The fickle and the stable:

Global Financial Cycle transmission via heterogeneous investors

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Abstract

I show that accounting for foreign investor base differences helps explain the heterogeneous influence of the Global Financial Cycle on sovereign borrowing of emerging market economies. Using security-level data and a quantitative model featuring heterogeneous investors, stochastic debt default risk and global financial shocks, I investigate the two-way interaction between asset attributes and investor composition. Facing global financial tightening, sovereign bonds with a higher institutional ownership by foreign investment funds suffer a larger price drop. The willingness for long-term investors, including banks, insurance companies and pension funds, to act as shock absorbers, however, is limited by their higher propensities to hold safer, home-currency-denominated bonds. Leveraging my estimate of long-term investors' demand elasticity, the model replicates the empirical relationship between foreign investor mix and sovereign yield spread sensitivity to global risk factors. Policy measures that encourage the participation of long-term foreign investors or limit the risk exposure of investment funds could substantially reduce the volatility of emerging markets' borrowing cost.

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 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 sensitivity to shifts in global risk factors is higher, when the share of its external liabilities or its government debt held by foreign non-banks increases relative to foreign banks. Among foreign holding, the higher is the share of investment funds, including mutual funds and exchange-traded funds (ETFs), the stronger is the sensitivity. Canonical frameworks with a single representative lender are unable to capture these salient facts and to be used to explore the implication of these correlations. Meanwhile, the role of foreign investor composition in the transmission of the Global Financial Cycle could be shaped by the interaction between investors' heterogeneous propensities to amplify the impact of global risk factors, and the fundamental attributes of debtor countries' liabilities that attract a particular type of investors. 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, Pan, Pedersen and Singleton (2011) show that the single principal component of emerging market credit default swap spreads is closely related to indicators of global risk factors. Early contribution on the influence of global variables also includes Calvo, Leiderman and Reinhart (1996), Mauro, Sussman and Yafeh (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, banks, insurers and pension funds remain more likely to hold home currency (Euro-denominated) assets. Insurers and pension funds additionally tilt their emerging market portfolio towards securities with a higher credit quality. Second, conditional on bond and issuer×time fixed effects that absorb the effect of investors' portfolio preferences towards asset characteristics on bond yields, emerging market sovereign bonds' 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 ex ante, and decreases with the ex ante share held by banks, insurers and pension funds. The distinct role played by different types of investors is also evident on the quantity side. 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 a key statistic governing shock sensitivity. For identification, I construct instrumental variables based on capital flow in and out of emerging market-focused mutual funds that moves prices and shifts the residual supply curve faced by long-term investors. The first instrument projects surprise fund flow onto each bond using past portfolio weights, in the spirit of Lou (2012) and van der Beck (2022). The second instrument exploits granularity of fund size distribution and extract idiosyncratic flow in and out of large mutual funds in the spirit of Gabaix and Koijen (2023). Using both approaches, I find a one percentage point increase in the annualized yield of Euro-denominated sovereign bonds expands the demand of long-term investors by 29 percent. I also find evidence that the demand for Euro-denominated bonds is more elastic than that for bonds denominated in other currencies, reflecting the connection between favorable asset characteristics and shock absorption capacities of long-term investors.

Informed by my empirical observations, I construct a quantitative model of sovereign debt market featuring heterogeneous investors, stochastic debt default risk and global financial shocks to reproduce the empirical patterns and analyze the impact of the 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 haircut. Motivated by a large empirical literature documenting the close relationship between open-ended investment fund flow and global risk (Jotikasthira, Lundblad and Ramadorai, 2012; Chari, Dilts Stedman and Lundblad, 2020, 2022), global financial tightening in my model induces capital redemption from investment funds, erodes the risk-bearing capacity, and triggers a drop in bond prices. The endogenous interaction between asset liquidation and wealth revaluation further amplifies the adverse impact of a tightening Global Financial Cycle. Meanwhile, consistent with data, long-term investors have stable, downward sloping asset demand that limits the exposure to default risk.[2] The elasticity of long-term investors' asset demand is a crucial determinant of the equilibrium sensitivity of bond prices to global risk factors. I calibrate the demand of the long-term investors leveraging my empirical estimates, and develop a solution algorithm that tackles multiple state variables, non-trivial boundary conditions and jump risk in continuous time.

The model matches key moments related to emerging market sovereign borrowing and replicates empirical patterns on the interaction between Global Financial Cycle and investor composition. Exogenous wealth fluctuations of asset managers account for more than 60 percent of the variation in the price of the risky bond, consistent with Longstaff, Pan, Pedersen and Singleton's (2011) estimate of the global factor's contribution to the comovement of emerging market sovereign spreads. The model generates a strong relationship between investor composition and sovereign spread sensitivity to wealth shocks, quantitatively in line with my empirical estimates. When the share of the risky perpetuity held by investment funds expands by 10% relative to the average, the sensitivity of bond spread to investment funds wealth shocks increases by 19%.

I use model-based counterfactual analysis to disentangle the two-way mechanism involving asset attributes and investor mix and derive quantitative implication of alternative configurations of investor composition on sovereign borrowing. My model suggests that recently implemented financial regulatory framework, such as Solvency II, by making long-term investors more accommodative to fundamental risk exposure, could reduce the volatility of the sovereign spread by 15% and limit the endogenous amplification of the Global Financial Cycle particularly when default risk is high. Policies governing the risk exposure of investment funds, such as converting open-ended funds to close-ended funds by eliminating risk-sensitive capital redemption, or levying a capital inflow tax on risky asset holding, are also effective in reducing the volatility of sovereign borrowing cost. Practically, my analysis highlights the value of a diverse investor base, and shows that the foreign investor composition could be an important metric to help assess emerging markets' resilience against adverse global financial shocks.

[2]The optimizing foundation of long-term investors, sketched in Appendix F, 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 first 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; Sauzet, 2023) and capital flow (Davis and van Wincoop, 2022).[3] Bai, Kehoe, Lopez and Perri (2022) jointly study global and local prices of risk and finds that the influence of Global Financial Cycle on emerging market sovereign spread is time-varying. Akıncı, Kalemli-Özcan and Queraltó (2022), Gilchrist, Wei, Yue and Zakrajšek (2022) and Morelli, Ottonello and Perez (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 market and habitat investors (Vayanos and Vila, 2021). Echoing Xiong (2001) and Kekre, Lenel and Mainardi (2023), my model highlights endogenous wealth revaluation of financial intermediaries as an important shock amplification channel.

Second, my paper speaks to the empirical literature, starting from the seminal contribution of Calvo, Leiderman and Reinhart (1993), that examines the relationship between emerging market sovereign risk and global financial risk, and the associated transmission channels.[5] Longstaff, Pan, Pedersen and Singleton (2011) and Tourre (2017) show that a single global factor can account for a substantial fraction of variation in emerging market sovereign spread. di Giovanni, Kalemli-Özcan, Ulu and Baskaya (2022) provide direct causal evidence on global financial shock transmission to Turkey's borrowing cost. I place these empirical findings in the intermediary asset pricing literature and build a model with realistic asset demand structure and shock transmission mechanism informed by novel micro datasets and use the model to conduct counterfactual analyses.[6]

My paper is also closely related to the emerging literature dissecting the implication

[3]At a broader level, the literature studies the equilibrium asset pricing implication of investor heterogeneity in various context. Recent theoretical contribution includes Pavlova and Rigobon (2008), Chabakauri (2013), Coimbra (2020), Coimbra and Rey (2020) and Kargar (2021). Cella, Ellul and Giannetti (2013) empirically demonstrate that investors with a shorter trading horizon amplify the impact of market-wide shocks. 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 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, Wei, Yue and Zakrajšek (2022) for recent empirical attempts to identify this linkage via VAR or local projection.

[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, Koulischer, Nguyen and Yogo, 2021, among others, further reviewed in Section 3.). My innovation is to incorporate the demand elasticity estimate into the calibration of a fully-specified model to perform quantitative analysis.

of investor base heterogeneity in a global context. Coppola (2022) analyzes investor base of corporate bond in advanced economies and shows that corporate bonds held by insurance companies could fend off adverse financial shocks. Converse, Levy-Yeyati and Williams (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, Hardy and Lewis (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. My paper focuses on a more detailed investor split – investment funds prone to risk-sensitive redemption, and banks, insurers and pension funds with a stable demand structure – relevant for the understanding of global financial shock transmission. Faia, Salomao and Veghazy (2022) and Bergant, Milesi-Ferretti and Schmitz (2023) also consider a variety of investor types in their security-level analysis. Bergant, Milesi-Ferretti and Schmitz (2023) show that the "home-currency bias" of Euro Area investors applies to emerging market securities, and investment funds retrench from emerging markets when global financial stress is high. Relative to these papers, I identify the demand equation of long-term investors in the data 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. Section 2 also reports the results from my empirical analysis using micro data and discuss potential economic mechanisms. Section 3 provides estimates of the demand elasticity of long-term investors. I introduce the quantitative model in Section 4 and reports my counterfactual exercises in Section 5. Section 6 concludes.

[7]In the emerging market context, numerous contribution 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, Schmukler and Williams (2017); Ng, Shim and Vidal Pastor (2019); Arslanalp, Drakopoulos, Goel and Koepke (2020); Chari, Dilts Stedman and Lundblad (2020, 2022); Kaufmann (2023); Bush, Cañon and Gray (2021); Lewrick and Claessens (2021). Chari (2023) and Goldberg (2023) are two recent overviews on the global footprint of non-bank financial institutions. Forbes, Friedrich and Reinhardt (2023) analyze the role of non-bank financial institutions in driving the dynamics of CDS spread during COVID-19. For the role of non-banks in the syndicated loan market, see Aldasoro, Doerr and Zhou (2023) and Fleckenstein, Gopal, Gutierrez and Hillenbrand (2023).

[8]Cerutti, Claessens and Puy (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. Moro and Schiavone (2022) separate mutual funds into global, regional, retail, and institutional funds. My analysis of the characteristics of investors' portfolio holding echoes the literature on home currency bias (Maggiori, Neiman and Schreger, 2020; Boermans and Burger, 2023) that belong to the growing literature using granular security holding statistics to study international capital allocation (Boermans and Vermeulen, 2020; Beck, Coppola, Lewis, Maggiori, Schmitz and Schreger, 2023).

2 Investor base and emerging market sensitivity to global risk: Aggregate and micro evidence

2.1 Setting the stage: Macro-level motivation

My analysis is motivated by the following cross-country pattern from aggregate data spanning 2004 to 2019: sovereign yield spread of emerging markets is more sensitive to shifts in global risk appetite when the share of foreign *non-bank* investors is high. For each major emerging market economy included in Arslanalp and Tsuda's (2014) sovereign bond investor base dataset, I calculate its sovereign risk-global risk β, 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, 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 implied volatility of 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.Calculated from monthly data, the spread sensitivity captures the high-frequency comovement between secondary-market prices of emerging market sovereign debt and global financial condition. It is nevertheless a macro-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 face more frequent need for debt rollover (Broner, Lorenzoni and Schmukler, 2013).[10]

Emerging market economies are differentially exposed to the Global Financial Cycle, as the estimated country-specific β_i indicates.[11] Both panels of Figure 1 plot the esti-

[9]See Kalemli-Özcan (2019), for instance. In Appendix B.1, I show that the pattern remains robust when I use alternative proxies for global risk. I also show that the pattern remains robust when I extend the sample to small emerging and frontier economies included in the JPMorgan EMBI+ index. Appendix B further shows that the relationship is robust after controlling for country characteristics.

[10]Appendix G provide further evidence to support the usage of secondary market prices to proxy for potential borrowing cost facing emerging market governments. Using disclosure of bond auction results from Indonesia, I show that investor types in the primary market resemble those in my analysis. I also show that yields from re-opening auctions closely track secondary market prices of the same bond the day before the auction.

[11]The coefficient estimates and standard errors are reported in Table B1.

mated sensitivity of sovereign yield spread 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 (China), the estimated sensitivity differs by 13.4 times. Notably, country risk cannot fully explain the ranking of the sensitivity. Countries with similar credit standing, such as Indonesia and Egypt, differ widely in their estimated βs.

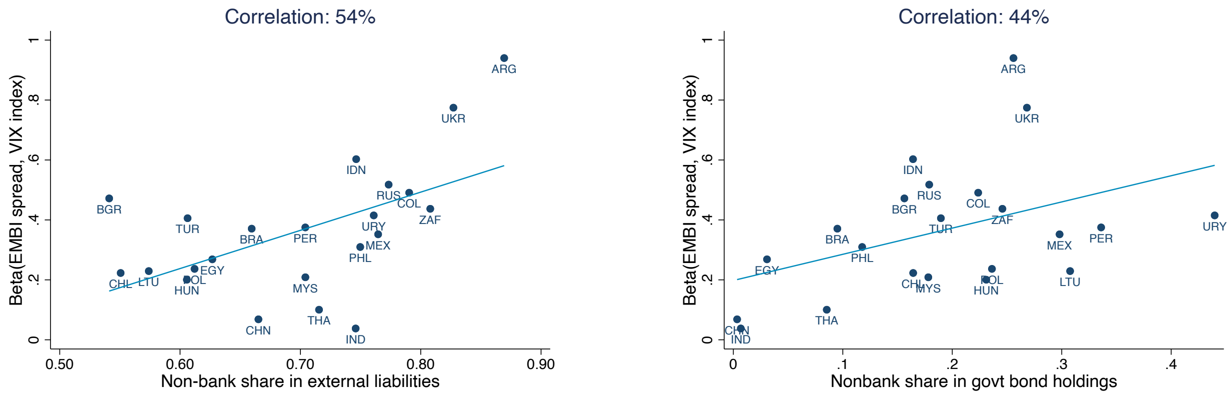
Figure 1 shows that sovereign yield spread sensitivity to global risk factors is strongly correlated with foreign investor composition, measured in various ways. Panel (a) plots the β coefficients (y-axis) against foreign *non-banks'* holding of total external liabilities of each country, obtained from subtracting total cross-border bank claims reported in the BIS Locational Banking Statistics from Lane and Milesi-Ferretti's (2017) international investment position.[12] Panel (b) focuses on the sovereign bond market, using the average market share of foreign *non-banks* reported by Arslanalp and Tsuda (2014). In both cases, the higher is the share held by foreign non-banks, the larger is the β coefficient.[13]

In the time-series dimension, I also find a close relationship between foreign investor composition and the dynamics of sovereign yield spread and credit default swap (CDS) spread after shocks to global risk factors. Figure B5 in Appendix B presents impulse response functions from a set of local projection exercises (Jordà, 2005) and show that an above-median foreign non-bank share in sovereign debt outstanding is associated with higher sensitivity to shifts in the global risk factor, and the effect remains persistent months after shocks occur.

Foreign "non-banks" refer to a diverse set of players across the spectrum of financial intermediaries. Insurance companies and pension funds are natural long-term investors, whose capital structure featuring stable, long-maturity liabilities shares similarly with banks, and is distinct from open-ended investment funds subject to volatile capital redemption. In Appendix B, I report two additional sets of evidence that motivate my subsequent separation of foreign investors into two categories: long-term investors (including banks, insurers and pension funds) and investment funds. First, IMF's Coordinated Portfolio Investment Survey (CPIS) provides data on bilateral cross-border portfolio position for major international investors, with detailed investor sector breakdown since 2013. Using the dataset and the nationality-based restatement provided by Coppola, Maggiori, Neiman and Schreger (2021), I show in Figure B1 in Appendix B.1

[12] For each country, the foreign investor composition is an average measure over 2004–2019. More details on the construction of foreign investor composition can be found in Appendix B.1.

[13] Country characteristics such as credit risk and debt burden do not affect the statistically significant relationship between foreign investor composition and sensitivity to global financial shocks, as Table B2 demonstrates through cross-country regressions.



(a) Foreign non-bank share in external liabilities

(b) Foreign non-bank share in total sovereign debt outstanding

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

Source: Arslanalp and Tsuda (2014); Lane and Milesi-Ferretti (2017), BIS Locational Banking Statistics, 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 spread (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. In Panel (b), the x-axis corresponds to foreign non-bank's share in total government bond outstanding averaged over the same period. Appendix A.2 contains more information on the construction of the data points.

that a stronger presence of foreign *investment funds* relative to other foreign investors corresponds to higher sensitivity of sovereign spread to changes in the VIX index. Based on country-level security holding by Euro Area institutions and bank-level sovereign exposure provided by the European Banking Authority, Appendix B.2 shows that banks, insurers and pension funds have more stable emerging market sovereign portfolios compared to investment funds, and banks designate nearly half of their exposure to emerging market sovereigns at amortised costs, indicating the intention to hold the underlying securities to maturity.

The aggregate relationship between foreign investor composition and the transmission of Global Financial Cycle potentially reflects the two-way feedback between fundamental attributes of assets investor composition. More specifically, investors' portfolio choice may be based on their preferences for particular attributes associated with the issuers and the instruments. Meanwhile, different types of investors may play distinct roles in transmitting the Global Financial Cycle, due to their unique institutional features and heterogeneous exposure to global shocks. To unpack the macro pattern in-depth, I utilize a micro-level dataset of securities holding data with rich information on issuer fundamentals, sectors of bond holders and asset characteristics.

2.2 Sovereign debt ownership: Granular data and stylized facts

Data My main micro-level dataset comes from the Securities Holdings Statistics Base plus database (Blaschke, Sachs and Yalcin-Roder, 2022) compiled by Deutsche Bundesbank.[14] Henceforth referred to as SHS-Base plus, 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. Institutions also report securities held in safe custody on behalf of their customers, regardless of the ultimate investors' countries of origin. For convenience, I refer to investors recorded in the SHS-Base plus data as "Germany-based" investors. For each security identified by the International Securities Identification Number (ISIN), information on the face value and market value as of the data reporting date, and the sector classification of the investors is available.

SHS-Base plus is the ideal dataset for this study for a number of reasons, highlighted in Table A1 in Appendix A in comparison with other datasets often used in the international finance research.[15] As a census, it has a wide coverage of securities, reporting institutions, and sectors of security holders. Securities issued worldwide, including emerging market sovereign bonds, are reported. The data covers all investors types in the ESA1995 and ESA2010 sector classification, including but not limited to domestic and foreign banks, insurance companies and pension funds, investment funds, governments and households. The custodian-based dataset also covers parts of non-German investors' security holding, given the significant role of German banks and clearing houses as asset depositories in Europe. Second, SHS-Base plus provides quarterly holdings statistics as early as 2005 and it becomes a monthly dataset starting from end-2012. This feature helps track high-frequency dynamics of asset holdings in response to fast-moving, volatile shocks such as changes in global financial condition. Finally, the reporting of face values of bond holdings provides an accurate picture of portfolio allocation at the sector level and makes my analysis immune to the usual concern of valuation effects.

Despite its wide coverage, the administrative data may not entirely recover the investor base of a security. I address this challenge in two ways. First, I substantially 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, investing primarily in emerging markets.[16] My Morningstar sample of funds report a total asset under

[14] DOI: 10.12757/SHSBaseplus.05122212.

[15] Timmer (2018) uses SHS-Base plus to understand heterogeneous portfolio allocation in response to past returns across different investor sectors.

[16] Mutual funds with an EM focus are broadly defined to include as much EM fixed income holdings as possible. I include funds with emerging markets as their primary investment category, as designated by

management exceeding \$600 billion as of 2021M6, the endpoint of my analysis.[17] Second, Germany is among the largest creditors to emerging market economies located in Eastern Europe, making German institutions important marginal investors for sovereign bonds issued by these countries. As a result, in subsequent analyses connecting investor base to bond price sensitivity (such as Table 2), I restrict the sample of issuers to 27 EM European countries.[18] In Figure A1 of Appendix A, I illustrate the dominance of German investors in the holding of EM European government debt using available aggregate data. Appendix A also reports benchmarking exercises demonstrating that the dynamics of the aggregate numbers derived from my micro dataset are in line with those reported by datasets with a wider global coverage, such as IMF CPIS, ECB SHS and BIS Debt Securities Statistics.

I merge the investor holdings data with the near-universe of emerging market sovereign bond issuance from 2005 to 2021. The bond universe consists of 14678 sovereign and quasi-sovereign bonds issued by 53 emerging market economies with a tenor of 1 year and above. Measured by total amount outstanding, my bond-level dataset accounts for more than 75% of the entire EM government bonds issued as of end-2019.[19] I obtain bond-level characteristics from Bloomberg and Refinitiv. Bond price information is based on combining Bloomberg, Refinitiv, and implied prices from SHS-Base plus. Taken together, the coverage of prices is significantly improved compared to using a single data source.[20] Appendix A.2 provides more detail on my cleaning procedure. I also account for Global Depositary Note issuance and RegS/144A offerings to avoid artificially introducing a separate security in the same bond offering.[21]

Morningstar, as well as global mutual funds partially or fully following EM-tracking benchmark indices. Appendix A.2 provides an extensive discussion of my fund screening criteria.

[17]Luxembourg and Ireland are important preferred habitats for mutual funds in Europe due to tax considerations, undertaking a majority of intermediation activities (Floreani and Habib, 2018). Beck, Coppola, Lewis, Maggiori, Schmitz and Schreger (2023) document that investment funds domiciled in these two countries account for 40 percent of cross-border security claims of Euro Area residents.

[18]27 countries are classified as EM European countries. 950 bonds over my sample period are 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.

[19]I also cross check the coverage of my bond universe against aggregate numbers provided by Onen, Shin and von Peter (2023) based on the debt securities statistcis compiled by the Bank for International Settlement. The results are similar.

[20]The implied bond prices are obtained by dividing market values from face values of holdings. For most fixed-coupon bonds, the results can be used to calculate yields to maturity.

[21]Multiple ISINs may be associated with a single bond, depending on the exact nature of the offerings.

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. The total amount of holding by Germany-based investors in the SHS-Base plus dataset is 97.5 billion EUR holding as of 2021M6. External issuance comprises 45% of the total number of bonds. My regression analysis uses monthly data available from the end of 2012 to June 2021, but I report aggregate data starting from an earlier period where needed. I focus on three broad sectors holding the majority of the bonds in my sample: banks, investment funds, and insurance companies and pension funds.[22] Banks cover both domestic (German) and foreign banks recorded in SHS-Base plus. In addition to mutual funds and ETFs, the category of investment funds also covers investment companies and other non-bank, non-ICPF financial intermediaries. Motivated by the discussion in Section 2.1 and Appendix B.2, I also analyze banks, insurers and pension funds as a single category labelled as "long-term investors".[23]

Foreign investor base: Aggregate facts 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 $s \in \{\text{Bank, ICPF, Investment Fund}\}$. I also calculate the aggregate share held by long-term investors. $\theta_{i,\text{Bank+ICPF},t}(n)$.[24] In Table A4 of Appendix A.3, I report average investor composition covered in my dataset. My dataset has a decent coverage of external issuance (an average of 15% of amount outstanding) and Euro-denominated bonds (18% on average).

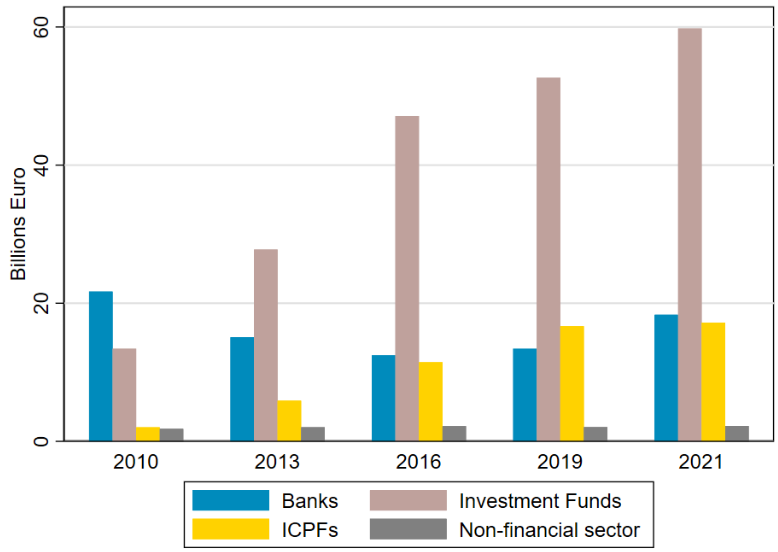
Figure 2(a) suggests that the marginal buyers for emerging market sovereign issuance may not be limited to investment funds, which have been the focus of the literature so

Global Depositary Note is an instrument settled in U.S. dollars that records an investor's ownership to an underlying local currency denominated bond. Emerging markets actively use 144A and Regulation S offerings to offer bond to both U.S.-based and non-U.S. investors.

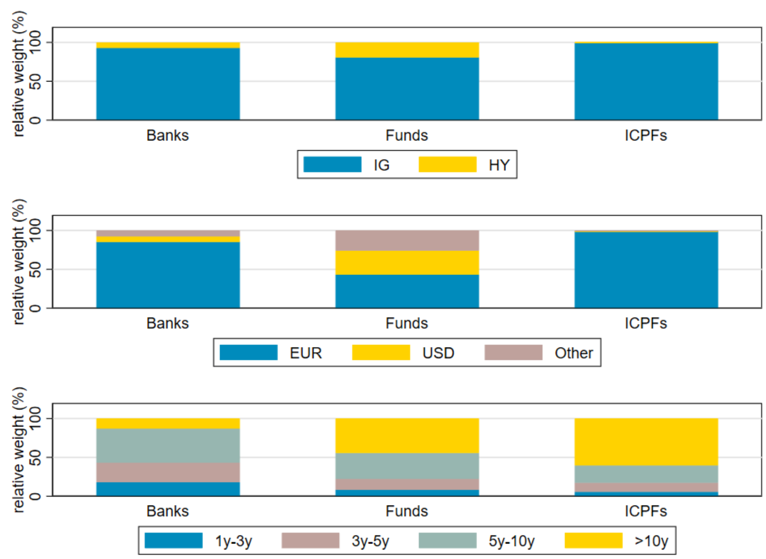
[22] I focus on private investors, as the government sector (including central banks) plays a small role as bond holders in my emerging market sovereign bond sample. With the exception of countries in the Eurozones, emerging market issuers are typically ineligible for large-scale purchases by major central banks such as the ECB.

[23] Table A2 in Appendix A.2 provides the mapping from the fine ESA-based sectors and the broad sectors used in this paper. In Figure 2, I also report a residual category ("non-financial sector"), which is mostly comprised of government, non-financial companies and households' direct holding. Table A3 collects the sources of key variables in the empirical analysis.

[24] Amount outstanding may be time-varying due to reopening of previous bond offerings and buybacks.



(a) By sector of holders



(b) By sector of holders and bond characteristics

Figure 2: EM sovereign bond held by Germany-based investors, face value in Euros

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics (SHS-Base plus), 2010Q1-2021Q2, own calculations.

Note: Figure 2, 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. A detailed mapping between the broad sector group and the ESA institutional classification is available in Table A2. Panel (b) reports the breakdown by bond characteristics (credit rating, currency denomination and residual maturity) based on holding at the end of 2020. "IG" refers to investment grade. "HY" corresponds to high-yield (non-IG) bonds. Residual maturity is partitioned into four buckets.

far.[25] The plot traces the evolution of Germany-based investor holding of EM sovereign bonds. Throughout my sample period, bank holding has been in decline until 2019, while investment funds, insurers and pension funds have been expanding their holding. Despite the underlying shifts, the overall investor base remains diverse.

The aggregate expansion of emerging market debt portfolio masks underlying heterogeneity across sectors. Figure 2(b) breaks down each sector's bond holding based on observable bond characteristics, along the dimension of currency denomination, credit rating, or residual maturities. Face values of each type of holding are converted to Euros and plotted as relative shares against other types of emerging market sovereign bonds. 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.

In Appendix A.3, I compute average measures of a larger set of bond characteristics held by each sector. Table A5 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.

Isolating the contribution of investors' portfolio preferences I augment Figure 2(b) using a set of regressions to measure investors' heterogeneous propensities of sorting into particular bond types. Using fixed effects at the issuer-time level, I control for the important confounding factors at the global and local level, as global financial market development, fundamental shifts and debt-issuing decision of each country may vary over time, affecting capital allocations to each type of bonds. I estimate the following linear probability model for each sector with fixed effects:

$$\mathbb{1}\{B_{ist}(n) > 0\} = \mathbf{X}_t(n)\boldsymbol{\beta}_s + \gamma_{i,t} + \varepsilon_{ist}(n) \tag{3}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. $\mathbf{X}_t(n)$ is a vector of a wide range of bond-level characteristics, including callability, (log) amount outstanding, coupon rate, maturity bucket, currency denomination, seniority, credit rating, and collateral eligibility.[26] Im-

[25]This finding is consistent with Bertaut, Bruno and Shin's (2023) analysis using U.S. supervisory data.

[26]Bond falls into one of the following maturity bucket based on its residual maturity: less than one year, 1–3 years, 3–5 years, 5–10 years, 10 years and above. In this exercise, currency denomination is

portantly, $\gamma_{i,t}$ is the issuer×time fixed effect. My baseline sample of bonds correspond to the "investment universe" of Germany-based investors – those held by at least one type of investors in the SHS-Base plus dataset at one point. The magnitude of each entry of the estimated $\boldsymbol{\beta}_s$ indicates the relative propensity of holding a bond with a particular characteristic compared to other bonds issued by the same country. Meanwhile, the fit of the regressions would indicate the degree to which bond characteristics can jointly explain the variations in each sector's bondholding decision.

The propensity to hold bonds with with a particular characteristic varies widely across investors. Table 1 reports the estimation results for Germany-based banks, insurers and pension funds, and investment funds. The estimated coefficients, stable across specifications with different combinations of fixed effects, reveal several patterns. Columns (4) to (6) correspond to the specification that includes the granular issuer×time fixed effect $\gamma_{i,t}$. The results show that while investment funds are more likely to hold a bond when it has a larger size, other important characteristics, such as maturity and currency denomination, do not explain their portfolio holding 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. Meanwhile, consistent with Figure 2(b), banks are more likely to hold bonds with a shorter duration compared to other investors. As shown in columns (1) to (3), the coefficient estimates are stable with less demanding issuer and time fixed effects that enable me to estimate the propensities to sort into time-varying issuer characteristics such as ratings. In particular, insurers and pension funds are 10 percent more likely to hold a bond if the issuer is rated at investment grade (column (3)). The R^2 associated with investment funds are one half of that associated with insurers and pension funds (column (2)).[27]

a dummy variable indicating whether the bond is denominated in Euro, and credit rating is a dummy variable indicating whether at least one of Fitch, Moody's and S&P rates a bond higher than investment grade. A small subset of emerging market sovereign bond can be accepted as collaterals for Eurosystem credit operations. I control for collateral eligibility to reflect the potential specialness of these assets.

[27]In Appendix B.3, Table B3 reports results generated using relative portfolio shares within the EM sovereign bond holding of each investors sector as the dependent variable. Incorporating intensive margin decision, home currency denomination remains a defining characteristic of long-term investors' emerging market portfolio.

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 1: 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 1 reports estimation results from a linear probability model (3) 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2.3 Propagation of global risk factors by different types of investors

As the reciprocal aspect of the two-way feedback mechanism, foreign investors may be associated with heterogeneous propensities to amplify the impact of global risk factors. I investigate whether the sovereign yield sensitivity to global risk factors varies with the ex-ante investor composition by running the following regressions:

$$\Delta y_{i,t}(n) = \beta_0 \Delta \log \text{VIX}_t + \beta_1 \Delta \log \text{VIX}_t \times \theta_{i,\text{Fund},t-1}(n) + \beta_2 \Delta \log \text{VIX}_t \times \theta_{i,\text{Bank+ICPF},t-1}(n) \\ + \mathbf{X}_{i,t}(n)\delta + \mathbf{\Theta}_{i,t-1}(n)\gamma + \alpha(n) + \eta_{i,t} + \varepsilon_{i,t}(n) \tag{4}$$

where $y_{i,t}(n)$ is the yield of bond n issued by country i; $\mathbf{X}_{i,t}(n)$ is a set of control variables at the issuer or bond level; and $\mathbf{\Theta}_{i,t-1}(n)$ 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.

Equation (4) 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, Leiderman and Reinhart (1993); Gilchrist, Wei, Yue and Zakrajšek (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 a rich set of fixed effects. In (4), identification of the coefficients β_1 and β_2 is partly based on within-bond time variation in the investor composition, through the inclusion of bond fixed effect $\alpha(n)$. In some specifications, I add issuer$\times$time fixed effect $\eta_{i,t}$ to absorb the potential effect of debt supply, investor selection on time-varying issuer-level characteristics, the base effect of changes in global risk factor β_0, as well as the impact of observed and unobserved global and local factors that affects the relationship between investor composition and bond yield sensitivity to VIX changes.

I include a rich set of global and local factors into the control vector $\mathbf{X}_{i,t}(n)$ at various aggregated levels. When excluding the issuer$\times$time fixed effect, I control for changes in 10-year Bund yield as the benchmark risk-free interest rate, changes in log industrial production index for each issuer, changes in credit qualities at issuance level and log amount outstanding, and switches of residual maturity buckets.[28] In some specifications, while allowing for a smaller sample due to imperfect data coverage, I also control for bid-ask spread (winsorized at 1% and 99% tail) to examine whether the potential heterogeneous

[28]The coefficients associated with risk-free rate and industrial production index are absorbed by the inclusion of issuer$\times$time fixed effect. When estimating Equation (4), I use a more refined categorical measure of credit quality by harmonizing credit ratings from Fitch, Moody's and S&P into five levels ranging from 1 (low quality) to 5 (high quality) according to Eurosystem's Credit Quality Steps (CQS). See `https://www.ecb.europa.eu/paym/coll/risk/ecaf/html/index.en.html` for the mapping. Bonds with a lower rating than BB are assigned a level of 0.

sensitivity to global risk factors due to investor composition can be explained by bond liquidity variation. Changes in bond yields are winsorized at their 1% and 99% tail.[29] I estimate Equation (4) using debt securities yet to default with a fixed coupon and a non-amortized redemption schedule. As discussed in previous sections, 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.

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 2 reports the estimation result with bond fixed effect. 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 yield, controlling for other global and local factors.[30] 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.

Time-varying issuer characteristics cannot explain the entirety of the heterogeneous sensitivity of bond yields to global risk factors. Adding issuer$\times$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 coefficients nevertheless remain statistically significant.

My results alleviate the concern that 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) focus on bonds in my sample with a large investor coverage (above 15%). The estimates are quantitatively similar to my baseline estimates. Column (5) shows that controlling for the changing

[29] 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.

[30] One standard deviation of monthly innovation of VIX index corresponds to a 28% change. My estimate is quantitatively similar to Gilchrist, Wei, Yue and Zakrajšek (2021), who find that a 8 basis point widening of bond yield for investment grade bonds. To illustrate the economic magnitude, for a 10-year, $1 billion bond with a duration of 8 years, the 5.4 basis point increase amounts to a $4.32 million increase in borrowing cost should the country issue new debt under the new market yield.

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 2: 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 2 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (4). 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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 A6).

Accounting for selection into observable bond characteristics Table B5 reports additional regression results. In column (1) and (2), I augment Equation (4) 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 score. Despite the finding of Table 1 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.[31] For additional verification, I take U.S. dollar and Euro sovereign 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, and use the residuals as the dependent variable in estimating (4), columns (3) and (4) of Table B5 suggest that my results remain robust.[32]

Appendix B.3 provides further robustness checks. Table B4 replaces the investor share variables in my baseline regression by the relative shares of banks, insurers and pension funds against investment funds. Table B6 interacts the investor composition measure with the implied volatility of Euro STOXX index (V2X). Both exercises yield similar conclusions compared to the baseline regressions.

2.4 Foreign demand for emerging market sovereign debt in risky times

The diverging patterns of portfolio holding response to heightened global risk further illustrate the distinct role played by different types of EM sovereign bond investors. Complementary to the evidence on bond pricing (Table 2), Figure 3 traces the quantities of EM sovereign bond held by investment funds and long-term investors 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

[31] Alternatively, controlling for Euro$\times$time or issuer$\times$Euro$\times$time fixed effects yields similar results.
[32] Additional details on constructing the bond risk factors are reported in Appendix B.3.

plans to taper asset purchases, the August 2015 global market selloff, when the VIX index jumped to its highest level between 2012 and 2019, and the start of the COVID-19 pandemic around February 2020. Holding as of the month prior to each event is normalized to one. According to Figure 3, prior to each event, investor demand is relatively stable and there is little evidence of clear pre-trends. Immediately following the shock, investment funds (dashed lines) swiftly liquidate their holding of EM sovereign bonds, while long-term investors steadily increase their holding months into each episode.[33]

The literature has identified several underlying mechanisms contributing to the distinct pattern of asset holding across investor sectors during these "risk-off" episodes shown in Figure 3. 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, Lundblad and Ramadorai, 2012). To support this mechanism, for the "risk-off" episodes studied in Figure 3, I document strong redemption pressure experienced by open-ended mutual funds from emerging market fixed income funds in Figure C1 in Appendix C using Morningstar data.[34] On the other hand, the stable liability structure of banks, insurers and pension funds, as well as accounting conventions and regulations based on book values enable these institutions to ride out transient fluctuations of market values of their portfolio holding (Hanson, Shleifer, Stein and Vishny, 2015; Chodorow-Reich, Ghent and Haddad, 2020). 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 the COVID-19 crisis (O'Hara, Rapp and Zhou, 2023).

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 investment 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 – which also

[33] Ng, Shim and Vidal Pastor (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.

[34] Chari, Dilts Stedman and Lundblad (2022) observe similar patterns using alternative data sources. Falato, Goldstein and Hortaçsu (2021) document outflow for U.S. corporate bond funds during the COVID-19 crisis. In related work, Brandao-Marques, Gelos, Ichiue and Oura (2022) show that the sensitivity of mutual fund flows to global risk factors is higher when fund shares are easier to redeem.

play a large role and sometimes are on the other side of the market – could provide a more precise understanding of emerging markets' sensitivity to global risk factors.

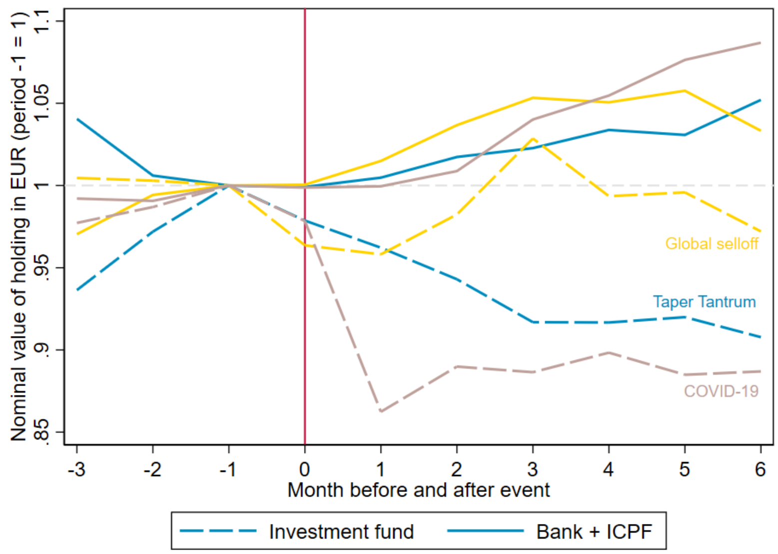


Figure 3: Aggregate holding of EM sovereign bond during important risk-off episodes

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

Note: Figure 3 plots the evolution of sectoral holding of emerging market sovereign bond around 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. Face values of bond holding expressed in current Euros are reported.

3 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 on bond characteristics, sovereign bonds with characteristics preferred by these investors may face a substantially different demand elasticity compared to those that do not possess such characteristics. I use mutual fund flow to construct plausibly exogenous shifts in the residual supply curve faced by long-term investors for different types of bonds. The estimated demand elasticity serves as the crucial input to discipline my quantitative model of the Global Financial Cycle (Section 4 and 5).

I posit the following demand equation of long-term investors, expressed in monthly differences:

$$\Delta \log B_{i,t}(n) = \alpha_{\mathcal{N}} + \beta_{\mathcal{N}} \Delta y_{i,t}(n) + \mathbf{X}_{i,t}(n)\delta_{\mathcal{N}} + \varepsilon_{i,t}(n) \tag{5}$$

Equation (5) pools all bonds with a common characteristic indexed by $\mathcal{N}$, such as currency denomination. $B_{i,t}(n)$ denote the total face value of bank, insurer and pension fund holding of bond n issued by country i at month t. $\mathbf{X}_{i,t}(n)$ denotes a set of bond- and issuer-level characteristics (expressed in monthly differences) that may enter investors' portfolio decision (also in first differences in logs or levels, similar to (4)). In my baseline specification, they include the industrial production index of country i and bid-ask spread. To account for the incentive to rebalance portfolio towards alternative assets, I also control for changes in the 10-year Bund yield. Finally, $\varepsilon_{i,t}(n)$ is an error term capturing demand disturbances unobservable to the econometrician. Equation (5) is similar to the estimating equation derived using a demand system asset pricing approach (Koijen, Koulischer, Nguyen and Yogo, 2021; Jansen, 2023), except that it is expressed in first differences and B is in face value terms (van der Beck, 2022). One advantage of using month-to-month net trades (as $B_{i,t}(n)$ is in face value terms) to identify demand slopes is its ability of absorb the confounding impact of observed and unobserved time-invariant characteristics. Using changes in position is also conceptually consistent with my instrumental variables, as I will now demonstrate.

3.1 Flow-based identification of demand elasticities: Two approaches

To obtain consistent estimation, one needs to overcome the endogeneity issue due to potential correlation between unobserved demand disturbances and prices. Motivated by the literature on flow-induced demand shocks, I propose two approaches to identify the demand elasticities. In both cases, I use mutual fund flow to construct bond-level shifters of residual supply faced by long-term investors. The validity of a flow-based instrument rests on the following intuition. First, flow-induced demand has price impact on emerging market assets following asset manager liquidation (Jotikasthira, Lundblad and Ramadorai, 2012). Second, flow lead to "forced trades" by mutual fund managers that are external to the decision of other types of institutional investors.[35] An appropri-

[35] Koijen and Yogo (2019) construct instruments to identify demand elasticities based on demand shocks of other investors arising from investment mandates. Recent work that uses flow-based instruments include Chaudhry (2022), Chaudhary, Fu and Li (2023), Fang (2023), and Sander (2023). Jansen (2023) uses

ately defined measure of idiosyncratic capital flow in and out of mutual funds would potentially satisfy the exclusion restriction.

Flow-induced demand pressure The first instrument I propose captures the allocation to each bond as a result of fund managers scaling up or down their investment following capital redemption and injection. More specifically, for each bond n, define

$$FID_t(n) = \frac{\sum_{j \in \mathcal{J}_t(n)} \frac{F_{j,t}}{S_{j,t-1}} \cdot Q_{j,t-1}(n)}{\text{Amount Outstanding}_{t-1}(n)} = \frac{\sum_{j \in \mathcal{J}_t(n)} \omega_{j,t-1}(n) \cdot F_{j,t}}{\text{Amount Outstanding}_{t-1}(n)} \tag{6}$$

where $f_{j,t} \equiv F_{j,t}/S_{j,t-1}$ denotes the dollar amount of flow in and out of mutual fund j holding bond n, normalized by the size of j in the previous period. $Q_{j,t-1}(n)$ is the lagged market value of fund j holding of bond n. Define $\omega_{j,t-1}(n)$ as the lagged portfolio weight of bond n of fund j, and the second equality follows. This definition follows Lou (2012), Gabaix and Koijen (2022) and van der Beck (2022), who compute flow-induced pressure at the bond level by projecting mutual fund flow onto individual bonds based on lagged portfolio weights. I transform FID into a measure of relative demand shocks by further normalizing it using the size of each bond.[36]

FID defined as above seeks to isolate the component of demand pressure facing each bond that is likely orthogonal to both the fundamentals and the discretion of fund managers, banks, insurers and pension funds. Ideally, FID affects asset demand of long-term investors only through its price impact. However, the plausibility of its exogeneity is challenged by the potential existence of common factors between mutual fund flow and unobserved demand disturbances of long-term investors, including underlying country fundamentals and global risk factors. Relatedly, mutual fund flow may reflect "return-chasing" behavior of ultimate investors (Gruber, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). To the extent that both flow and latent demand of banks, insurers and pension funds respond to the same current or past shocks that affect fund performance, FID may instead be highly endogenous.

In Appendix C, I provide descriptive evidence to alleviate the concern that global risk factors could drive the common comovement between fund flow and latent demand. Figure C2 shows that quarterly changes in the major components of German banks and ICPFs' liabilities – deposit and technical reserves – have close to zero corre-

regulatory shocks to pension funds as the instrument to identify other investors' demand elasticities.

[36]Equation (6) can be further rewritten using the definiton of $f_{j,t}$, so that $FID_t(n)$ is equal to $\sum_{j \in \mathcal{J}_t(n)} \left(\frac{\omega_{j,t-1}(n) S_{j,t-1}}{\text{Amt Outstanding}_{t-1}(n)} \right) \cdot f_{j,t}$. Expressed in this way, FID is similar to a Bartik (1991) shift-share IV, albeit with "shares" that do not sum to one.

lation with changes in the VIX index, suggesting that unlike investment funds (Figure C1), long-term investors' liability structure is more stable and less sensitive to global risk factors. In addition, using lagged portfolio weights to project fund flow onto bonds alleviates the concern that both $\varepsilon_{i,t}(n)$ and $FID_t(n)$ are driven by current innovations in country fundamentals. Mutual funds in my sample largely benchmark their performance against major global and emerging market bond indices, such as FTSE WGBI and JP Morgan EMBI, whose constituents are set externally. I also follow Sander (2023) and present a formal decomposition of bond demand pressure in Appendix C.1 to show that contemporary country-specific fundamental shocks are unlikely to affect FID directly.

To further address the threat to identification, I replace the raw fund flow measure $f_{j,t}$ in Equation (6) with $\tilde{f}_{j,t}$, defined as the residual from regressing raw flow on the time fixed effect and fund performance (measured by monthly portfolio return $R_{j,t-s}$) from month $t - T$ to $t - t_0$:

$$f_{j,t} = \alpha_t + \sum_{s=t_0}^{T} \beta_s R_{j,t-s} + \tilde{f}_{j,t}. \tag{7}$$

Write $\hat{\tilde{f}}_{j,t}$ as the sample analog of $\tilde{f}_{j,t}$. The FID instrument accordingly becomes

$$\widetilde{FID}_t(n) = \frac{\sum_{j \in \mathcal{J}_t(n)} \hat{\tilde{f}}_{j,t} \cdot Q_{j,t-1}(n)}{\text{Amount Outstanding}_{t-1}(n)}. \tag{8}$$

The inclusion of time fixed effect α_t in (7) strips out common time-series variation of fund flow due to global factors. By residualizing against fund returns, I further take into account cross-sectional variations that might be endogenous, by controlling for the return-chasing behavior of ultimate investors and funds' heterogeneous exposure to fundamental shocks through their portfolio tilt.[37]

Granular flow shocks A second instrument I consider is based on idiosyncratic flow shocks from large mutual funds in the spirit of Gabaix and Koijen (2023). Given the

[37] Ben-David, Li, Rossi and Song (2021) show that observable simple metrics of fund performance are strongly correlated with fund flow for both active and passive funds.

residualized flow $\hat{\hat{f}}_{j,t}$, I take the size-weighted average:[38]

$$\tilde{G}_t = \sum_{j \in \mathcal{J}_{t-1}} \mathcal{S}_{j,t-1} \hat{\hat{f}}_{j,t} \tag{9}$$

where $\mathcal{S}_{j,t-1}$ is fund j's lagged size weight based on assets under management. As $\tilde{G}_t$ varies at the time level only, I define the granular fund inflow at the bond level as

$$\tilde{G}_t(n) = \frac{N_{\mathcal{J}_{t-1}(n)}}{N_{\mathcal{J}_{t-1}}} \cdot \tilde{G}_t \tag{10}$$

where $N_{\mathcal{J}_{t-1}(n)}$ 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 $t-1$.

The instrument $\tilde{G}_t(n)$ captures the intuition that size-weighted average flow represent idiosyncratic wealth fluctuation associated with large mutual funds, independent from demand shocks of banks, insurers and pension funds, that may nevertheless affect aggregate market condition due to granularity. Multiplying by the share of funds holding a particular bond allocates shock exposure to each bond in an intuitive manner – the larger the number of funds holding a particular bond, the more likely the residual supply curve shifts idiosyncratically for that bond. To understand the validity of this approach, I sketch a simple analytical framework involving bond demand and fund flow in Appendix C.1. I present further evidence in Appendix C.1 that the granular fund flow has little correlation with global factors such as the VIX index and U.S. monetary policy rate. As a final validation test, I provide narrative support in Table C1 based on news coverage of large mutual funds to show that the instrument reflects idiosyncratic flow shocks associated with major fund companies.[39]

3.2 Yield elasticities of demand for long-term investors

The flow-induced demand instrument relies on the following intuitive exclusion restrictions. When making their portfolio choices, long-term investors cannot exploit information in investment funds' capital allocation into the bond that are orthogonal to the

[38] As the flow have already been purified, the expectation of equal-weighted average is zero. I set t_0 in (7) to 0 (i.e., including current fund return) when calculating $\hat{\hat{f}}_{j,t}$ for FID and -1 for GIV, to allow for idiosyncratic current performance of large funds driving the granular surprise flow.

[39] A clear example of such idiosyncratic fund flow shocks occurred around October 2014, after 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 outflow they suffered in the subsequent two months after the announcement is reflected in my granular flow instrument.

funds' current and past performance and common economic factors. For the granular flow instrument, I maintain that long-term investors' demand cannot directly affect or respond to idiosyncratic investment flow in and out of large mutual funds.

With these assumptions, I estimate the demand elasticity using bonds with a fixed coupon and non-amortized principal not in default, similar to the sample for the push-pull regressions (4). Changes in bond yields are winsorized at 1% and 99% tail.

Table 3 reports my estimates of the demand equation (5) via two-stage least squares. The first three columns show estimates using different versions of my proposed instruments on Euro-denominated bonds. The instruments differ in whether they are based on flow-induced demand or granular fund flow, and in the length of past fund returns used to residualize mutual fund flow (T in (7)). Despite the differences, numerical estimates of the slope of the demand equation with respect to yields are very stable across these three columns, with the coefficient estimates around 0.29. Raising the annualized bond yield by one percentage point would increase long-term investors' demand by 29%. My estimates imply a price elasticity of demand of 5.8 for a five-year zero-coupon sovereign bond denominated in Euros.[40] Meanwhile, the coefficients associated with Bund yield is negative, indicating plausible substitution between emerging market bonds and risk-free alternatives.

Finally, columns (4) and (5) show that the coefficients associated with yields of non-EUR bonds are negative and less precisely estimated. These two columns provide evidence that within the intensive margin where the estimation takes place, banks, insurers and pension funds exhibit the most elastic demand in accordance with their higher propensity to invest in bonds with a favorable characteristics, such as home-currency denomination. In Appendix C, I include observations with $B_{i,t}(n) = 0$ and $B_{i,t-1}(n)$ to account for the extensive margin of adjustment, and estimate an exponentially-transformed version of (5). Table C4 shows that in this case, investment grade bonds face a more elastic demand compared to high-yield bonds.

First-stage regressions reported in Table C2 and the Lee, McCrary, Moreira and Porter (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 representativeness of the mutual fund flow data contributes to a strong first stage – my dataset covers the largest open-ended mutual funds focused on

[40]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, Koulischer, Nguyen and Yogo, 2021; Jiang, Richmond and Zhang, 2022). I provide an in-depth discussion in Appendix C.3. The implied elasticity of my quantitative model (Section 4) 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 3: 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 3 reports IV estimates of long-term investors' (banks, insurers and pension funds) demand equation (5). 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 3.1. 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 (see Equation (8)). 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 (10) 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, McCrary, Moreira and Porter's (2022) tF standard errors for the demand slope, which are robust against weak identification under just identification.

emerging markets. In Appendix C, Table C3, 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.[41] The estimated demand slopes remain similar to the baseline levels (column 1 and 2). While my pre-

[41]Not all funds report data on returns and flow. As a result, FID as defined in Equation (6) implicitly assumes zero flow to funds with missing data, potentially violating the assumption of random assignment of shocks. Controlling for investment fund share in the estimation of (5) addresses this issue, in the spirit of Borusyak, Hull and Jaravel (2022) and Sander (2023). To see why the appropriate control is $p_{t-1}(n) \cdot \theta_{ift-1}(n)$, note that (6) can be rewritten as

$$FID_t(n) = \sum_{j \in \mathcal{J}_t(n)} \frac{\text{Market value of holding}_{j,t-1}(n)}{\text{Amount Outstanding}_{t-1}(n)} \cdot f_{j,t} = \sum_{j \in \mathcal{J}_t(n)} \frac{p_{t-1}(n) \cdot \text{Face value of holding}_{j,t-1}(n)}{\text{Amount Outstanding}_{t-1}(n)} \cdot f_{j,t}.$$

ferred specification (5) aligns with the demand system literature (see Koijen, Koulischer, Nguyen and Yogo (2021)) that relies on time-series variation to identify demand elasticities, I also add time fixed effect to (5) and report the estimation in Table C3 (column 3 and 4), with FID as the instrument.[42] The estimated slope coefficients roughly double. The associated 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.

4 A quantitative model of sovereign debt market with heterogeneous global investors

Informed by the empirical estimates, I develop a quantitative model of sovereign debt market with heterogeneous investors to capture salient patterns of Global Financial Cycle's transmission to emerging markets. The model builds on Xiong (2001), Vayanos and Vila (2021) and Kekre, Lenel and Mainardi (2023), featuring inelastic asset market and endogenous amplification of global financial shocks through wealth effects. I tightly calibrate the model using micro data, taking my estimate of the yield elasticity of demand in Section 3 to the model. The model quantifies the relative contribution of global and local factors in driving sovereign spread and replicates the relationship between investor base and shock sensitivity. In Section 5, I also study counterfactual demand shifts that highlight the unique role of policies targeting at different types of investors in affecting the level and volatility of sovereign borrowing costs.

4.1 Environment

Time is continuous and runs from $t = 0$ to infinity. The asset space contains a risk-free bond paying a constant 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". Default is exogenous and follows a Poisson jump process N_t with random arrival rate λ_t. Upon default, investors suffer a loss of δ per unit of investment (in face value

[42] As time-series variation of the granular flow is key for the identification using GIV, I focus on FID with time fixed effects in this robustness exercise.

terms) as haircut. I assume that δ is non-random.[43]

Default risk of the risky perpetuity is characterized by the arrival rate λ_t, which follows a Cox, Ingersoll and Ross (1985, CIR) process reflected at boundaries $\lambda_{\min}$ and $\lambda_{\max}$, both positive:

$$\mathrm{d}\lambda_t = \kappa_\lambda(\overline{\lambda} - \lambda_t)\mathrm{d}t + \sigma_\lambda\sqrt{\lambda_t}\mathrm{d}B_{\lambda,t}, \qquad \lambda_t \in [\lambda_{\min}, \lambda_{\max}] \tag{11}$$

where $B_{\lambda,t}$ is a standard Wiener process. CIR process is a natural candidate to capture default as a "rare disaster" (Wachter, 2013). A high default risk away from the long-run mean $\overline{\lambda}$ is itself unusual, but the volatility of default risk increases as default risk goes up, making subsequent realizations of a high default risk more likely.[44] I calibrate the process (11) to match cross-country moments associated with sovereign spread and default rate, so that states with high and low λ can be interpreted as comparing issuers with different country fundamentals.

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

$$F(\lambda) = \mathbb{E}\left[\int_{t=0}^{\infty} e^{-rt}(\kappa\mathrm{d}t - \delta\mathrm{d}N_t) \mid \lambda_0 = \lambda\right] = \int_{t=0}^{\infty} e^{-rt}(\kappa - \delta\mathbb{E}[\lambda_t \mid \lambda_0 = \lambda])\mathrm{d}t \tag{12}$$

where the second equality follows from the property of Poisson processes with random intensity. I relegate a detailed proof to Appendix D.1.[45] 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 $\overline{\lambda}$.[46]

[43] Costain, Nuño and Thomas (2022) use a similar modeling device to incorporate default risk into a prefered-habitat model of term structure. In their model, default rate is deterministic and investor wealth is not an endogenous state variable, so that the equilibrium bond price is exponentially affine in the state variables.

[44] In my calibration, the parameters in Equation (11) 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. In Appendix Figure E1(a), I show that the invariant distribution of λ_t under my calibration is highly skewed and has a long tail.

[45] The process N_t satisfies $\mathbb{E}[N_t] = \mathbb{E}\left[\int_0^t \lambda_s \mathrm{d}s\right]$. It follows that $\mathbb{E}\left[\int_0^\infty f(t)\mathrm{d}N_t\right] = \int_0^\infty f(t)\mathbb{E}[\lambda_t]\mathrm{d}t$ for continuous f. The integral $\int_0^\infty f(t)\mathrm{d}N_t$ is defined in the Riemann–Stieltjes sense.

[46] Without the reflecting barriers, the conditional expectation $\mathbb{E}[\lambda_s \mid \lambda_t = \lambda]$ has a closed form expression, and F_t is equal to $\frac{\kappa-\delta\overline{\lambda}}{r} + \frac{\delta(\overline{\lambda}-\lambda)}{r+\kappa_\lambda}$. The analytical expression for $F_t(\lambda)$ is complicated and difficult to evaluate directly in the presence of reflecting barriers (Linetsky, 2005). I nevertheless show in Appendix D.3 that the conditional expectation can be backed out by solving a *Kolmogorov backward equation* using the standard finite-difference method.

Asset manager A unit mass of investment fund asset managers have log utility and 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 consumes every period and solves the following portfolio choice problem:

$$\begin{aligned} &\max_{c_t,x_t} \mathbb{E}_0 \int_0^\infty e^{-(\rho+\xi)t} \log c_t \mathrm{d}t \\ &\text{s.t. } \mathrm{d}w_t = (rw_t - c_t + \xi w_t)\mathrm{d}t + x_t \cdot (\mathrm{d}P_t + \kappa \mathrm{d}t - rP_t\mathrm{d}t - \delta \mathrm{d}N_t) + \sigma_z w_t \mathrm{d}B_{z,t} \end{aligned} \tag{13}$$

where x_t is the amount of the risky perpetuity held by the asset manager in face value terms.[47] Compared to the standard Merton (1971) problem, asset managers in my model are subject to a Brownian *wealth shock* $\mathrm{d}B_{z,t}$ with standard deviation σ_z. Exogenous wealth shocks in my model introduce random fluctuations in asset managers' absolute risk aversion, capturing funding shocks faced by open-ended investment funds through capital injection and redemption by the ultimate global fund investors that drive asset liquidation, as discussed in Section 2.4. For this reason, I call $\mathrm{d}B_{z,t}$ the *Global Financial Cycle shock*. For simplicity, I further assume that the shock processes $B_{z,t}$, $B_{\lambda,t}$ and N_t are pairwise independent.[48]

Asset managers are atomistic and all funds receive the same funding shock. Using uppercase letters to denote aggregate quantities, aggregate wealth of asset managers, W_t, follows

$$\frac{\mathrm{d}W_t}{W_t} = \left(r + \xi - \frac{C_t}{W_t}\right)\mathrm{d}t + \frac{X_t}{W_t} \cdot (\mathrm{d}P_t + \kappa \mathrm{d}t - rP_t\mathrm{d}t - \delta \mathrm{d}N_t) + \xi\left(\frac{\underline{W}}{W_t} - 1\right)\mathrm{d}t + \sigma_z \mathrm{d}B_{z,t}. \tag{14}$$

In equilibrium, aggregate asset manager holding of the risky perpetuity X_t is equal to x_t. As discussed in Kekre, Lenel and Mainardi (2023), with $\xi < \infty$, the state variables of the model include endogenous asset manager wealth. In my model, the exogenous mean-reverting bond fundamental risk λ_t is another state variable.

[47] 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 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.

[48] 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, Hoerova and Lo Duca, 2013; Boehm and Kroner, 2023), as well as pure shifts in the risk appetite.

Long-term investor A second type of investors participate in the market for the risky perpetuity. I model their aggregate risky asset demand, Z_t, as downward-sloping in the log deviation of bond price from its fundamental value, as well as the default risk:

$$Z_t = -\alpha(\lambda_t) \cdot \log\left(\frac{P_t}{F_t}\right) - \theta_1 \lambda_t \tag{15}$$

where $\alpha(\cdot) > 0, \alpha'(\cdot) < 0$. (15) builds on Xiong (2001) and the recent preferred-habitat demand literature (Vayanos and Vila, 2021; Gourinchas, Ray and Vayanos, 2022; Costain, Nuño and Thomas, 2022; Kekre, Lenel and Mainardi, 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. 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 would deliver a higher payoff when the bond becomes cheaper.[49] The scale of demand adjustment, however, directly depends on bond attributes. Equation (15) models this dependence through a demand slope term $\alpha(\lambda)$ that is decreasing 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

$$Z_t = -\alpha \cdot \exp(-\delta_\lambda \lambda_t) \cdot \log\left(\frac{P_t}{F_t}\right) - \theta_1 \lambda_t \tag{16}$$

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. An additional linear term $-\theta_1 \lambda_t$ with $\theta_1 > 0$ captures this idea in reduced form.

In practice, the direct dependence 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. Appendix F sketches a static optimizing foundation, closely following Gabaix and Maggiori (2015), to motivate this dependence. In particular, the variable demand slope $\alpha(\lambda)$ in (15) 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

[49] 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.

and Solvency II. The linear term $\theta_1 \lambda_t$ is motivated by the additional holding cost faced by long-term investors to be exposed to default risk, such as costly equity issuance to cover book value loss upon default (Dvorkin, Sánchez, Sapriza and Yurdagul, 2021).

Equilibrium conditions I look for a Markov equilibrium in which the bond price depends on the default risk and asset manager wealth as states.

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

- *Asset managers make optimal portfolio choice given P.*
- *Long-term investors' demand follows (15).*
- *Market for the risky perpetuity clears: $X(\lambda, W) + Z(\lambda, W) = s$.*

I restrict attention to the equilibrium in which bond price follows a jump-diffusion:

$$\mathrm{d}P_t = \omega_t \mathrm{d}t + \eta_{\lambda,t} \mathrm{d}B_{\lambda,t} + \eta_{z,t} \mathrm{d}B_{z,t} + \eta_{N,t} \mathrm{d}N_t \tag{17}$$

and that the endogenous aggregate asset manager wealth process follows

$$\frac{\mathrm{d}W_t}{W_t} = \Phi_{1,t} \mathrm{d}t + \Phi_{2,t} \mathrm{d}B_{\lambda,t} + \Phi_{3,t} \mathrm{d}B_{z,t} + \Phi_{4,t} \mathrm{d}N_t \tag{18}$$

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 variable (λ, W). I omit time subscript below for brevity. Solving for the associated Hamilton-Jacobi-Bellman equation with problem (13) in combination with (17) and (18), utilizing the property of log utility and Itô's lemma for jump-diffusions, I prove the following proposition on the equilibrium bond price.

Proposition 1. *The equilibrium bond price $P(\lambda, W)$ is a solution to the following partial differential equation:*

$$\begin{aligned} rP =& \kappa + \lambda \cdot \frac{\Phi_4}{\chi(1+\Phi_4)} + P_\lambda[\kappa_\lambda(\overline{\lambda} - \lambda) - \sigma_\lambda \sqrt{\lambda} \Phi_2] + P_W[\Phi_1 - (\Phi_2^2 + \Phi_3^2)]W \\ &+ \frac{1}{2} P_{\lambda\lambda} \sigma_\lambda^2 \lambda + \frac{1}{2} P_{\lambda W} \sigma_\lambda \sqrt{\lambda} \Phi_2 W + \frac{1}{2} P_{WW} W^2 (\Phi_2^2 + \Phi_3^2). \end{aligned} \tag{19}$$

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

$$P_\lambda(\lambda_{\min}, W) = P_\lambda(\lambda_{\max}, W) = 0, \qquad W \in (0, \infty), \tag{20}$$

$$P(\lambda, 0) = F(\lambda) \cdot \exp\left(\frac{s + \theta_1 \lambda}{-\alpha(\lambda)}\right), \qquad \lambda \in (\lambda_{\min}, \lambda_{\max}), \tag{21}$$

$$\lim_{W \to \infty} P(\lambda, W) = F(\lambda), \qquad \lambda \in (\lambda_{\min}, \lambda_{\max}). \tag{22}$$

The associated quantities $\Phi_1, \Phi_2, \Phi_3, \Phi_4$ are functions of the states and follows Equation (54), (55), (56), (53) in Appendix D.1.

Proof. See Appendix D.1. □

The boundary conditions can be intuitively understood as follows. Equation (20) corresponds to reflecting barriers of λ_t at the lower and upper bound. When aggregate asset manager wealth is zero, asset managers exit the market.[50] (21) is derived from (15), setting $Z_t = s$. Taking asset manager wealth to infinity (Equation (22)), asset managers become effectively risk neutral and take over the entire market. As a result, the bond price at infinite wealth equals the fundamental value.

Equilibrium pricing of risk The first-order condition of the asset managers implies that the ex-ante excess return of the risky perpetuity can be decomposed into three terms (omitting dt for simplicity):

$$\begin{aligned} \underbrace{\frac{\mathbb{E}_t[\mathrm{d}P_t] + \kappa}{P_t} - r}_{\text{Excess return}} = & P_t^{-1} \cdot \Big[\underbrace{\Phi_{2,t}\eta_{\lambda,t}}_{\substack{\text{Comovement of wealth and price} \\ \text{exposure to default risk shocks}}} + \underbrace{\Phi_{3,t}\eta_{z,t}}_{\substack{\text{Comovement of wealth and price} \\ \text{exposure to wealth shocks}}} \\ & + \underbrace{\lambda_t \cdot \frac{\delta - \eta_{N,t}}{1 - \chi_t(\delta - \eta_{N,t})}}_{\text{Outright default premium}} \Big]. \end{aligned} \tag{23}$$

According to (23), investors 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. Comparing (23) with (17) and (18), the risk premia reflect the comovement between asset price and asset manager wealth as they both respond to exogenous shocks.

The final term captures the pricing of Poisson default shocks, including both its direct impact through the dependence on haircut δ, as well as its indirect impact on asset

[50]The market is incomplete given more sources of risk compared to the number of assets. As a result, there is no nontrivial zero-cost portfolio for zero-wealth asset managers.

manager wealth wealth. The term $\eta_{N,t}$ is implicitly defined by the price difference before and after jump due to default-induced changes in wealth, and is less than zero:

$$\eta_{N,t} = P(\lambda, W(1+\Phi_4)) - P(\lambda, W)$$

where $\Phi_4 < 0$ corresponds to the wealth exposure to Poisson jump shock (see (18)).

4.2 Economic mechanism

My model captures the interdependence between asset attributes and investor composition and their contribution to the transmission of global financial shocks.[51] Investors are differentially exposed to global financial shocks. With log utility, asset managers' portfolio allocation to the risky perpetuity directly responds to changes in the risk-bearing capacity driven by wealth fluctuations. Following a negative wealth shock, asset managers become more risk-averse and liquidate their risky asset holding, pushing down bond price given long-term investors' downward-sloping demand curve. Long-term investors stabilize the market by acting as bond buyers in response to the negative wealth shock to asset managers. Meanwhile, dependence of the elasticity and level of long-term investor demand on the default risk λ (15) 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 revaluation of asset managers internally amplifies exogenous shocks.[52] As shown in Appendix D.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:

$$\eta_{z,t} = \overbrace{P_{W,t}W_t\sigma_z}^{\text{Direct impact}} + \overbrace{P_{W,t}X_t\eta_{z,t}}^{\text{Wealth revaluation}} = \frac{P_{W,t}W_t\sigma_z}{1 - X_tP_{W,t}} \tag{24}$$

$$\Phi_{3,t} = \sigma_z + P_{W,t}X_t\Phi_{3,t} = \frac{\sigma_z}{1 - X_tP_{W,t}} \tag{25}$$

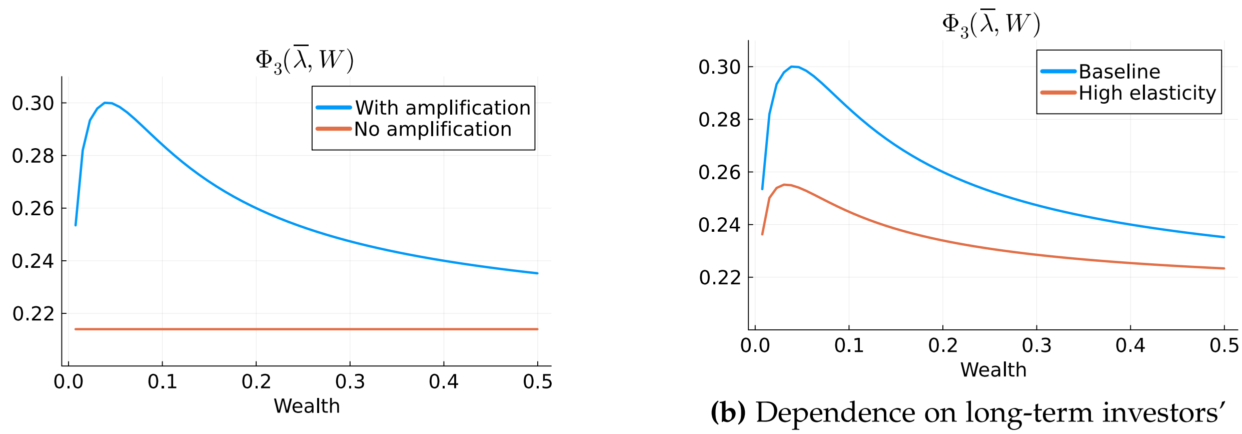
where X_t is the risky asset position. (24) suggests that a negative wealth shock with size σ_z has a direct impact on the bond price due to liquidation. The price impact of such liquidation leads to wealth loss and further erosion of asset managers' risk-bearing capacity, pushing down the asset price. This mechanism is captured by the second term.

[51] Table E1 in Appendix E summarizes the mapping from the model to the empirical regularities.

[52] This force would be absent in sovereign default models with exogenous risk-premium or wealth shocks (Aguiar, Chatterjee, Cole and Stangebye, 2016; Bianchi, Hatchondo and Martinez, 2018).

In equilibrium, the 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 $(1 - X_t P_{W,t})^{-1}$. The factor depends on asset managers' current risky asset position X_t, and is greater than one when $0 < X_t P_{W,t} < 1$, a condition that holds in my quantitative exercises.[53]

Setting default risk at its long-run mean $\overline{\lambda}$, Figure 4(a) plots $\Phi_{3,t}$ along the wealth dimension around its stationary mean. Without wealth revaluation, the wealth sensitivity simply equals the volatility of exogenous wealth shock, σ_z (see (25)). Wealth revaluation enlarges the exposure of asset manager wealth to the shock, especially when the risk-bearing capacity is low.



(a) With and without shock amplification

(b) Dependence on long-term investors' demand elasticity

Figure 4: Equilibrium asset manager wealth sensitivity to exogenous wealth shocks

Note: Figure 4 illustrates the amplification of default risk shocks and wealth shocks, by plotting volatility terms associated with the law of motion for asset manager wealth (18). Panel (a) plots $\Phi_{3,t}$ (blue line), the equilibrium exposure of asset manager wealth with respect to exogenous wealth shock $dB_{z,t}$ (see (25)), setting default risk to its long-run mean $\overline{\lambda}$. The red line in illustrates the sensitivity to the wealth shock prior to endogenous wealth revaluation due to asset liquidation. The size of the exposure is equal to σ_z, the shock volatility. Panel (b) compares the size of $\Phi_{3,t}$ implied by the baseline calibration (blue line) to a calibration such that long-term investors' yield elasticity of demand is around 3 times larger (red line), illustrating the role of long-term investors' demand elasticity in dampening the impact of exogenous wealth shocks.

The role of long-term investors' demand elasticity The demand elasticity of long-term investors plays a crucial role in shaping yield spread, volatility, and bond sensitivity to shocks. For a given level of default risk $\lambda_t = \lambda$, denote $\alpha = \alpha(\lambda)$ in long-term investors' demand equation (15). I further rewrite (24) by replacing X_t using the market clearing

[53] The mechanism formalizes the knock-on price impact in the corporate bond market due to fund fire sales and common holdings, found in Falato, Hortaçsu, Li and Shin (2021). A similar amplification channel through wealth revaluation is present for the transmission of fundamental shocks (also see Park (2012) and Bocola (2016)). Appendix D.1 shows that the exposure of price and wealth to fundamental shock is amplified by the same factor.

condition, such that

$$\eta_{z,t} = \overbrace{P_{W,t} W_t \sigma_z}^{\text{Direct impact}} + \overbrace{(\eta_{z,t} \cdot [s + \alpha \log(P_t/F_t) + \theta_1 \lambda]) P_{W,t}}^{\text{Wealth revaluation}} \tag{26}$$

Holding all else unchanged, as $\log(P_t/F_t) < 0$ for finite asset manager wealth, (26) implies that a larger demand elasticity of long-term investors through a higher α corresponds to a lower price sensitivity to wealth shocks.

The mechanism can be best understood based on a simple demand-supply diagram (Figure 5). 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 demand slope parameter α. In response to a negative wealth shock indicated by the horizonal dashed arrows, asset managers liquidate their holding of the risky perpetuity. Log utility implies that holding the return of the bond unchanged, investors scale down their demand proportionately, as the portfolio weight of the risky perpetuity depends on asset manager wealth only through bond prices (see (23) or (40) in Appendix D).

When asset managers liquidate, 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. Because of downward-sloping demand, however, bond price declines. The right panel of Figure 5 compares the degree of price drop in response to the negative wealth shock by plotting long-term investor holding against the bond price. With 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 $\mathrm{d}B_{z,t}$ between the case of high and low demand elasticity in the region around the average level wealth implied by the stationary distribution.

4.3 Calibration

I adopt a multi-pronged approach to pin down the parameter values in my model. Most parameters are tightly estimated based on macro and micro-data in order to be consistent with important facts related to emerging market debt and default, as well as lender characteristics. I provide an overview in this section, list the parameter values for my baseline calibration in Table 4, and relegate the details to Appendix D.2.

Parameters externally set/estimated I set the values of a number of parameters in accordance with literature and matching important moments estimated externally from

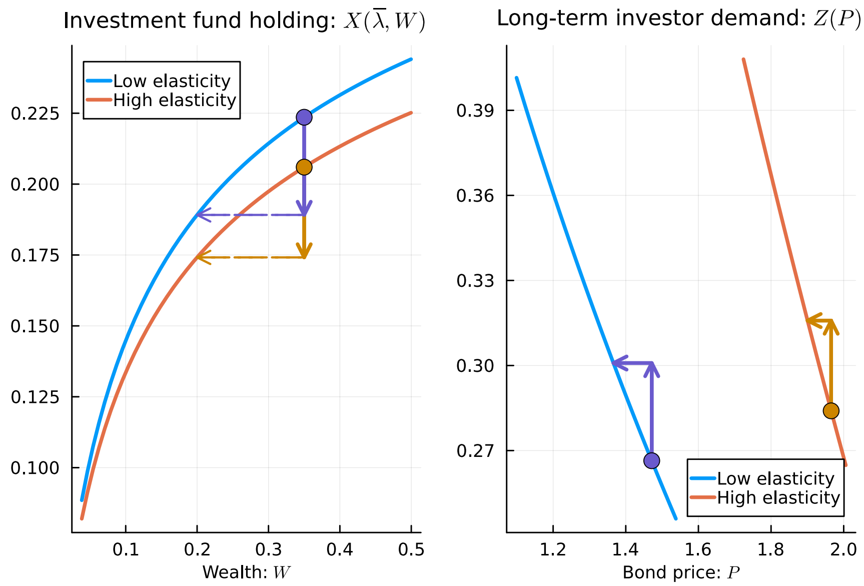


Figure 5: Exogenous wealth shocks and long-term investors' demand elasticity

Note: Figure 5 illustrates the importance of demand elasticities of long-term investors in determining bond price sensitivity to asset manager wealth shocks. The left panel 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).

aggregate and micro data. For bond characteristics, risk-free rate r is set at 2 percentage point per annum. Defaultable bond's coupon rate is set at 6 percentage point per annum, following the estimate of Meyer, Reinhart and Trebesch (2022). Default in my model should be interpreted as including both preemptive and post-default restructuring episodes that may involve face value haircut to the investors. Accordingly, I set the long-run average default intensity to 0.038, higher than the 2 percent annual outright default probability typically used in the literature, but consistent with the estimates by Arteta and Hale (2008) and Tomz and Wright (2013) incorporating restructuring events.[54] Bond supply parameter s is set to be 0.49, matching an average value of 49% GDP from IMF Global Debt Database for central governments across countries in my empirical sample. In this way, the model quantities can be interpreted as expressed in multiples of GDP.

The loss-after-jump parameter δ is an important structural parameter in my model governing bond prices, fundamental values, and fund allocations. A jump in the model

[54] As the default risk process is reflecting at both boundaries, I also set the value of $\lambda_{\min}$ and $\lambda_{\max}$ externally 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.

is conceptually closest to a "partial default" explored in Arellano, Mateos-Planas and Ríos-Rull (2023). I follow a similar approach to pin down the value of δ, using a combination of data on arrears and external debt stocks from World Bank International Debt Statistics and haircuts after restructuring (measured by Cruces and Trebesch (2013)). More specifically, δ is given by

$$\delta = \frac{\kappa \cdot \Lambda \cdot H}{\overline{\lambda}} \tag{27}$$

where Λ is an average measure of debt in arrear as a fraction of total external debt stock (28%), and H is 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 arrear, and in present value terms, 37% of the debt in arrear is eventually lost as haircut to investors.

Asset managers in my model are analogous to investment funds in my empirical analysis. I calibrate the values of related parameters based on the literature and micro data on mutual fund characteristics. I set the exogenous liquidation intensity at 4.1% per year. This number is within the range of the average life span of global bond funds (23–25 years), estimated by Maqui, Sydow and Gourdel (2019) using Refinitiv Lipper data.[55] Based on mutual funds in my Morningstar sample, I calculate a standard deviation of wealth shock ($dB_{z,t}$) of 0.214, matching a monthly flow volatility of 6.18% AUM in the data.[56] The discount rate ρ is set to 0.02, matching an 2% average annual return of mutual funds in my empirical sample.

Parameters internally calibrated The remaining five parameters on the default risk process and long-term investor's demand are estimated to match five moments between simulated and actual data. The parameters include the persistence and variance parameters of default risk process, $\kappa_\lambda, \sigma_\lambda$, 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%, an average yield volatility of 0.6% (both are based on EMBI Global

[55] I assume the liquidated funds are reborn with an exogenous initial wealth level of 0.005, a number close to zero.

[56] As a comparison, Rakowski (2010) estimates a daily fund flow volatility of 4% TNA. My assumption that the shock processes are mutually independent attributes the variations in $dB_{z,t}$ to fluctuations not directly related to local fundamentals. Sarno, Tsiakas and Ulloa (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.

data from 2013 to 2022), and an average bond demand response to a 1 percentage point increase in yield of 21%. As a final moment to target, the model matches a correlation between default risk and bond yield of 0.4 to reflect a moderate comovement between country fundamentals and sovereign spread observed in the data (Aguiar, Chatterjee, Cole and Stangebye, 2016).[57]

As a crucial step to tightly connect the model to the data, I compute long-term investors' 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 3 to guide the calibration.[58] In my model, long-term investors should be interpreted as not only including foreign banks, insurance companies and pension funds, but also include domestic private agents with a more inelastic demand for sovereign debt (Fang, Hardy and Lewis, 2022). For this reason, I set the target at 21% – a weighted average of the foreign component – 29% according to my estimate for Euro-denominated bonds in Table 3 – and a domestic demand elasticity that is roughly one third of my estimate, based on Fang, Hardy and Lewis (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, a representative emerging market economy in the Eurozone. Appendix D.2 provides a step-by-step guide on how I obtain the calibration target.[59]

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 D.3 provides more detail on my solution and simulation method.

[57] 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.

[58] The number is derived from running OLS regression as a counterpart to (5):

$$\Delta \log Z_t = \alpha + \beta_0 \Delta y_t + \beta_1 \Delta \lambda_t + \varepsilon_t. \tag{28}$$

[59] 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, Richmond and Zhang (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, Reinhart and Trebesch (2022)
δ	Loss after default	0.16	Equation (27), Arellano, Mateos-Planas and Ríos-Rull (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
Technical parameters			
$W\_$	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%

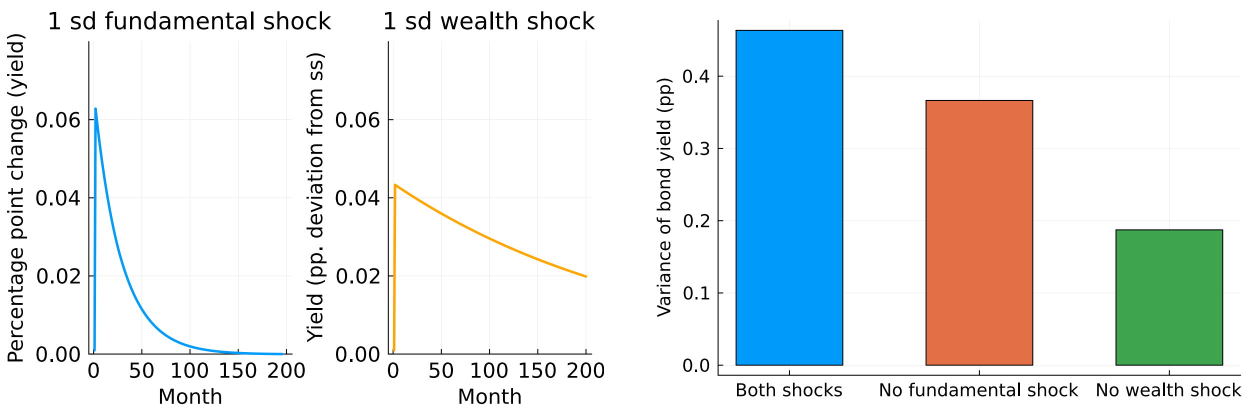
(b) Parameters internally calibrated and targeted moments

Table 4: 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. Appendix D.2 contains 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 3 and domestic investors reported in Fang, Hardy and Lewis (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 (28)).

4.4 Quantitative findings and model validation

The calibrated model fits the targeted moments well (see Table 4). I use the calibrated model to quantitatively explore the contribution of 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. Panel (a) of Figure 6 plots the impulse responses of bond yield to a one-time, one standard deviation shock to default risk and asset manager wealth in the model.[60] For ease of comparison, the left panel plots a positive shock to default risk while the right panel plots a negative shock to asset manager wealth, representing the tightening of the Global Financial Cycle. Starting from the stochastic steady state with default risk equal to its long-run mean, on impact, bond yield is more sensitive to fundamental risk innovations. However, the impact of a negative exogenous wealth shock is much more persistent, with the quantitative response (4 basis points widening per one standard deviation negative wealth shock) in line with my empirical estimates (see Table 2) with VIX as the stand-in for global factors.



(a) Impulse responses

(b) Variance of bond yields

Figure 6: Impulse responses to shocks and variance decomposition

Note: Figure 6 plots the impulse response functions of bond yield to fundamental (default risk) shock and wealth shock, as well as the results of a variance decomposition exercise that highlights the role of individual exogenous shock in driving the variation of bond yield. Panel (a) compares the impulse responses of bond yield to different types of shocks. The impulse responses are generated from simulations given a one time, one standard deviation shock to default intensity $(\mathrm{d}B_{\lambda,t})$ (left panel) or asset manager wealth $(\mathrm{d}B_{z,t})$ (right panel), holding the realized paths of other shocks to zero. For ease of comparison, wealth shock is negative while default risk shock is positive. The simulations start from the stochastic steady state $(\overline{\lambda}, \overline{W})$ where $\overline{\lambda}$ is the long-run mean of the default risk process (11) and $\overline{W}$ is the level of asset manager wealth that sets the drift of log wealth to zero. The shock sizes are set to one standard deviation implied by the normal distribution $\mathcal{N}(0, \Delta t)$ where Δt denotes the time step of the simulation (1/12). Panel (b) 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.

Figure 6, Panel (b) reports the results of a variance decomposition exercise. To gauge the contribution of wealth shocks and default risk shocks to the variation of bond yield, I set the actual realization of either shock to zero and compare the variance of bond yield under this alternative set of shock paths against the baseline simulation with both

[60] As the model is nonlinear, I choose a particular size of the shock and plot the simulated path starting from the stochastic steady state while setting the path of the other shock to zero throughout. The stochastic (risk-adjusted) steady state for asset manager wealth is pinned down by setting $\Phi_{1,t} - 0.5(\Phi_{2,t}^2 + \Phi_{3,t}^2)$ to zero, corresponding to zero drift for the log of asset manager wealth.

shocks activated.[61] Wealth shock 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, Pan, Pedersen and Singleton (2011), who find that a single principal component of emerging market CDS spread strongly comoves with global risk factors and accounts for 64 percent of the variation.[62]

I use the simulated data from the model to reproduce and revisit empirical patterns observed in the actual data. In the spirit of (4), I regress changes in bond yield spread on lagged asset manager share (demeaned), exogenous wealth shock, and their interactions, controlling for default risk and lagged asset manager wealth in some specifications. As I simulate the model multiple times, I also add replication fixed effects to account for randomness across simulations. As a stand-in for Global Financial Cycle shocks, exogenous wealth shock is multiplied by shock volatility σ_z and expressed in percentage AUM terms, with its sign flipped similar to Figure 6(a) so that a positive shock is comparable to a global financial tightening.[63]

Table 5 shows that consistent with my empirical analysis, my model generates a positive interaction coefficient between wealth shock and asset manager share. This observation holds true across specifications with different controls and sample cuts. Controlling for changes in the fundamental risk, a 10 percentage point higher asset manager share relative to the average would amplify the sensitivity to asset manager wealth shocks on average by 19 percent ((0.0129/10)/0.0068), consistent with Table 2. When looking at the global relationship, I show in Figure E4 of Appendix E that model-implied yield spread sensitivity increases with asset manager share for the majority of the asset manager share distribution and decreases at the tail of the distribution. Intuitively, when the risk-bearing capacity is low, asset managers require a higher compensation to absorb a large share of bond holding.

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

[62] On the level of sovereign yield spreads, Tourre (2017) shows that the first principal component of EMBI spreads accounts for 81.7% of variance.

[63] Formally, the full regression I run that generates Column (3) of Table 5 is $\Delta y_{j,t} = \alpha_j + 100\beta_0(-\sigma_z \Delta B_{j,z,t}) + \beta_1 \frac{X_{j,t-1} - \overline{X}_j}{s} + 100\beta_2(-\sigma_z \Delta B_{j,z,t}) \times \frac{X_{j,t-1} - \overline{X}_j}{s} + \gamma \Delta \lambda_t + \eta W_{t-1} + \varepsilon_{j,t}$ 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. Two differences from Table 2 include: 1) the investment fund share is expressed in absolute levels instead of percentage points; 2) the asset manager share is demeaned.

VARIABLES	(1) Δ Yield	(2) Δ Yield	(3) Δ Yield	(4) No default Δ Yield
Negative wealth shock	0.0068	0.0068	0.0068	0.0068
Lagged asset manager share		0.0236	0.0307	0.0288
Negative wealth shock × Lagged share		0.0129	0.0129	0.0128
Lagged asset manager wealth			-0.0149	-0.0113
Δ Default risk			0.1375	0.1374
Observations	9,000,000	9,000,000	9,000,000	8,971,761
R-squared	0.2227	0.2334	0.8227	0.8795
Replication FE	✓	✓	✓	✓

Table 5: Bond yield sensitivity to Global Financial Cycle and investor composition: Model-based simulated data

Note: Table 5 reports regression coefficients based on simulated data from the quantitative model under the baseline calibration. The estimating equation is the counterpart to (4), regressing changes in bond yield on negative wealth shocks ($-100 \times \mathrm{d}B_{z,t}$) (a model counterpart to shocks to global risk factors), lagged investor composition (asset manager share), and their interaction. I include replication fixed effect to account for randomness across different simulations. Column (1) reports results with negative wealth shocks only. Column (2) add lagged investor composition and the interaction term. Column (3) further controls for bond fundamental (changes in default risk λ), and column (4) restricts the sample to periods with no outright default (i.e. no realization of jumps $\mathrm{d}N_t > 0$). Asset manager share is demeaned, so that the interaction coefficient can be interpreted as relative to the average asset manager share.

5 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 Global Financial 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 become more accommodative to credit risk. By making $\delta_\lambda = 0$ in (16), this counterfactual setting resembles the treatment of exposure to sovereign credit risk in the EU-wide Solvency II insurance regulatory scheme in effect since 2016. For bonds issued by EU governments denominated in the domestic currency of the issuers, Solvency II assigns zero risk weight when calculating the capital requirement against credit risk.[64] In the optimizing foundation of long-term investor demand

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

(Appendix F), a demand slope α independent of default risk captures this regulatory design. Different levels of fundamental risk λ are associated with the same degree of credit constraint tightness. In the model, this regulatory scheme is only applied to long-term investors while asset managers are not directly affected.

I also study the consequences of a shrinking long-term investor sector. In particular, I lower the magnitudes of both α and θ_1 in (16) by 20% relative to the baseline ("fewer long-term investors"), assuming homogeneous demand curves across all long-term investors. Alternatively, I solve the model with a higher bond supply parameter s to reflect a 60% debt-to-GDP ratio ("higher residual supply") that increases the exposure of both types of investors to the risky asset. This counterfactual parameterization can also be thought of as capturing the inability of outside investors such as reserve managers to inelasticly absorb debt supply.[65]

I also consider two policy measures that change the liability structure and risk 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 the shift from an open-ended capital structure of to a close-ended setup, without changing the nature of long-term investors' asset demand. Second, I consider the scenario in which emerging market issuers may be able to observe the identity of bondholders and discriminate across different types of investors, by charging a 15% inflow tax on the asset managers' return from holding the risky perpetuity. Long-term investors are not affected by the tax, such that the buy-and-hold value $F(\lambda)$ is the same as the baseline calibration.[66]

5.1 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 bond yield spread to the Global Financial Cycle shock $\mathrm{d}B_{z,t}$. Following the discussion in Section 4.2 and (24), 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 amplification effect

[65] 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 F. δ_λ reflects the dependence of the tightness of the credit constraint on asset fundamentals. θ_1 captures the size of the additional cost of being exposed to sovereign default risk.

[66] The law of motion for individual asset manager wealth in (13) 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 $\lim_{W\to\infty} P(\lambda, W) = (1-\tau)F(\lambda)$.

through endogenous wealth revaluation.

Figure 7 plots the fraction of yield spread sensitivity explained by endogenous amplification across the spectrum of the bond's fundamental risk, when asset manager wealth is set to be equal to the mean of the stationary distribution of each counterfactual scenario. The size of each dot in Figure 7 corresponds to the degree of yield spread sensitivity, reported in Table 6 along with their subcomponents.[67] In my baseline specification (in blue), 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, endogenous amplification can explain 31 percent of the total response to the same exogenous wealth shock.

When default risk is high, encouraging a wider participation of long-term investors in the sovereign debt market by weakening their preference for lower fundamental risk dampens the contribution of endogenous amplification to the response of bond yield spread by 20% (from 2.1 basis points to 1.7 basis points). Compared to the baseline, asset managers hold a higher share of the risky perpetuity when the default risk is low, but substantially lower their risky asset demand when the default risk is high, as long-term investors become more accommodative to credit risk. Consequently, the share of yield spread sensitivity to exogenous wealth shocks increases more slowly with default risk. The difference in the sensitivity of bonds with a high default risk and a low default risk shrinks by 64% relative to the baseline calibration. This flatter relationship also suggests that in the model, bond fundamentals affect the risk sensitivity primarily through their impact on investor composition via long-term investors' demand shift.

Shrinking the size of the long-term investor sector substantially enlarges the sensitivity of bond yield spread to the Global Financial Cycle, while limiting the risk exposure of asset managers through inflow tax helps reduce the sensitivity. Figure 7 shows that across all levels of default risk, the amplification effect is stronger than that in the baseline specification with a larger 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 the sensitivity by more than 60%, partly driven by a 68% higher amplification effect.[68] Meanwhile, a 15% tax on asset managers'

[67]The yield spread sensitivity of wealth shock $\mathrm{d}B_{z,t}$ at a given state (λ, W) is $-\kappa\eta_z(\lambda, W)/(P(\lambda, W))^2$. It can be derived from (17) and the definition of bond yield $y(\lambda, W) = \kappa/P(\lambda, W)$ applying Itô's lemma. The direct and amplification components in Table 6 follow from applying the decomposition of Equation (24) for $\eta_z(\lambda, W)$.

[68]For visual convenience, Figure 7 omits the counterfactual scenario with a higher bond supply, from

risky asset return weakens the endogenous amplification of shocks by 19%.

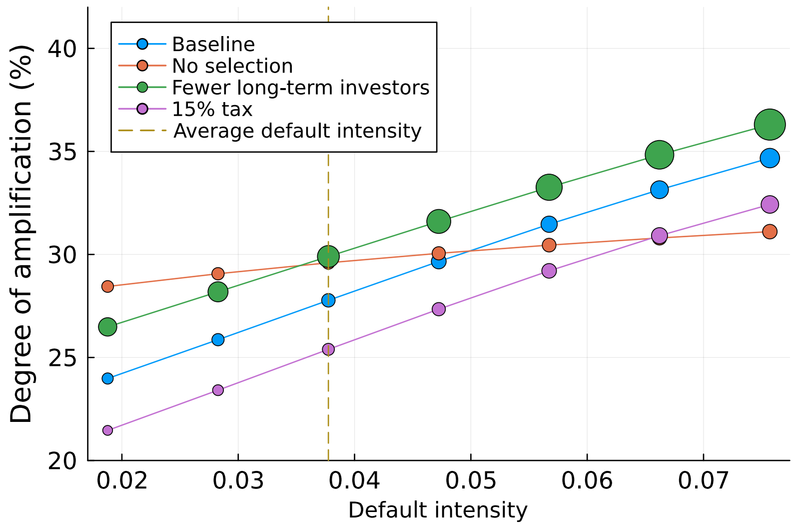


Figure 7: Yield spread sensitivity to wealth shocks: Amplification effect across scenarios

Note: Figure 7 plots the share of bond yield sensitivity to a one standard deviation exogenous wealth shock $dB_{z,t}$ explained by endogenous wealth amplification. I decompose the sensitivity into a component due to direct shock impact (see Table 6) and an amplification component due to wealth revaluation for different levels of fundamental risk. The scenario “no selection” corresponds to the counterfactual parameterization where I set the parameters δ_λ in Equation (16) to zero. By doing so, I remove the direct dependence between asset demand elasticity on 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 (16) to 0.8 times the original value. “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. Sizes of the dots represent the level of bond yield sensitivity.

5.2 Implication for emerging market borrowing cost

The mechanism formalized in the model is relevant for understanding the cost of sovereign borrowing. Table 7 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 would result in a 0.3 percentage point average decline in sovereign borrowing cost, and a 0.1 percentage point reduction in the volatility of sovereign spread (a 8.6% and a 14.7% reduction in relative terms, respectively). The demand responsiveness 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 risky perpetuity, equilibrium average share held by the risk-averse asset managers slightly increases.

Reducing the mass of long-term investors by 20% substantially pushes up spread and volatility (31% and 62% in relative terms, respectively), driven by a decline in the demand responsiveness of long-term investors by 30% and a higher share held by the

which I draw a similar quantitative conclusion as reflected in Table 6.

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

Note: Table 6 decomposes yield spread sensitivity (expressed in basis points) to a one standard deviation negative exogenous wealth shock ($\mathrm{d}B_{z,t}$ in (18)) 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 (16) 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 (16) 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.

asset managers. A rise in the residual supply facing private investors works similarly. Asset manager absorb over 60% of the additional asset supply, resulting in a rise of bond spread by one percentage point, and a 56% relative increase in bond yield volatility.

Policy measures on the asset managers have distinct implication for the equilibrium investor composition and asset prices. Changing the liability structure of the asset managers by eliminating exogenous wealth shocks significantly reduce the borrowing cost of the sovereign (by 0.8 percentage points relative to the baseline), mostly through an enlarged asset demand by the asset manangers. Yield spread volatility is 13% lower. As a result of the increased demand, their fundamental risk exposure substantially widens relative to those implied by the baseline calibration, partially offsetting the dampening of volatility when wealth shocks are removed.[69] On the other hand, the 15% inflow tax on the risky asset return discourages asset manager from large exposure to the risky perpetuity, lowering the fraction held by asset managers by 2.6 percentage points relative

[69] In Appendix E, I show in Figure E5 that asset managers' wealth exposure to fundamental shocks is larger when exogenous wealth shocks are eliminated.

to the baseline. Unlike the previous scenario, yield spread rises by 0.2 percentage points under the inflow tax to induce long-term investors to step in the market. The taxation 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 7: Model implied moments: Baseline and counterfactual parameterization

Note: Table 7 reports model-implied moments across the baseline calibration and various counterfactual parameterizations. The scenario "no selection" corresponds to the counterfactual where I set the parameters δ_λ in Equation (16) 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 (16) 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%. "Stable flow" reports moments from an alternative parameterization of the model in which I set the volatility of asset manager wealth σ_z in (13) to zero. "Tax on asset managers" considers the effect of levying a 15% tax on asset managers for the the return of holding the risky perpetuity. 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 (28)).

6 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 may be limited by various constraints that give rise to their appetite towards safe, home-currency assets.

Recent effort by emerging markets to expand the access to their local-currency bond market could alleviate the concern on currency mismatches, but may also attract risk-sensitive foreign investors that play a destabilizing role, as both Bertaut, Bruno and Shin (2023) and my empirical finding imply. For these countries, the quest towards a stable funding condition may involve a careful design of issuance and open-up strategy to accommodate stable, long-term investors. Clayton, Dos Santos, Maggiori and Schreger (2022) advocate gradualism in the context of reserve currency competition. For emerging markets, analyzing the key tradeoff facing sovereign borrowers and the optimal composition of foreign investor base under the influence of the Global Financial Cycle is an important next step that I leave for future work.

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Online Appendix

A A closer look at the data

A.1 Benchmarking the coverage of micro-data

This section demonstrates that the main dataset I use in my analysis – SHS-Base plus – has reasonable coverage of the investor base of emerging market debt issuance, especially for European issuers. I illustrate this point in Figure A1 to Figure A3, and compare qualitative features of my novel dataset against extant data sources in Table A1.

Figure A1 uses IMF Coordinated Portfolio Investment Survey (CPIS) at the end of June 2021 with sectoral breakdown to show that Germany-based banks and ICPFs are among the biggest foreign holders of EM European long-term debt. German investment funds' aggregate holding of EM long-term debt is slightly smaller than U.S. funds. My micro data contains holding for both countries.

Figure A2 plots the quarterly evolution of aggregate market values of EM European sovereign debt recorded in the SHS-Base plus dataset with European Central Bank's aggregate security holding statistics by sector. With a substantial coverage, the time-series variation of aggregates from my micro data also closely tracks that of Euro Area-wide numbers.

Figure A3 compares the coverage of my data against Germany's cross-border holding of long-term portfolio debt by sector, reported by CPIS. For important Eastern European countries in my sample, I plot the evolution of the market values of holdings reported in my data as a share of CPIS aggregates. The coverage is close to 100%, even taking into consideration that one cannot separate corporate from sovereign issuance in the CPIS data.

A.2 Data sources, data processing, and sample selection

In this section, I report the sources of the key datasets used in my analysis (Table A3), the mapping of investor sectors in the SHS-Base plus data to the coarse classification I use in Section 2 (Table A2), and the procedure I adopt to generate the final dataset for analysis.

Bond universe and characteristics The universe of emerging market sovereign bond is constructed by searching over Bloomberg. The data includes floating, fixed, or zero coupon bonds with a maturity date after 2005. Defaulted, exchanged, funged bonds are

SHS-Base plus (this paper)	Other datasets
Custodian-based census; wide sectoral coverage	Mostly focus on mutual fund allocations (Morningstar, EPFR)
Security-level holdings	May ignore within-country heterogeneity (EPFR, CPIS).
Long panel (2005 onwards); monthly after 2013	May not capture secular trends and high-frequency portfolio shifts. (ECB SHS: quarterly and starts from 2013Q4)
Face value reported for individual bond holding	May confound valuation effects with holding decisions (EPFR, CPIS)

Table A1: Overview of SHS-Base plus and comparison with other datasets

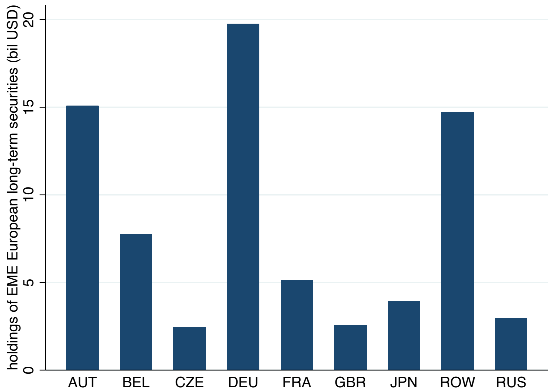
Note: Table A1 highlights the core features of the SHS-Base plus data used in my main empirical analysis. SHS-Base plus refers to Securities Holdings Statistics Base plus by Deutsche Bundesbank (Blaschke, Sachs and Yalcin-Roder, 2022). The data is compared with other datasets used in the international finance literature. "Morningstar" refers to mutual fund and ETF portfolio holding provided by Morningstar. "EPFR" provides information on mutual fund flow and country-level allocation. "CPIS" refers to IMF Coordinated Portfolio Investment Survey recorded at bilateral country level. ECB compiles quarterly Security Holdings Statistics (SHS) for the broader Euro Area investors, starting from 2013Q4.

excluded. Bond prices, yields, and bid-ask spreads are obtained by combining data from Bloomberg, Refinitiv Datastream, and implied prices from SHS-Base plus. For bonds with pricing information from commercial data sources, I cross-check with SHS-Base plus and find that they align well with each other. The implied prices from SHS-Base plus are calculated via dividing the market values of bond holdings by the face values of bond holdings, and multiply by 100 for bonds with a par value of 100.

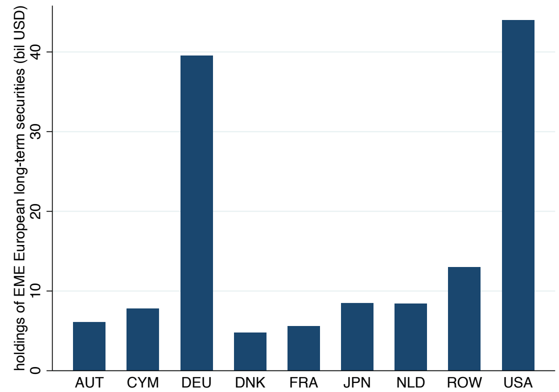
In the context of emerging market sovereign issuance, taking into account Global Depositary Notes (GDN) and RegS/144a issuance are important to avoid doublecounting, as multiple ISINs may refer to the same bond (see Footnote 21). For instance, Costa Rica's 12% bond maturing in March 2012 has three ISINs: CRG0000B29G6 (underlying), US221597AT40 (144A), US221597AU13 (RegS). I obtain GDN information from Citi[70] and creates mappings between RegS/144a issuance based on data from Refinitiv.

Mutual fund selection and information Characteristics (flow, returns) of the mutual funds and ETFs in my sample are obtained through queries using Morningstar Direct. Portfolio holdings are obtained from Morningstar Analytics Lab via the Jupyter Notebook API. Any mutual fund in my sample satisfies one of the following inclusion criteria: 1) The fund is an emerging market fixed-income fund according to Morningstar's Global Category; 2) The fund's Morningstar Category suggests its a regional fixed-income fund

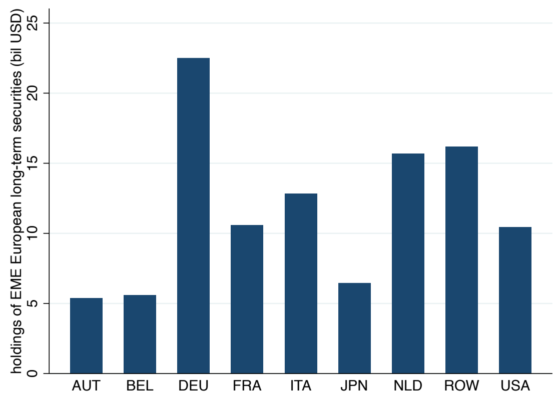
[70] https://depositaryreceipts.citi.com/adr/common/linkpageUL.aspx?pageId=3&subpageid=179.



(a) Banks



(b) Other financial institutions (incl. investment funds)



(c) Insurance companies and pension funds

Figure A1: Germany-based investors as the major holders of EM European debt

Source: IMF CPIS, own calculations.

Note: Figure A1 shows that Germany-based investors are of the most important creditors to emerging market European countries for each of the three sectors I consider in the paper. Each bar in the three panels correspond to the level of holding of long-term debt securities isseud by EM European countries, separately for each major investor country and sector. ROW refers to "rest of the world".

as it belongs to one of "EAA Fund Emerging Europe", "EAA Fund Asia", "EAA Fund Other", "EAA Fund China", "EAA Fund RMB". Some funds classified into very small categories such as "EAA Fund PLN/IDN" are also included. Finally, to account for global mutual funds partially benchmarked to EM, I search Morningstar and find all funds including in its "Primary Prospectus Benchmark" emerging market-tracking indices designed by JPMorgan and Bloomberg, as well as the FTSE World Government Bond Index (WGBI). A total of 1484 mutual funds and 107 ETFs are included after the screening, of which 1276 funds, or 80% of the total number of funds, report portfolio data at one point in the sample.

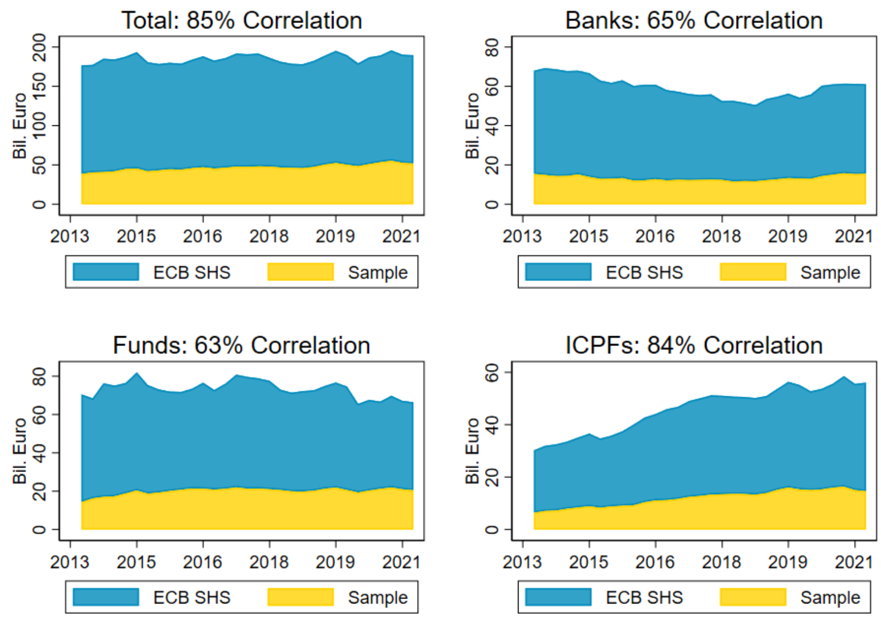


Figure A2: Benchmarking micro data against ECB Security Holdings Statistics

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

Note: Figure A2 examines the coverage of SHS-Base plus dataset, which focuses primarily on Germany-based investors, against the aggregate figures reported by European Central Bank's Security Holding Statistics covering Euro-Area members. I focus on government bond issued by emerging market economies in Europe. For each general sector (total, banks, investment funds and insurance companies and pension funds), I plot the evolution of the aggregate holding of emerging market sovereign bond reported in ECB (in blue) and that reported in SHS-Base plus (in yellow). I also report the correlation between two series expressed in quarter-over-quarter changes.

Benchmarking Mutual funds investing in emerging markets are heavily benchmarked against established bond indices, including but not limited to JP Morgan EMBI, GBI-EM, and Bloomberg Emerging Market Index (also see Arslanalp and Tsuda (2015)). In my sample of mutual funds, 80% (1178) of the funds report benchmark-following in their prospectus. Less than 6 percent of the funds explicitly state that they do not follow benchmarks, and 15% of the funds do not report benchmarking information.

Portfolio holding data from Morningstar requires extensive cleaning as a significant portion of the securities have missing ISINs. To impute ISINs, I take a number of steps. First, for bonds with CUSIPs but no ISINs, I conduct internal imputation as other funds may hold the same securities and report both. Otherwise, I query ISIN information using Refinitiv's symbology conversion API. For securities with no identifiers at all, I develop an algorithm that allows me to match these securities to ISINs based on their coupon, maturity date, issuer and currency denomination. I remove securities that are not government bonds. I also correct reporting inconsistencies in the case of legacy

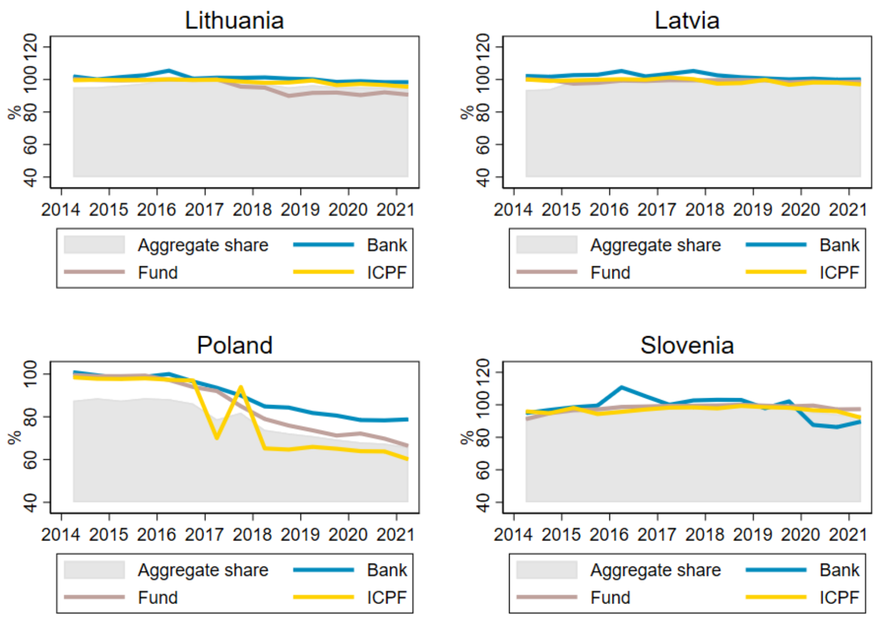


Figure A3: Benchmarking micro data against Coordinated Portfolio Investment Survey

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

Note: Figure A3 compare Germany-based investors' aggregate holding of long-term government bond issued by a selected set of European countries as implied by the SHS-Base plus dataset against its counterpart reported in IMF's Coordinated Portfolio Investment Survey (CPIS), with the caveat that the public CPIS data do not separate government debt from corporate debt. Each line as well as the gray shade (representing aggregate holding by Germany) corresponds to the shares accounted for in my micro data,

currencies prior to the Euro as well as Chile, some of whose bonds are denominated in Chilean Unit of Account (CLF). After aggregation, 0.23% of all observations have a total share of mutual funds and ETFs exceeding 100. I replace numbers between 100 and 120 with 100, and I do not use those observations with a number larger than 120 when merging with SHS-Base plus.

One concern with the holdings data is that funds may report their portfolios in a lower-than-monthly frequency, which may introduce mechanical variations in the monthly investor composition measure used in the regression. Monthly portfolios are however prevalent in the post-2013 sample I use to merge with SHS-Base plus. I observe that more 85 percent of funds reporting in 2021 remain in the sample after dropping portfolios as of quarter ends (March, June, September, December). In 2013, this number is more than 70 percent. Nevertheless, I further make sure that reporting frequency is not driving the variation in the investor base in my analysis by restricting to the funds that consistently report monthly portfolios, by dropping the funds with less than 90% monthly coverage in their portfolio holdings when calculating the investment fund share measure θ (see Equation (2)).

Monthly fund flow data and monthly return data are available for 1229 funds. For fund returns, I use the return for the oldest share class for each fund wherever applicable. Otherwise, return for the share class with the longest data is used. Following Jotikasthira, Lundblad and Ramadorai (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).

The flow-induced demand instrument used in Section 3 is constructed based on a merged sample of portfolio holdings, flow and returns of 1092 mutual funds. I drop fund whose reported aggregate market value of holdings differ from sizes by more than 20% to account for the potential discrepancy between reported portfolio holdings data and fund AUM. When constructing the FID and granular fund flow instruments, I also follow the approach taken in Section 2 to restrict to funds with consistent monthly reporting of asset positions to avoid introducing mechanical variations due to incomplete coverage.

Security holdings data: Sample selection I use almost all observations matched to my emerging market bond universe, except the following subsets of the data: 1) short positions (a very small portion, as it is in general difficult to short emerging market securities); 2) positions held by investment funds domiciled in the U.S. and offshore financial centers, including Cayman Islands, Guensey, Curaçao, Liechtenstein, Ireland and Luxembourg; 3) "domestic" holdings, defined as positions held by investors from the same country as the issuers. A bond must show up in the sample for more than 12 months for it to be included in the regressions. I drop 2) to avoid doublecounting when merging with Morningstar investment fund data. I drop 3) to focus on the positions held by foreign investors.

A.3 Summary statistics

Table A5 to A6 report summary statistics associated with key variables used in the empirical analysis.

Classification	Code 2013 onwards	Code before 2013	Description (ESA)
Bank	1224	1224	Domestic bank
	1225	1225	Foreign banks – excluding central securities depositories
	1228	1299	Foreign central securities depositories
ICPF	1280	1250	Insurance corporations
	1290		Pension funds
Investment Fund	1230	1226	Money market funds
	1240	1231	Non MMF investment funds
	1251	1323	Other financial intermediaries (excluding ICPFs)
	1252	1233	Financial vehicle corporations
	1261	1241	Investment companies
	1262	1242	Financial auxiliaries
	1270	/	Captive financial institutions and money lenders

Table A2: Sectoral classification based on ESA

Note: Table A2 reports the sectoral classification of investors according to two vintages of the European System of Accounts (ESA). I further separate investors into three broad groups reported in the first column.

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 A3: Key data sources

Note: Table A3 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, Sachs and Yalcin-Roder, 2022) compiled by Research Data and Service Centre (RDSC) of the Deutsche Bundesbank.

	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 A4: 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 A4 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 A5: 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 A5 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 (5). 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 A6: Summary statistics: Fund characteristics and holdings (Morningstar), miscellaneous data

Source: Morningstar and miscellaneous data sources outlined in Table A3.

Note: Table A6 reports summary statistics related to mutual fund characteristics according to Morningstar data, as well as miscellaneous control variables when estimating (4) and (5). 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 2.1. Following Jotikasthira, Lundblad and Ramadorai (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).

B Empirical analysis: Additional results

B.1 Investor composition and sensitivity to global factors: More evidence on the aggregate pattern

Defining foreign non-bank share Figure 1(a) in the main text plots the relationship between sovereign spread-VIX β and a broad measure of investor composition: the share of foreign *non-banks* in a country's external liabilities. I construct this measure by combining data on international investment position of countries (Lane and Milesi-Ferretti, 2017) and cross-border bank claims data from the Locational Banking Statistics (LBS) compiled by the Bank for International Settlements (BIS). For my purpose, the external liability of a country is defined by the total stock of portfolio debt, equity, and other investment (mostly comprised of bank loans) liability. The LBS data covers assets reported on all banks residing in each reporting country, including bank loans, debt securities, equity securities, and other financial instruments. 48 countries report the LBS data to the BIS, with an estimated global coverage exceeding 90 percent since 2004.[71]

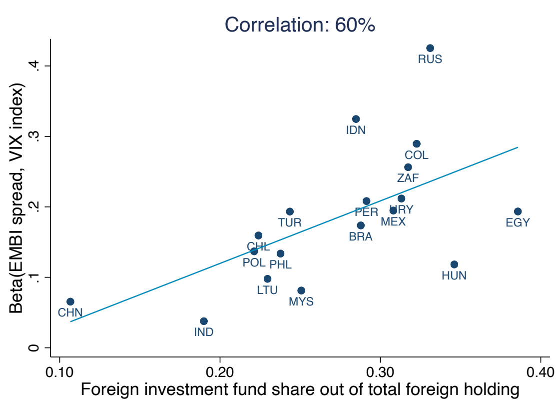
The foreign non-bank share in government bond outstanding is directly obtained from the Arslanalp and Tsuda (2014) estimates. The foreign non-bank share in external liabilities is defined as the residual from the subtracting bank claims reported by the BIS from total external liabilities reported in Lane and Milesi-Ferretti (2017):

$$\text{Non-bank share (broad)}_{it} := \frac{\text{Total external liabilities}_{it} - \text{BIS bank claims}_{it}}{\text{Total external liabilities}_{it}}.$$

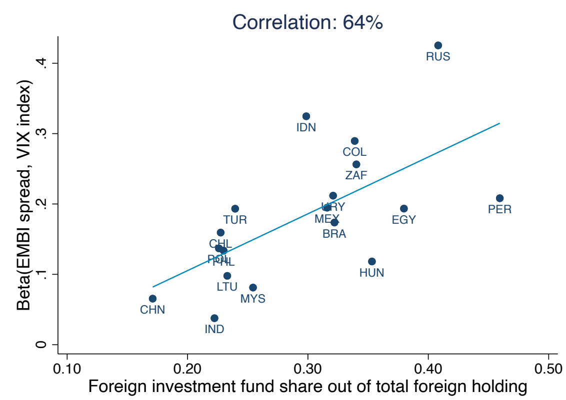
Isolating the role of foreign investment funds I use IMF Coordinated Portfolio Investment Survey (CPIS) to further investigate the role of detailed sectoral heterogeneity in driving the correlation between foreign non-bank share and sovereign spread sensitivity. Towards this end, I aggregate bilateral cross-border portfolio position on long-term debt securities to the issuer country level and focus on holding by the "Other Financial Corporations: Other" sector. This sector consists of investment funds that are not money market funds, other financial intermediaries except ICPFs, financial auxiliaries, and captive financial institutions and money lenders. In particular, this sector include important holders of emerging market debt such as mutual funds and exchange-traded funds. Consistent with the sector labeling of my micro data, I call this sector "investment funds".

[71] See the estimated global coverage of LBS at https://www.bis.org/statistics/lbs_globalcoverage.pdf.

While CPIS provides sectoral breakdown, it comes with a number of limitations. First, its residency-based recording principal means that issuance through off-shore financial centers is not directly captured. I use the reallocation matrix provided by Coppola, Maggiori, Neiman and Schreger (2021) based on mutual fund holding.[72] Second, sectoral breakdown is only available since 2013. I recompute EMBI-β for each country using 2013–2019 data.[73] In this process, I drop Argentina, Ukraine due to sovereign default dominating the post-2013 sample, Bulgaria (as its EMBI spread data is only sporadically available after 2013), and Thailand (EMBI spread is not available after 2006). Figure B1 plots the cross-sectional relationship along with a strong correlation for both the residency-based measure (Panel (a)) and adjusted measured based on nationality (Panel (b)).



(a) Residency-based raw measure



(b) Nationality-based adjustment (Coppola, Maggiori, Neiman and Schreger, 2021)

Figure B1: Sovereign spread-global risk β: The role of foreign investment funds

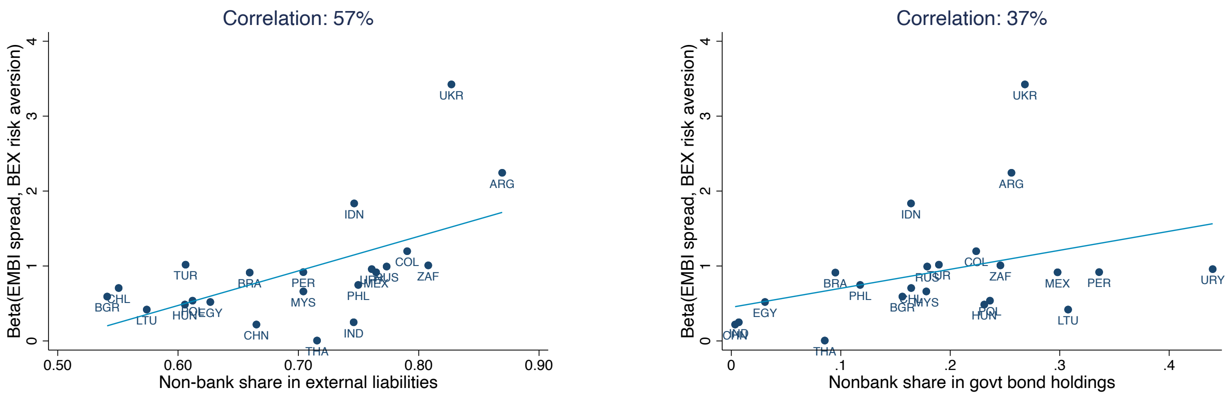
Source: IMF CPIS, World Bank Global Economic Monitor, own calculations.

Note: Figure B1 plots the cross-sectional relationship between the sensitivity of emerging market sovereign borrowing cost to innovations in global risk factors and a measure of foreign investment funds' share in foreign holding of emerging market long-term debt. In both panels, the y-axis corresponds to time-series regression coefficients of monthly changes in sovereign bond spread (proxied by JPMorgan EMBI spread) on monthly changes in the log of CBOE VIX index, controlling for changes in U.S. monetary policy. The regressions are restricted to 2013–2019. The x-axis of Panel (a) plots foreign investment fund holding as a share of total cross-border long-term debt holding of foreign investors, calculated using CPIS data and averaged over 2013 to 2019. The x-axis of Panel (b) plots a transformed measure, by converting the residency-based measure used in Panel (a) to the nationality-based measure through the use of the restatement matrix provided by Coppola, Maggiori, Neiman and Schreger (2021). Compared to Figure 1, I drop Argentina and Ukraine due to sovereign default dominating the post-2013 sample, and Bulgaria due to insufficient coverage of the EMBI data.

[72] Coppola, Maggiori, Neiman and Schreger (2021) provide adjustment multipliers for multiple asset classes. For holding of U.S. investors, I use the reallocation matrix for "government debt". For all other investors, I use the matrix for "all bonds". I apply the adjustment directly to the "Other Financial Corporations: Other" sector, and use the difference between the unadjusted and adjusted series to modify the total holding and compute the share attributed to investment funds.

[73] EMBI spreads are available via World Bank's Global Economic Monitor as of 2022: https://databank.worldbank.org/id/d79f5818?Report_Name=EMBI-TS.

Robustness I check that the aggregate patterns uncovered in Figure 1 is robust across the following dimensions. First, Figure B2 shows that the pattern remains if I replace the VIX index used in the calculation of sovereign spread-risk β with the Bekaert, Engstrom and Xu (2021) global risk aversion index (BEX).Second, Figure B3 displays the positive and strong relationship between the sensitivity of 5-year USD-denominated CDS spread to VIX innovations and foreign non-bank share in external liabilities. Figure B4 substantially expands the country coverage by including countries not covered in the Arslanalp and Tsuda (2014) dataset. The positive correlation remains.



(a) Foreign non-bank share in external liabilities

(b) Foreign non-bank share in total sovereign debt outstanding

Figure B2: Sovereign yield spread-global risk β and investor composition: Alternative risk proxies

Source: Arslanalp and Tsuda (2014); Lane and Milesi-Ferretti (2017); Bekaert, Engstrom and Xu (2021), World Bank, own calculations.

Note: Figure B2 further illustrates the cross-country pattern between foreign non-banks' presence through portfolio investment and emerging market economies' sensitivity to shifts in global risk aversion. In this figure, global risk aversion is proxied by the Bekaert, Engstrom and Xu (2021) risk aversion index. In both panels, the y-axis corresponds to time-series regression coefficients of monthly changes in sovereign bond spread (proxied by JPMorgan EMBI spread) on monthly changes in the Bekaert, Engstrom and Xu (2021) index, controlling for changes in U.S. monetary policy. In Panel (a), the x-axis corresponds to foreign non-banks' share in total non-FDI external liabilities averaged over 2004–2019. In Panel (b), the x-axis corresponds to foreign non-bank's share in total government bond outstanding averaged over the same period. Appendix A.2 contains more information on the construction of the data points.

Finally, through cross-sectional regressions, I show that the relationship between a country's sensitivity to the Global Financial Cycle remains statistically significant even after controlling for a number of issuer-level characteristics related to credit risk, financial development and openness. This pattern is shown in Table B2, where the estimated β_i from (1) is regressed on the investor composition measure used in Figure 1, average stock market capitalization, debt to GDP ratio, GDP per capita and the Chinn and Ito (2006) index of capital account openness, and a measure of credit rating.[74]

[74] In untabulated results (with 16 countries), I show that the share of a country corporate debt denomi-

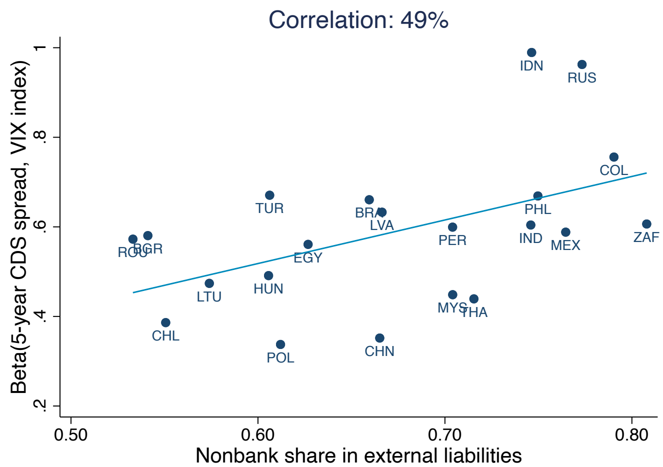


Figure B3: Sovereign CDS spread-VIX β and investor composition

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

Note: Figure B3 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.

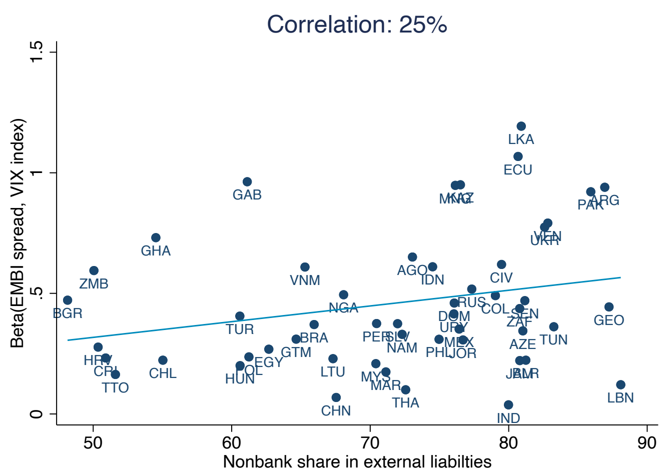


Figure B4: Sovereign yield spread-VIX β and investor composition: Expanded sample

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

Note: Using a substantially enlarged sample based on EMBI spread of a wider range of countries, Figure B4 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.

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nated in foreign currency can also explain sovereign β to global risk factors (Du and Schreger, 2022), but the role of foreign investor composition remains robust and statitically significant.

Country	β	s.e.	t -statistics
Argentina	.94	.55	1.7
Brazil	.37	.12	3
Bulgaria	.47	.18	2.61
Chile	.22	.06	3.57
China	.07	.05	1.3
Colombia	.49	.13	3.83
Egypt	.27	.11	2.53
Hungary	.2	.1	1.95
India	.04	.03	1.12
Indonesia	.6	.2	3.08
Lithuania	.23	.11	2.03
Malaysia	.21	.06	3.26
Mexico	.35	.1	3.5
Peru	.37	.12	3.11
Philippines	.31	.09	3.27
Poland	.24	.06	3.99
Russia	.52	.17	2.98
South Africa	.44	.12	3.58
Thailand	.1	.08	1.2
Turkey	.41	.13	3.21
Ukraine	.77	.76	1.02
Uruguay	.42	.12	3.52

Table B1: Sovereign spread sensitivity to shifts in global risk factors at the macro level

Source: World Bank, FRED, own calculations.

Note: Table B1 reports the regression coefficients β_i from estimating Equation (1), representing the sensitivity (in basis points) of emerging market sovereign spread to 1% increase in the VIX index. Newey-West standard errors with the bandwidth set at $\left\lfloor T_i^{1/4} \right\rfloor$, where T_i is the sample size for each country.

Time-series dimension: Local projection exercises I present additional evidence on the relationship between foreign investor composition and EM sovereign spread's sensitivity to global risk factors, by exploiting time-series variation. More specifically, I run the following local projection (Jordà, 2005) at monthly frequency:

$$\Delta_h y_{i,t+h} = \alpha_i^h + \delta_t^h + \sum_{k=1}^{6} \beta_k^h \Delta \mathbf{r}_{i,t-k} + \sum_{k=0}^{6} \lambda_k^h \mathrm{NB}_{i,t-k-3} + \kappa^h \Delta \mathrm{Risk}_t \times \mathrm{NB}_{i,t-3} + \varepsilon_{i,t+h} \tag{29}$$

where the vector $\mathbf{r}$ contains both the lagged levels of the dependent variable y as well as each country i's debt-to-GDP ratio. α_i^h is a country-specific intercept and δ_t^h denotes time fixed effect. $\mathrm{NB}_{i,t-k}$ is an indicator variable for each country, each month that

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

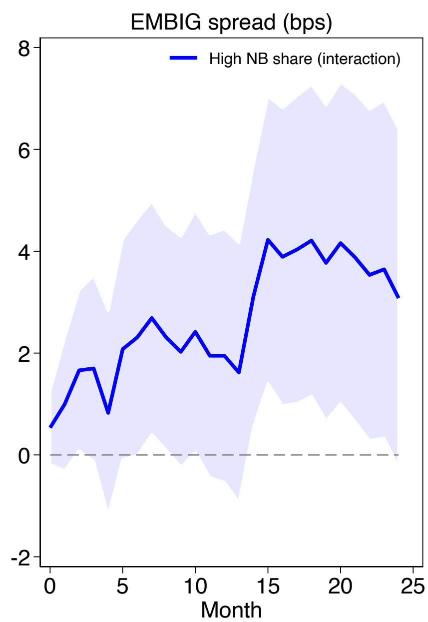
Table B2: The relationship between sensitivity to the Global Financial Cycle and foreign investor composition: Adding issuer-level characteristics

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

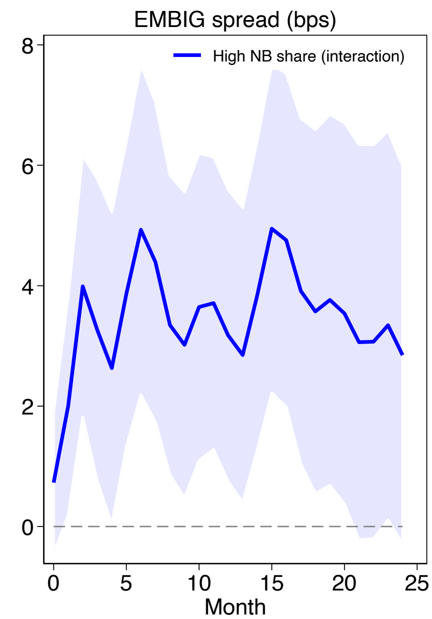
Note: Table B2 reports cross-sectional regression results relating country-specific sovereign yield spread sensitivity to log changes in the VIX index (β_i in (1)) and measures of foreign investor composition, controlling for issuer-level characteristics. Issuer-level characteristics are averaged over 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.

takes value 1 if its Arslanalp and Tsuda (2014) foreign non-bank share in sovereign debt market are above median across all countries that month in my sample. The coefficient κ^h traces the *relative* impulse response between countries with an above-median foreign non-bank share and a below-median foreign non-bank share to a shock in global risk factors, captured in the index Risk_t. I lag the non-bank share dummy by three months. Monthly non-bank share is obtained from quarterly data via linear interpolation. 16 countries enter into my final sample for local projection as their EMBI spread series are the most complete. I also drop Argentina and Ukraine to purge the effect of sovereign default/restructuring and focus on the sensitivity in normal period. The sample period is 2004 to 2019.

Figure B5 plots the relative impulse response to changes in global risk factors, proxied by either the VIX index (baseline, Panel (a)), or the Bekaert, Engstrom and Xu (2021) risk aversion index. Relative to countries with a low foreign non-bank share in its sovereign bond issuance, countries with a high foreign non-bank share reacts more strongly to changes in global financial conditions driven by risk shocks.



(a) VIX index



(b) Bekaert, Engstrom and Xu (2021) risk aversion index

Figure B5: Relative impulse responses to global risk tightening: Above-median foreign non-bank share

Source: Arslanalp and Tsuda (2014); Bekaert, Engstrom and Xu (2021), World Bank, FRED, own calculations.

Note: Figure B5 plots relative impulse responses to an increase in the VIX index (left panel) and Bekaert, Engstrom and Xu (2021) risk aversion index (right panel), between countries with an above-median foreign non-bank share in government bond outstanding (according to the data of Arslanalp and Tsuda (2014)) and countries with a below-median share, based on the local projection equation (29). In particular, the local projection is based on regressing changes in sovereign spread (EMBI spread) on time fixed effect, issuer-specific intercept, current and lagged value of controls, lagged non-bank share, and interaction between lagged non-bank share and global financial shocks. The relative impulse responses correspond to the set of interaction coefficients. I lag the non-bank share dummy by three months. Monthly non-bank share is obtained from quarterly data via linear interpolation. 16 countries enter into my final sample for local projection as their EMBI spread series are the most complete. I also drop Argentina and Ukraine to purge the effect of sovereign default/restructuring and focus on the sensitivity in normal period. The sample period is 2004 to 2019. The control vector contains lagged levels of the dependent variable as well as debt-to-GDP ratio of each country. 68% error bands based on heteroskedasticity-robust standard errors are reported.

B.2 Banks and ICPFs as long-term investors: Empirical support

My classification of banks and ICPFs as "long-term" investors is supported by two sets of observations based on recently available data on European financial institutions.

First, "held-to-maturity" accounting is associated with higher stability of banks' security portfolio. IFRS 9 requires a bank to classify financial assets after first recognition based on the bank's objective related to its business models. An asset can be recorded at "amortised cost" if the intention is to hold the asset for investment. The assets with this designation will enter the bank's balance sheet by its book value. Gains and losses that result from market price movements are not recognized unless the securities are sold. Otherwise, assets are designated as "fair value" or "held for trading" (mostly for a very short term). Market value fluctuations of assets in these categories would affect metrics in the bank's income statement.[75]

Panel (a) of Figure B6 breaks down European banking institutions' financial claims on the governments of European emerging market economies based on accounting treatment. The data comes from the annual EU-wide transparency exercises conducted by the European Banking Authority. The graph shows that for the past five years, more than 40 percent of the exposure is designated as "held to maturity," indicating that a substantial portion of the banks' emerging market sovereign portfolio is not intended to be actively traded.

Like banks, insurance companies also have stable liabilities and have incentives to hold investments to maturity (Johnson and Wong, 2023). Data on Euro-Area institutions' aggregate EM sovereign bond portfolios reflects such stability for both sectors. Starting from 2021, ECB publish the enhanced Security Holding Statistics (SHSS) that include country-sector-level exposure in both face value and market value terms. Focusing on the emerging market sovereign issuers available in SHSS[76], I measure the frequency at which each investor sector adjust their holding by computing the "churn rate", following Gaspar, Massa and Matos (2005) and Cella, Ellul and Giannetti (2013):

$$CR_{s,t} = \frac{\sum_i \frac{MV_{i,s,t}}{F_{i,s,t}} \cdot |F_{i,s,t} - F_{i,s,t-1}|}{\sum_i \frac{MV_{i,s,t}+MV_{i,s,t-1}}{2}} \tag{30}$$

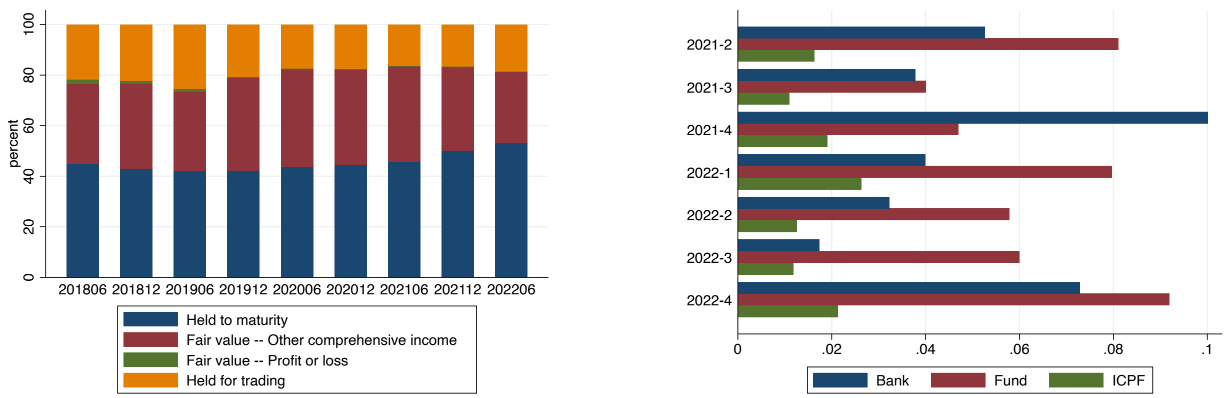
where $MV_{i,s,t}$ is the market value of sector s holding of country i's long-term government bond at quarter t, and $F_{i,s,t}$ is the corresponding face value. The churn rate measures the

[75] In the US context, fair-value designation is called "available for sale". It indicates an intention to hold the security for investment, but gives the banks more flexibility to manage the securities. For more details on the implication of the accounting standard, see Vickery, Deng and Sullivan (2015).

[76] The set of countries include Cyprus, Estonia, Croatia, Lithuania, Lativa, Malta, Slovenia and Slovakia.

frequency at which a sector rotates its positions on the underlying investment. Inactive investors have a churn rate of 0, while an investor that enters the market at time t would have a churn rate of 2.[77]

Panel (b) of Figure B6 plots the evolution of churn rates for banks, investment funds and ICPFs based on the SHSS data. In all but one recent quarter, investment funds have the highest churn rate of all three sectors. The churn rates of ICPFs are consistently the lowest. Banks have intermediate churn rates. I conclude that banks and ICPFs have more stable exposure to emerging market sovereigns compared to investment funds.



(a) Accounting designation of exposure

(b) Churn rate of bond holding

Figure B6: Banks and ICPFs have stable emerging market sovereign portfolios

Source: European Banking Authority, ECB Securities Holdings Statistics, own calculations.

Note: Panel (a) reports the breakdown of the financial exposure of European banks to emerging market governments by accounting treatment, based on whether the underlying assets is held for investment or trading purposes. An asset with the "held to maturity" designation is intended to stay at the balance sheet for cash flow. Panel (b) calculates the "churn rate" to measure the turnover of the portfolios of sovereign bonds issued by Euro Area emerging market economies and held by Euro Area banks, investment funds and ICPFs. A lower churn rate (computed according to (30)) corresponds to higher portfolio stability.

B.3 Micro data analysis: Additional results

B.3.1 Investor preferences and sorting

Table B3 reports regressions similar to Equation (3), except that the dependent variable is the weight of each bond in the emerging market sovereign bond portfolio. The weight is defined as $B_{s,t}(n)/\sum_m B_{s,t}(m)$, where I omit the issuer subscript. Table B3 shows that at the intensive margin of each sector's bond holding decision, it remains the case that

[77] I use the ratio between the market value and the face value of claims, $MV_{i,s,t}/F_{i,s,t}$, to proxy for the price of the assets. With aggregate data, the price is sector-specific, allowing for differences in the underlying portfolios for each country.

banks and ICPFs exhibit stronger preferences over Euro-denominated debt compared to investment funds.

B.3.2 Propagation of shocks: Additional push-pull regressions

Table 2 in the main text shows that the sensitivity of sovereign yield to global risk factors depend on the ex ante investor composition. The results remain robust if I replace the investor base measure θ with the relative share held by banks and ICPFs, defined as

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

The estimates are reported in Table B4. Table B6 demonstrates that the results remain robust under alternative proxies for global risk factors, when I replace $\log \text{VIX}$ with $\log \text{V2X}$ representing the implied volatility of the Europe STOXX index. I find similar results (untabulated) when I replace VIX index with S&P500 stock return.

B.3.3 Forming long-short portfolios of emerging market sovereign bonds

Table B5 (columns (3) and (4)) show that my main results relating investor composition to shock sensitivity remains robust when I use bond yield changes residualized by a set of bond risk factors as the dependent variable. To generate the bond risk factors, for Euro and U.S. dollar denominated sovereign bonds in my sample, I sort them into terciles based on currency, credit rating or residual maturity and form equal-weighted portfolios rebalanced at the end of each month. The data runs from 2012M12 to 2021M6.

Table B7 reports simple summary statistics associated with the portfolio. For the portfolios associated with credit risk, P1 stands for bonds with the highest credit ratings and P3 contains bonds with the lowest credit ratings in my sample. Similarly, the P3 portfolio for duration risk contains bonds with the highest residual maturity. The results confirm that in the emerging market sovereign bond market, credit risk and duration risk are priced. The excess return of investing in the rating-sorted portfolios are in line with those reported by Borri and Verdelhan (2011).

Finally, the credit risk factor and the duration factor are define as the return from a long-short strategy, buying bonds in portfolio P3 and selling bonds in portfolio P1 short.

VARIABLES	(1) Bank	(2) Fund	(3) ICPF	(4) Bank	(5) Fund	(6) ICPF
Callable	-0.046	0.015	-0.068**	-0.058	0.012	-0.078**
	(0.029)	(0.022)	(0.032)	(0.035)	(0.020)	(0.032)
Log amount outstanding (EUR))	0.026**	0.037***	0.033**	0.027**	0.038***	0.035**
	(0.010)	(0.007)	(0.014)	(0.011)	(0.007)	(0.015)
Coupon	0.008	-0.001	0.010	0.008	-0.001	0.010
	(0.005)	(0.002)	(0.006)	(0.005)	(0.002)	(0.006)
Maturity bucket	-0.020*	0.018***	0.051***	-0.020*	0.019***	0.052***
	(0.010)	(0.003)	(0.018)	(0.010)	(0.003)	(0.019)
Euro denomination	0.463***	0.127***	0.577***	0.468***	0.133***	0.584***
	(0.159)	(0.019)	(0.141)	(0.162)	(0.019)	(0.145)
Seniority	0.116*	0.059***	0.068**	0.122*	0.060***	0.072**
	(0.062)	(0.010)	(0.031)	(0.064)	(0.010)	(0.032)
Collateral eligibility	0.069	-0.032	-0.122	0.073	-0.038	-0.090
	(0.179)	(0.030)	(0.205)	(0.187)	(0.030)	(0.234)
Investment grade	-0.055	0.014*	0.005			
	(0.049)	(0.007)	(0.027)			
Observations	105,212	105,212	105,212	104,802	104,802	104,802
R-squared	0.314	0.345	0.248	0.324	0.376	0.264
Issuer FE	✓	✓	✓	-	-	-
Time FE	✓	✓	✓	-	-	-
Issuer*Time FE	-	-	-	✓	✓	✓

(a) Relative portfolio weight as the dependent variable

Table B3: Characteristic-based portfolio choice: Additional regressions

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

Note: Table B3 reports estimation results from a linear probability model (3) relating holding decision to bond characteristics. The sample period is 2012M12 to 2021M6. For Panel (a), I compute the relative portfolio weight for each bond, defined as the amount held by each sector as the share of total emerging market sovereign bond held by that sector. This measure 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, as well as fixed effects that vary at the issuer and time level. 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. Collateral eligibility refers to eligibility for Eurosystem credit operations. 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 B4: 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.

Note: Table B4 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (4). 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 B5: 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 B5 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (4). 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, constructed according to Appendix B.3. 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)
			large share		large share
VARIABLES	Δ yield	Δ yield	Δ yield	Δ yield	Δ yield
Δ log V2X	0.2870***				
	(0.0196)				
Δ log V2X $\times$ lag bank+ICPF share	-0.0092***	-0.0012**	-0.0011		
	(0.0013)	(0.0005)	(0.0008)		
Δ log V2X $\times$ lag fund share	0.0097***	0.0057***	0.0049***		
	(0.0016)	(0.0010)	(0.0011)		
Δ log V2X $\times$ 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 B6: 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 B6 reports push-pull regressions relating month-to-month changes in bond yield to "push" (global) factors and "pull" (local) factors according to (4). 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$\times$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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Factors	Rating			Duration		
Statistics	P1	P2	P3	P1	P2	P3
USD bonds						
Average excess return (%)	1.81	2.84	5.27	2.38	3.84	4.24
Average standard deviation (%)	2.3	5.78	7.6	4.14	5.57	9.42
Sharpe ratio	.79	.49	.69	.58	.69	.45
EUR bonds						
Average excess return (%)	2.41	3.16	11.72	.87	3.18	8.64
Average standard deviation (%)	2.41	4.05	9.27	2.35	2.92	6.65
Sharpe ratio	1	.78	1.26	.37	1.09	1.3

Table B7: Summary statistics: Portfolios of emerging market sovereign bonds (USD and EUR) sorted by bond characteristics

Source: Bloomberg, Refinitiv, and own calculations.

Note: Table B7 reports excess returns associated with investing in bond portfolios formed according to bond characteristics (credit rating and residual maturity, respectively). The level and standard deviations are annualized from monthly returns. For each characteristic and each currency of denomination (USD or EUR), sovereign bonds issued by emerging market countries in my sample are sorted into three equal-weighted portfolios based on the characteristic. For rating-sorted portfolios, rating becomes lower as one moves from P1 to P3. For duration-sorted portfolios, residual maturity becomes higher as one moves from P1 to P3. For USD bonds, the risk-free benchmark is Refinitiv US 5-year government benchmark index (`.TRXVUSGOV5U`). For EUR bonds, the risk-free return is computed from Refinitiv German 5-year government benchmark index (`.TRXVBDGOV5E`).

C Estimating demand elasticities: Additional details

C.1 More on identification assumptions

I use simple analytical frameworks to further illustrate the validity of my flow-induced demand pressure (FID) instrument and the granular fund flow IV in the spirit of Gabaix and Koijen (2023).

Flow-induced demand pressure I conduct a decomposition exercise similar to Sander (2023). To a first-order approximation, the *overall* demand pressure facing a bond n (in face value terms) is captured by the total capital inflow into n coming from investment funds, or

$$\mathrm{d}B_t(n) = \sum_{j\in\mathcal{J}_t} \mathrm{d}\omega_{j,t}(n)A_{j,t} + \sum_{j\in\mathcal{J}_t} \omega_{j,t}(n)\mathrm{d}A_{j,t} - r_t(n)\cdot \sum_{j\in\mathcal{J}_t} \omega_{j,t}(n)A_{j,t}. \tag{31}$$

where $A_{j,t}$ is each fund's current net worth (assets under management). The first term captures fund managers' discretion as they shift their portfolio towards or away from bond n. The second term captures the scaling effect from changes in fund net worth, as fund manager allocates the additional capital according to current portfolio weight ω. The final term performs the valuation adjustment, as market value fluctuations of the security mechanically introduce period-to-period shifts in the portfolio weights.

By definition, the change in fund net worth satisfies $\mathrm{d}A_{j,t} = F_{j,t} + r_{j,t}A_{j,t}$, where $r_{j,t}$ is the current return of fund j and $F_{j,t}$ is the dollar flow to fund j. Equation (31) can be rewritten as

$$\mathrm{d}B_t(n) = \underbrace{\sum_{j\in\mathcal{J}_t} \mathrm{d}\omega_{j,t}(n)A_{j,t}}_{\text{Fund manager discretion}} + \underbrace{(r_{j,t} - r_t(n))\sum_{j\in\mathcal{J}_t} \omega_{j,t}(n)A_{j,t}}_{\text{Portfolio rebalancing / valuation}} + \underbrace{\sum_{j\in\mathcal{J}_t} \omega_{j,t}F_{j,t}}_{\text{Flow-induced demand}} . \tag{32}$$

The first two terms of (32) are likely correlated with news about issuer country fundamentals priced in at time t, as the first term may involve active changes in portfolio weight, and the second term involves forward-looking bond return. On the other hand, the instrument FID (see Equation (6)) uses variation that only comes from the final component in (32). As discussed above, FID separates the change in fund demand for a particular bond due to potential changes in the fundamentals from the mechanical scaling of portfolio allocation due to capital redemption and injection.

Granular flow shocks To understand the validity of using granular fund flow to construct the alternative instrument (10) in my context, consider a simple model of fund flow and long-term investor demand:

$$B_{0,t} = \alpha_0 p_t + \eta_t + \varepsilon_{0,t} \tag{33}$$

$$f_{j,t} = \beta R_{j,t-1} + \lambda \eta_t + \varepsilon_{j,t} \tag{34}$$

for a set of funds $j \in \{1, \ldots, J\}$ and a single asset.[78] Equation (33) posits that the demand of investor 0 (for which I take as long-term investors) depends on asset price p_t and a *latent* demand term $\eta_t + \varepsilon_{0,t}$. As the common unobserved shock component η_t may be correlated with p_t, a simple OLS regression of holding on asset price would yield an inconsistent estimate of α_0.

(34) captures a stylized relationship between fund flow, return-chasing behavior, and global factors. By assumption, the demand shock due to long-term investors, $\varepsilon_{0,t}$, is uncorrelated with idiosyncratic flow shock $\varepsilon_{j,t}$. Define z_t as the difference between fund size-weighted average of $\varepsilon_{j,t}$ and the equal-weighted average of $\varepsilon_{j,t}$. Then z_t satisfies the exogeneity condition $\mathbb{E}[z_t \eta_t] = 0$, as λ is assumed to be a scalar, and ε_t and η_t are assumed to be independent. To the extent that z_t also satisfies the relevance condition, z_t would be a candidate instrument to recover α_0. In practice, z_t is constructed from the size-weighted average of the residuals from projecting fund flow on returns and time fixed effect. The relevance condition, which likely holds due to the price impact of flow, can be tested through first-stage regressions.

The case for multiple asset follows, as I can multiply z_t by a lagged bond-level factor that by design will be uncorrelated with latent demand shocks occuring in the current period. Figure C1 also plots the time-series evolution of the granular fund flow shock (size-weighted average of the residual). The granular flow has small correlation with monthly changes in global factors (-0.12 with log VIX index, 0.09 with Federal Funds rate and 0.13 against Gilchrist and Zakrajšek (2012) excess bond premium). When compared with the raw fund flow (green line), there is no significant movement for the granular flow during important episodes of heightened global risk aversion, such as the onset of the COVID-19 crisis or Taper Tantrum. Table C1 reports results from news searches in Factiva related to large funds that drive the realization of large observations associated with the time series of granular fund flow.

[78] Darmouni, Siani and Xiao (2023) expand this stylized framework into an estimable two-layer demand system.

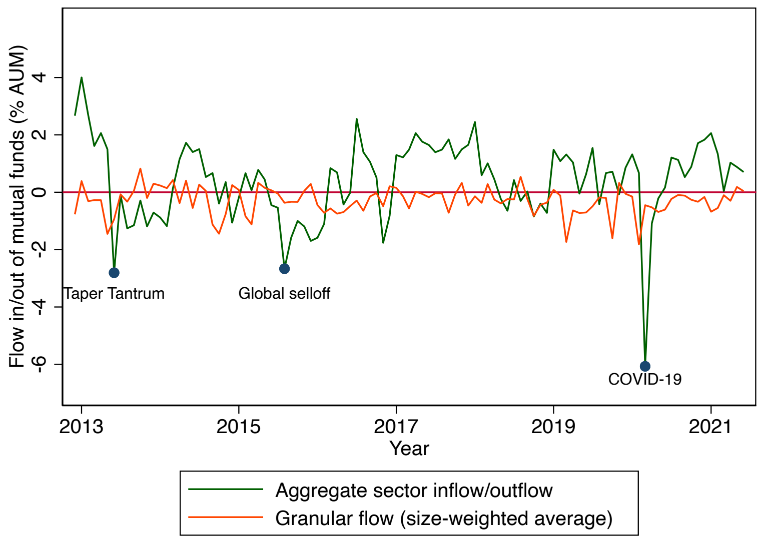


Figure C1: EM-focused mutual fund flow during global "risk-off" episodes

Source: Own calculations base on Morningstar data.

Note: Figure C1 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. 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 (5). The granular fund flow series is constructed by taking the size-weighted average of "surprise" fund flow (see Equation (9)), computed using regression (7) by residualizing fund flow 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.

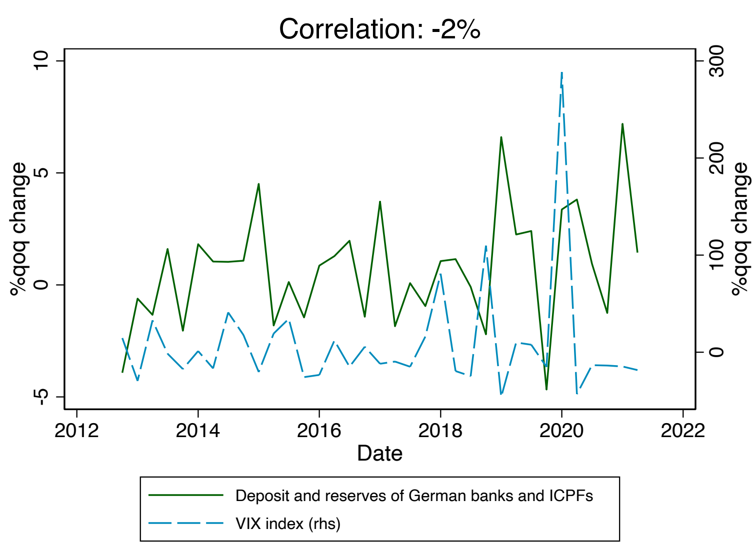


Figure C2: Stability of bank and ICPF liabilities against global risk factors

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

Note: Figure C2 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 C1: Narrative evidence for granular fund flow shocks: News articles

Source: Factiva.

Note: Table C1 provides narrative support to the granular fund flow shocks extracted from Morningstar mutual fund flow data to form the instrument (10). 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`).

C.2 Robustness and additional results

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 C2: 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 C2 complements the weak-instrument-robust Lee, McCrary, Moreira and Porter (2022) standard error reported in Table 3 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 3.1. 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 (see Equation (8)). 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 (10) with the idiosyncratic flow being the lagged fund size-weighted average of mutual fund flow. Standard errors are clustered at bond level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Accounting for zero holding My baseline demand elasticity estimates according to (5) drops observations for which $B_{i,t}(n) = 0$. In Table C4, I report results obtained from estimating a non-linear version of (5):

$$\frac{B_{i,t}(n)}{B_{i,t-1}(n)} = \exp\left[\alpha_{\mathcal{N}} + \beta_{\mathcal{N}}\Delta y_{i,t}(n) + \mathbf{X}_{i,t}(n)\delta_{\mathcal{N}} + \varepsilon_{i,t}(n)\right] \tag{35}$$

Using $\frac{B_{i,t}(n)}{B_{i,t-1}(n)}$ in the estimation account for selling off bond n in month t when hold-

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 C3: 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 C3 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

ing the same bond a month earlier–one particular extensive margin of demand adjustment. I estimate (35) using GMM, under the alternative assumption that the proposed instruments $z_{i,t}(n)$ and $\varepsilon_{i,t}(n)$ satisfies $\mathbb{E}[z_{i,t}(n)(\exp(\varepsilon_{i,t}(n)) - 1)] = 0$. To alleviate the influence of outliers and facilitate convergence, I winsorize $\frac{B_{i,t}(n)}{B_{i,t-1}(n)}$ at the 99th percentile.

Table C4 presents two versions of the GMM estimation using $FID3$ or $FID12$ as the instrument (see Table 3). Overall, the results are less statistically precise. Columns (1) and (2) in both panels confirm the finding in Table 3 that bonds denominated in Euros (home currency of the long-term investors) face a more elastic demand compared to non-EUR bonds. Column (3) and (4) in both panels show that the point estimates are higher for investment-grade bonds compared to those associated with bonds whose credit ratings are below investment grade.

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

(a) Flow-induced demand instrument (FID), residualized by 3 lags of monthly returns

VARIABLES	(1) EUR	(2) Non-EUR	(3) IG	(4) HY
$\Delta y_t(n)$	0.419	-0.423**	0.042	-0.438**
	(0.266)	(0.197)	(0.235)	(0.194)
$\Delta y_{10Y,t}(Bund)$	-0.151	0.209	-0.015	-0.006
	(0.096)	(0.159)	(0.148)	(0.121)
Δ log IP	-0.067	-0.157	-0.189	0.019
	(0.150)	(0.229)	(0.142)	(0.242)
Δ Bid-ask spread	-0.069	0.204	-0.109	0.169
	(0.093)	(0.244)	(0.212)	(0.174)
Δ log Exchange rate against EUR			0.942	-0.792
			(1.837)	(1.300)
Observations	6,375	25,270	24,671	6,974

(b) Flow-induced demand instrument (FID), residualized by 12 lags of monthly returns

Table C4: 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 C4 reports demand slopes of banks, insurers and pension funds by bond types, estimating the nonlinear equation (35) 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 different lengths of lags of fund returns used to residualize bond flows (see Equation (7), 3 months for panel (a) and 12 months for panel (b)). 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.3 Comparison with elasticity estimates in the literature

My baseline estimate of the "micro" elasticity of demand implies a 29% increase in long-term investors' demand for emerging market sovereign debt. This number is just above the empirical range of 3.75%–25% response summarized by Jiang, Richmond and Zhang (2022) for a 5-year bond.[79] The number is nevertheless smaller than the estimates of Fang, Hardy and Lewis (2022) using aggregate data (so that they estimate a "macro" elasticity). To explain the difference, I note that Fang, Hardy and Lewis (2022) use annual data. As such, they estimate an elasticity at a longer horizon. Using monthly changes in positions and yields, my estimation focuses on the short-run elasticity.

D Quantitative model: Derivation and computation method

D.1 Model derivation and proofs

Mathematical preliminaries I rigorously derive the expression for the fundamental value of risky perpetuity $F(\lambda)$ (see (12)) when the underlying default process is "doubly stochastic".

Consider a Poisson process N_t with random intensity λ_t. By definition of the Poisson process, the expectation of N_t is given by

$$\mathbb{E}[N_t] = \sum_{k\geq 0} k \cdot \Pr(N_t = k) = \mathbb{E}\Big(\sum_{k\geq 1} \frac{1}{(k-1)!}\Lambda_t^k \exp(-\Lambda_t)\Big) = \mathbb{E}[\Lambda_t] \tag{36}$$

where I define the cumulative intensity $\Lambda_t = \int_0^t \lambda_s \mathrm{d}s$. The third equality follows from the definition of $\exp(\cdot)$, and the expectation in the final term is taken over λ.

For continuous function $f : [0, \infty) \to \mathbb{R}$, define the integral

$$\int_0^\infty f(t)\mathrm{d}N_t = \sum_{i=1}^{\infty} f(T_i) \cdot \mathbb{1}\{T_i \leq +\infty\}$$

where $\{T_i\}_{i=1}^\infty$ is a set of stopping times associated with N_t. As the Poisson process has discontinuous paths, the integral is a Stieltjes integral. For the Poisson process, by

[79] The corresponding price elasticity range is 0.75–5. For insurers and pension funds, Koijen, Koulischer, Nguyen and Yogo (2021) find an upward-sloping demand for Euro Area government bonds.

definition N_t and T_i satisfy

$$N_t = \sum_{i=1}^{\infty} \mathbb{1}\{T_i \leq t\}$$
$$T_i = \inf\{t : \Lambda_t^i \geq E_{1,i}\}$$

where Λ_t^i is the cumulative intensity, and $E_{1,i}$ is an exponential random variable with rate parameter equal to one.

Lemma 1. *For a continuous function* $f : [0, \infty) \to \mathbb{R}$, $\mathbb{E}\Big[\int_0^\infty f(t)\mathrm{d}N_t\Big] = \int_0^\infty f(t)\mathbb{E}[\lambda_t]\mathrm{d}t$.

Proof. Consider the function $f(t) = \mathbb{1}\{t \in [0, T]\}$ for some T. Then we have

$$\begin{aligned}\mathbb{E}\Big[\int_0^\infty \mathbb{1}\{t \in [0, T]\}\mathrm{d}N_t\Big] &= \mathbb{E}\Big[\sum_{i=1}^{\infty} \mathbb{1}\{T_i \in [0, T]\}\mathbf{1}\{T_i \leq \infty\}\Big] = \mathbb{E}\Big[\sum_{i=1}^{\infty} \mathbb{1}\{T_i \in [0, T]\}\Big] \\ &= \mathbb{E}[N_T] = \mathbb{E}\Big[\int_0^T \lambda_t \mathrm{d}t\Big] = \mathbb{E}\Big[\int_0^\infty \mathbb{1}\{t \in [0, T]\}\lambda_t \mathrm{d}t\Big].\end{aligned}$$

Therefore, the function $f(t) = \mathbb{1}\{t \in [0, T]\}$ satisfies the relationship. By linearity, step functions $f(t) = \sum_j \alpha_j \mathbb{1}\{t \in (T_{j-1}, T_j]\}$ also satisfy the relationship. The lemma is proved by approximating a general, continuous function f using the step functions.

□

(12) is obtained by replacing the expectation operator by the conditional expectation and applying Lemma 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 (17) is

$$\frac{\mathrm{d}w_t}{w_t} = \Big(r + \xi - \frac{c_t}{w_t} + \chi_t(\omega_t + \kappa - rP_t)\Big)\mathrm{d}t + \chi_t \eta_{\lambda,t}\mathrm{d}B_{\lambda,t} + (\chi_t \eta_{z,t} + \sigma_z)\mathrm{d}B_{z,t} + \chi_t(\eta_{N,t} - \delta)\mathrm{d}N_t \tag{37}$$

where I define $\chi_t = X_t/W_t$. Dropping the time subscript for convenience, the associated HJB equation is

$$(\rho+\xi)V(\lambda,w) = \partial_t V + \max_{c,\chi}\Big\{\log c + \partial_\lambda V\cdot[\kappa_\lambda(\overline{\lambda}-\lambda)] + \partial_w V\cdot\Big[r+\xi-\frac{c}{w}+\chi(\omega+\kappa-rP)\Big]w$$
$$+\frac{1}{2}\partial_{\lambda\lambda}V\sigma_\lambda^2\lambda + \frac{1}{2}\partial_{ww}V\cdot\Big[(\chi\eta_z+\sigma_z)^2+(\chi\eta_\lambda)^2\Big]w^2$$
$$+\partial_{\lambda w}V\cdot(\sigma_\lambda\sqrt{\lambda}\chi\eta_\lambda) + \lambda(V[\lambda, w(1+\chi(\eta_N-\delta))] - V(\lambda,w))\Big\}. \tag{38}$$

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 $V(\lambda,w) = (\rho+\xi)^{-1}\cdot(\log w + g(\lambda))$ for some function g that depends on λ only. Then $V_{\lambda w} = 0$. The first-order conditions associated with the HJB equations are

$$[c]: c = (\rho+\xi)w \tag{39}$$
$$[\chi]: \omega+\kappa-rP+\lambda\frac{\eta_N-\delta}{1+\chi(\eta_N-\delta)} = (\chi\eta_z+\sigma_z)\eta_z+\chi\eta_\lambda^2. \tag{40}$$

From (40), the optimal χ does not depend directly on asset manager wealth. Plug in the functional form guess and (40) into (38), and canceling $\log w$ on both sides, the functional form guess is verified as the remaining PDE with respect to λ does not explicitly depend on w. Aggregation implies that we can replace w by W in (39), and χ is also the aggregate asset manager normalized position, X/W. The aggregate equivalent of (37) is

$$\frac{dW_t}{W_t} = (r-\rho+\chi_t(\omega_t+\kappa-rP_t))\mathrm{d}t + \xi\Big(\frac{W}{W_t}-1\Big)\mathrm{d}t + \chi_t\eta_{\lambda,t}\mathrm{d}B_{\lambda,t} + (\chi_t\eta_{z,t}+\sigma_z)\mathrm{d}B_{z,t} + \chi_t(\eta_{N,t}-\delta)\mathrm{d}N_t. \tag{41}$$

Given the conjecture for the law of motion of aggregate wealth W_t in (18), as we are looking for a Markov equilibrium $P(\lambda, W)$, we can apply Itô's lemma for jump-diffusions to obtain

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

Matching coefficient with the conjectured form for P_t (17), we have

$$\omega_t = P_{\lambda,t}[\kappa_\lambda(\overline{\lambda} - \lambda_t)] + P_{W,t}\Phi_{1,t}W_t + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2 + \Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t} \tag{42}$$

$$\eta_{\lambda,t} = P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t} + P_{W,t}\Phi_{2,t}W_t \tag{43}$$

$$\eta_{z,t} = P_W\Phi_{3,t}W_t \tag{44}$$

$$\eta_{N,t} = P(\lambda, W(1+\Phi_{4,t})) - P(\lambda, W). \tag{45}$$

Matching coefficients between (18) and (41), I get

$$\Phi_{1,t} = r - (\rho + \xi) + \chi_t(\omega_t + \kappa - rP_t) + \xi\frac{W}{W_t} \tag{46}$$

$$\Phi_{2,t} = \chi_t\eta_{\lambda,t} \tag{47}$$

$$\Phi_{3,t} = \chi_t\eta_{z,t} + \sigma_z \tag{48}$$

$$\Phi_{4,t} = \chi_t(\eta_{N,t} - \delta). \tag{49}$$

Combining (42)–(45) and (46)–(49), the Φ functions can be rewritten as

$$\begin{aligned}\Phi_{1,t} =& r - (\rho+\xi) + \xi\frac{W}{W_t} + \chi(\kappa - rP_t) \\ &+ \chi\cdot\left[P_{\lambda,t}[\kappa_\lambda(\overline{\lambda} - \lambda_t)] + P_{W,t}\Phi_{1,t}W_t + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2 + \Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t}\right]\end{aligned} \tag{50}$$

$$\Phi_{2,t} = \chi_t[P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t} + P_{W,t}\Phi_{2,t}W_t] \tag{51}$$

$$\Phi_{3,t} = \chi_t P_W\Phi_{3,t}W_t + \sigma_z \tag{52}$$

$$\Phi_{4,t} = \chi_t[P(\lambda, W(1+\Phi_{4,t})) - P(\lambda, W) - \delta] \tag{53}$$

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

$$\Phi_{1,t} = \frac{r - (\rho+\xi) + \xi\frac{W}{W_t} + \chi(\kappa - rP_t) + \chi\cdot\left[P_{\lambda,t}[\kappa_\lambda(\overline{\lambda} - \lambda_t)] + \frac{1}{2}P_{\lambda\lambda,t}\sigma_\lambda^2\lambda_t + \frac{1}{2}P_{WW,t}(\Phi_{2,t}^2 + \Phi_{3,t}^2) + P_{\lambda W,t}\Phi_{2,t}W\sigma_\lambda\sqrt{\lambda_t}\right]}{1 - \chi_t P_{W,t}W_t} \tag{54}$$

$$\Phi_{2,t} = \frac{\chi_t P_{\lambda,t}\sigma_\lambda\sqrt{\lambda_t}}{1 - \chi_t P_{W,t}W_t} \tag{55}$$

$$\Phi_{3,t} = \frac{\sigma_z}{1 - \chi_t P_{W,t}W_t}. \tag{56}$$

Proof of Proposition 1 Combine the first-order condition (40) with (43), (44), (47), (48), (49), 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 (19) follows from (42) and rearranging terms.

D.2 Calibration details

This section describes the way moments in the data are derived and used to discipline model parameters, adding to the overview in Section 4.3.

Bond supply Average debt-to-GDP ratio for central governments disciplines the bond supply parameter s in the model. The data comes from the IMF Global Debt Database (Mbaye, Badia and Chae, 2018).[80] For most countries, the data on public debt comes from reliable national primary sources, IMF and World Bank databases. The final sample used to generate the 49% number covers 45 countries in my empirical analysis, and is based on observations in year 2019.[81]

Haircut In my model, the parameter δ can be interpreted as the fraction of debt permanently not paying off. Equation (27) summarizes the relationship between 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, Mateos-Planas and Ríos-Rull (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.[82] For these countries, I follow AMR

[80] Available at `https://www.imf.org/external/datamapper/datasets/GDD`.

[81] The countries include Albania, Argentina, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Dominican Republic, Estonia, Hungary, India, Indonesia, Jamaica, Latvia, Lithuania, Malaysia, Malta, Mexico, Moldova, Montenegro, Morocco, North Macedonia , Pakistan, Peru, Poland, Romania, Russian Federation, Serbia, Slovak Republic, Slovenia, South Africa, Sri Lanka, Thailand, Turkey, Ukraine, Uruguay, Venezuela, and Vietnam.

[82] 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.

and compute the fraction of long-term debt (including principals and interest payments) in default in a particular year, conditional on having arrears:[83]

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

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

Bond spread and volatility I estimate average sovereign bond spread and volatility based on country-level data from the JP Morgan EMBI+ spread (based on dollar-denominated emerging market sovereign bonds), downloaded from the Central Bank of Dominican Republic's website.[84] The average spread and volatility (3.6%/0.6%) used in my calibration is taken over the 2013M1–2021M6 subsample, matching the sample span of the main empirical analysis. One important advantage of using index-based bond spread is to control for important heterogeneity in bond characteristics. Directly estimating bond spread using panel data on bond prices without controlling for characteristics would introduce mechanical volatility due to term premia and currency premia. The baseline EMBI data is only based on issuers included in the index. Alternatively, I estimate a Nelson-Siegel yield curve for dollar-denominated sovereign bond for my bond universe based on a wider spectrum of countries. The average spread and volatility of 10-year bonds is 2.75% (0.53%).

Mutual fund characteristics Mutual fund annualized returns (2%) are built upon monthly return data from Morningstar (multiplied by 12). From 2013M1 to 2021M6, annual average return is 2.43%. Prior to COVID-19, the number is 1.89%. The monthly returns are first trimmed at the 1% and 99% tails to remove outliers. Annualized volatility of flow (as a percentage of AUM) is obtained by multiplying monthly flow volatility (also from Morningstar, trimmed at 1% and 99% tails) by $\sqrt{12}$, to arrive at $\sigma_z = 0.214$.

[83] 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).

[84] https://www.bancentral.gov.do/a/d/2585-entorno-internacional.

Foreign investment fund share I estimate a foreign investment fund share of 17.2% for emerging market sovereign debt. To arrive at this number, I combine aggregate data from IMF Coordinated Portfolio Investment Survey (CPIS), which offers a refined breakdown of sectoral cross-border portfolio holdings for recent data, and the emerging market investor composition dataset of Arslanalp and Tsuda (2014), both updated to 2022Q2. For countries covered in the Arslanalp and Tsuda (2014) dataset, I compute the market value of long-term portfolio debt held by "Other financial corporations: Other" (OFX) as a share of total amount held (T). The OFX sector contains holdings by investment funds, while holdings by banks and ICPFs are recorded separately (sector ODX and IPF, respectively). The 17.2% share is obtained by multiplying the average percentage share across countries with average foreign share of emerging market sovereign debt holding in Arslanalp and Tsuda (2014).

Yield elasticity of demand In Section 3, I focus on foreign banks, insurance companies, and pension funds and estimate a yield elasticity of demand for Euro-denominated emerging market sovereign bond of 29.4.[85] In reality, various other investors, in particular EM's domestic banks and non-banks, may as well be important marginal investors during episodes of global financial tightening. My calibration strategy takes this fact into account, and target a weighted average elasticity of 21. 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 3), and the estimates by Fang, Hardy and Lewis (2022) using a global demand system.[86]

1. As a first step, I combine SHSS data and the Fang, Hardy and Lewis (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, Hardy and Lewis (2022) for an average emerging market economy, I calculate the domestic weighted average yield elasticity at 11.3.

[85] This number is the arithmetic average of the demand slop coefficients reported in Table 3, columns (1) to (3).

[86] 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.

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, Hardy and Lewis (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.[87]

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 (28) on the simulated data. The target should match $100 \times \beta_0$.

D.3 Computation algorithm

The equilibrium of my quantitative model is a solution to the fully nonlinear partial differential equation (57). I extend the finite difference scheme to solve this PDE. Compared to the canonical problem (see Brunnermeier and Sannikov (2014) and Achdou, Han, Lasry, Lions and Moll (2021)), the solution process is more challenging, due to three reasons:

1. The presence of jump risk introduces a *delay term* into the PDE (captured by the term involving Φ_4 in (57)). I tackle this issue through a time-iteration step where the quantities in the previous iteration are used as the argument to interpolate against in the current iteration.[88]

2. The problem imposes a non-trivial (Dirichlet) boundary condition, as the levels of the bond price at the wealth boundaries are well-defined. As a comparison, standard problems involving portfolio choice often abstract away from imposing boundary conditions by assuming that the states drift inward close to the boundary. My algorithm is able to accommodate various forms of boundary conditions even in the presence of multiple state variables.

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

[88] Li (2019) also solves a continuous-time problem with jumps using a fixed-point iteration method, utilizing the recursive structure of his model.

3. The problem has more than one state variable, and the PDE involves cross-derivatives. In the case of cross-derivatives, the usual fully implicit finite difference discretization does not satisfy the Barles and Souganidis (1991) condition for monotonicity, thereby not guaranteeing that the algorithm converges to the correct solution. I address this issue by following the explicit-implicit scheme suggested by Hansen, Huang, Khorrami and Tourre (2018) and using the previous iteration's cross-derivative to compute prices for the current iteration.[89]

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

$$\begin{aligned} rP =& \kappa + \lambda\cdot\frac{\Phi_4}{\chi(1+\Phi_4)} + P_\lambda[\kappa_\lambda(\overline{\lambda}-\lambda) - \sigma_\lambda\sqrt{\lambda}\Phi_2] + \frac{1}{2}(1+Y)(1-Y)P_Y\Big[\Phi_1 - \Big(\frac{1+Y}{2}+1\Big)(\Phi_2^2+\Phi_3^2)\Big] \\ &+ \frac{1}{2}P_{\lambda\lambda}\sigma_\lambda^2\lambda + \frac{1}{2}(1+Y)(1-Y)P_{\lambda Y}\sigma_\lambda\sqrt{\lambda}\Phi_2 + \frac{1}{2}P_{YY}\Big(\frac{1}{2}(1+Y)(1-Y)\Big)^2(\Phi_2^2+\Phi_3^2). \end{aligned} \tag{57}$$

where

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

[89] Merkel (2020) and d'Avernas, Petersen and Vandeweyer (2022) exploit transformations of the grid space to restore monotonicity. Neither of the papers tackle boundary conditions directly, however.

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.

Figure E2 illustrates the initialization of price function guesses by comparing the guesses with the solution for different levels of asset manager wealth and default risk. The horizontal lines on Panel (a) depict the boundary conditions at zero and infinite wealth, respectively, showing that the solution is initialized imposing the same boundary conditions. The initial guess for the price function is larger in the case of low default risk and smaller for high default risk scenarios compared to the final solution as the initial guess, by assuming a constant default probability, does not account for mean-reversion in the default rates.

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 (11), 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 (11) 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 (11) with reflecting barriers further satisfies the backward equation:[90]

$$\partial_t u = \mathscr{L} u, \qquad u(\lambda, 0) = \lambda, \quad \partial_\lambda u \mid_{\lambda \in \{\lambda_{\min}, \lambda_{\max}\}} = 0 \tag{58}$$

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

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 (12) 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 (57), 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.

Inner loop: Consider a non-uniform grid of state variables of length $[I, J]$. Denote a grid point in the default risk dimension as $\lambda_i, i = 1, \ldots, I$ and a grid point in the transformed wealth dimension as $Y_j, j = 1, \ldots, J$. For a function of the states f, denote $f(\lambda_i, Y_j)$ by $f_{i,j}$. I adopt a mixed (explit-implicit) upwind scheme. At iteration $n+1$, the finite difference discretization of the transformed PDE is given by

[90] 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.

$$
\begin{aligned}
rP_{i,j}^{(n+1)} =& \frac{P_{i,j}^{(n)} - P_{i,j}^{(n+1)}}{\Delta t} + \kappa + \lambda_j \cdot \frac{\Phi_{4,i,j}^{(n)}}{\chi_{i,j}^{(n)} \Phi_{4,i,j}^{(n)}} \\
&+ \frac{P_{i+1,j}^{(n+1)} - P_{i,j}^{(n+1)}}{\Delta \lambda_i^+} \cdot \underbrace{[\kappa_\lambda(\bar{\lambda} - \lambda_i) - \sigma_\lambda \sqrt{\lambda_i} \Phi_{2,i,j}^{(n)}]^+}_{\mu_{\lambda,i,j}^{+,(n)}} + \frac{P_{i,j}^{(n+1)} - P_{i-1,j}^{(n+1)}}{\Delta \lambda_i^-} \cdot \underbrace{[\kappa_\lambda(\bar{\lambda} - \lambda_i) - \sigma_\lambda \sqrt{\lambda_i} \Phi_{2,i,j}^{(n)}]^-}_{\mu_{\lambda,i,j}^{-,(n)}} \\
&+ \frac{P_{i,j+1}^{(n+1)} - P_{i,j}^{(n+1)}}{\Delta Y_j^+} \cdot \underbrace{\left\{ \frac{1}{2}(1+Y_j)(1-Y_j) \left[\Phi_{1,i,j}^{(n)} - \left(\frac{1+Y_j}{2} + 1 \right) ((\Phi_{2,i,j}^{(n)})^2 + (\Phi_{3,i,j}^{(n)})^2) \right] \right\}^+}_{\mu_{Y,i,j}^{+,(n)}} \\
&+ \frac{P_{i,j}^{(n+1)} - P_{i,j-1}^{(n+1)}}{\Delta Y_j^-} \cdot \underbrace{\left\{ \frac{1}{2}(1+Y_j)(1-Y_j) \left[\Phi_{1,i,j}^{(n)} - \left(\frac{1+Y_j}{2} + 1 \right) ((\Phi_{2,i,j}^{(n)})^2 + (\Phi_{3,i,j}^{(n)})^2) \right] \right\}^-}_{\mu_{Y,i,j}^{-,(n)}} \\
&+ \frac{1}{2} \underbrace{\frac{\Delta\lambda^- \cdot P_{i+1,j}^{(n+1)} - (\Delta\lambda^+ + \Delta\lambda^-) \cdot P_{i,j}^{(n+1)} + \Delta\lambda^+ \cdot P_{i-1,j}^{(n+1)}}{\frac{1}{2}(\Delta\lambda^+ + \Delta\lambda^-) \cdot \Delta\lambda^+ \cdot \Delta\lambda^-}}_{\hat{P}_{\lambda\lambda,i,j}} \underbrace{\sigma_\lambda^2 \lambda_i}_{\Sigma_{\lambda,i,j}^{(n)}} + \frac{1}{2}(1+Y_j)(1-Y_j) P_{\lambda Y,i,j}^{(n)} \sigma_\lambda \sqrt{\lambda_i} \Phi_{2,i,j}^{(n)} \\
&+ \frac{1}{2} \underbrace{\frac{\Delta Y^- \cdot P_{i,j+1}^{(n+1)} - (\Delta Y^+ + \Delta Y^-) \cdot P_{i,j}^{(n+1)} + \Delta Y^+ \cdot P_{i,j-1}^{(n+1)}}{\frac{1}{2}(\Delta Y^+ + \Delta Y^-) \cdot \Delta Y^+ \cdot \Delta Y^-}}_{\hat{P}_{YY,i,j}} \cdot \underbrace{\left(\frac{1}{2}(1+Y_j)(1-Y_j) \right)^2 \cdot \left((\Phi_{2,i,j}^{(n)})^2 + (\Phi_{3,i,j}^{(n)})^2 \right)}_{\Sigma_{Y,i,j}^{(n)}}
\end{aligned}
\tag{59}
$$

for $1 < i < I$, $1 < j < J$. In (59), $[\cdot]^+$ denotes $\max\{\cdot, 0\}$ and similarly for $[\cdot]^-$. $\Delta\lambda^+ = \lambda_{i+1} - \lambda_i$; $\Delta\lambda^- = \lambda_i - \lambda_{i-1}$ and similarly for the wealth dimension. $(n+1)$ is used to denote iteration-$n+1$ quantities while (n) denotes iteration-n quantities. For non-uniform grids, the discretization of second-order derivatives are given by $\hat{P}_{\lambda\lambda,i,j}$ and $\hat{P}_{YY,i,j}$.

The boundary conditions are incorporated by introducing "ghost nodes" $\lambda_0, \lambda_{I+1}, Y_0, Y_{J+1}$ and imposing

$$
P_{i,0} = \exp\left(\frac{s + \theta_1 \lambda_i}{-\alpha(\lambda_i)} \right) \cdot F(\lambda_i), \qquad P_{i,J+1} = F(\lambda_i)
$$

for $1 < i < I$ and

$$
P_{0,j} = P_{1,j}, \qquad P_{I+1,j} = P_{I,j}
$$

for $1 < j < J$.

Collect terms, the coefficients associated with the bond price at each grid are

$$
\begin{aligned}
[P_{i,j}] : x_{i,j} &= r + \frac{1}{\Delta t} + \frac{\mu^{+,(n)}_{\lambda,i,j}}{\Delta\lambda_i^+} - \frac{\mu^{-,(n)}_{\lambda,i,j}}{\Delta\lambda_i^-} + \frac{\mu^{+,(n)}_{Y,i,j}}{\Delta Y_j^+} - \frac{\mu^{-,(n)}_{Y,i,j}}{\Delta Y_j^-} + \frac{\Sigma^{(n)}_{\lambda,i,j}}{\Delta\lambda_i^+ \cdot \Delta\lambda_i^-} + \frac{\Sigma^{(n)}_{Y,i,j}}{\Delta Y_j^+ \cdot \Delta Y_j^-} \\
[P_{i+1,j}] : y_{i,j} &= -\frac{\mu^{+,(n)}_{\lambda,i,j}}{\Delta\lambda_i^+} - \frac{\Sigma^{(n)}_{\lambda,i,j}}{(\Delta\lambda_i^+ + \Delta\lambda_i^-) \cdot \Delta\lambda_i^-} \\
[P_{i-1,j}] : z_{i,j} &= \frac{\mu^{-,(n)}_{\lambda,i,j}}{\Delta\lambda_i^-} - \frac{\Sigma^{(n)}_{\lambda,i,j}}{(\Delta\lambda_i^+ + \Delta\lambda_i^-) \cdot \Delta\lambda_i^+} \\
[P_{i,j+1}] : \zeta_{i,j} &= -\frac{\mu^{+,(n)}_{Y,i,j}}{\Delta Y_j^+} - \frac{\Sigma^{(n)}_{Y,i,j}}{(\Delta Y_j^+ + \Delta Y_j^-) \cdot \Delta Y_j^-} \\
[P_{i,j-1}] : \eta_{i,j} &= \frac{\mu^{-,(n)}_{Y,i,j}}{\Delta Y_j^-} - \frac{\Sigma^{(n)}_{Y,i,j}}{(\Delta Y_j^+ + \Delta Y_j^-) \cdot \Delta Y_j^-}.
\end{aligned}
$$

Imposing reflective boundary conditions for λ, the coefficients at the boundaries are modified to

$$
\begin{aligned}
[P_{1,j}] : x_{1,j} &= r + \frac{1}{\Delta t} + \frac{\mu^{+,(n)}_{\lambda,1,j}}{\Delta\lambda_i^+} + \frac{\mu^{+,(n)}_{Y,1,j}}{\Delta Y_j^+} - \frac{\mu^{-,(n)}_{Y,1,j}}{\Delta Y_j^-} + \frac{\Sigma^{(n)}_{\lambda,1,j}}{\Delta\lambda_1^+ \cdot \Delta\lambda_1^-} + \frac{\Sigma^{(n)}_{Y,1,j}}{\Delta Y_j^+ \cdot \Delta Y_j^-} - \frac{\Sigma^{(n)}_{\lambda,1,j}}{\Delta\lambda_1^- \cdot (\Delta\lambda_1^+ + \Delta\lambda_1^-)} \\
[P_{I,j}] : x_{I,j} &= r + \frac{1}{\Delta t} - \frac{\mu^{-,(n)}_{\lambda,I,j}}{\Delta\lambda_I^-} + \frac{\mu^{+,(n)}_{Y,I,j}}{\Delta Y_j^+} - \frac{\mu^{-,(n)}_{Y,I,j}}{\Delta Y_j^-} + \frac{\Sigma^{(n)}_{\lambda,I,j}}{\Delta\lambda_I^+ \cdot \Delta\lambda_I^-} + \frac{\Sigma^{(n)}_{Y,1,j}}{\Delta Y_j^+ \cdot \Delta Y_j^-} - \frac{\Sigma^{(n)}_{\lambda,1,j}}{\Delta\lambda_I^+ \cdot (\Delta\lambda_I^+ + \Delta\lambda_I^-)}
\end{aligned}
$$

I construct the infinitesimal generator matrix $\mathbf{A}$ with the coefficients above. As an illustration, suppose $I = J = 3$. Then $\mathbf{A}$ is a 9×9 matrix that equals

$$
\begin{pmatrix}
x_{1,1} & y_{1,1} & 0 & \zeta_{1,1} & 0 & 0 & 0 & 0 & \\
z_{2,1} & x_{2,1} & y_{2,1} & 0 & \zeta_{2,1} & 0 & 0 & 0 & 0 \\
0 & z_{3,1} & x_{3,1} & 0 & 0 & \zeta_{3,1} & 0 & 0 & 0 \\
\eta_{1,2} & 0 & 0 & x_{1,2} & y_{1,2} & 0 & \zeta_{1,2} & 0 & 0 \\
0 & \eta_{2,2} & 0 & z_{2,2} & x_{2,2} & y_{2,2} & 0 & \zeta_{2,2} & 0 \\
0 & 0 & \eta_{3,2} & 0 & z_{3,2} & x_{3,2} & 0 & 0 & \zeta_{3,2} \\
0 & 0 & 0 & \eta_{1,3} & 0 & 0 & x_{1,3} & y_{1,3} & 0 \\
0 & 0 & 0 & 0 & \eta_{2,3} & 0 & z_{2,3} & x_{2,3} & y_{2,3} \\
0 & 0 & 0 & 0 & 0 & \eta_{3,3} & 0 & z_{3,3} & x_{3,3}
\end{pmatrix}
\begin{pmatrix}
P_{1,1} \\ P_{2,1} \\ P_{3,1} \\ P_{1,2} \\ P_{2,2} \\ P_{3,2} \\ P_{1,3} \\ P_{2,3} \\ P_{3,3}
\end{pmatrix}
$$

Define $P^{(n+1)}$ as the $IJ \times 1$ vector that stacks $P^{(n+1)}_{i,j}$. Then $P^{(n+1)}$ is obtained from solving the following linear system:

$$\mathbf{A}^{(n)} P^{(n+1)} = \mathbf{U}^{(n)} + \mathbf{b}^{(n)} \tag{60}$$

where $\mathbf{U}^{(n)}$ is an $IJ \times 1$ vector that stacks

$$\frac{P_{i,j}^{(n)}}{\Delta t} + \kappa + \lambda_j \cdot \frac{\Phi_{4,i,j}^{(n)}}{\chi_{i,j}^{(n)} \Phi_{4,i,j}^{(n)}} + \frac{1}{2}(1 + Y_j)(1 - Y_j) P_{\lambda Y,i,j}^{(n)} \sigma_\lambda \sqrt{\lambda_i} \Phi_{2,i,j}^{(n)},$$

and $\mathbf{b}^{(n)}$ encodes the Dirichlet boundary condition associated with wealth by stacking the $I \times J$ matrix $B^{(n)}$ with elements

$$\begin{aligned} B_{i,1}^{(n)} &= -P_{i,0} \cdot \Big(\frac{\mu_{Y,i,1}^{-,(n)}}{\Delta Y_1^-} + \frac{\Sigma_{Y,i,1}^{(n)}}{\Delta Y_1^- \cdot (\Delta Y_1^+ + \Delta Y_1^-)} \Big) \\ B_{i,J}^{(n)} &= P_{i,J} \cdot \Big(\frac{\mu_{Y,i,J}^{+,(n)}}{\Delta Y_1^-} + \frac{\Sigma_{Y,i,J}^{(n)}}{\Delta Y_J^+ \cdot (\Delta Y_J^+ + \Delta Y_J^-)} \Big). \end{aligned}$$

and zero elsewhere.

As $\mathbf{A}^{(n)}$ is sparse, the linear system is solved efficiently. Following Hansen, Huang, Khorrami and Tourre (2018), the cross-derivative is not included in the implicit component of the scheme. Rather, the cross-derivative computed from the previous iteration is used and included in the right-hand-side of Equation (60). Similarly, while Φ_4 can be expressed in terms of P, I do not include it in the implicit component. In this way, the scheme consists of a mix of explicit and implicit stepping.

Outer loop: With $P^{(n+1)}$ obtained in the inner loop, I compute $\chi^{(n+1)}$ and the associated derivatives using finite difference. In particular, the cross-derivative is computed from the following formula for non-uniform grids:

$$P_{\lambda Y,i,j}^{(n)} = \frac{P_{i+1,j+1}^{(n+1)} + P_{i-1,j-1}^{(n+1)} - P_{i+1,j-1}^{(n+1)} - P_{i-1,j+1}^{(n+1)}}{\Delta\lambda_i^+ \cdot \Delta Y_i^+ + \Delta\lambda_i^+ \cdot \Delta Y_i^- + \Delta\lambda_i^- \cdot \Delta Y_i^+ + \Delta\lambda_i^- \cdot \Delta Y_i^-}.$$

For derivatives at the boundaries and corners, I follow Hansen, Huang, Khorrami and Tourre (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 (54), (55), (56) , (53). 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 $W_j(1+\Phi^{(n)}_{4,i,j})$, 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.

λ_t follows a Cox, Ingersoll and Ross (1985) process according to (11). Alfonsi (2005) proposes a Milstein scheme guaranteeing strong convergence:

$$\lambda^n_{t_{i+1}} = \left(\frac{\sigma_\lambda(B_{\lambda,t_{i+1}} - B_{\lambda,t_i}) + \sqrt{\sigma^2_\lambda(B_{\lambda,t_{i+1}} - B_{\lambda,t_i})^2 + 4(\lambda^n_{t_i} + (a - \frac{\sigma^2_\lambda}{2})\Delta t)(1+\kappa_\lambda \Delta t)}}{2(1+\kappa_\lambda\Delta t)}\right)^2.$$

where $a = \kappa_\lambda\overline{\lambda}$ and $B_{\lambda,t_{i+1}} - B_{\lambda,t_i} \sim \mathcal{N}(0, \Delta t)$. Compared to the usual Euler-Maruyama scheme, the advantage of this scheme is that, if the Feller condition $2\kappa_\lambda\overline{\lambda} > \sigma^2_\lambda$ is satisfied, the simulation will always generate a positive λ.

In my model, default arrives with time-varying stochastic intensity λ_t. To simulate default events $\{N_t\}$, I use Çinlar's inversion method, motivated by the following lemma (Çinlar, 1975):

Lemma 2. *Given a positive, continuous, and nondecreasing function $\Lambda(t), t \geq 0$. The following statements are equivalent:*

1. *Random variables $T_1, T_2, \ldots$ are times of arrival for a nonhomogeneous Poisson process N_t with $\Lambda(t) \equiv \mathbb{E}[N_t]$.*

2. *$\Lambda(T_1), \Lambda(T_2), \ldots$ are times of arrival corresponding to a homogeneous Poisson process N^*_t with intensity equal to 1.*

Define $\Lambda(t)$ as the expected cumulative number of default events up to time t.

$$\Lambda(t) = \int_0^t \lambda_s \mathrm{d}s = \mathbb{E}[N_t].$$

Clearly, $\Lambda(t)$ satisfies the condition for the above lemma, such that we can first simulate $\Lambda(T_1), \Lambda(T_2), \ldots$, then map back to $T_1, T_2, \ldots$ using the invertible mapping Λ and the time grid $\mathbb{T}$. To simulate $\Lambda(T_1), \Lambda(T_2), \ldots, \Lambda(T_N)$, note that the total number of events N follows a Poisson distribution with rate $\Lambda(T)$, where T is the endpoint of the time grid $\mathbb{T}$, and $\frac{\Lambda(T_i)}{\Lambda(T)}, i = 1, \ldots, N$ follows a uniform distribution over $[0, 1]$ as N_t^* has unit intensity.

Finally, I discretize the log of the wealth process using an Euler-Maruyama scheme, then generate the level of wealth by making the exponential transformation. Define $S_t = \log W_t$, Itô's lemma implies

$$\begin{aligned} \mathrm{d}S_t =& \Big(\Phi_1(\lambda, Y) - 0.5[\Phi_2^2(\lambda, Y) + \Phi_3^2(\lambda, Y)]\Big)\mathrm{d}t \\ &+ \Phi_2(\lambda, Y)\mathrm{d}B_{\lambda,t} + \Phi_3(\lambda, Y)\mathrm{d}B_{z,t} + \log(1 + \Phi_4(\lambda, Y))\mathrm{d}N_t. \end{aligned}$$

The corresponding Euler-Maruyama scheme is

$$\begin{aligned} S_{t_{i+1}} - S_{t_i} =& \Big(\Phi_1(\lambda_{t_i}, Y_{t_i}) - 0.5[\Phi_2^2(\lambda_{t_i}, Y_{t_i}) + \Phi_3^2(\lambda_{t_i}, Y_{t_i})]\Big)\Delta t \\ &+ \Phi_2(\lambda_{t_i}, Y_{t_i})\Delta B_{\lambda,t_{i+1}} + \Phi_3(\lambda_{t_i}, Y_{t_i})\Delta B_{z,t_{i+1}} + \log(1 + \Phi_4(\lambda_{t_i}, Y_{t_i}))\Delta N_{t_{i+1}}. \end{aligned}$$

where $Y_{t_i} = Y(\exp(S_{t_i}))$. Off-grid values for $\Phi_j(\cdot, \cdot), j = 1, \ldots, 4$ are evaluated using billinear interpolation.

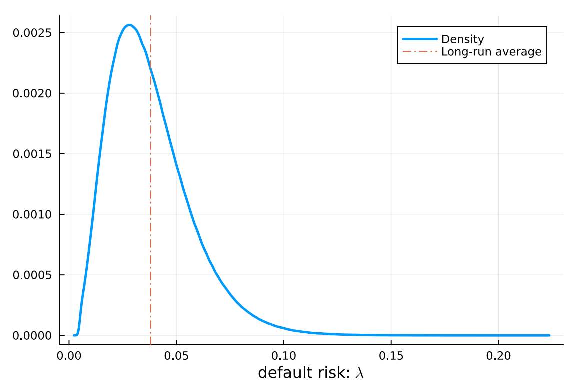
E Quantitative model: Additional results

This section reports auxiliary results associated with the quantitative model presented in Section 4. Table E1 illustrates the correspondence between my model and the institutional features discussed in Section 2. Figure E1 reports the equilibrium distribution of the state variables (λ, W). Figure E6 plots the equilibrium bond price as a function of the state variables. Figure E2 plots slices of the bond price function along one dimension of the state variables, as well as the associated initial guesses to illustrate the solution algorithm. Figure E3 reports important endogenous objects associated with the wealth of asset managers, including its drift and volatility, and loading on the jump risk. Figure E5 compares the volatility of asset manager wealth associated with default risk shocks between the baseline calibration and the case with no wealth shocks to illustrate the additional exposure to default risk when wealth shocks are turned off.

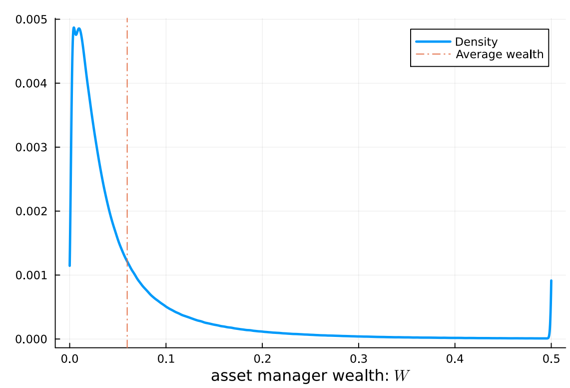
Model elements	**Mapped to / Characteristics**
Long-term investors $\rightarrow$ Banks and ICPFs	
Fundamental value inside demand equation	Insensitivity to temporary market value fluctuations
Variable demand elasticity	Characteristic-based demand; regulatory constraints
Aversion to default risk	
Asset managers $\rightarrow$ Investment funds	
Brownian wealth shocks	Open-ended structure: capital redemption/injection
Unconstrained log investor	Wide investment scope with myopic demand
Risky perpetuity $\rightarrow$ EM sovereign bond	
Doubly stochastic process with jumps	Default and fundamental risk

Table E1: Model elements mapped to empirical observations

Note: Table E1 summarizes how the quantitative model is able to speak to institutional features and economic mechanisms associated with foreign investment in emerging markets discussed in Section 2.4.



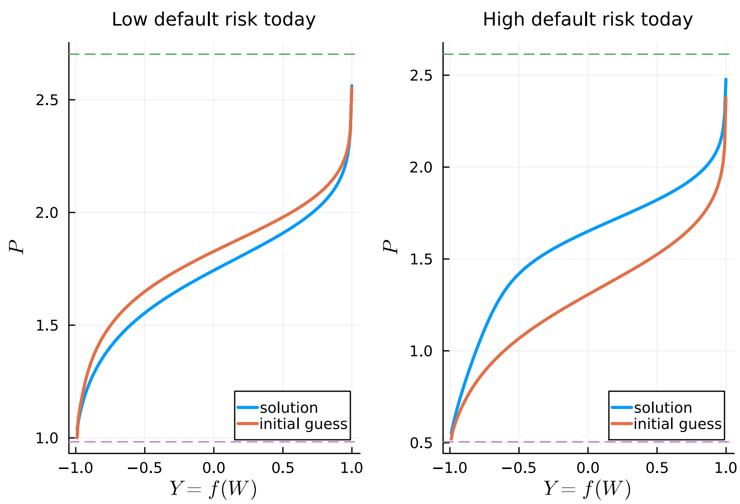
(a) Distribution of default risk



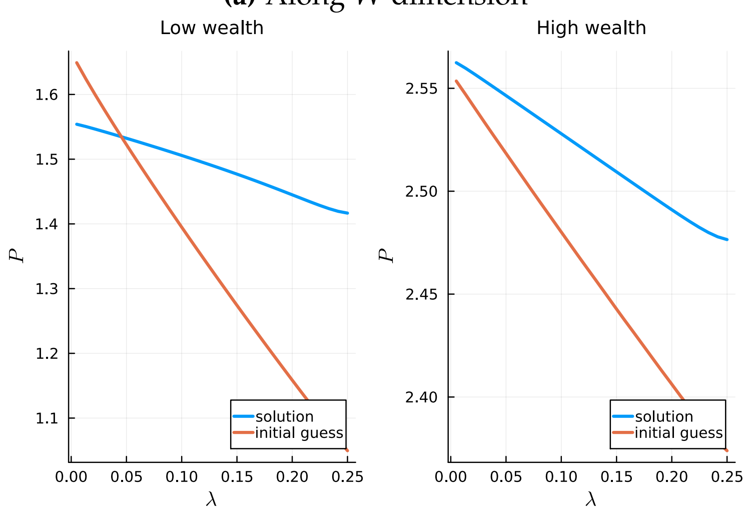
(b) Marginal distribution of wealth (truncated)

Figure E1: Invariant distributions of state variables

Note: Figure E1 plots the invariant distribution of state variables, using 750 years of simulated data from the calibrated model. Panel (a) plots the density of exogenous default risk. Panel (b) plots the distribution of endogenous asset manager wealth. The wealth distribution is truncate at 0.5, with the mass added to the truncation point.



(a) Along W dimension



(b) Along λ dimension

Figure E2: Price function and initial guesses

Note: Figure E2 plots the solution to the pde (19) for each dimension of the two state variables, along with the initial guesses to illustrate the solution algorithm. In Panel (a), I compare the bond price function when default risk is close to zero against when default risk is close the upper boundary $\lambda_{\max}$. The purple dashed line corresponds to the boundary condition at $W = 0$ and the gree dashed line corresponds to the boundary condition at $W \to \infty$. Asset manager wealth W is transformed to a variable in $[-1, 1]$ using the monotonic mapping $Y = \frac{W - \vartheta}{W + \vartheta}$. $\vartheta = 1.5$ is a scaling constant. In Panel (b), I compare the price function when asset manager wealth is relative low ($W = 0.5$) vs. relatively high ($W = 3000$).

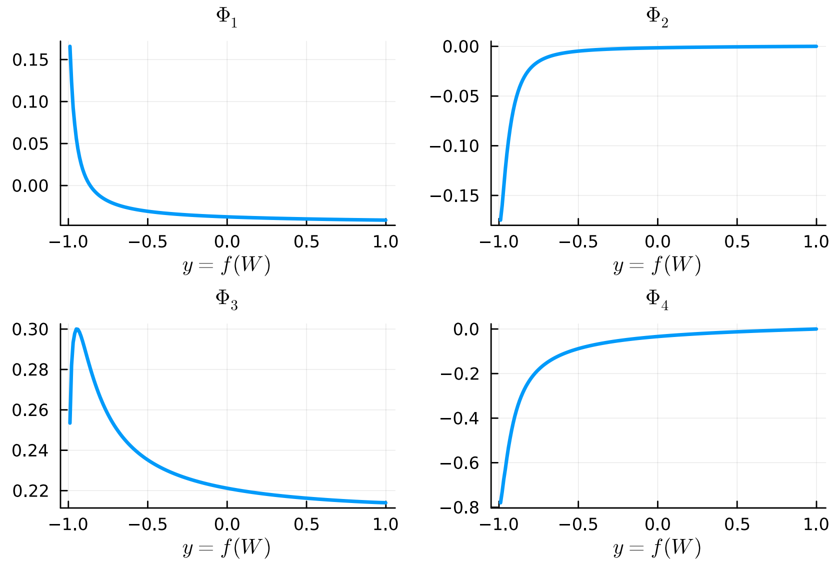


Figure E3: Drift and volatilities of asset manager wealth, $\lambda = \bar{\lambda}$

Note: Figure E3 plots the endogenous drift and volatility terms associated with the law of motion for asset manager wealth (18). Φ_1 corresponds to the drift of asset manager wealth. Φ_2, Φ_3, Φ_4 refer to, respectively, asset manager wealth exposure to default risk shock $dB_{\lambda,t}$, wealth shock $dB_{z,t}$, and default shock dN_t. Asset manager wealth W is transformed to a variable in $[-1, 1]$ using the monotonic mapping $Y = \frac{W-\vartheta}{W+\vartheta}$. $\vartheta = 1.5$ is a scaling constant. Default risk is set to its long-run mean.

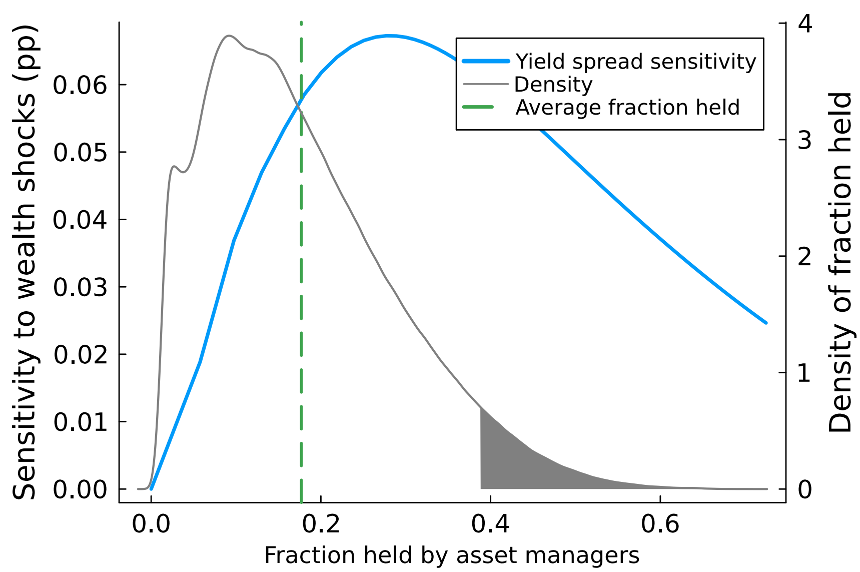


Figure E4: Sensitivity to wealth shocks and share held by asset managers

Note: Figure E4 shows that the equilibrium sensitivity of bond yield spread to a negative exogenous wealth shock is increasing in the share of asset held by asset managers for a large fraction of the distribution of asset manager holding. The left-hand-side y-axis corresponds to the equilbrium yield spread sensitivity $-\kappa\eta_{z,t}/(P_t)^2$ in response to a one standard deviation negative wealth shock, expressed in basis points and plotted in blue, as a function of asset manager share X_t/s when default risk λ is held at its long-run mean. The right-hand-side y-axis (plotted in gray) corresponds to the distribution of asset manager share $f(X)$ when $\lambda = \bar{\lambda}$, obtained by drawing from the invariant marginal distribution of wealth and applying the policy function $X(\bar{\lambda}, W)$. Shaded area indicates 95th percentile and above.

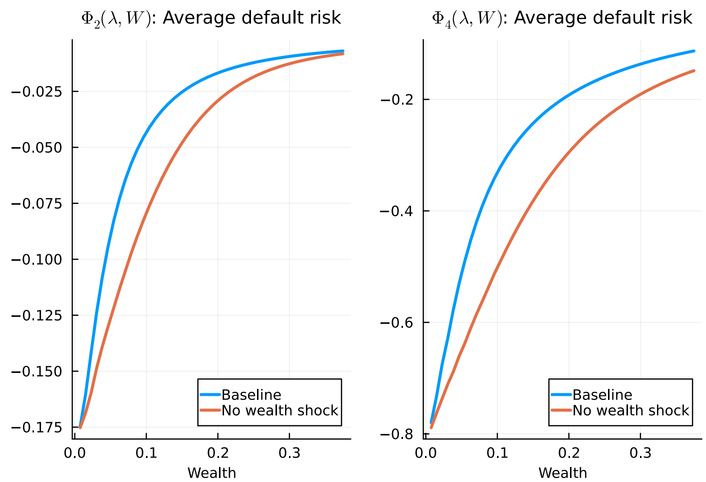


Figure E5: Asseet manager wealth exposure to default risk shocks: Baseline vs. no exogenous wealth shock

Note: Figure E5 compares the volatility terms associated with the law of motion for asset manager wealth (18) for the baseline calibration (blue lines) and the counterfactual setting in which I set the volatility of asset manager wealth shock to zero (red lines). The left panel plots the volatility term associated with exposure to default risk shock $\mathrm{d}B_{\lambda,t}$ and the right panel plots the exposure to default shock dN_t. The plots focus on neighborhoods around the average level of wealth.

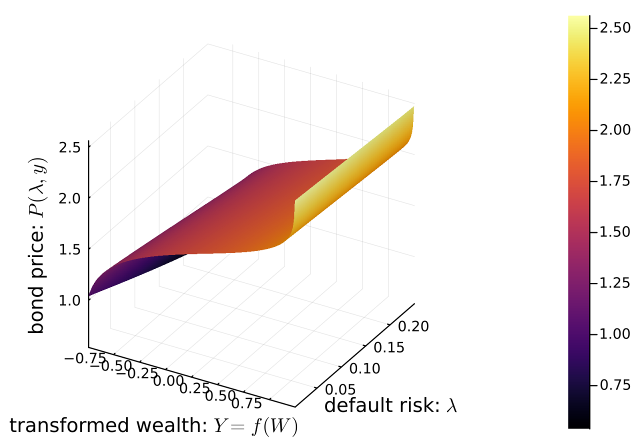


Figure E6: Bond price as a function of state variables

Note: Figure E6 plots the solution to the pde (19) as a function of state variables. Asset manager wealth W is transformed to a variable in $[-1, 1]$ using the monotonic mapping $Y = \frac{W-\vartheta}{W+\vartheta}$. $\vartheta = 1.5$ is a scaling constant.

F Asset demand of long-term investors: An optimizing foundation

This section sketches a stylized optimization problem to motivate the long-term investors' demand structure (16) and the interpretation of the counterfactual exercise discussed in Section 5.

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 (64). $\mathrm{d}Q_{F,t}$ 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:

$$\mathrm{d}Q_{F,t} = \mathrm{d}F_t + (\kappa \mathrm{d}t - \delta\lambda_t \mathrm{d}t) - rF_t \mathrm{d}t. \tag{61}$$

Abstracting from the reflecting boundary, the property of the CIR process (11) and the definition of F_t (12) 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:

$$\begin{aligned}
\mathrm{d}Q_{F,t} &= -\frac{\delta}{r+\kappa_\lambda}\mathrm{d}\lambda_t + \kappa \mathrm{d}t - \delta\lambda_t \mathrm{d}t - \Big(\kappa - \delta\overline{\lambda} + \frac{\delta r}{r+\kappa_\lambda}(\overline{\lambda} - \lambda_t)\Big)\mathrm{d}t \\
&= -\frac{\delta}{r+\kappa_\lambda}[\kappa_\lambda(\overline{\lambda} - \lambda_t)\mathrm{d}t + \sigma_\lambda\sqrt{\lambda_t}\mathrm{d}B_{\lambda,t}] + \delta(\overline{\lambda} - \lambda)\mathrm{d}t - \frac{\delta r}{r+\kappa_\lambda}(\overline{\lambda} - \lambda_t)\mathrm{d}t \\
&= -\frac{\delta\sigma_\lambda}{r+\kappa_\lambda}\sqrt{\lambda_t}\mathrm{d}B_{\lambda,t}.
\end{aligned} \tag{62}$$

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:

$$\max_{Z_{i,t}} V_{i,t} = (F(\lambda_t) - P_t)Z_{i,t} - \mathbb{E}_t[c(\lambda_t)\mathrm{d}N_t]P_t Z_{i,t} \tag{63}$$

$$\text{s.t.} V_{i,t} \geq \underbrace{\Gamma|Z_{i,t}|}_{\text{Divertible portion}} \times \underbrace{|P_t Z_{i,t}|}_{\text{Value of claims}} . \tag{64}$$

(63) 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 (12)). 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 (64). 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 (64).

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

$$\Gamma = \gamma f(\sigma^2_{F,t}) \tag{65}$$

for some positive function f satisfying $f'(\cdot) \geq 0$ and $\gamma > 0$.[91] 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 $\sigma^2_{F,t}$, the variance associated with the risk-neutral excess return. The constraint becomes looser when $\sigma^2_{F,t}$ decreases. By (62), $\sigma^2_{F,t} \propto \lambda_t$, 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 Section 2.4 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

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

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, Shleifer, Stein and Vishny, 2015; Chodorow-Reich, Ghent and Haddad, 2020).[92]

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, Shleifer, Stein and Vishny, 2015; Morelli, Ottonello and Perez, 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, Sánchez, Sapriza and Yurdagul, 2021). The default provision term in (63) reflects these considerations.

The credit constraint (64) 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 (65) 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, Shin and Zigrand, 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, Nuño and Thomas, 2022). This case is analyzed in the "no selection" counterfactual scenario in Section 5.

Asset demand To arrive at (16), I observe that risk-neutrality of the long-term investor implies (64) always binds. As a result, optimal risky asset position for each long-term investor is given by

$$Z_{i,t} = \frac{1}{\Gamma(\lambda_t)} \cdot \frac{F(\lambda_t) - P_t}{P_t} - \frac{c(\lambda_t)}{\Gamma(\lambda_t)} \cdot \lambda_t. \tag{66}$$

(16) is obtained by making the approximation $\log(1+x) \approx x$ on $x = (F-P)/P$,

[92] As an alternative motivation for (16), (63) reflects the potential inability of long-term investors with maxmin preferences to adjust portfolio every period (Xiong, 2001).

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 5 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 7) can also be mapped to this framework under a different interpretation. Slightly modifying the problem (63) to incorporate an additional term:

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

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.

G Linkages between primary and second markets

The main analysis in the paper uses data on ownership structures and prices on the secondary market for emerging market sovereign bonds. This section provides direct evidence on the close connection between primary and secondary markets. First, using Indonesia as a case study, I show that the same types of foreign investors participate in both the primary and the secondary market. Second, by studying 41 cases of re-opening of emerging market sovereign bond issue, I illustrate the close interaction between primary market bond pricing and the prevailing market prices.

Investor composition in the primary market: The case of Indonesia Data on primary market investor composition is scarce. From Bank Indonesia's press release of the Indonesian government's international bond auctions, I manually collect information related to the primary market shares of different types of participants for 19 bond issues, covering bonds denominated in U.S. dollar, Euro, and Japanese Yen settled from

2013 to 2017.[93] Table G1 reports the fundamental characteristics of each issue and the associated investor composition in the primary market. All investor types observed in the securities holding data (see Figure 2) participate in the primary market. By the total amount purchased in the primary market, asset managers account for over one half of the total issuance, while banks and insurers/pension funds account for 18% and 17%, respectively. These numbers are also very similar to Figure 2 on Germany-based investors' holding shares. To the extent that similar investors participate in both markets, sovereign issuers do not seem to serve different investor clientele in different markets.

The degree of investor participation in the primary market depends on bond characteristics. I find a close connection between bond tenor and long-term investors' participation in Table G1. In line with Table 1, banks tend to purchase a higher share of shorter-term bonds (around 5-years) compared to long-term bonds (30 years to maturity). Insurance companies and pension funds, on the other hand, increase buying when bond tenor rises.

Pricing linkages through the lens of bond re-opening Using pricing information for new bond auctions the re-opens previous issues, I show that primary market price – the actual borrowing cost of emerging market governments – is closely related to secondary market price of the same instrument prior to the new auction. For cost-saving purpose, governments frequently re-opens a previous bond issue to issue new debt with the same ex-ante characteristics, increasing the supply of the same debt security. Consequently, the difference between primary-market outcome and secondary-market prices would not be driven by ex-ante differences in bond characteristics.

I compare auction price and secondary-market price of the day before the auction date for each bond with available data to examine whether auction prices sufficiently reflect market dynamics. For 41 cases of external bond re-opening since the end of 2012 for which auction prices are reported in CBonds (a data vendor for bond issuance), Table G2 summarizes the yield differential between auction yield and secondary market yield of the same bond one trading day before the auction date (obtained from Refinitiv). Auction yields track secondary market condition closely. On average, auction yields are 14.6 basis points higher than the secondary market yields the previous trading day. Given the high volatility of the market prices, the yield differential is small, suggesting that the borrowing terms are substantially influenced by market condition.

In all but one case of re-opening analyzed in Table G2, the re-opened bonds are issued

[93] See https://www.bi.go.id/en/iru/highlight-news/default.aspx.

at a small premium compared to the previous secondary market prices.[94] This "issuance premium" (Siani, 2023) suggests that during episodes of global financial tightening, secondary market prices may in fact understate the actual cost of additional issuance faced by emerging market governents.

[94] Cole, Neuhann and Ordoñez (2022) attributes the spread between trading prices and auction prices of new issuance to information frictions.

							Share held by:				
Bond	Tenor (Years)	Currency	Coupon	Yield	Settlement Date	Amount Issued (Billions USD)	Asset managers	Banks	Insurers/Pensions	Governments	Other
1	10	USD	3.38%	3.50%	4/15/13	1.50	68%	21%	11%	0%	0%
2	30	USD	4.63%	4.75%	4/15/13	1.50	81%	10%	9%	0%	0%
3	7	EUR	2.88%	2.98%	7/8/14	1.36	65%	15%	8%	12%	0%
4	10	EUR	3.38%	3.56%	7/30/15	1.37	66%	16%	9%	9%	0%
5	10	JPY	0.91%	0.91%	8/13/15	0.44	88%		11%		0.90%
6	7	EUR	2.63%	2.77%	6/14/16	1.68	68%	21%	4%	7%	0%
7	12	EUR	3.75%	3.91%	6/14/16	1.68	76%	6%	8%	10%	0%
8	5	USD	3.70%	3.75%	12/8/16	0.75	74%	21%	0%	5%	0%
9	10	USD	4.35%	4.40%	12/8/16	1.25	53%	24%	18%	5%	0%
10	30	USD	5.25%	5.30%	12/8/16	1.50	27%	5%	62%	6%	0%
11	3	JPY	0.65%	0.65%	6/8/17	0.91	9%	49%	16%		26%
12	5	JPY	0.89%	0.89%	6/8/17	0.91	23%	29%	25%		23%
13	7	JPY	1.04%	1.04%	6/8/17	0.91	8%	20%	20%		52%
14	7	EUR	2.15%	2.18%	7/18/17	1.16	52%	17%	17%	14%	0%
15	10	USD	3.85%	3.90%	7/18/17	1.00	56%	27%	7%	10%	0%
16	30	USD	4.75%	4.80%	7/18/17	1.00	55%	11%	28%	6%	0%
17	5	USD	2.95%	3.00%	12/11/17	1.00	54%	28%	10%	8%	
18	10	USD	3.50%	3.55%	12/11/17	1.25	47%	32%	19%	2%	
19	30	USD	4.35%	4.40%	12/11/17	1.75	59%	10%	27%	4%	

Table G1: Investor composition in the primary market: Indonesian external government bonds (2013–17)

Note: Table G1 reports the institutional composition of primary market participants in Indonesia's external bond auctions from 2013 to 2017, based on public information released by Bank Indonesia. For each offering, I report information on bond characteristics (currency denomination, size, maturity, settlement date and coupon). Blank cells on investor composition represent the case where no information on a particular investor is available.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Yield differential (bps)	41	14.57	12.32	-13.07	59.49	7.84	12.19	20.08

Table G2: External bond reopening: Auction yield minus secondary market yield on the previous trading day (bps)

Note: Table G2 reports the difference between auction (primary market) bond yield and the secondary market yield on the previous trading day for the same bond issue offered through reopening auctions. The yield differential is expressed in basis points. I focus on 41 cases of bond re-opening of emerging market governments starting from the end of 2012.

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