for the changing bond-specific liquidity condition through bid-ask spreads has little impact on my estimates. While a worsening bond liquidity is associated with a higher bond yield, the robustness of my estimates goes against the intuition that bonds held primarily by long-term investors are insensitive to global shocks because those bonds may be less actively traded. My finding is nevertheless consistent with my empirical observation, that investors in my sample are more likely to hold bonds with a larger amount outstanding, and those held by long-term investors are more liquid on average (see Table I.A.3).

3.4 Robustness

Measurement and coverage I provide more results in the Online Appendix to alleviate the concern that measurement issues and incomplete coverage of investor base and bond liquidity condition could explain the results. In addition to controlling for lagged overall exposure through the inclusion of $\theta_{i,s,t-1}(n)$, columns (2) and (4) in Table 1 focus on bonds in my sample with a large investor coverage (above 15%). Table I.A.7 replaces the investor share variables in my baseline regression with the relative shares of banks, insurers and pension funds against investment funds. Table I.A.9 interacts the investor composition measure with the implied volatility of Euro STOXX index (V2X), arguably

[17]One standard deviation of monthly innovation of VIX index corresponds to a 28% change.

more relevant for Germany-based investors than VIX. I reach similar conclusions from these exercises.

Accounting for selection into observable bond characteristics In column (1) and (2) of Table I.A.8 in the Online Appendix, I augment (3) with interactions between the VIX index and characteristics of the bond issuance as additional controls. The interactions include credit quality (at the issuance level), an indicator of Euro denomination, and residual maturity bucket. Despite the finding of Table I.A.6 that banks, insurers and pension funds exhibit strong preferences towards certain bond characteristics, the relationship between investor composition and bond yield comovement with VIX remains unchanged.[18] In another exercise reported in Columns (3) and (4) of Table I.A.8, I take the USD- and EUR-denominated bonds in my sample, residualize yield changes for each bond with a credit risk factor and a duration factor estimated from long-short portfolios of sovereign bonds (by sorting bonds based on terciles of credit qualities or residual maturities separately for each currency), and use the residuals as the dependent variable in estimating (3). My results remain robust.

Addressing reverse causality Another concern of estimating (3) is that the positive relationship between shares held by investment fund and VIX sensitivity of bonds may be due to funds directly loading on bond-specific exposure to the global volatility factor. This is unlikely for two main reasons. First, major fund investors in EM sovereign bonds, such as mutual funds and ETFs, are not natural holders of volatility risk. Heighten global risk is closely associated with outflows from emerging market bond funds (see Figure I.A.2 in the Appendix,) which could significantly lower fund manager compensation (Cen et al., 2023). There is also little evidence suggesting that end investors of the funds, who are predominantly retail (Shek et al., 2017), are sufficiently sophisticated so as to voluntarily expose themselves to VIX fluctuations (Ben-David et al., 2021b). Second, EM funds' capital allocation across bonds are subject to substantial rigidity due to index following. In my Morningstar investment fund sample, 80 percent of funds refer to indices such as EMBI or GBI-EM as benchmarks.

Taken together, my empirical findings establish the complementary mechanism between foreign investor base and asset attributes. With a diverse investor base, asset prices are determined through the interaction of investors with substantial differences in portfolio preferences and abilities to transmit shocks. Whether foreign portfolio in-

[18]Alternatively, controlling for Euro$\times$time or issuer$\times$Euro$\times$time fixed effects yields similar results.

vestment destabilizes the financing condition of emerging markets thus depend on who holds the assets. Meanwhile, the composition of foreign investors is shaped by local fundamentals and types of the securities being offered. While risk-sensitive investors such as investment funds have been the primary focus of the literature, my analysis suggests that examining the demand structure of banks, insurers and pension funds could provide a more precise and complete understanding of emerging markets' sensitivity to global risk factors.

4 Shock impact and demand elasticity for sovereign debt

Long-term investors' yield (semi-)elasticity of demand reflects the capacity of these investors to act as shock absorbers when a tightening global risk factor puts downward pressure on asset prices, and therefore is pivotal in the determination of bond price sensitivity to global risk factors. As long-term investors' bond holding decision depends heavily on bond characteristics (Table I.A.6), sovereign bonds with characteristics preferred by these investors may face a substantially larger demand elasticity compared to those that do not possess such characteristics. To identify the yield elasticity, I use mutual fund flows to construct plausibly exogenous shifts in the residual supply curve faced by long-term investors for different types of bonds. The estimated demand elasticity would serve as a crucial input for my quantitative model (Section 5).

I posit the following demand equation of long-term investors in the spirit of Koijen and Yogo (2019) and Vayanos and Vila (2021), expressed in monthly differences:[19]

$$\Delta \log B_{i,t}(n) = \alpha_{\mathcal{N}} + \beta_{\mathcal{N}} \Delta y_{i,t}(n) + \mathbf{X}_{i,t}(n)\delta_{\mathcal{N}} + \varepsilon_{i,t}(n) \tag{4}$$

Equation (4) pools all bonds with a common characteristic indexed by $\mathcal{N}$, such as currency denomination. $B_{i,t}(n)$ denotes the total face value of bank, insurer and pension fund holdings of bond n issued by country i at month t. $\mathbf{X}_{i,t}(n)$ denotes a set of bond- and issuer-level characteristics that may enter investors' portfolio decision (also in first differences in logs or levels, similar to (3)). In my baseline specification, they include the industrial production index of country i and the bid-ask spread. To account for investors' incentive to rebalance portfolios towards alternative assets, I also control for changes in the 10-year Bund yield, following Koijen et al. (2021) and Jansen (2023). Finally, $\varepsilon_{i,t}(n)$

[19]The recent demand-based asset pricing literature estimate similar equations (see Jiang et al. (2022); Nevova (2023); Chaudhary et al. (2024); Jansen et al. (2024), among others).

is an error term capturing demand disturbances unobservable to the econometrician. Equation (4) is expressed in first differences and B is expressed in face value terms, similar to van der Beck (2022). One advantage of using month-to-month net trades (as $B_{i,t}(n)$ is expressed in face value terms) to identify the slope of demand is its consistency with a flow-based identification strategy, and that first differences absorb the confounding impact of observed and unobserved time-invariant characteristics.

4.1 Flow-based identification of demand elasticities

Motivated by the literature on flow-induced demand shocks, I propose two approaches to identify the demand elasticities and overcome the simultaneity bias arising in regressions involving prices and quantities. In both cases, I use mutual fund flows to construct bond-level shifters of residual supply faced by long-term investors. The validity of a flow-based instrument rests on the intuition that flow-induced demand has price impact on emerging market assets following asset manager liquidation (Jotikasthira et al., 2012, relevance), through "forced trades" by mutual fund managers that are external to the decision of other types of institutional investors (exogeneity).

To arrive at appropriate measures of capital flows in and out of bonds exogenous to long-term investors, I consider two flow-based instruments. The first one, in the spirit of Lou (2012), Gabaix and Koijen (2022) and van der Beck (2022), captures the change in capital allocation to each bond as a result of funds scaling up or down their position using predetermined weights after capital injection or redemption. For bond n, define

$$FID_t^{(T)}(n) = \frac{\sum_{j \in \mathcal{J}_t(n)} \tilde{f}_{j,t}^{(T)} \cdot Q_{j,t-1}(n)}{\text{Amount Outstanding}_{t-1}(n)} \tag{5}$$

where $\tilde{f}_{j,t}^{(T)}$ captures the surprise amount of flow in or out of mutual fund j holding bond n, normalized by the size of fund j in the previous period. I obtain $\tilde{f}_{j,t}^{(T)}$ taking the residuals from a pooled regression of raw fund flows (as a percentage of lagged fund size) on T lags of monthly fund returns and a time fixed effect, to account for the predictability of fund flows due to return-chasing (Gruber, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998) and for the impact of global factors.[20] $Q_{j,t-1}(n)$ is the lagged market value of fund j holding of bond n. I transform FID into a measure of relative

[20] Alternatively, I extract residuals from fund-by-fund time-series regressions to construct $\tilde{f}_{j,t}^{(T)}$, and the estimation results are robust to this choice.

demand shocks by normalizing it using each bond's lagged outstanding amount.

Using FID_t as the instrument assumes that long-term investors cannot exploit changes in investment funds' bond allocation driven by factors orthogonal to fund performance and common economic drivers. This assumption is supported by several lines of arguments. First, there is little evidence that outflows from emerging market bond funds mechanically induce rising bond demand from long-term investors due to corresponding inflows. In the data, deposits and technical reserves of German banks have close to zero correlation with changes in the VIX index (see Figure I.A.3 in the Online Appendix). This pattern suggests that unlike investment funds (Figure I.A.2), flows in and out of long-term investors are more stable against global risk factors. Second, mutual fund managers' discretionary trading in response to shocks does not directly enter the measure, as funds' predetermined portfolio weights, partially tied to some predetermined external benchmark indices, are used to compute hypothetical demand pressure. Finally, security-level mutual fund portfolio holdings and flows are available with a lag, hindering the ability for other investors to respond in real time.

I construct a second instrument based on the assumption that long-term investors cannot trade on idiosyncratic flow shocks from large mutual funds, by taking the fund size-weighted average of the residualized flows $\hat{\hat{f}}_{j,t}$ (Gabaix and Koijen, 2023). I define the granular instrument at the bond level as[21]

$$GIV_t^{(T)}(n) = \frac{N_{\mathcal{J}_{t-1}(n)}}{N_{\mathcal{J}_{t-1}}} \cdot \Big(\sum_{j \in \mathcal{J}_{t-1}} \mathcal{S}_{j,t-1} \hat{\hat{f}}_{j,t}^{(T)} \Big) \tag{6}$$

where $\mathcal{S}_{j,t-1}$ is fund j's lagged size weight based on assets under management, $N_{\mathcal{J}_{t-1}(n)}$ denotes the number of funds holding bond n as of time $t-1$, and $N_{\mathcal{J}_{t-1}}$ is the total number of funds at $t-1$.

GIV_t captures the intuition that size-weighted average flows represent idiosyncratic wealth fluctuation associated with large mutual funds that affects bond prices due to granularity but is otherwise exogenous from the standpoint of long-term investors. Multiplying by the share of funds holding a particular bond allocates the shock exposure to each bond in an intuitive manner – the more funds holding the bond, the more strongly the residual supply curve would shift idiosyncratically for that bond. To shed light on the validity of this approach in extracting an exogenous shock series, I provide narrative

[21] As the flows have already been purified, the expectation of their equal-weighted averages is zero. I include fund return in the current month when calculating $\hat{\hat{f}}_{j,t}^{(T)}$ for FID but not for GIV, to allow for idiosyncratic current performance shocks of large funds to drive their granular surprise flows.

support in Table I.A.13 of the Online Appendix based on news coverage to show that the measure indeed reflects idiosyncratic factors affecting major fund companies.[22]

4.2 Yield elasticities of demand for long-term investors

I estimate Germany-based long-term investors' demand elasticity for non-default bonds with a fixed coupon and non-amortized principal. Different from the sample used in the push-pull regressions (Table 1), I also include issuers outside Eastern Europe to increase statistical power. Changes in bond yields are winsorized at their 1% and 99% tails.

The first three columns of Table 2 report estimates using different versions of my proposed instruments for Euro-denominated bonds. The instruments differ in whether they are based on flow-induced demand or granular fund flows, and in the lags of fund returns used to residualize mutual fund flows. Despite the differences, estimates of the slope of the demand equation with respect to yields sit stable across columns (1) to (3) at around 0.29. Raising the annualized bond yield by one percentage point would increase long-term investors' demand by 29%. My estimates thus imply a price elasticity of demand of 5.8 for a five-year zero-coupon sovereign bond denominated in Euros.[23] Meanwhile, the coefficients associated with Bund yield is negative, indicating plausible substitution between emerging market bonds and risk-free alternatives.

I also find price elasticities of demand differ across bond types for long-term investors. Columns (4) and (5) show that there is hardly any evidence that long-term investors are price-elastic towards bonds for which they are not the natural holders, such as non-Euro bonds. In the Online Appendix, I report GMM estimation results (Table I.A.12) including observations with $B_{i,t}(n) = 0$ and $B_{i,t-1}(n)$ to account for the extensive margin of adjustment. I find that investment grade bonds also face a more elastic demand from long-term investors compared to high-yield bonds, although the point estimate is much noisier.

First-stage regressions reported in Table I.A.10 of the Online Appendix and the Lee

[22] A clear example of such idiosyncratic fund flow shocks occurred in October 2014, when Bill Gross announced his departure from PIMCO. PIMCO's emerging market funds are consistently among the top-five largest funds in my data. The substantial outflows PIMCO suffered in the subsequent two months after the announcement is reflected in my granular flow instrument.

[23] Estimated at the bond level, the elasticity should be regarded as a "micro elasticity" (see the discussion in Gabaix and Koijen (2022)). My estimate is slightly larger than the "macro elasticity" estimates in the literature measuring country portfolio responses (Koijen et al., 2021; Jiang et al., 2022). The implied elasticity of my quantitative model (Section 5) for the long-term investors will be set at a value lower than my estimate.

VARIABLES	(1) FID3 EUR	(2) FID12 EUR	(3) GIV12 EUR	(4) FID12 Non-EUR	(5) GIV12 Non-EUR
$\Delta y_t(n)$	0.298**	0.288**	0.297***	-0.237*	-0.531
	(0.146)	(0.145)	(0.103)	(0.141)	(0.387)
$\Delta y_{10Y,t}(Bund)$	-0.120*	-0.114*	-0.120**	0.090	0.232
	(0.064)	(0.063)	(0.047)	(0.084)	(0.192)
Δ log IP	0.047	0.040	0.066	-0.061	-0.062
	(0.087)	(0.087)	(0.084)	(0.076)	(0.078)
Δ Bid-ask spread	-0.126	-0.121	-0.170**	0.196	0.416
	(0.081)	(0.081)	(0.070)	(0.150)	(0.308)
Observations	6,445	6,372	7,902	24,471	25,052
tF standard error	0.158	0.158	0.113	0.141	0.430

Table 2: Demand equation of banks, insurers and pension funds: IV estimates

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table 2 reports IV estimates of long-term investors' (banks, insurers and pension funds) demand equation (4). The sample runs from 2012M12 to 2021M6. Month-to-month changes in face value of total sector holding of each bond is regressed on changes in bond yield, 10-year Bund yield, log industrial production index and bid-ask spread (winsorized at 1% and 99% tail). Bond yield is instrumented using flow-induced demand shock (FID) or granular flow shock discussed in Section 4.1. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. Monthly changes in bond yield are winsorized at 1% and 99% tail. Columns (1) to (3) report estimates on the Euro-denominated bond sample, while columns (4) and (5) focus on the non-EUR sample. In column (1), the instrument is FID generated from residualizing mutual fund flow by current and lagged monthly returns for 3 months. Column (2) and (4) use FID with mutual fund flow residualized by time fixed effect, current and lagged monthly returns for 12 months. Column (3) and (5) use the granular flow instrument (6) with the idiosyncratic flow being the lagged fund size-weighted average of mutual fund flow. Standard errors are clustered at bond level. *** p<0.01, ** p<0.05, * p<0.1. The table also reports Lee et al.'s (2022) tF standard errors for the demand slope, which are robust against weak identification under just identification.

et al. (2022) tF standard errors reported in the baseline table indicate that both FID and the granular flow shock instrument are strong instruments and thus are likely unaffected by weak identification. The coverage of my mutual fund flow data contributes to the strong first stage, as the dataset includes the largest open-ended mutual funds focused on emerging markets. In the Online Appendix, Table I.A.11, I report two extensions to my estimation procedure. First, I include $p_{t-1} \times \theta_{i,\text{Fund},t-1}(n)$, the total lagged share of investment funds holding each bond n, multiplied by the lagged price of bond n, to control for the overall exposure of individual bonds to flow-based demand shocks.The estimated demand slopes remain similar to the baseline levels (columns 1 and 2). While my preferred specification (4) aligns with the demand system literature (see Koijen et al. (2021)) that relies on time-series variation to identify demand elasticities, I also add time fixed effects to (4) and report the estimation in Table I.A.11 (columns 3 and 4), with FID as the instrument.[24] The estimated slope coefficients roughly double. The associated

[24]As time-series variation of the granular flow is key for the identification using GIV, I focus on FID

first-stage F statistics are significantly smaller, as the fixed effect weakens the power of the instrument by partially absorbing time-series variation in the data.

5 A quantitative model of sovereign debt markets with heterogeneous global investors

I introduce a quantitative model of the sovereign debt market with heterogeneous investors that can be taken to the data to capture the transmission of the Global Finanical Cycle to emerging market sovereign borrowing. Building on Xiong (2001), Vayanos and Vila (2021) and Kekre et al. (2023), the model features inelastic asset markets and endogenous amplification of global financial shocks through wealth effects. I use my estimate of the yield elasticity of demand from Section 4 to discipline the model. The model quantifies the relative contribution of global and local factors in driving sovereign spreads and replicates the empirical relationship between investor base and bond yield sensitivity to shocks. I then use the model as a laboratory to quantitatively evaluate counterfactuals.

5.1 Environment

Time is continuous. The asset space contains a risk-free bond paying a constant, exogenous interest rate r, and a perpetual coupon bond subject to random face value haircuts, as a stand-in to characterize emerging market sovereign bonds.

Risky perpetuity The risky perpetuity is in constant supply s with price P_t at time t. At each instant $\mathrm{d}t$, the bond pays a coupon $\kappa \mathrm{d}t$, but is also subject to a "partial default shock". To focus on the role of investor demand, I make the simplifying assumption that default is exogenous and follows a Poisson jump process N_t with random arrival rate λ_t. Upon default, investors suffer a deterministic loss of δ per unit of investment (in face value terms) as a haircut.[25]

The arrival rate of default, denoted λ_t, follows a square root process reflected at

with time fixed effects in this robustness exercise.

[25] Costain et al. (2022) use a similar modeling device to incorporate default risk into a prefered-habitat model of the term structure. They asume a fixed default rate, and investor wealth is not a state variable.

boundaries $0 < \lambda_{\min} < \lambda_{\max}$:

$$d\lambda_t = \kappa_\lambda(\overline{\lambda} - \lambda_t)dt + \sigma_\lambda \sqrt{\lambda_t} dB_{\lambda,t}, \qquad \lambda_t \in [\lambda_{\min}, \lambda_{\max}] \tag{7}$$

where $B_{\lambda,t}$ is a standard Wiener process. The CIR process is a natural candidate to capture default as a "rare disaster" (Wachter, 2013).[26] I calibrate the process (7) to match cross-country moments associated with sovereign spreads and default rate, so that states with high and low λ can be interpreted as comparing issuers with different country fundamentals. Alternatively, λ can also be interpreted as the propensity for the bond issuer to devalue its local currency, so that the model can be also mapped to the case of foreign versus local currency nominal bonds.

For reference, I define the *fundamental value* of the risky perpetuity as the present value of expected cash flow if an investor never sells the perpetuity that it holds, discounted by the risk free rate. The fundamental value is a function of the default risk at time t and parameters of the default risk process, and is given by

$$F(\lambda) = \mathbb{E}\Big[\int_{t=0}^{\infty} e^{-rt}(\kappa dt - \delta dN_t) \mid \lambda_0 = \lambda\Big] = \int_{t=0}^{\infty} e^{-rt}(\kappa - \delta \mathbb{E}[\lambda_t \mid \lambda_0 = \lambda])dt \tag{8}$$

where the second equality follows from the property of Poisson processes with random intensity.[27] The fundamental value $F_t \equiv F(\lambda_t)$ is increasing in the coupon rate κ and decreasing in the current default risk λ_t, as well as long-run default risk $\overline{\lambda}$.[28]

Asset managers A unit mass of investment fund managers have log utility and an infinite horizon. The asset managers have discount rate ρ, and face exogenous liquidation with intensity ξ. I introduce liquidation to match empirical moments on the average life span of bond funds. When an asset manager is liquidated, a new manager sets up a fund with an exogenous level of initial wealth $\underline{W}$. An asset manager with wealth w_t

[26] In my calibration, the parameters in Equation (7) always satisfy the Feller condition: $2\kappa_\lambda\overline{\lambda} > \sigma_\lambda^2$, so that the default risk process is always strictly positive. I impose a reflecting barrier $\lambda_{\min}$ close to zero for numerical tractability.

[27] The process N_t satisfies $\mathbb{E}[N_t] = \mathbb{E}\Big[\int_0^t \lambda_s ds\Big]$. It follows that $\mathbb{E}\Big[\int_0^\infty f(t)dN_t\Big] = \int_0^\infty f(t)\mathbb{E}[\lambda_t]dt$ for continuous f. The integral $\int_0^\infty f(t)dN_t$ is defined in the Riemann–Stieltjes sense.

[28] Without the reflecting barriers, both $\mathbb{E}[\lambda_s \mid \lambda_t = \lambda]$ and F_t can be analytically expressed. The semi-closed form expression for $F_t(\lambda)$ is difficult to evaluate directly in the presence of reflecting barriers. I nevertheless show in Appendix I.B.4 that the conditional expectation can be backed out by solving a *Kolmogorov backward equation* using the standard finite-difference method.

consumes every period and solves the following portfolio choice problem:

$$\begin{aligned} &\max_{c_t, x_t} \mathbb{E}_0 \int_0^\infty e^{-(\rho+\xi)t} \log c_t \mathrm{d}t \\ \text{s.t. } &\mathrm{d}w_t = (rw_t - c_t + \xi w_t)\mathrm{d}t + x_t \cdot (\mathrm{d}P_t + \kappa \mathrm{d}t - rP_t \mathrm{d}t - \delta \mathrm{d}N_t) + \sigma_z w_t \mathrm{d}B_{z,t} \end{aligned} \tag{9}$$

where x_t is the amount of the risky perpetuity held in face value terms.[29] Asset managers in my model are subject to an aggregate Brownian *wealth shock* $\mathrm{d}B_{z,t}$ with standard deviation σ_z, capturing funding shocks faced by open-ended investment funds through capital injections and redemptions by the ultimate global fund investors that drive asset liquidation. As fund flows are closely connected to global risk, I call $\mathrm{d}B_{z,t}$ the *Global Financial Cycle shock*. For simplicity, I assume that asset managers are atomistic, and the shock processes $B_{z,t}$, $B_{\lambda,t}$ and N_t are independent.[30]

Long-term investor I model long-term investors by an aggregate risky asset demand function Z_t downward-sloping in the log deviation of bond price from its fundamental value and in the default risk:

$$Z_t = -\alpha(\lambda_t) \cdot \log\left(\frac{P_t}{F_t}\right) - \theta_1 \lambda_t \tag{10}$$

where $\alpha(\cdot) > 0, \alpha'(\cdot) < 0$. (10) builds on Xiong (2001) and the recent preferred-habitat demand literature (Vayanos and Vila, 2021; Costain et al., 2022; Kekre et al., 2023). The demand function captures key characteristics of asset demand of long-term investors, such as banks, insurers and pension funds. Wealth does not enter the demand function, consistent with the deep-pocketed nature of these investors. (10) does not load on $\mathrm{d}B_{z,t}$, reflecting the demand's "safe hand" nature in the face of global risk shocks. Holding all else constant, long-term investors increase their demand for the risky perpetuity when its price falls below the fundamental (long-run) value, as a buy-and-hold strategy

[29] I follow the standard assumption in perpetual youth models (Blanchard, 1985) and add $\xi \mathrm{d}t$ fraction of each unit of wealth to the drift of asset manager wealth as an annuity payment from outside competitive insurers. For simplicity, I assume that the annuity policy is written over the entirety of asset manager wealth, and the outside insurer is able to hedge the stochastic fluctuations.

[30] As a result of this assumption, $\mathrm{d}B_{z,t}$ captures fluctuations in factors external to asset fundamentals that affect the risk-bearing capacity of asset managers. The ultimate sources of external fluctuations that affect the financial cycle may include center-country monetary policy and economic news (Bekaert et al., 2013; Boehm and Kroner, 2023), pure shifts in the risk appetite, or non-fundamental noise trader shocks (De Long et al., 1990). The shock is assumed to scale with investment funds' wealth only, making it easier to calibrate using fund flow data.

would deliver a higher payoff when the bond becomes cheaper.[31] The scale of demand adjustment, however, depends on bond attributes. Equation (10) models this dependence through a demand slope term $\alpha(\lambda)$ that is decreasing (in absolute value) in bond default risk. In my calibration, I follow the preferred-habitat investor literature and assume that $\alpha(\cdot)$ takes the exponential form, so that the demand function can be rewritten as

$$Z_t = -\alpha \cdot \exp(-\delta_\lambda \lambda_t) \cdot \log\left(\frac{P_t}{F_t}\right) - \theta_1 \lambda_t \tag{11}$$

where $\delta_\lambda > 0$ is a pivot parameter that controls for the speed at which the elasticity of demand changes across the default risk spectrum. Long-term investors' demand for the risky asset may also respond directly to shifts in bond fundamentals, with investors selling assets when default risk increases. The additional linear term $-\theta_1\lambda_t$ with $\theta_1 > 0$ captures this idea in reduced form.

In practice, the direct dependence on default risk of the elasticity and level of long-term investors' risky asset demand reflects the impact of regulatory constraints and risk management concerns that limit the risk exposure of these investors. Section I.B.2 in the Online Appendix sketches a static optimizing foundation, based on Gabaix and Maggiori (2015), to motivate this dependence. In particular, the variable demand slope $\alpha(\lambda)$ in (10) measures the dependence of a credit constraint facing long-term investors on default risk, resembling the risk-weighted capital requirement based on sovereign credit risk stipulated in Basel III and Solvency II. The linear term $\theta_1\lambda_t$ is motivated by the additional holding costs faced by long-term investors exposed to default risk, such as costly equity issuance to cover book value losses upon default (Dvorkin et al., 2021).

I look for a Markov equilibrium in which the bond price depends on the default risk and aggregate asset manager wealth, W, and restrict attention to the equilibrium in which both bond price and aggregate asset manager wealth follow jump-diffusions:

$$\mathrm{d}P_t = \omega_t \mathrm{d}t + \eta_{\lambda,t}\mathrm{d}B_{\lambda,t} + \eta_{z,t}\mathrm{d}B_{z,t} + \eta_{N,t}\mathrm{d}N_t \tag{12}$$

$$\frac{\mathrm{d}W_t}{W_t} = \Phi_{1,t}\mathrm{d}t + \Phi_{2,t}\mathrm{d}B_{\lambda,t} + \Phi_{3,t}\mathrm{d}B_{z,t} + \Phi_{4,t}\mathrm{d}N_t \tag{13}$$

where $\omega_t, \eta_{\lambda,t}, \eta_{z,t}, \eta_{N,t}, \Phi_{1,t}, \Phi_{2,t}, \Phi_{3,t}$ and $\Phi_{4,t}$ are functions of the state variables (λ, W). In the Online Appendix, I provide a formal definition of the equilibrium, and prove Proposition 1 which characterizes the equilibrium bond price $P(\lambda, W)$ as a solution to

[31] The dependence of bond demand on the fundamental value F_t can also be seen as a direct extension of the preferred-habitat demand function, introduced in Vayanos and Vila (2021), to coupon-paying bonds.

a partial differential equation subject to a series of boundary conditions. The boundary conditions pin down the behavior of the bond price when aggregate asset manager wealth is zero or infinity. In the former case, the bond is entirely priced by the downward-sloping demand of long-term investors. In the latter case, asset managers become effectively risk neutral and take over the entire market, and set the bond price equal to its fundamental value.

5.2 Economic mechanism

Equilibrium pricing of risk The first-order conditions of the asset managers imply that the ex-ante excess return of the risky perpetuity can be decomposed into three terms:

$$\underbrace{\frac{\mathbb{E}_t[\mathrm{d}P_t]+\kappa}{P_t}-r}_{\text{Excess return}} = P_t^{-1}\cdot\Big[\underbrace{\Phi_{2,t}\eta_{\lambda,t}}_{\substack{\text{Comovement of wealth and price}\\ \text{exposure to default risk shocks}}} + \underbrace{\Phi_{3,t}\eta_{z,t}}_{\substack{\text{Comovement of wealth and price}\\ \text{exposure to wealth shocks}}} + \underbrace{\lambda_t\cdot\frac{\delta-\eta_{N,t}}{1-\chi_t(\delta-\eta_{N,t})}}_{\text{Outright default premium}}\Big]. \tag{14}$$

According to (14), asset managers price three sources of risk. The first two terms on the right hand side capture the risk premia associated with Brownian asset manager wealth shocks and default risk shocks. The final term captures the role of Poisson default shocks, including both its direct impact through the dependence on haircut δ, as well as its indirect impact on asset manager wealth. The term $\eta_{N,t}$ is implicitly defined by the price difference before and after jumps due to default-induced changes in wealth:

$$\eta_{N,t} = P(\lambda, W(1+\Phi_{4,t})) - P(\lambda, W) < 0$$

where $\Phi_{4,t} < 0$ corresponds to the wealth exposure to the default shock.

My model captures the interdependence between asset attributes and investor composition and their contribution to the transmission of global financial shocks.Investors are differentially exposed to global financial shocks. Asset managers' portfolio allocation to the risky perpetuity directly responds to changes in their risk-bearing capacity driven by wealth fluctuations. Following a negative wealth shock, asset managers become more risk-averse and liquidate their risky asset holdings, exerting downward pressure on the bond price. Long-term investors stabilize the market by buying bonds in response. Meanwhile, the dependence on default risk of the elasticity and level of long-term investor demand reflects the reverse influence of fundamental asset attributes on the investor composition and thus on bond yield sensitivity to shocks.

Endogenous shock amplification through wealth revaluation In my model, wealth revaluations of asset managers endogenously amplify exogenous shocks.[32] As shown in Appendix I.B.1, the sensitivity of bond price to exogenous wealth shocks $\eta_{z,t}$ and the equilibrium sensitivity of wealth to the same shock $\Phi_{3,t}$ can be intuitively expressed as:

$$\eta_{z,t} = \overbrace{P_{W,t} W_t \sigma_z}^{\text{Direct impact}} + \overbrace{P_{W,t} X_t \eta_{z,t}}^{\text{Wealth revaluation}} = \frac{P_{W,t} W_t \sigma_z}{1 - X_t P_{W,t}} \tag{15}$$

$$\Phi_{3,t} = \sigma_z + P_{W,t} X_t \Phi_{3,t} = \frac{\sigma_z}{1 - X_t P_{W,t}} \tag{16}$$

where X_t is the risky asset position. (15) suggests that a negative wealth shock with size σ_z has a direct impact on the bond price due to liquidation. The price impact of such liquidation leads to an additional wealth loss and further erosion of asset managers' risk-bearing capacity, further pushing down the asset price. This mechanism is captured by the second term. In equilibrium, asset manager wealth is revalued by an amount given by $\eta_{z,t} X_t$, and the sensitivity of the bond price to wealth shocks is multiplied by an amplification factor $(1 - X_t P_{W,t})^{-1}$. This factor depends on asset managers' current risky asset position X_t, and is greater than one and increasing in X_t when $0 < X_t P_{W,t} < 1$, a condition that holds in my quantitative exercises.[33]

The role of long-term investors' demand elasticity The demand elasticity of long-term investors plays a crucial role in shaping yield spreads, volatility, and bond price sensitivity to shocks. For a given level of default risk $\lambda_t = \lambda$, denote $\alpha = \alpha(\lambda)$ in long-term investors' demand equation (10). (15) can be written as

$$\eta_{z,t} = \overbrace{P_{W,t} W_t \sigma_z}^{\text{Direct impact}} + \overbrace{(\eta_{z,t} \cdot [s + \alpha \log(P_t / F_t) + \theta_1 \lambda]) P_{W,t}}^{\text{Wealth revaluation}} \tag{17}$$

[32] This force is absent in sovereign default models with exogenous risk-premium or wealth shocks (Aguiar et al., 2016; Bianchi et al., 2018).

[33] The mechanism formalizes the knock-on price impact in the corporate bond market due to fund fire sales and common holdings (Falato et al., 2021). The same wealth revaluation channel also applies to the transmission of fundamental shocks (also see Bocola (2016)). Appendix I.B.1 shows that the exposure of price and wealth to fundamental shock is amplified by the same factor.

Holding all else unchanged, since $\log(P_t/F_t) < 0$ given finite asset manager wealth, (17) implies that a larger demand elasticity of long-term investors through a higher α corresponds to a lower bond price sensitivity to wealth shocks.

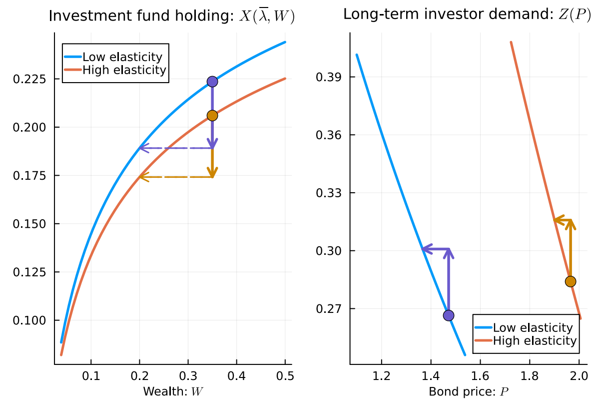
The mechanism can be best understood based on a simple demand-supply diagram (Figure 4(a)). The left panel plots the policy function of asset manager demand as a function of wealth for an average level of default risk and different values of long-term investors' demand slope parameter α. In response to a negative wealth shock indicated by the horizontal dashed arrows, asset managers liquidate their holding of the risky perpetuity. Log utility implies for a given return, investors scale down their demand proportionately, as the portfolio weight of the risky perpetuity depends on asset manager wealth only through bond prices (see equations (14) or (IA.27) in the Online Appendix).

When asset managers liquidate, bond prices fall and long-term investors move up along their demand curves to absorb the residual supply, as total supply of the bond is assumed to be fixed. The right panel of Figure 4(a) compares the degree of price drop in response to the negative wealth shock for low and high values of α, by plotting long-term investor holdings against the bond price. With a lower elasticity, the demand curve is flatter, requiring a larger price response to induce the long-term investor to provide liquidity. In equilibrium the impact of exogenous wealth shocks would be dampened by a higher demand elasticity, as Figure 4(b) shows by comparing the wealth exposure to $dB_{z,t}$ between the case of high and low demand elasticity in the region around the average level wealth implied by the stationary distribution (see (16)).

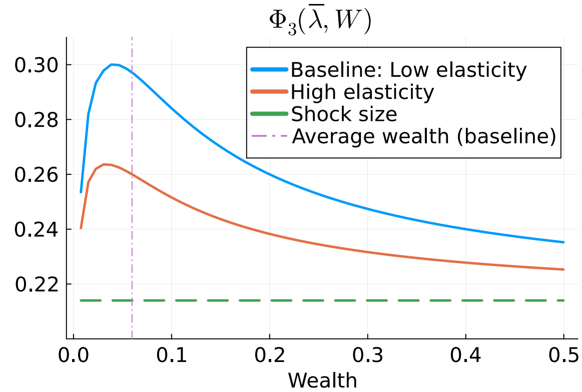
5.3 Calibration

I pin down the parameter values based on macro and micro data to be consistent with important facts related to issuers and lenders in the emerging market space. To preserve space, I report the baseline calibration in Table 3, highlight a few important parameters, and relegate additional details to the Online Appendix.

Haircut upon default A jump shock in my model is a partial default on perpetuities. As such, I follow Arellano et al. (2023) in pinning down the value of haircut δ. I calculate its value from (18) using data on arrears and external debt stocks from World Bank International Debt Statistics and haircuts after restructuring (measured by Cruces and



(a) The transmission of wealth shocks to risky asset prices



(b) Shock amplification

Figure 4: Illustration of key model mechanisms: Connection with long-term investors' demand elasticity

Note: Panel (a) connects the response of bond price to a negative wealth shock to asset managers to long-term investors' demand elasticity. The left chart plots asset manager's demand for the risky perpetuity as a function of wealth. Default risk is set to its long-run mean for illustration purposes. The dashed arrows illustrate a negative shock to asset manager wealth. They are associated with solid arrows indicating the intended amount of risky assets to be liquidated following the wealth shock. The right panel plots long-term investor holdings as a function of bond price. The vertical solid arrows represent the amount of risky assets long-term investors need to absorb given no price change. Due to downward-sloping demand, bond price adjusts according to the horizontal arrows. The calibration with high elasticity (red lines) are associated with lower price decline compared with a calibration with low demand elasticity (blue lines).
Panel (b) plots $\Phi_{3,t}$, the equilibrium exposure of asset manager wealth with respect to exogenous wealth shock $dB_{z,t}$ (see (16)), when default risk is at its long-run mean $\overline{\lambda}$. Two cases are compared, in that the baseline (blue line) parameterization has the long-term investors' demand being less price elastic compared to that plotted in red. The vertical dashed line reports the mean of the stationary wealth distribution under the baseline calibration. The horizontal dashed line reports the value of σ_z, the size of the wealth shock.

Trebesch (2013)):

$$\delta = \frac{\kappa \cdot \Lambda \cdot H}{\overline{\lambda}} \tag{18}$$

where Λ is an average measure of debt in arrears as a fraction of the total external debt stock (28%), and H is the average haircut after restructuring (37%). To interpret this formula, note that in my model, the present value of the cash flow of a risk-free bond with coupon κ is κ/r. With $\overline{\lambda}$ probability, Λ fraction of the bond would be in arrears, and in present value terms, 37% of the debt in arrears is lost as a haircut to investors.

Demand elasticity The long-term investors' demand elasticity is an important parameter in my model. I compute their average demand response to a 1 percentage point change in bond yield using simulated data and use the yield (semi-)elasticity of demand for Euro-denominated bonds estimated in Section 4 to guide the calibration.[34] In my model, long-term investors should be interpreted as including foreign banks, insurance companies and pension funds, and domestic private agents possibly with an even lower demand elasticity for sovereign debt (Fang et al., 2022). For this reason, I set the target at 21%, which is a weighted average of the foreign component (29%, according to my estimate for Euro-denominated bonds in Table 2) and a domestic demand elasticity that is roughly one third of that estimate, based on Fang et al. (2022). As my empirical estimation focuses on Euro-denominated bonds, the weights for foreign and domestic long-term investors are calculated using aggregate data from the new Securities Holdings Statistics by Sector (SHSS) data published by the ECB for Slovakia. The Online Appendix provides a step-by-step guide on how I obtain the calibration target.[35]

I solve for the equilibrium using an algorithm based on the finite difference method that handles discontinuous shocks, multiple state variables with cross derivatives, and nontrivial boundary conditions. Statistics in the model come from simulating the model multiple times at the monthly frequency for 7500 years. Appendix I.B.4 provides more detail on my solution and simulation method.

5.4 Quantitative findings and model validation

The calibrated model fits the targeted moments well (see Table 3). I use the calibrated model to quantitatively explore the contribution of the Global Financial Cycle to emerging markets' sovereign borrowing cost. My model's implied quantitative relationship between sovereign spread, investor base, and wealth shocks, while untargeted, is also consistent with observed patterns in the data.

Figure 5, Panel (a) reports the results of a variance decomposition exercise. To gauge the contribution of wealth shocks and default risk shocks to the variation of bond yields, I set the actual realization of one shock to zero and compare the variance of bond yields assuming that only the other shock is active, against the baseline simulation with both

[34] The number is derived from running an OLS regression similar to (4):

$$\Delta \log Z_t = \alpha + \beta_0 \Delta y_t + \beta_1 \Delta \lambda_t + \varepsilon_t. \tag{19}$$

[35] Setting the elasticity to a smaller number than my empirical estimate – a "micro elasticity" – is consistent with a small "macro elasticity" estimated by the literature (Gabaix and Koijen, 2022). The 21% response to a 1 percentage point increase in yield implied by the model matches the macro elasticity estimates by Jiang et al. (2022) for long-term debt.

Parameter	Description	Value	Sources/Moments in data
Bond characteristics			
r	Risk-free rate	0.02	Standard value
$\overline{\lambda}$	Average default intensity	0.038	Arteta and Hale (2008); Tomz and Wright (2013)
κ	Coupon rate	0.06	Meyer et al. (2022)
δ	Loss after default	0.16	Equation (18), Arellano et al. (2023)
s	Bond supply	0.49	Debt-to-GDP ratio of 49% (IMF)
Asset manager characteristics			
ρ	Discount rate	0.02	2% annual mutual fund return (Morningstar)
σ_z	Volatility of %-AUM shock	0.214	6.18% monthly volatility (Morningstar)
ξ	Liquidation probability	0.041	Average lifetime of 24.3 years (Maqui et al., 2019)
Technical parameters			
$\underline{W}$	Initial wealth after rebirth	0.005	
$\lambda_{\min}$	Lower boundary of default risk	0.005	
$\lambda_{\max}$	Upper boundary of default risk	0.25	

(a) Parameters set/estimated externally

Parameter	Description	Value	Targeted moments	Target	Model
κ_λ	Persistence of default risk process	0.420	Corr(Default risk, Yield)	0.4	0.4
σ_λ	Volatility of default risk process	0.09	Average yield spread	3.6%	3.5%
α	Demand slope common parameter	0.489	Yield volatility	0.6%	0.68%
δ_λ	Demand slope pivot parameter	1.422	Yield (semi-)elasticity of demand	21	20
θ_1	Aversion to default risk	0.334	Asset manager share	17%	17%

(b) Parameters internally calibrated and targeted moments

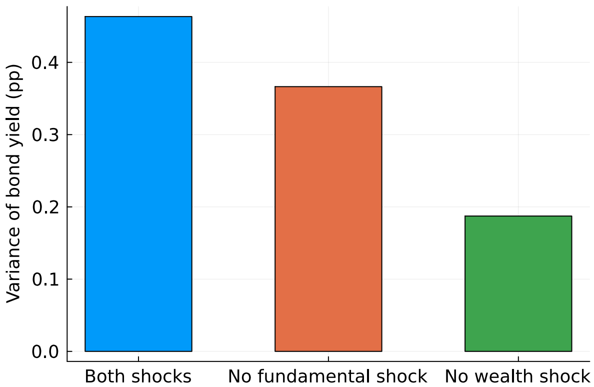
Table 3: Model calibration

Note: This table reports calibrated parameters and targeted moments. Panel (a) focuses on parameters set externally based on literature or data. Sources are specified whenever possible. Panel (b) reports values of the parameters set via internal calibration. The Online Appendix reports more details on the selection and calculation of targeted moments. In particular, yield spread and volatility are calculated from EMBI data. Demand elasticity is a combination of my estimates for foreign long-term investors in Section 4 and domestic investors reported in Fang et al. (2022). Asset manager share is computed from ECB SHS and IMF CPIS data. The yield elasticity of demand in the model is computed by regressing log changes in long-term investor holdings on changes in bond yield based on simulated data (see Equation (19)).

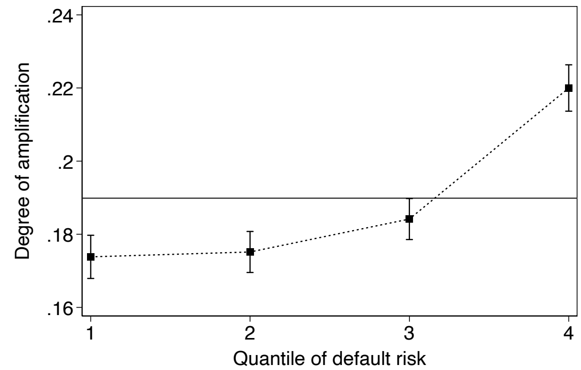
shocks activated.[36] Wealth shocks explain a large proportion of bond yield variability: shutting down exogenous wealth shocks leads to a decrease of bond yield variance by 60 percent, while default risk shocks account for 21 percent of the total variation. The significant contribution of wealth shocks in my model is quantitatively close to the estimate of Longstaff et al. (2011), who find that the first principal component of EM CDS spreads

[36] I start from the long-run mean of default risk with zero drift and make sure that randomness is not driving the results by using the same realizations of shocks across different specifications.

strongly comoves with global risk factors and accounts for 64 percent of the variation.



(a) Variance decomposition of yields



(b) Wealth shock amplification by default risk quartile: Simulated data

Figure 5: Variance decomposition of bond yields and the amplification of wealth shocks

Note: Figure 5 provides evidence for model validation. Panel (a) compares the variance of simulated bond yields under three cases with different shock configurations, holding the equilibrium objects constant (i.e. no re-optimization of agents). The first simulation ("both shocks") corresponds to the baseline simulation with non-zero realized paths for both shocks. The second simulation ("no fundamental shock") sets the realization of bond default risk shocks to zero, while maintaining the same path of the wealth shock as the baseline simulation. The third simulation shuts down wealth shocks instead. Panel (b) reports the estimated degree of amplification of bond yield sensitivity to wealth shocks, when asset managers' holding share is 10 percentage points higher than the average. The horizontal line captures the average degree (19%) while the dots denote the degrees of amplification at varying quantiles of bond default risk. 95% confidence intervals based on 100 replications are plotted.

I use the simulated data from the model to reproduce and revisit empirical patterns observed in the actual data. In the spirit of (3), I regress changes in bond yield spreads on the lagged asset manager share (demeaned), the exogenous wealth shock, and their interactions, controlling for default risk and lagged asset manager wealth in some specifications. As a stand-in for Global Financial Cycle shocks, I multiply the exogenous wealth shock by its volatility σ_z and express it in percentage AUM terms, with its sign flipped so that a positive shock is comparable to a global financial tightening.[37]

Figure 5(b) reports the estimated interaction coefficients from simulated data, scaled by 10 times the coefficients associated with the wealth shock, so that the dots represents the degree of amplification when asset managers' holding share exceeds the average by 10 percentage points. The average degree of amplication is 19%, suggesting that my model is able to explain more than 60% of investment funds' role in amplifying the impact of financial shocks in the data (see Table 1). I also report the same interaction

[37]Formally, the full regression I run that generates Panel (b) is $\Delta y_{j,t} = \alpha_j + 100\beta_{0,j}(-\sigma_z \Delta B_{j,z,t}) + \beta_{1,j}\frac{X_{j,t-1}-\overline{X}_j}{s} + 100\beta_{2,j}(-\sigma_z \Delta B_{j,z,t}) \times \frac{X_{j,t-1}-\overline{X}_j}{s} + \gamma_j \Delta\lambda_t + \eta_j W_{t-1} + \varepsilon_{j,t}$ where j denotes a replication in the simulation and $\Delta B_{j,z,t}$ corresponds to the exogenous wealth shock between $t-1$ and t in replication j. There are two differences relative to Table 1: 1) the investment fund share is expressed in absolute levels instead of percentage points; 2) the asset manager share is demeaned.

coefficients by running regressions on partitions of simulated data by quantiles of default risk. Consistent with the aggregate data (see Table I.A.5), the model is also able to generate an inverse relationship between creditworthiness and bond yield sensitivity to financial shocks. Bond yields is 20% less sensitive to fund outflows when default risk is at the bottom 25% relative to when default risk is at the top 25%.

6 Counterfactuals and policy analysis

I use counterfactual parameterizations of the model to further disentangle the contribution of asset attributes and investor composition to the transmission of shocks. These counterfactual scenarios are tied to hypothetical shifts in the asset demand structure of long-term investors and asset managers, potentially shaped by various policy measures. Consequently, this section also speaks to the spillover of changes to financial regulations governing key global intermediaries for emerging markets.

I solve the model under five alternative parameterizations. On the side of the long-term investors, I consider a scenario ("no selection") in which long-term investors do not explicitly favor safer assets and are more accommodative to credit risk. By making $\delta_\lambda = 0$ in (11), this counterfactual setting resembles the treatment of exposure to sovereign credit risk in the EU-wide Solvency II regulatory scheme in effect since 2016, which only affects long-term investors such as insurers. For bonds issued by EU governments denominated in the domestic currency of the issuers, Solvency II assigns zero risk weight when calculating capital requirements against credit risk.[38] In the optimizing foundation of long-term investor demand (Appendix I.B.2), this regulatory design is consistent with a demand slope α independent of default risk.

I also study the consequences of a shrinking long-term investor sector. In particular, I consider lowering the magnitudes of both α and θ_1 in (11) by 20% relative to the baseline ("fewer long-term investors"), assuming homogeity among long-term investors. I also solve the model with a higher bond supply parameter s to reflect a 11% higher debt-to-GDP ratio ("higher residual supply"), mechanically increasing the exposure of both types of investors to the risky asset. One can also regard this scenario as capturing the inability of outside investors such as reserve managers to easily absorb debt supply.[39]

[38] This treatment is specified in Article 180(2,3) of Delegated Regulation (EU) 2015/35.

[39] The mappings between parameters to my counterfactual experiments are clearly spelled out in the optimizing foundation of long-term investor demand laid out in Appendix I.B.2. δ_λ reflects the dependence of the tightness of the credit constraint on asset fundamentals. θ_1 captures the size of the additional

I also consider changes in the liability structure and shock exposure of the asset managers. First, I reduce the volatility of exogenous wealth shocks σ_z to zero. By assuming that asset managers do not face exogenous wealth shocks, this experiment ("stable flow") can be thought of as considering a shift from an open-ended to a close-ended capital structure for funds. Second, I consider a scenario in which emerging market authorities may be able to observe the identity of bondholders and selectively charging a 15% tax on the returns earned by asset managers. Long-term investors are not affected by the tax, so that the buy-and-hold value $F(\lambda)$ is kept unchanged.[40]

6.1 Sensitivity to the Global Financial Cycle and amplification of shocks

As a first step in comparing the counterfactuals, I focus on the endogenous amplification mechanism in the model that affects the sensitivity of the bond yield spread to the Global Financial Cycle shock $\mathrm{d}B_{z,t}$. Following the discussion in Section 5.2 and (15), I decompose the bond yield spread sensitivity to a one standard deviation negative exogenous wealth shock into two components – direct effect of the shock, and the amplification effect through endogenous wealth revaluation, and report the numbers associated with various counterfactual scenarios in Table 4.[41]

In my baseline specification (labelled "average default risk" in Table 4,) endogenous wealth revaluation accounts for 28% of the sensitivity to Global Financial Cycle shock at the long-run average level of default risk. Both the total sensitivity to global financial shocks and the contribution of endogenous amplification systematically vary with bond fundamentals. When the default risk is one standard deviation higher than its long-run average (labelled "high default risk",) endogenous amplification can explain 31 percent of the total response to a given exogenous wealth shock.

When default risk is high, encouraging wider participation of long-term investors in the sovereign debt market by weakening their preference for lower fundamental risk (the "no selection" case) dampens the contribution of endogenous amplification to the response of the bond yield spread by 20% (from 2.1 basis points to 1.7 basis points).

cost of being exposed to sovereign default risk.

[40]The law of motion for individual asset manager wealth in (9) becomes

$$\mathrm{d}w_t = (rw_t - c_t + \xi w_t)\mathrm{d}t + x_t \cdot ((1-\tau)\cdot(\mathrm{d}P_t + \kappa \mathrm{d}t - \delta \mathrm{d}N_t) - rP_t\mathrm{d}t) + \sigma_z w_t \mathrm{d}B_{z,t}$$

where τ is the tax rate. The boundary condition for $W \to \infty$ becomes $\lim_{W\to\infty} P(\lambda, W) = (1-\tau)F(\lambda)$.

[41](12) and the definition of bond yield imply that yield spread sensitivity of wealth shock $\mathrm{d}B_{z,t}$ at a given (λ, W) is $-\kappa\eta_z(\lambda, W)/(P(\lambda, W))^2$. The individual components in Table 4 follow from (15).

Compared to the baseline, asset managers hold a higher share of the risky perpetuity when the default risk is low, but significantly cut their risky asset demand when the default risk is high, as long-term investors become more accommodative to credit risk. Consequently, the sensitivity of yield spreads to exogenous wealth shocks increases more slowly with default risk. The difference in the sensitivity of yields between bonds with high default risk and low default risk shrinks by 64% relative to the baseline calibration. Bond fundamentals affect risk sensitivity in the model primarily through their impact on investor composition, via shifts in the demand of long-term investors.

Shrinking the size of the long-term investor sector substantially enlarges the sensitivity of bond yield spreads to the Global Financial Cycle, while limiting the risk exposure of asset managers through inflow tax helps reduce this sensitivity. Table 4 shows that across all levels of default risk, the amplification effect is stronger than in the baseline specification with a smaller long-term investor sector, and is weaker when a tax is levied on asset managers. For average default risk, a 20% reduction in the demand of long-term investors is associated with a rise in sensitivity of more than 60%, partly driven by a 68% higher amplification effect. Meanwhile, a 15% tax on asset managers' returns weakens the endogenous amplification of shocks by 19% (from 1.1 basis points to 0.9 basis points).

6.2 Implication for emerging market borrowing cost

The mechanism formalized in the model is relevant for understanding the cost of sovereign borrowing. Table 5 reports a key set of model-implied moments associated with the baseline and the counterfactual specifications. Relative to the baseline, policy measures such as Solvency II that remove the direct dependence of long-term investors' demand on default risk result in a 0.3 percentage point average decline in sovereign borrowing costs, and a 0.1 percentage point reduction in the volatility of sovereign spreads (an 8.6% and 14.7% reduction in relative terms, respectively). The responsiveness of long-term investors' demand to bond price fluctuations increases by 25% in relative terms compared to the baseline calibration. Despite the rising willingness of long-term investors to hold the bond, the average share held by the asset managers in equilibrium increases slighly.

Reducing the mass of long-term investors by 20% substantially pushes up spread and volatility (by 31% and 62% in relative terms, respectively), driven by a decline in the responsiveness of long-term investors' demand by 30% and a higher share held by the asset managers. An increase in the residual supply facing private investors works similarly. Asset managers absorb over 60% of the additional asset supply, resulting in a

Component	Baseline	No selection $\delta_\lambda = 0$	Fewer LT investors α, θ_1 0.8×baseline	Large supply $s = 0.6$	Tax on asset managers $\tau = 0.15$
Low default risk:					
Total	4.6	4.9	7.6	7.3	4.1
Direct	3.5	3.5	5.6	5.4	3.2
Amplification	1.1	1.4	2.0	1.9	0.9
Average default risk:					
Total	5.6	5.3	9.1	8.7	5.0
Direct	4.0	3.8	6.4	6.1	3.7
Amplification	1.6	1.6	2.7	2.6	1.3
High default risk:					
Total	6.8	5.7	10.9	10.5	6.1
Direct	4.6	4.0	7.3	7.0	4.3
Amplification	2.1	1.7	3.6	3.5	1.8

Table 4: Decomposition of yield spread sensitivity to exogenous wealth shocks (basis points response to a one standard deviation negative shock)

Note: Table 4 decomposes yield spread sensitivity (expressed in basis points) to a one standard deviation negative exogenous wealth shock ($dB_{z,t}$ in (13)) into two components. The direct component corresponds to the direct effect of the shock on bond yield. The amplification component refers to the shock impact on bond yield due to endogenous amplification through wealth revaluation. I compute the decomposition for different levels of fundamental risk. The numbers for "average default risk" correspond to to bond yield spread sensitivity to exogenous wealth shocks when default risk is at its long-run mean $\overline{\lambda}$. "Low default risk" and "high default risk" corresponds to one standard deviation below and above the long-run mean, respectively. The scenario "no selection" corresponds to the counterfactual where I set the parameters δ_λ and θ_1 in Equation (11) to zero. By doing so, I remove the direct dependence between asset demand elasticity and default risk. The case "fewer LT investors" is associated with the counterfactual where I shrink the size of long-term investor sector by 20% compared to the baseline, by setting α and θ_1 in (11) to 0.8 times the original value. "Larger supply" considers an increase of bond supply to 60% debt-to-GDP ratio compared to the baseline number of 49%. "Tax on asset managers" refers to the scenario in which the asset managers are levied a 15% tax on the return from holding the risky perpetuity.

one percentage point rise of bond spreads, and a 56% relative increase in yield volatility.

Policy measures on the asset managers have distinct implications for equilibrium investor composition and asset prices. Changing the liability structure of asset managers by eliminating wealth shocks significantly reduces the borrowing costs (by 0.8 percentage points relative to the baseline), mostly through an enlarged demand of asset manangers, while yield spread volatility is 13% lower. As a result of the increased demand, the fundamental risk exposure of asset managers substantially widens relative to that implied by the baseline calibration, partially offsetting the dampening of volatility when wealth shocks are removed. On the other hand, a 15% inflow tax on risky asset returns discourages asset managers from large exposure to the risky perpetuity, lowering the fraction held by asset managers by 2.6 percentage points relative to the baseline. Unlike the previous scenario, the yield spread must rise by 0.2 percentage points under the inflow tax, to induce long-term investors to step into the market. The asset manager tax lowers the volatility of the yield spread by 9.1% in relative terms.

Moment/Scenario	Baseline	No selection	Fewer LT investors	Larger supply	Stable flow	Tax on asset managers
		$\delta_\lambda = 0$	α, θ_1 0.8×baseline	$s = 0.6$	$\sigma_z = 0$	$\tau = 0.15$
Spread (%)	3.5	3.2	4.6	4.5	2.7	3.7
Volatility (%)	0.68	0.58	1.1	1.06	0.59	0.62
Demand response to 1% yield increase (%)	20	25	14	14	21	19
Asset manager share (%)	17.5	18.3	21.1	20.5	32.7	14.9
Corr(yield, default risk)	0.4	0.21	0.35	0.36	0.48	0.44

Table 5: Model implied moments: Baseline and counterfactual parameterization

Note: Table 5 reports model-implied moments across the baseline calibration and alternative parameterizations. Details on each counterfactual scenario are given in the notes following Table 4. Long-term investors' demand response to 1% yield increase is computed by regressing log changes in long-term investor holding Z on changes in bond yield y based on simulated data, controlling for changes in default risk λ (see Equation (19)).

7 Conclusion

This paper provides empirical and quantitative evidence that foreign investor composition is an important metric to evaluate emerging markets' resilience against the potential adverse impact of a shifting Global Financial Cycle. Fostering a diverse, stable foreign investor base is desirable. When global financial condition worsens, long-term investors such as banks, insurers and pension funds could dampen the upward pressure on borrowing costs as investment funds retreat from emerging markets. However, their capability to act as shock absorbers could be limited by various constraints biased towards safe, home-currency assets.

Recent efforts by emerging markets to expand the access to their local-currency bond market could alleviate concerns on currency mismatches, but may also attract risk-sensitive foreign investors that play a destabilizing role, as suggested by my empirical findings. For these countries, the quest for a stable funding conditions may involve a careful design of issuance and opening strategy to attract stable, long-term investors. For emerging markets, future work based on this paper can analyze the key tradeoff facing sovereign borrowers and the optimal composition of foreign investor base under the influence of the Global Financial Cycle.

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Online Appendix (for online publication only)

I.A Empirical appendix

I.A.1 Data and summary statistics

Table I.A.1 to I.A.3 report summary statistics associated with key variables used in the empirical analysis. Table I.A.4 collects the key data used in the analysis.

	all	external	domestic	EM Europe	other issuers	EUR-denominated
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
total share (%)	9.50	14.91	4.61	8.08	11.67	18.41
	(11.31)	(12.41)	(7.35)	(9.86)	(12.93)	(15.35)
bank share (%)	1.48	2.28	0.75	0.31	3.26	5.74
	(5.68)	(7.33)	(3.44)	(2.81)	(8.01)	(8.32)
fund share (%)	7.10	11.26	3.34	7.40	6.64	7.97
	(8.22)	(9.19)	(4.72)	(8.54)	(7.67)	(8.84)
ICPF share (%)	0.93	1.39	0.52	0.37	1.79	4.75
	(4.19)	(4.96)	(3.29)	(2.44)	(5.84)	(8.55)
Observations	105184	49938	55246	63577	41607	20117

Table I.A.1: Summary statistics: Investor base measure θ

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.1 reports summary statistics related to the investor composition measure θ. For each sector and each bond, θ is calculated by dividing the total face value by the amount outstanding, and is expressed in percentage points. In the case where a bond has aggregate θ exceeding 100% from the calculation, it is dropped from the analysis.

	held by bank mean/sd	held by fund mean/sd	held by ICPF mean/sd	all mean/sd
callable bond	0.043	0.030	0.033	0.028
	(0.20)	(0.17)	(0.18)	(0.17)
EUR-denominated	0.318	0.183	0.584	0.201
	(0.47)	(0.39)	(0.49)	(0.40)
USD-denominated	0.347	0.247	0.144	0.242
	(0.48)	(0.43)	(0.35)	(0.43)
local currency (non-EUR)	0.283	0.530	0.219	0.515
	(0.45)	(0.50)	(0.41)	(0.50)
coupon rate	4.555	5.278	3.636	5.188
	(2.87)	(3.85)	(2.50)	(3.83)
senior bond	0.630	0.557	0.718	0.537
	(0.48)	(0.50)	(0.45)	(0.50)
collateral eligibility	0.130	0.066	0.194	0.079
	(0.34)	(0.25)	(0.40)	(0.27)
Observations	1450	2337	599	2499

(a) Static characteristics

	held by bank mean/sd	held by fund mean/sd	held by ICPF mean/sd	all mean/sd	count
credit quality (higher = better)	3.63	3.62	4.16	3.64	105044
	(1.32)	(1.37)	(1.07)	(1.38)	
size (bil Euros)	1.77	2.69	1.92	2.58	104788
	(2.03)	(4.89)	(2.87)	(4.79)	
bid-ask spread (%)	0.15	0.15	0.11	0.15	88931
	(0.21)	(0.23)	(0.14)	(0.23)	
bond yield (%)	3.50	4.47	1.83	4.36	103626
	(3.46)	(4.12)	(2.30)	(4.08)	
θ (%)	13.48	9.66	17.29	9.50	105184
	(12.61)	(11.06)	(14.50)	(11.31)	
% held by banks	2.88	1.18	4.31	1.48	104788
	(7.67)	(4.43)	(7.11)	(5.68)	
% held by funds	8.84	7.53	8.45	7.10	105184
	(8.22)	(8.27)	(7.87)	(8.22)	
% held by ICPFs	1.76	0.96	4.52	0.93	104788
	(5.68)	(4.29)	(8.30)	(4.19)	

(b) Dynamic characteristics

Table I.A.2: Summary statistics: Bonds matched to SHS-Base plus

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.2 reports summary statistics on bonds held by Germany-based investors in the SHS-Base plus dataset. Time-invariant characteristics are grouped in Panel (a) while time-varying characteristics are grouped in Panel (b). The table also reports statistics by groups of bonds held by banks, investment funds and insurance companies and pension funds (ICPFs) separately. Dynamic characteristics also include instrumental variables used in the estimation of demand equation (4). Credit quality refers to Eurosystem's Credit Quality Step that harmonizes credit ratings into six bins. Collateral eligibility refers to eligibility for Eurosystem credit operations. Standard errors are double clustered at issuer and time level.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Mutual fund flow (% fund size)	114,669	1.263	13.17	-50	200
Log fund size (USD)	116,136	18.88	1.669	15.42	25.02
Monthly return (%)	120,439	0.135	3.228	-48.84	21.87
Log VIX index	103	2.790	0.321	2.252	3.980
BEX risk aversion index	103	2.870	0.475	2.495	5.679
Federal Funds rate	103	0.716	0.805	0.0500	2.420
10-year Bund yield	103	0.405	0.701	-0.700	2.030
EMBI spread (bps)	3,780	285.0	416.5	14	5,799
5-year CDS spread (bps)	4,464	273.3	662.5	5.564	6,631
Log industrial production index	4,563	4.679	0.179	2.806	5.456
Spot exchange rate against EUR	9,373	877.0	3,356	0.0261	29,236

Table I.A.3: Summary statistics: Fund characteristics and holdings (Morningstar), miscellaneous data

Source: Morningstar and miscellaneous data sources outlined in Table I.A.4.

Note: Table I.A.3 reports summary statistics related to mutual fund characteristics according to Morningstar data, as well as miscellaneous control variables when estimating (3) and (4). Mutual fund characteristics (flow, return, size) are used compute flow-based instrument for the estimation of bank and ICPF's demand equation. Mutual fund flow, size, return use all data available since the end of 2007. I report summary statistics for global factors (VIX to Bund yield), industrial production index, and exchange rate from end-2012 to 2021M6. I report summary statistics for local factors (EMBI spread, 5-year CDS spread) from 2004 to 2019, corresponding to my sample period in Section 2. Following Jotikasthira et al. (2012), I drop fund-year-month observations with fund size lower than 5 million USD, and I winsorize the flow at -50% and 200% the size of each fund (these constitutes less than 1% of the sample).

Variables	Sources
Bond-level information:	
Static bond characteristics	Bloomberg
Amount outstanding history	Refinitiv
Germany-based investor holding	Deutsche Bundesbank, SHS-Base plus
Bond yield, price, bid-ask spread	Bloomberg, Refinitiv Datastream, SHS-Base plus
Credit rating	Refinitiv, WRDS
Day-count convention, coupon frequency	Refinitiv
Mutual-fund information:	
Mutual fund/ETF portfolio, flow, return	Morningstar
Country-level information:	
Global risk measure (VIX)	FRED
Industrial production	National sources, CEIC
Stock price index	National sources, CEIC
German Bund yield curve	Deutsche Bundesbank, Time Series Database
Portfolio and other investment liabilities	Lane and Milesi-Ferretti (2017)
Foreign non-bank share in EM government bond market	Arslanalp and Tsuda (2014)
Cross-border bank claims on EM	BIS
EMBI spread	World Bank Global Economic Monitor

Table I.A.4: Key data sources

Note: Table I.A.4 reports the data sources of key variables used in my empirical and quantitative analysis. SHS-Base plus refers to the Securities Holdings Statistics Base plus database (Blaschke et al., 2022) compiled by Research Data and Service Centre (RDSC) of the Deutsche Bundesbank.

I.A.2 Robustness and additional results

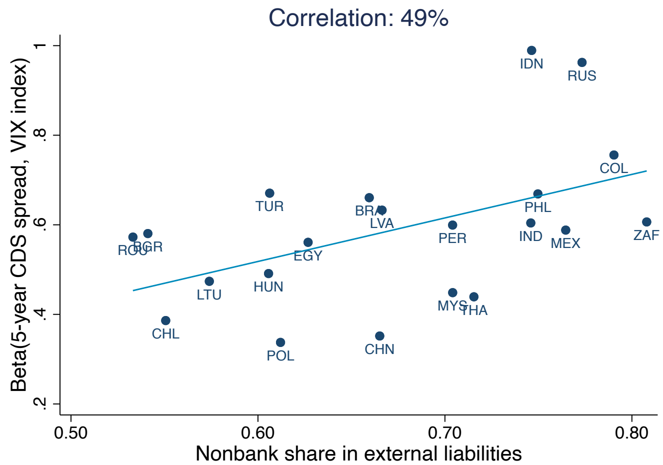

Figure I.A.1: Sovereign CDS spread-VIX β and investor composition

Source: Lane and Milesi-Ferretti (2017), Markit, FRED, own calculations.

Note: Figure I.A.1 further illustrates the cross-country pattern between foreign non-banks' presence through portfolio investment and emerging market economies' sensitivity to shifts in global risk factors. The y-axis corresponds to time-series regression coefficients of monthly changes in 5-year USD CDS spread on monthly changes in the log CBOE VIX index, controlling for changes in U.S. monetary policy. The x-axis corresponds to foreign non-banks' share in total non-FDI external liabilities averaged over 2004–2019.

VARIABLES	(1) Beta	(2) Beta	(3) Beta	(4) Beta
Non-bank share in external liabilities	0.013***	0.011**		
	(0.005)	(0.005)		
Foreign non-bank share in government bond			1.093***	1.253**
			(0.381)	(0.684)
Stock market capitalization		0.000		-0.000
		(0.000)		(0.000)
Debt to GDP ratio		0.000		-0.005
		(0.002)		(0.003)
GDP per capita		0.119**		0.056
		(0.044)		(0.065)
Capital account openness		0.135		-0.120
		(0.135)		(0.125)
Credit quality step (score, 1-6)		-0.126***		-0.112***
		(0.025)		(0.032)
Observations	21	21	21	21
R-squared	0.295	0.785	0.219	0.778

Table I.A.5: The relationship between sensitivity to the Global Financial Cycle and foreign investor composition: Adding issuer-level characteristics

Source: World Bank, CEIC, Chinn and Ito (2006), own calculations.

Note: Table I.A.5 reports cross-sectional regression results relating country-specific sovereign yield spread sensitivity to log changes in the VIX index (β_i in (1)) and measures of foreign investor composition, controlling for issuer-level characteristics. Issuer-level characteristics are averaged over the sample period used to calculate β_i. The characteristics include stock market capitalization (World Bank and CEIC), external debt to GDP ratio (World Bank), GDP per capita (World Bank) and the Chinn and Ito (2006) capital account openness index. For coefficients related to foreign investor composition, I report bootstrap standard errors based on a two-stage estimation of the cross-sectional regression in conjuction with (1). For other coefficients, heteroskedasticity-robust standard errors are reported. Uruguay is dropped from the cross-sectional regressions due to data constraints. Credit quality step is the credit score assigned to issuers based on S&P rating translated to six levels. The higher is the score, the higher is the corresponding credit rating for the issuer country.

VARIABLES	(1) Bank	(2) Fund	(3) ICPF	(4) Bank	(5) Fund	(6) ICPF
Callable	0.129***	-0.015	0.016	0.134***	-0.007	0.025
	(0.038)	(0.024)	(0.027)	(0.039)	(0.023)	(0.027)
Log amount outstanding (EUR))	0.026	0.055***	0.035***	0.030	0.054***	0.037***
	(0.023)	(0.017)	(0.012)	(0.023)	(0.017)	(0.013)
Coupon	-0.004	0.004	0.001	-0.002	0.004	0.002
	(0.009)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)
Maturity bucket	-0.022***	0.008	0.003	-0.021***	0.008	0.003
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Euro denomination	0.234***	0.019	0.662***	0.229***	0.023	0.662***
	(0.072)	(0.026)	(0.047)	(0.074)	(0.026)	(0.048)
Seniority	0.267***	0.088***	0.066***	0.278***	0.079***	0.062**
	(0.062)	(0.021)	(0.025)	(0.062)	(0.019)	(0.025)
Collateral eligibility	-0.036	-0.056	-0.175**	-0.039	-0.068	-0.181**
	(0.073)	(0.054)	(0.072)	(0.071)	(0.057)	(0.076)
Investment grade	-0.034	0.020	0.097**			
	(0.037)	(0.012)	(0.048)			
Observations	105,212	105,212	105,212	104,802	104,802	104,802
R-squared	0.477	0.282	0.566	0.506	0.341	0.591
Issuer FE	✓	✓	✓	-	-	-
Time FE	✓	✓	✓	-	-	-
Issuer*Time FE	-	-	-	✓	✓	✓

Table I.A.6: Propensity of holding EM sovereign debt and the role of bond characteristics

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.6 reports estimation results from a linear probability model relating holding decision to bond characteristics. The sample period is 2012M12 to 2021M6. For each sector, an indicator variable of whether the sector holds a particular bond is regressed on a set of bond-level characteristics, including callability, log amount outstanding, coupon rate, residual maturity bucket, Euro denomination, Seniority and collateral eligibility. Maturity bucket is defined by separating bonds into five bins (assigned scores from 0 to 4) according to residual maturity shorter than 1 year, between 1 and 3 years, 3 and 5 years, 5 and 10 years, and above 10 years. Collateral eligibility refers to eligibility for Eurosystem credit operations. Columns (1) to (3) report estimation with issuer and time fixed effect for banks, investment funds, and insurers and pension funds (ICPFs) respectively. Columns (4) to (6) report results generated with the fixed effect of issuer interacted with time. Standard errors are double clustered at issuer and time level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) Δ yield	(2) large share Δ yield	(3) Δ yield	(4) large share Δ yield	(5) Δ yield
Δ log VIX	0.3154***	0.3858***			
	(0.0147)	(0.0278)			
Δ log VIX × lag bank+ICPF relative share	-0.0032***	-0.0041***	-0.0004	-0.0015***	-0.0005**
	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
lag bank+ICPF relative share	-0.0002*	0.0002	-0.0002**	0.0001	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Δ 10y Bund yield	0.4222***	0.5245***			
	(0.0154)	(0.0183)			
Δ log IP index	-0.2706***	-0.9766***			
	(0.0754)	(0.1009)			
Δ credit quality	0.0923***	-0.0424	-0.0993***	-0.0464	-0.1860***
	(0.0225)	(0.0280)	(0.0367)	(0.0334)	(0.0444)
Δ amt outstanding	-0.0375	0.0979*	0.0077	0.0922***	0.0129
	(0.0349)	(0.0580)	(0.0213)	(0.0331)	(0.0202)
Δ maturity bucket	0.0164	0.0451**	0.0063	0.0274***	0.0141*
	(0.0133)	(0.0195)	(0.0091)	(0.0084)	(0.0083)
Δ bid-ask spread					0.1628***
					(0.0320)
Observations	32,793	10,671	33,001	10,495	30,555
R-squared	0.0732	0.1722	0.6148	0.7995	0.6843
Bond FE	✓	✓	✓	✓	✓
Issuer*Time FE	–	–	✓	✓	✓

Table I.A.7: Push-pull regressions: Relative shares of long-term investors

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

The relative shares of long-term investors are defined as

$$100 \times \frac{\theta_{\text{Bank+ICPF}}}{\theta_{\text{Bank+ICPF}} + \theta_{\text{Fund}}}.$$

Note: Table I.A.7 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (3). The sample runs from 2012M12 to 2021M6. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. Maturity bucket is defined by separating bonds into bins according to residual maturity shorter than 1 year, between 1 and 3 years, 3 and 5 years, 5 and 10 years, and above 10 years. Each bucket is assigned a score from 0 to 4 with rising residual maturities. "Switch maturity bucket" takes on value 0 if the maturity bucket does not change from the previous month, and takes on value -1 if the maturity bucket switches from the previous month. The regressions are augmented with measures of lagged relative investor composition. The measure is computed as the total holding of banks and ICPFs as a share of total holding of banks, ICPFs and mutual funds for a particular bond in my sample. The risk factor is further interacted with the relative investor share variable. Credit quality refers to Eurosystem's Credit Quality Step that harmonizes credit ratings into six bins. I winsorize monthly changes in bond yield at 1% and 99% tail. Columns (1) to (2) report results with bond fixed effect only, while columns (3) to (5) add issuer×time fixed effect. Columns (1) and (3) use all EM European sovereign bonds while columns (2) and (4) focus on bonds with a large investor base (larger than 15%) coverage in my data. Column (5) further add bid-ask spread as an additional control. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) Δ yield	(2) Δ yield	(3) Δ residualized yield	(4) Δ residualized yield
Δ log VIX			0.0405***	0.1008***
			(0.0151)	(0.0157)
Δ log VIX × lag bank+ICPF share	-0.0010*		-0.0013***	
	(0.0006)		(0.0005)	
Δ log VIX × lag fund share	0.0051***		0.0037***	
	(0.0008)		(0.0013)	
Δ log VIX × lag bank+ICPF relative share		-0.0007***		-0.0008***
		(0.0002)		(0.0002)
Δ log VIX × Euro	0.0131	0.0306*		
	(0.0147)	(0.0171)		
Δ log VIX × credit quality (issuance)	0.1241***	0.0908***		
	(0.0268)	(0.0265)		
Δ log VIX × residual maturity bucket (score)	-0.0049	0.0033		
	(0.0052)	(0.0048)		
Observations	30,500	30,224	17,216	17,065
R-squared	0.6802	0.6820	0.0480	0.0475
Bond FE	✓	✓	✓	✓
Issuer*Time FE	✓	✓	–	–
Controls	✓	✓	✓	✓

Table I.A.8: Push-pull regressions: Robustness checks

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.8 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (3). The sample runs from 2012M12 to 2021M6. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. Maturity bucket is defined by separating bonds into bins according to residual maturity shorter than 1 year, between 1 and 3 years, 3 and 5 years, 5 and 10 years, and above 10 years. Each bucket is assigned a score from 0 to 4 with rising residual maturities. "Switch maturity bucket" takes on value 0 if the maturity bucket does not change from the previous month, and takes on value -1 if the maturity bucket switches from the previous month. Columns (1) and (2) add interactions between Δlog VIX index and a set of observable characteristics at the bond level, including Euro denomination, credit quality at issuance level and residual maturity bucket. In columns (3) and (4), the sample is restricted to USD and EUR bonds, and the dependent variableis residualized monthly changes in bond yield. The residuals are obtained from regressing monthly changes in raw bond yields on monthly changes in a set of bond risk factors calculated from excess returns investing in long-short portfolios. The bond risk factors include a credit risk factor and a duration risk factor. Columns (1) and (3) focus on raw measures of investor composition associated with investment funds and banks, insurers and pension funds. Columns (2) and (4) use lagged relative investor composition, computed as the total holding of banks and ICPFs as a share of total holding of banks, ICPFs and mutual funds for a particular bond in my sample. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) Δ yield	(2) Δ yield	(3) large share Δ yield	(4) Δ yield	(5) large share Δ yield
Δ log V2X	0.2870***				
	(0.0196)				
Δ log V2X × lag bank+ICPF share	-0.0092***	-0.0012**	-0.0011		
	(0.0013)	(0.0005)	(0.0008)		
Δ log V2X × lag fund share	0.0097***	0.0057***	0.0049***		
	(0.0016)	(0.0010)	(0.0011)		
Δ log V2X × lag bank+ICPF rel. share				-0.0005**	-0.0018***
				(0.0003)	(0.0004)
Observations	32,743	32,918	10,432	32,642	10,432
R-squared	0.0818	0.6138	0.8003	0.6151	0.8004
Bond FE	✓	✓	✓	✓	✓
Issuer*Time FE	–	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

Table I.A.9: Push-pull regressions: V2X index as the proxy for global risk factors

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.9 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (3). The sample runs from 2012M12 to 2021M6. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. I winsorize monthly changes in bond yield at 1% and 99% tail. Maturity bucket is defined by separating bonds into bins according to residual maturity shorter than 1 year, between 1 and 3 years, 3 and 5 years, 5 and 10 years, and above 10 years. Each bucket is assigned a score from 0 to 4 with rising residual maturities. "Switch maturity bucket" takes on value 0 if the maturity bucket does not change from the previous month, and takes on value -1 if the maturity bucket switches from the previous month. The regressions are augmented with measures of lagged investor composition, including both investment fund share and total share of banks, insurance companies and pension funds. The implied volatility of European STOXX index (V2X) is further interacted with the measure of investor composition for each sector (columns (1) to (3)), or the measure of amount held by banks and insurance company relative to investment funds (columns (4) to (5)). Columns (1) reports the result with bond fixed effect only, while columns (2) to (5) add issuer×time fixed effect. Columns (1), (2) and (4) use all EM European sovereign bonds while columns (3) and (5) focus on bonds with a large investor base (larger than 15%) coverage in my data. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) FID3 EUR	(2) FID12 EUR	(3) GIV12 EUR	(4) FID12 Non-EUR	(5) GIV12 Non-EUR
FID3	-0.315***				
	(0.043)				
FID12		-0.313***		-0.291***	
		(0.043)		(0.022)	
GIV12			-1.816***		-0.353***
			(0.261)		(0.052)
$\Delta y_{10Y,t}(Bund)$	0.409***	0.402***	0.413***	0.479***	0.474***
	(0.026)	(0.026)	(0.021)	(0.016)	(0.016)
Δ log IP	-0.510***	-0.508***	-0.528***	0.008	0.018
	(0.184)	(0.183)	(0.183)	(0.039)	(0.039)
Δ Bid-ask spread	0.373***	0.373***	0.502***	0.773***	0.759***
	(0.117)	(0.119)	(0.134)	(0.070)	(0.067)
Observations	6,445	6,372	7,902	24,471	25,052
First-stage F	53.86	52.03	48.58	172.2	45.35

Table I.A.10: Demand equation of banks and ICPFs: First stage for baseline estimates

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.10 complements the weak-instrument-robust Lee et al. (2022) standard error reported in Table 2 by reporting results from the first-stage regression of bond yield on flow-based instruments and control variables. The sample runs from 2012M12 to 2021M6. Month-to-month changes in bond yields is regressed on the instruments, 10-year Bund yield, log industrial production index as well as bond characteristics (bid-ask spread winsorized at 1% and 99% tail). The instruments are either flow-induced demand shock (FID) or granular flow shock discussed in Section 4.1. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. I winsorize monthly changes in bond yield at 1% and 99% tail. Columns (1) to (3) report estimates on the Euro-denominated bond sample, while column (4) and (5) focus on the non-EUR sample. In column (1), the instrument is FID generated from residualizing mutual fund flow by current and lagged monthly returns for 3 months. Column (2) and (4) use FID with mutual fund flow residualized by time fixed effect, current and lagged monthly returns for 12 months. Column (3) and (5) use the granular flow shocks (6) with the idiosyncratic flow being the lagged fund size-weighted average of mutual fund flow. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) FID3 EUR	(2) FID12 EUR	(3) FID3 EUR	(4) FID12 EUR
$\Delta y_t(n)$	0.312**	0.326**	0.613**	0.613**
	(0.146)	(0.147)	(0.299)	(0.310)
$\Delta y_{10Y,t}(Bund)$	-0.126*	-0.130**		
	(0.064)	(0.063)		
Δ log IP	0.054	0.060	-0.008	-0.007
	(0.089)	(0.091)	(0.056)	(0.057)
Δ Bid-ask spread	-0.130	-0.135	-0.166	-0.161
	(0.082)	(0.084)	(0.106)	(0.107)
Lagged overall exposure to investment funds	0.003***	0.003***		
	(0.001)	(0.001)		
Observations	6,445	6,372	6,445	6,372
Time FE	-	-	✓	✓
First-stage F	53.55	51.79	23.45	21.02

Table I.A.11: Yield elasticity of demand estimation: Robustness

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.11 reports additional IV estimation results. Columns (1) and (2) include one additional control in regressions otherwise the same as the baseline estimation. The additional control – lagged overall exposure – is defined as the product of lagged bond price and lagged share held by investment funds in my Morningstar sample. Columns (3) and (4) add time fixed effect to the estimation. I winsorize monthly changes in bond yield at 1% and 99% tail. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

VARIABLES	(1) EUR	(2) Non-EUR	(3) IG	(4) HY
$\Delta y_t(n)$	0.543	-0.277	0.362	-0.198
	(0.330)	(0.186)	(0.223)	(0.183)
$\Delta y_{10Y,t}(Bund)$	-0.198*	0.137	-0.169	-0.051
	(0.116)	(0.148)	(0.129)	(0.082)
Δ log IP	-0.016	-0.139	-0.147	0.014
	(0.168)	(0.211)	(0.116)	(0.200)
Δ Bid-ask spread	-0.104	0.059	-0.307	-0.073
	(0.112)	(0.225)	(0.195)	(0.176)
Δ log Exchange rate against EUR			-0.010	-1.059
			(1.555)	(0.871)
Observations	6,448	25,326	24,796	6,978

Table I.A.12: Yield elasticity of demand estimation: Accounting for zero current holding

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2012M12–2021M6, own calculations.

Note: Table I.A.12 reports demand slopes of banks, insurers and pension funds by bond types, estimating the nonlinear equation (IA.58) via GMM taking into account zero values of $B_{i,t}(n)/B_{i,t}(n-1)$ in the data. I winsorize monthly changes in bond yield at 1% and 99% tail, and ratio between month t and month $t-1$ holding at 99% tail. The sample runs from 2012M12 to 2021M6. Bond yield is instrumented using flow-induced demand shock with 3 lags of fund returns used to residualize bond flows. Credit quality refers to Eurosystem's Credit Quality Step, harmonizing credit ratings into six bins. Monthly changes in bond yield are winsorized at 1% and 99% tail. Weighting matrix clustered at the bond level is used to compute standard errors. *** p<0.01, ** p<0.05, * p<0.1.

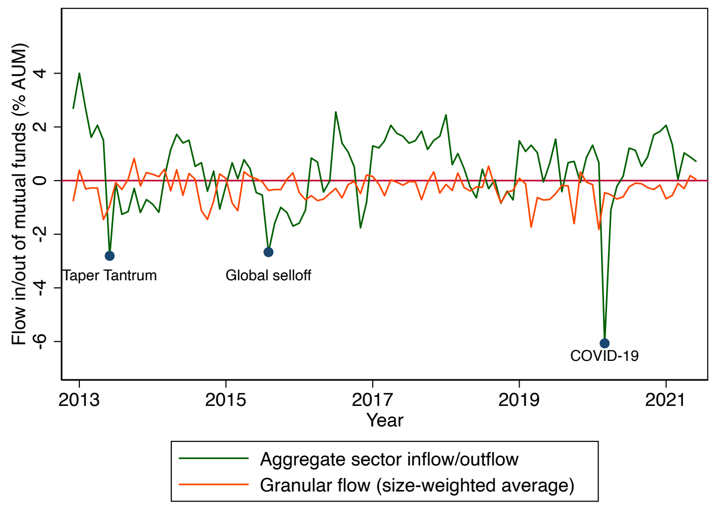

Figure I.A.2: EM-focused mutual fund flow during global "risk-off" episodes

Source: Own calculations base on Morningstar data.

Note: Figure I.A.2 plots the evolution of capital flow in and out of mutual funds with a focus on emerigng market bonds. The green line aggregates all flow and divide by the total size of the mutual funds included in my Morningstar dataset for Section 2. Dotted observations correspond to the peak of important global "risk-off" episodes analyzed in Figure 3(b). The red line plots the time-series evolution of granular fund flow between 2012M12 and 2021M6, which is used as an input to construct bond-level granular inflow instrument in the estimation of Equation (4). The granular fund flow series is constructed by taking the size-weighted average of "surprise" fund flow, computed by residualizing fund flows against time fixed effect, current and past fund-level monthly returns up to 12 months prior to the current period. Sample period is 2012M12 to 2021M6.

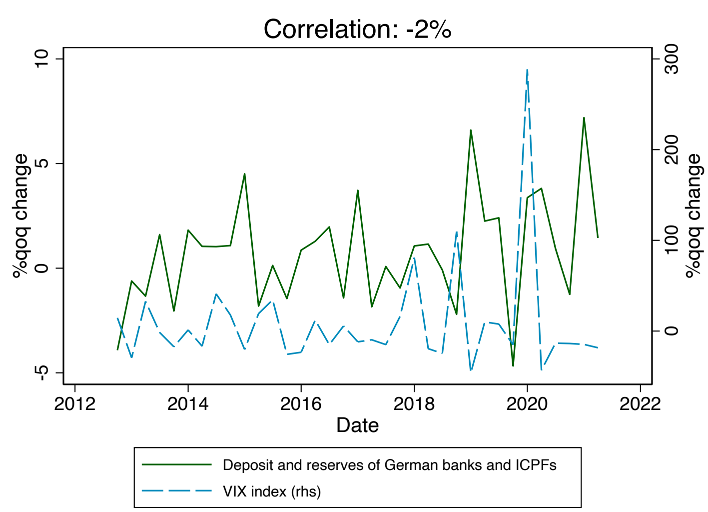

Figure I.A.3: Stability of bank and ICPF liabilities against global risk factors

Source: Deutsche Bundesbank, Time Series Database, FRED, own calculations.

Note: Figure I.A.3 plots the comovement between key components of long-term investors' liabilities – deposit and policy reserves – and VIX index as the proxy for global risk factors. Sample period is 2012Q4 to 2021Q2.

No.	Period	Shock size	Key fund	Article Date	Title/Explanation
1	2019M3	-1.73	Blackrock	01/10/2019	BlackRock enters 2019 facing substantial competition as fund commissions drop across the industry and flow slows down, and it also faces hurdle in opening up new territories such as private equity. In January, BlackRock announced layoffs.
2	2020M2	-2.82	BlackRock	02/27/2020	Junk bond funds suffered their biggest outflow in more than a year. Of the $6.8 billion outflow from mutual funds and ETFs that invest in high-yield bonds over the previous week, outflow from BlackRock accounts for nearly 60%.
3	2014M9–2014M10	-1.12, -1.45	PIMCO	09/26/2014	Bill Gross, the legendary bond investor, left PIMCO for Janus over internal rifts.
4	2013M5	-1.45	PIMCO	05/31/2013	The PIMCO Total Return Fund suffered its biggest monthly loss since the global financial crisis due to selloffs in the U.S. Treasury market. An analyst suggests that Bill Gross did not "substantially get out of Treasuries".
5	2019M10	-1.60	GAM Holdings	10/08/2019	Following an earlier Bloomberg report on potential merger deal with an Italian company, GAM announces that it is not currently under any negotiation on potential takeover. The subsequently released quarterly result is considered "[continued] sobering reading for shareholders", with a 2% quarter-on-quarter decline in assets, mostly driven by fixed income.
6	2015M3	-1.12	Franklin Templeton	03/25/2015	Ukraine announced that bondholders may be required to suffer a haircut in the bond restructuring deal. Franklin Templeton is the country's largest single creditor.

Table I.A.13: Narrative evidence for granular fund flow shocks: News articles

Source: Factiva.

Note: Table I.A.13 provides narrative support to the granular fund flow shocks extracted from Morningstar mutual fund flow data to form the instrument (6). I look for news coverage on the biggest mutual fund in my sample around the period in which the granular shocks are large in absolute values, by searching over Factiva. The complete source of news articles are listed below (Factiva document ID / web URL in parentheses):
1: WSJ: BlackRock Cutting Roughly 500 Jobs; Money manager will shed about 3% of its staff in latest industry cost-reduction effort (WSJO000020190110ef1a004s9), WSJ: BlackRock Fund Misses Deadlines (DJDN000020190225ef2p000gh) ; 2. Financial Times: Junk bond funds suffer worst outflow in more than a year (FTCOM00020200228eg2s000gp); 3. WSJ: Bill Gross leaves PIMCO for Janus. (https://www.wsj.com/articles/bill-gross-leaves-pimco-for-janus-1411736217); 4. Dow Jones Newswire: Pimco Total Return Fund Set for Biggest Monthly Loss Since September 2008 (RTNW000020130531e95v0001j); 5. Citywire: GAM distances itself from Generali takeover talk (CWIRE00020191008efa8000p1), GAM Holding AG : Interim management statement for the three-month period to 30 September 2019 (DJDN000020191017efah0005j), Citywire: The two years of turmoil that shaped the GAM of today (https://citywire.com/selector/news/the-two-years-of-turmoil-that-shaped-the-gam-of-today/a1383851); 6. NYT: Bond Trouble (NYTF000020150325eb3p0007g); 7. FT: Investors withdrew nearly $50bn from Franklin Templeton last year (FTFT000020210130eh1u000er).

I.B Model appendix

I.B.1 Model derivation and proofs

Equilibrium definition and main proposition The definition of Markov equilibrium follows from usual optimization and market clearing:

Definition 1. *A Markov equilibrium consists of a bond price function $P(\lambda, W)$, and associated demands $X(\lambda, W), Z(\lambda, W)$ such that*

- *Asset managers make optimal portfolio choices given P.*
- *Long-term investors' demand follows (10).*
- *The market for the risky perpetuity clears: $X(\lambda, W) + Z(\lambda, W) = s$.*

I state the partial differential equation (PDE) characterizing the equilibrium bond price $P(\lambda, W)$ in the model.

Proposition 1. *The equilibrium bond price $P(\lambda, W)$ solves the following PDE:*

$$\begin{aligned} rP =& \kappa + \lambda \cdot \frac{\Phi_4}{\chi(1+\Phi_4)} + P_\lambda[\kappa_\lambda(\overline{\lambda} - \lambda) - \sigma_\lambda\sqrt{\lambda}\Phi_2] + P_W[\Phi_1 - (\Phi_2^2 + \Phi_3^2)]W \\ &+ \frac{1}{2}P_{\lambda\lambda}\sigma_\lambda^2\lambda + \frac{1}{2}P_{\lambda W}\sigma_\lambda\sqrt{\lambda}\Phi_2 W + \frac{1}{2}P_{WW}W^2(\Phi_2^2 + \Phi_3^2). \end{aligned} \tag{IA.20}$$

where $\chi \equiv X/W$ is the asset manager position on the risky bond normalized by wealth, subject to the boundary conditions

$$P_\lambda(\lambda_{\min}, W) = P_\lambda(\lambda_{\max}, W) = 0, \qquad W \in (0, \infty), \tag{IA.21}$$

$$P(\lambda, 0) = F(\lambda) \cdot \exp\left(\frac{s + \theta_1\lambda}{-\alpha(\lambda)}\right), \qquad \lambda \in (\lambda_{\min}, \lambda_{\max}), \tag{IA.22}$$

$$\lim_{W\to\infty} P(\lambda, W) = F(\lambda), \qquad \lambda \in (\lambda_{\min}, \lambda_{\max}). \tag{IA.23}$$

The associated quantities $\Phi_1, \Phi_2, \Phi_3, \Phi_4$ are functions of the states and follow Equation (IA.41), (IA.42), (IA.43) and (IA.40) in Appendix I.B.1.

Portfolio choice I first derive the Hamilton-Jacobi-Bellman (HJB) equation associated with the asset manager's optimal portfolio choice problem. The evolution of asset manager wealth given the conjecture (12) is

$$\frac{\mathrm{d}w_t}{w_t} = \Big(r + \xi - \frac{c_t}{w_t} + \chi_t(\omega_t + \kappa - rP_t)\Big)\mathrm{d}t + \chi_t\eta_{\lambda,t}\mathrm{d}B_{\lambda,t} + (\chi_t\eta_{z,t} + \sigma_z)\mathrm{d}B_{z,t} + \chi_t(\eta_{N,t} - \delta)\mathrm{d}N_t \tag{IA.24}$$

where I define $\chi_t = x_t/w_t$. Use v_t as the shorthand for the value function $v(\lambda_t, w_t, W_t)$. The associated HJB equation is

$$\begin{aligned}(\rho+\zeta)v_t =& \omega_t v_{W,t} + \frac{1}{2}(\Phi_{2,t}^2 + \Phi_{3,t}^2)W_t^2 v_{WW,t} + \sigma_\lambda\Phi_{2,t}W_t\sqrt{\lambda_t}v_{\lambda W,t} \\ & + \kappa_\lambda(\overline{\lambda} - \lambda_t)v_{\lambda,t} + \frac{1}{2}\sigma_\lambda^2\lambda_t v_{\lambda\lambda,t} + \lambda_t\Big[V(\lambda_t, w_t, W_t(1+\Phi_{4,t})) - v_t\Big] \\ & + \max_{c_t,\chi_t}\Big\{\log c_t + \Big[(r - \frac{c_t}{w_t} + \zeta) + \chi(w_t + \kappa - rP_t)\Big]w_t v_{w,t} \\ & + \frac{1}{2}\Big[\chi_t^2\eta_{\lambda,t}^2 + (\chi_t\eta_{z,t} + \sigma_z)^2\Big]w_t^2 v_{ww,t} + (\chi_t\eta_{z,t} + \sigma_z)w_t\Phi_{3,t}W_t v_{wW,t} \\ & + (\chi_t\eta_{\lambda,t}w_t)\cdot\Big[\sigma_\lambda\sqrt{\lambda_t}v_{w\lambda,t} + \Phi_{2,t}W_t v_{wW,t}\Big] \\ & + \lambda_t\Big[V(\lambda_t, w_t(1+\chi_t(\eta_{N,t} - \delta)), W_t(1+\Phi_{4,t})) - v_t\Big]\Big\}.\end{aligned} \tag{IA.25}$$

where we use $v_{x,t}$ and $v_{xy,t}$ to denote the first-order and second-order partial derivatives of v_t with respect to an arbitrary x or y. No expectation sign appears in the final term of the HJB equation that captures the value function jumps after default shock arrival, as the distribution of the jump size associated with N_t is degenerate (equal to δ).

Given log utility, I guess and verify that the value function takes the functional form $v = V(\lambda, w, W) = (\rho + \xi)^{-1}\cdot(\log w + g(\lambda, W))$ for some function g that depends on λ and aggregate wealth W only. Dropping the time subscript for simplicity, the first-order conditions associated with the HJB equations are

$$[c] : c = (\rho + \xi)w \tag{IA.26}$$

$$[\chi] : \omega + \kappa - rP + \lambda\frac{\eta_N - \delta}{1 + \chi(\eta_N - \delta)} = (\chi\eta_z + \sigma_z)\eta_z + \chi\eta_\lambda^2. \tag{IA.27}$$

From (IA.27), the optimal χ does not depend directly on asset manager wealth. Plug in the functional form guess and (IA.27) into (IA.25) and (IA.26), and canceling $\log w$ on both sides, the functional form guess is verified as both sides of the PDE do not directly depend on w. Aggregation implies that χ is also the aggregate asset manager normalized position, X/W. The aggregate equivalent of (IA.24) is

$$\frac{dW_t}{W_t} = (r-\rho+\chi_t(\omega_t+\kappa-rP_t))\mathrm{d}t + \xi\Big(\frac{W}{W_t}-1\Big)\mathrm{d}t + \chi_t\eta_{\lambda,t}\mathrm{d}B_{\lambda,t} + (\chi_t\eta_{z,t}+\sigma_z)\mathrm{d}B_{z,t} + \chi_t(\eta_{N,t}-\delta)\mathrm{d}N_t. \tag{IA.28}$$

Given the conjecture for the law of motion of aggregate wealth W_t in (13), as we are looking for a Markov equilibrium $P(\lambda, W)$, we can apply Itô's lemma for jump-diffusions to obtain

$$\begin{aligned}\mathrm{d}P_t =& \Big[P_{\lambda,t}[\kappa_\lambda(\overline{\lambda}-\lambda_t)] + P_{W,t}\Phi_{1,t}W_t + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2+\Phi_{3,t}^2)W_t^2 + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t}\Big]\mathrm{d}t \\ &+ [P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t} + P_{W,t}\Phi_{2,t}W_t]\mathrm{d}B_{\lambda,t} + P_{W,t}\Phi_{3,t}W_t\mathrm{d}B_{z,t} + [P(\lambda, W(1+\Phi_{4,t})) - P(\lambda,W)]\mathrm{d}N_t.\end{aligned}$$

Matching coefficient with the conjectured form for P_t (12), we have

$$\omega_t = P_{\lambda,t}[\kappa_\lambda(\overline{\lambda}-\lambda_t)] + P_{W,t}\Phi_{1,t}W_t + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2+\Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t} \tag{IA.29}$$

$$\eta_{\lambda,t} = P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t} + P_{W,t}\Phi_{2,t}W_t \tag{IA.30}$$

$$\eta_{z,t} = P_W\Phi_{3,t}W_t \tag{IA.31}$$

$$\eta_{N,t} = P(\lambda, W(1+\Phi_{4,t})) - P(\lambda, W). \tag{IA.32}$$

Matching coefficients between (13) and (IA.28), I get

$$\Phi_{1,t} = r-(\rho+\xi)+\chi_t(\omega_t+\kappa-rP_t)+\xi\frac{W}{W_t} \tag{IA.33}$$

$$\Phi_{2,t} = \chi_t\eta_{\lambda,t} \tag{IA.34}$$

$$\Phi_{3,t} = \chi_t\eta_{z,t}+\sigma_z \tag{IA.35}$$

$$\Phi_{4,t} = \chi_t(\eta_{N,t}-\delta). \tag{IA.36}$$

Combining (IA.29)–(IA.32) and (IA.33)–(IA.36), the Φ functions can be rewritten as

$$\begin{aligned}\Phi_{1,t} =& r-(\rho+\xi)+\xi\frac{W}{W_t}+\chi(\kappa-rP_t) \\ &+\chi\cdot\Big[P_{\lambda,t}[\kappa_\lambda(\overline{\lambda}-\lambda_t)] + P_{W,t}\Phi_{1,t}W_t + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2+\Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t}\Big]\end{aligned} \tag{IA.37}$$

$$\Phi_{2,t} = \chi_t[P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t} + P_{W,t}\Phi_{2,t}W_t] \tag{IA.38}$$

$$\Phi_{3,t} = \chi_t P_W \Phi_{3,t} W_t + \sigma_z \tag{IA.39}$$

$$\Phi_{4,t} = \chi_t[P(\lambda, W(1+\Phi_{4,t})) - P(\lambda, W) - \delta] \tag{IA.40}$$

and $\Phi_{1,t}, \Phi_{2,t}, \Phi_{3,t}$ can be further simplified to

$$\Phi_{1,t} = \frac{r - (\rho+\xi) + \xi\frac{W}{W_t} + \chi(\kappa - rP_t) + \chi\cdot\left[P_{\lambda,t}[\kappa_\lambda(\overline{\lambda} - \lambda_t)] + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2 + \Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t}\right]}{1 - \chi_t P_{W,t}W_t} \tag{IA.41}$$

$$\Phi_{2,t} = \frac{\chi_t P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t}}{1 - \chi_t P_{W,t}W_t} \tag{IA.42}$$

$$\Phi_{3,t} = \frac{\sigma_z}{1 - \chi_t P_{W,t}W_t}. \tag{IA.43}$$

Proof of Proposition 1 Combine the first-order condition (IA.27) with (IA.30), (IA.31), (IA.34), (IA.35), (IA.36), we have

$$rP = \omega + \kappa + \lambda\frac{\Phi_4}{\chi(1+\Phi_4)} - \Phi_2\cdot(P_\lambda\sigma_\lambda\sqrt{\lambda} + P_W\Phi_2 W) - \Phi_3\cdot P_W\Phi_3 W,$$

and the PDE (IA.20) follows from (IA.29) and rearranging terms.

I.B.2 Asset demand of long-term investors: An optimizing foundation

This section sketches a stylized optimization problem to motivate the long-term investors' demand structure (11) and the interpretation of the counterfactual exercise discussed in Section 6.

Risk-neutral return I first introduce the risk-neutral excess return process $\mathrm{d}Q_{F,t}$ associated with the fundamental value F_t of the risky perpetuity, following Xiong (2001). This will be useful to motivate the credit constraint (IA.47). $\mathrm{d}Q_{F,t}$ is given by the hypothetical mark-to-market profits of holding one unit of the risky perpetuity fully levered, collecting coupon payment each period subject to face value haircut:

$$\mathrm{d}Q_{F,t} = \mathrm{d}F_t + (\kappa\mathrm{d}t - \delta\lambda_t\mathrm{d}t) - rF_t\mathrm{d}t. \tag{IA.44}$$

Abstracting from the reflecting boundary, the property of the CIR process (7) and the definition of F_t (8) implies that F_t is given by

$$F_t = \frac{\kappa - \delta\overline{\lambda}}{r} + \frac{\delta(\overline{\lambda} - \lambda_t)}{r + \kappa_\lambda},$$

so that $\mathrm{d}Q_{F,t}$ has no drift term:

$$\begin{aligned} \mathrm{d}Q_{F,t} &= -\frac{\delta}{r+\kappa_\lambda}\mathrm{d}\lambda_t + \kappa \mathrm{d}t - \delta\lambda_t \mathrm{d}t - \Big(\kappa - \delta\overline{\lambda} + \frac{\delta r}{r+\kappa_\lambda}(\overline{\lambda} - \lambda_t)\Big)\mathrm{d}t \\ &= -\frac{\delta}{r+\kappa_\lambda}[\kappa_\lambda(\overline{\lambda} - \lambda_t)\mathrm{d}t + \sigma_\lambda\sqrt{\lambda_t}\mathrm{d}B_{\lambda,t}] + \delta(\overline{\lambda} - \lambda)\mathrm{d}t - \frac{\delta r}{r+\kappa_\lambda}(\overline{\lambda} - \lambda_t)\mathrm{d}t \\ &= -\frac{\delta\sigma_\lambda}{r+\kappa_\lambda}\sqrt{\lambda_t}\mathrm{d}B_{\lambda,t}. \end{aligned} \tag{IA.45}$$

The variance of the excess return process, denoted $\sigma^2_{F,t}$, is proportional to λ_t, the default intensity.

Setup Consider an atomistic agent out of a unit mass of identical long-term investors. The agent, indexed by i, chooses its position of the risky perpetuity each period by solving a static problem, given each period's realization of default risk, λ_t:

$$\max_{Z_{i,t}} V_{i,t} = (F(\lambda_t) - P_t)Z_{i,t} - \mathbb{E}_t[c(\lambda_t)\mathrm{d}N_t]P_t Z_{i,t} \tag{IA.46}$$

$$\text{s.t.} V_{i,t} \geq \underbrace{\Gamma|Z_{i,t}|}_{\text{Divertible portion}} \times \underbrace{|P_t Z_{i,t}|}_{\text{Value of claims}}. \tag{IA.47}$$

(IA.46) is the value function of the long-term investor, who compares the price of the risky perpetuity against the *fundamental* value of the bond obtained by purchasing the bond at time t and holding the bond forever (see (8)). In addition, the long-term investor needs to set provision against default, occurring in the next instant with probability λ_t. For each dollar of the market value of risky asset holdings, default provisions cost $c(\lambda_t)$. I assume $c(\cdot)$ is sufficiently small to guarantee $V_{i,t} \geq 0$.

I assume that long-term investors are subject to a credit constraint in the form of (IA.47). The constraint is motivated by a contracting problem, in which the long-term investor each period can divert a fraction of the risky asset position and sell them at market value. I assume that the ultimate investors can only recover a portion $1 - \Gamma|Z_t|$

of their position $|Z_t|$. Ultimate investors rationally anticipate this incentive for diversion and imposes the constraint (IA.47).

Similar to Gabaix and Maggiori (2015), I assume Γ takes the following form:

$$\Gamma = \gamma f(\sigma_{F,t}^2) \tag{IA.48}$$

for some positive function f satisfying $f'(\cdot) \geq 0$ and $\gamma > 0$.[42] As in Gabaix and Maggiori (2015), risk taking of the investors are limited by both the size of the position and by the expected riskiness measured by the variance. The relevant variance for these investors is $\sigma_{F,t}^2$, the variance associated with the risk-neutral excess return. The constraint becomes looser when $\sigma_{F,t}^2$ decreases. By (IA.45), $\sigma_{F,t}^2 \propto \lambda_t$, so we can also write Γ explicitly as a function of the default intensity, $\Gamma(\lambda_t)$.

Discussion The problem of the long-term investors is motivated by the discussion in the main text on the institutional features of banks and ICPFs. Due to the structure of its liability (stable retail deposits with long duration) and regulatory treatment of assets (held-to-maturity accounting), long-term investors care about risk through its relationship with the long-term, stable income flow generated by their asset holdings. This is captured by the dependence of the optimization problem on the deviation of the current price from the fundamental value of the asset. The focus on the fundamental value of the asset also suggests that long-term investors can ride out transient fluctuations in the market value of the risky perpetuity (especially those driven by non-fundamental shocks) and provide liquidity when asset prices drop (Hanson et al., 2015; Chodorow-Reich et al., 2020).[43]

Providing liquidity is not without cost, however. Long-term investors may be particularly sensitive to the prospect of default, as the associated book equity loss from default tightens the regulatory constraint based on book values, and needs to be compensated by costly equity raising (Hanson et al., 2015; Morelli et al., 2022). In the sovereign debt context, costly equity financing results in the incentive of banks to rely on maturity extension for restructuring and the disincentive to classify investment to emerging markets as impaired (Guttentag and Herring, 1989; Rieffel, 2003; Dvorkin et al., 2021). The default provision term in (IA.46) reflects these considerations.

[42]In Gabaix and Maggiori (2015), $\Gamma = \gamma(\sigma_{e,t}^2)^\alpha$ where $\sigma_{e,t}^2$ is the variance of the next-period exchange rate.

[43]As an alternative motivation for (11), (IA.46) reflects the potential inability of long-term investors with maxmin preferences to adjust portfolio every period (Xiong, 2001).

The credit constraint (IA.47) represents regulatory or risk-manager concern that limit the risky asset position of long-term investors. For instance, Basel III and Solvency II compute capital requirement based on the riskiness of the underlying holding, captured by the volatility proportional to λ_t. The function f in (IA.48) can be defined flexibly to reflect varying degrees of constraints that affect the relationship between demand elasticity and default risk. A convex f is consistent with a Value-at-Risk constraint (Danielsson et al., 2012). A linear f replicates the usual demand slope associated with a mean-variance investor. The case $f' = 0$ (a constant Γ) corresponds to the assumption of a constant demand slope typically associated with preferred-habitat investors (Vayanos and Vila, 2021; Costain et al., 2022). This case is analyzed in the "no selection" counterfactual scenario in Section 6.

Asset demand To arrive at (11), I observe that risk-neutrality of the long-term investor implies (IA.47) always binds. As a result, optimal risky asset position for each long-term investor is given by

$$Z_{i,t} = \frac{1}{\Gamma(\lambda_t)} \cdot \frac{F(\lambda_t) - P_t}{P_t} - \frac{c(\lambda_t)}{\Gamma(\lambda_t)} \cdot \lambda_t. \tag{IA.49}$$

(11) is obtained by making the approximation $\log(1+x) \approx x$ on $x = (F-P)/P$, setting $\Gamma(\lambda_t) = \alpha^{-1} \cdot \exp(\delta\lambda_t)$, $c(\lambda_t) = \theta_1 \Gamma(\lambda_t)$, and aggregating across the entire unit mass of long-term investors.

Mapping to the counterfactuals Two counterfactual scenarios analyzed in Section 6 map directly to the optimizing foundation in this section. Long-term investors exhibit an explicit aversion to default risk due to costly equity issuance and risk-based credit constraint. Removing the aversion of these investors through each of the two channels amounts to setting $c(\lambda) = 0$ or $\Gamma(\lambda)$ to a scalar. The model assumes that all long-term investors are identical. Scaling down the slope coefficients with respect to $\log(P_t/F(\lambda_t))$ and λ_t by an equal proportion corresponds to reducing the mass of long-term investors.

Scenario "larger supply" (see Table 5) can also be mapped to this framework under a different interpretation. Slightly modifying the problem (IA.46) to incorporate an additional term:

$$\max_{Z_{i,t}} V_{i,t} = (F(\lambda_t) - P_t)Z_{i,t} - \theta(\lambda_t)P_t Z_{i,t} - \mathbb{E}_t[c(\lambda_t)\mathrm{d}N_t]P_t Z_{i,t}$$

where $\theta(\lambda_t) > 0$. Intuitively, long-term investors are not natural holders of the risky perpetuity, as the investors would only get one unit of the risky asset per $1 + \theta(\lambda)$ units bought. Assume $\theta(\lambda)/\Gamma(\lambda) = s$ for some scalar $s < 0$, a more negative s correspond to a strong overall aversion to risky assets.

I.B.3 Details on calibration

Parameters externally set/estimated I calibrate the default risk process guided by the literature. Default in my model should be interpreted as including both preemptive and post-default restructuring episodes that may involve face value haircuts to the investors. Among the parameters, the long-run average default intensity is set at 0.038, higher than the 2 percent annual outright default probability typically used in the literature, but consistent with the estimates of Arteta and Hale (2008) incorporating restructuring events.[44] The bond supply parameter s is set to 0.49, matching an average value of 49% GDP from IMF Global Debt Database for central governments across countries in my empirical sample.

Asset managers in my model are analogous to investment funds in my empirical analysis. I set the exogenous liquidation intensity ξ at 4.1% per year. This number is within the range of the average life span of global bond funds (23–25 years, see Maqui et al. (2019)).[45] I set the standard deviation of wealth shock ($\mathrm{d}B_{z,t}$) to 0.214, matching a monthly flow volatility of 6.18% AUM in my Morningstar data for mutual funds.[46]

More on setting δ In my model, the parameter δ can be interpreted as the fraction of debt permanently not paying off. Equation (18) summarizes the relationship between

[44] As the default risk process is reflecting at both boundaries, I set the value of $\lambda_{\min}$ and $\lambda_{\max}$ to 0.005 and 0.25, respectively. The upper bound is a large number compared to the standard deviation implied by the stationary distribution. I check that the boundary values do not affect my results quantitatively.

[45] I assume that liquidated funds are reborn with an exogenous initial wealth level of 0.005.

[46] Rakowski (2010) estimates a daily fund flow volatility of 4% TNA. My assumption that the shock processes are mutually independent attributes the variations in $\mathrm{d}B_{z,t}$ to fluctuations not directly related to local fundamentals. Sarno et al. (2016) show that more than 80% of portfolio flow variation is driven by external factors. I therefore use the overall variation of mutual fund flow to calibrate σ_z.

δ, coupon rate, haircut, and long-run average default probability. The inclusion of a haircut fraction is due to the fact that part of the debt in arrear will be restructured rather than permanently lost. I calibrate δ based on the methodology of Arellano et al. (2023) (henceforth AMR) in accounting for partial defaults in emerging market sovereign debt. In particular, I follow AMR and use data on arrears and external debt service from World Bank International Debt Statistics. The data covers 37 countries, with a maximum sample span from 1970 to 2021.[47] For these countries, I follow AMR and compute the fraction of long-term debt (including principals and interest payments) in default in a particular year, conditional on having arrears:[48]

$$\text{Partial default}_{it} = \frac{\text{Principal and interest in arrear}_{it}}{\text{Principal and interest in arrear}_{it} + \text{Total debt service}_{it}}.$$

For haircuts due to restructuring, I use the 37% estimate from Meyer et al. (2022), based on a sample of 23 recent bond restructurings since 1998. As a comparison, average haircuts including bank debt default is 39% (Meyer et al., 2022); average haircuts using a longer historical sample and weighted by amount restructured is 38%. Cruces and Trebesch (2013) also estimate a 38% haircut.

Parameters internally calibrated The remaining five parameters on the default risk process and long-term investors' demand are estimated to match five moments between simulated and actual data. The parameters include the persistence and variance parameters of the default risk process, κ_λ and σ_λ, the default risk aversion parameter θ_1 and demand progressivity parameter δ_λ, as well as the overall demand slope α of long-term investors. I set the parameter values to match the following moments: a foreign mutual fund share of 17% (estimated from a combination of CPIS and ECB SHS data), an average bond yield spread of 3.6%, and an average yield volatility of 0.6% (both are based on EMBI Global data from 2013 to 2022). The model matches a correlation between default risk and bond yield of 0.4 to reflect the moderate comovement between country

[47] The countries include Albania, Argentina, Armenia, Azerbaijan, Bulgaria, Bosnia and Herzegovina, Belarus, Brazil, China, Colombia, Costa Rica, Dominican Republic, Egypt, Georgia, Indonesia, India, Jamaica, Kazakhstan, Lebanon, Sri Lanka, Morocco, Moldova, Mexico, North Macedonia, Montenegro, Pakistan, Peru, Philippines, Russian Federation, Serbia, Thailand, Tajikistan, Turkey, Ukraine, Uzbekistan, Vietnam, and South Africa.

[48] The corresponding tickers are `DT.IXA.DLXF.CD` (interest in arrear), `DT.AXA.DLXF.CD` (principal in arrear), and `DT.TDS.DPPG.CD` (debt service). Note that the debt concept here refers to all public and publically-guaranteed debt (PPG).

fundamentals and sovereign spreads observed in the data (Aguiar et al., 2016).[49]

More on the yield elasticity target I target a weighted average elasticity of 21 in my baseline calibration. This number is obtained step-by-step, using data on holding of Slovak long-term government securities by sector as of 2021Q2 (ECB SHSS), my estimate of foreign long-term investors' demand elasticity (Table 2), and the estimates by Fang et al. (2022) using a global demand system.[50]

1. As a first step, I combine SHSS data and the Fang et al. (2022) estimates to get the demand elasticity of domestic investors. I ignore central bank holdings throughout. As of 2021Q2, out of all domestic holding, banks account for 81% while non-banks account for 19%. ICPFs account for the bulk of domestic non-bank holding. Given a demand elasticity of 10.46 for domestic banks and 14.89 of domestic non-banks estimated by Fang et al. (2022) for an average emerging market economy, I calculate the domestic weighted average yield elasticity at 11.3.

2. Using a similar approach, I calculate a foreign weighted average elasticity of 33.0. In the data, foreign banks account for 39% of the private foreign holdings of Slovak government bond. Demand elasticity estimates of Fang et al. (2022) are 29.05 for banks and 35.45 for non-banks, respectively. As a result, domestic yield elasticity of demand is roughly one-third of its foreign counterpart.[51]

3. The final step is to compute a weighted average demand elasticity for the long-term investors in my model. Using my estimate of foreign yield elasticity of demand at 29.4, the domestic demand elasticity is around 10 when scaled by the result from Step 2. Of total bank and ICPF holding, domestic institutions account for 43%. The weighted average demand elasticity is 21.08.

To get the model counterpart to the demand (semi-)elasticity, I estimate (19) on the simulated data. The target should match $100 \times \beta_0$.

[49]The yield of the risky perpetuity, y, is defined as the constant interest rate associated with a perpetual bond that promises a coupon κ and is priced at P, such that $P_t = \int_t^{\infty} e^{-yt}\kappa dt$. The yield spread is obtained by subtracting the risk-free rate r from y.

[50]The SHSS data, available since 2021, can be found at `https://sdw.ecb.europa.eu/browse.do?node=9691594`. In particular, I use face value (`F`) of total (`U2`) and domestic holding (`SK`) of long-term debt (`L`) issued by the general government sector.

[51]The underlying assumption is that domestic and foreign holding have the same average residual maturity.

I.B.4 Computation algorithm

The equilibrium of my quantitative model is a solution to the fully nonlinear partial differential equation (IA.50). I extend the finite difference scheme to solve this PDE.

The entire algorithm consists of four main blocks:

Transformation The state variable W takes value in the interval $[0, \infty)$. Therefore, I follow Xiong (2001) to make the following monotonic transformation. Define $Y = Y(W) = \frac{W-\vartheta}{W+\vartheta}$, where ϑ is a scaling parameter (set to 1.5 in my computation). Then $Y(0) = -1, \lim_{W\to\infty} Y(W) = 1$, so that Y resides in the interval $[-1, 1)$. Accordingly, we have $W = \vartheta\frac{1+Y}{1-Y}$ and

$$\frac{\partial}{\partial W} = \frac{(1-Y)^2}{2\vartheta}\frac{\partial}{\partial Y} \qquad \frac{\partial^2}{\partial^2 W} = \frac{(1-Y)^4}{4\vartheta^2}\frac{\partial^2}{\partial^2 Y} - \frac{(1-Y)^3}{2\vartheta}\frac{\partial}{\partial Y},$$

and

$$\frac{\partial}{\partial W}\cdot W = \frac{(1+Y)(1-Y)}{2}\cdot\frac{\partial}{\partial Y}.$$

The transformed partial differential equation is

$$\begin{aligned} rP =& \kappa + \lambda\cdot\frac{\Phi_4}{\chi(1+\Phi_4)} + P_\lambda[\kappa_\lambda(\overline{\lambda}-\lambda) - \sigma_\lambda\sqrt{\lambda}\Phi_2] + \frac{1}{2}(1+Y)(1-Y)P_Y\Big[\Phi_1 - \Big(\frac{1+Y}{2}+1\Big)(\Phi_2^2+\Phi_3^2)\Big] \\ &+ \frac{1}{2}P_{\lambda\lambda}\sigma_\lambda^2\lambda + \frac{1}{2}(1+Y)(1-Y)P_{\lambda Y}\sigma_\lambda\sqrt{\lambda}\Phi_2 + \frac{1}{2}P_{YY}\Big(\frac{1}{2}(1+Y)(1-Y)\Big)^2(\Phi_2^2+\Phi_3^2). \end{aligned} \tag{IA.50}$$

where

$$\Phi_1 = \frac{r-\rho+\xi\Big(\frac{\overline{W}}{\vartheta\frac{1+Y}{1-Y}}-1\Big) + \chi(\kappa - rP) + \chi\cdot\Big[P_\lambda[\kappa_\lambda(\overline{\lambda}-\lambda)] + \frac{1}{2}P_{\lambda\lambda}\sigma_\lambda^2\lambda + \frac{(1-Y)(1+Y)}{2}P_{\lambda Y}\sqrt{\lambda}\sigma_\lambda\Phi_2 + \frac{1}{2}P_{YY}\cdot\Big(\frac{(1-Y)(1+Y)}{2}\Big)^2(\Phi_2^2+\Phi_3^2)\Big]}{1-\chi\frac{(1+Y)(1-Y)}{2}P_Y}$$

and

$$\Phi_2 = \frac{\chi P_\lambda\sqrt{\lambda}\sigma_\lambda}{1-\chi\frac{(1+Y)(1-Y)}{2}P_Y} \qquad \Phi_3 = \frac{\sigma_z}{1-\chi\frac{(1+Y)(1-Y)}{2}P_Y}$$
$$\Phi_4 = \chi[P(W(Y)\cdot(1+\Phi_4)) - P(W(Y)) - \delta].$$

Initialization Obtaining an appropriate initial guess is crucial for the convergence of my time-iteration (pseudo time-transient) procedure. I initialize my guess $P^{(0)}(\lambda, Y)$ by solving a simplified problem, where the default risk λ is no longer time-varying. In this case, the problem becomes a one-dimensional PDE for each point on the λ-grid. As λ becomes non-stochastic in the simplified problem, $F(\lambda)$ may differ from those in the baseline model. I make sure the initial guess has boundary values $P^{(0)}(\lambda, Y_{\min})$ and $P^{(0)}(\lambda, Y_{\max})$ that correspond to the baseline values, by adjusting the parameter value of coupon rate κ accordingly in the simplified problem.

In the initialization phase, I also compute the fundamental value of the risky perpetuity $F(\lambda)$ for each λ on the grid used to solve the PDE in the next step. The calculation of conditional expectation $\mathbb{E}[\lambda_s \mid \lambda_t = \lambda]$ is complicated by the existence of reflecting barriers for the process (7), as no analytical expressions are available. I calculate the conditional expectation numerically by solving an associated *Kolmogorov backward equation*, explicitly incorporating the boundary conditions. Formally, the *generator* of the CIR process (7) without reflecting barriers is defined as the operator $\mathscr{L}$ that satisfies

$$(\mathscr{L}f)(\lambda) = \kappa_\lambda(\overline{\lambda} - \lambda) \cdot f'(\lambda) + \frac{1}{2}\sigma_\lambda^2 \lambda \cdot f''(\lambda)$$

for a function $f \in C^2(\mathbb{R})$. For Markov processes X_t, the *transition density*, $p(x, t \mid y, s)$, is such that

$$P(X_t \in A \mid X_s = y) = \int_A p(x, t \mid y, s) \mathrm{d}x.$$

The conditional expectation of function $f(X)$, $u(y, s)$, is defined as

$$u(y, s) := \mathbb{E}^{y,s} f(X_t) = \int f(x) p(x, t \mid y, s) \mathrm{d}x.$$

Setting $f(\lambda) = \lambda$, the conditional expectation of CIR process (7) with reflecting barriers further satisfies the backward equation:[52]

$$\partial_t u = \mathscr{L}u, \qquad u(\lambda, 0) = \lambda, \quad \partial_\lambda u \mid_{\lambda \in \{\lambda_{\min}, \lambda_{\max}\}} = 0 \tag{IA.51}$$

which can be solved forward starting from the initial condition $u(\lambda, 0) = \lambda$ using standard finite difference method.

[52] Time goes forward in this "backward equation" because of time-homogeneity of CIR processes. See Holmes-Cerfon (2019) for an overview of incorporating boundary conditions into forward and backward equations.

For each λ, the procedure yields a vector $u(\lambda, s)$ from time 0 to a large truncation point T, where I set $T = 500$. For a large t, the transition density well approximates the stationary distribution. I compute $F(\lambda)$ by discretizing the integral in (8) and splitting the integral into two parts. For $t < T$, I compute the integral using u. For $t \geq T$, I compute the integral using the unconditional expectation based on the stationary distribution.

Solving the nonlinear PDE To solve the PDE (IA.50), I combine the finite-difference method with a time-relaxation algorithm, by adding a pseudo time transient $\partial_t P$ and iterate from the initial guess until convergence. The solution is divided into an outer loop, where given a candidate price function $P^{(n)}$ at iteration n, I compute its associated derivatives and back out other equilibrium quantities, and an inner loop, where given the equilibrium quantities, I solve for a new price function $P^{(n+1)}$. The algorithm stops when $P^{(n+1)}$ is sufficiently close to $P^{(n)}$. More specifically, I declare convergence when $\frac{|P^{(n+1)} - P^{(n)}|}{\Delta t} < 10^{-4}$, where Δt is the time step chosen in the finite difference procedure. In practice, Δt is to the order of 0.05.

For derivatives at the boundaries and corners, I follow Hansen et al. (2018) and fill the entries with the derivatives next to them away from boundaries and corners.

With the derivatives, I update the functions $\Phi_1^{(n+1)}, \Phi_2^{(n+1)}, \Phi_3^{(n+1)}, \Phi_4^{(n+1)}$ using Equations (IA.41), (IA.42), (IA.43) , (IA.40). In particular, for the update of Φ_4, I compute $P(\lambda, W(1 + \Phi_4))$ via linear interpolation for each λ_i with interpolant $W_j(1 + \Phi_{4,i,j}^{(n)})$, i.e., using $\Phi_{4,i,j}$ from the previous iteration.

Simulation The algorithm obtains a solution $P(\lambda, W)$ in the previous step, along with its associated partial derivatives. With these objects, I simulate Brownian and Poisson shocks, use discretization schemes to trace the evolution of the wealth process and the default risk process (starting from some arbitrary initial wealth and default risk), and back out the bond prices. For each simulation n, I choose the length of the series T and a step size $\Delta t = 1/12$ to generate a time grid $\mathbb{T} = \{t_0 = 0, t_1 = 1/12, \ldots, t_i, t_{i+1}, \ldots, T\}$. I drop the first one-fourth of the simulated series as burn-ins. In the counterfactual analyses, I hold the simulated exogenous shocks constant to make sure sampling differences are not driving the differences across specifications. I simulate λ_t using the strong convergence scheme of Alfonsi (2005). I simulate the default process using Çinlar's inversion method (Çinlar, 1975). For the log wealth process, I use the Euler-Maruyama scheme.

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