Global or Regional Safe Assets: Evidence from Bond Substitution Patterns*

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Abstract

This paper provides novel empirical evidence on portfolio rebalancing in international bond markets through the prism of investors' demand for bonds. Using a granular dataset of global government and corporate bond holdings by mutual funds domiciled in the world's two largest currency areas, I estimate heterogeneous and time varying demand elasticities for bonds. Safe assets such as US Treasuries or German Bunds face especially inelastic demand from investment funds compared to riskier bonds. But spillovers from these safe assets to global bond markets are strikingly different. Funds substitute US Treasuries with global bonds, including risky corporate and emerging market bonds, whereas German Bunds are primarily substitutable within a narrow set of euro area safe government bonds. Substitutability deteriorates in times of stress, impairing the transmission of monetary policy.

Keywords: International Finance, Portfolio Choice, Safe Assets

JEL Classification: F30, G11, G15

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1 Introduction

International bond markets play a key role in the transmission of monetary policy, financial intermediation and the unfolding of financial crises. In all these roles, knowledge of the demand elasticities and substitutability of fixed income assets is key for policy makers. And the demand elasticities with respect to safe assets, in particular, are crucial. For example, central banks need such information to judge how monetary policies that directly target the return on safe assets would translate into the broader costs of firm and household borrowing or which fixed income assets might benefit from "flight to safety" demand during global distress. Safe assets are naturally more attractive for risk averse investors but their appeal may also emanate from non-pecuniary benefits related to their liquidity, collateral pledgeability, simplicity or regulatory requirements (often summarized as an asset's "convenience yield"[1]) or from assets' hedging properties[2]. For all these reasons, investors may choose to hold safe assets in spite of a lower return, implying that demand for safe assets may be less elastic. However, the literatures on safe assets and on monetary policy transmission, more broadly, have an important gap as they lack carefully estimated rich own and cross demand elasticities for the world's safe assets.

This paper fills the gap in our understanding of safe asset demand by directly estimating elasticities for global government and corporate bonds held by mutual funds that are domiciled in the world's two largest currency areas – US and the euro area. I recover the funds' own and substitution elasticities that vary in the cross-section of international bonds as well as over time for approximately 5,000 granular bond portfolios with a face value of $74 trillions or nearly 60% of global debt securities outstanding. Not only can I describe how elastic demand for this diverse set of bonds is but also I can discuss how substitutable safe assets are with other bonds. These are the first estimates of substitution elasticities in global bond markets, at a granular bond level. They offer a unique view of financial turmoil – during the Global Financial Crisis of 2007-08, the euro area sovereign debt crisis as well as the market fallout from the outbreak of the COVID-19 pandemic in early 2020 – through the lens of bond markets and their investors.

Methodologically, this paper builds on a rapidly growing finance literature that applies demand system estimation techniques to financial assets (Koijen and Yogo, 2019, 2020, Koijen, Richmond and Yogo, 2020b). To estimate an international bond demand model using a broader and more granular set of assets and investors than in any previous application, I make several methodological advances. First, the more granular fund and bond data allow me to control for a more comprehensive set of bond and fund mandate characteristics to recover precise estimates of demand elasticities. Along with observable characteristics, I can control for unobservable heterogeneous and time-varying risk aversion at the individual fund level in recognition of the extensive empirical evidence of its role in the transmission of monetary policy via risk-taking by financial intermediaries (Rey, 2013, Bauer, Bernanke and Milstein, 2023). Second, I estimate flexible substitution elasticities across bonds by allowing both heterogeneous investor preferences (as in Koi-

[1] See *inter alia* Krishnamurthy and Vissing-Jorgensen (2012), Nagel (2016) for a discussion of likely factors behind and measurement of the convenience yield priced into US Treasuries.

[2] In an international setting, the hedging properties of the US dollar or US Treasuries may reflect a return covariance with non-traded income and the real exchange rate (Coeurdacier and Rey, 2013, Gourinchas and Rey, 2022).

jen and Yogo, 2019) and relaxing the functional form which pre-determines dimensions of market segmentation in Koijen and Yogo (2020), Koijen, Richmond and Yogo (2020b). The latter innovation implies that investors may have heterogeneous substitution patterns across bonds of different countries, currencies, credit ratings, maturities or issuer types (e.g. corporate or government) and brings insights from a long-standing empirical industrial organization literature on demand system estimation (Berry and Haile, 2021, Gandhi and Nevo, 2021) to demand-based asset pricing. Third, I propose a new instrument to identify exogenous variation in bond returns in a setting where the market-clearing-based instruments of Koijen and Yogo (2019, 2020) are not feasible due to observing only part of bond ownership. Monetary policy shocks of the Fed and ECB along the entire yield curve (Miranda-Agrippino and Nenova, 2022) spill over heterogeneously across international bond markets and provide a strong instrument for bond returns.

So what do we learn about safe assets from international bond demand? Bonds normally perceived as safe assets – US Treasuries and German Bunds – do indeed face some of the lowest demand elasticities from international mutual funds, supporting the notion that these bond provide additional benefits to the holders beyond what is captured, for instance, by their expected return or low credit risk. But, more broadly, demand elasticities increase continuously with bond credit ratings, suggesting some perceived safety benefits across a range of bonds and not just advanced-economy government debt. In addition, demand elasticities also vary with the country of issuer and bond maturity. Bonds issued by the US or advanced economies and with short maturity face the lowest demand elasticities. This heterogeneity in demand elasticities across bonds provides a new measure of safe asset 'specialness' – safe assets are those estimated to face particularly low demand elasticity from private investors.

But not all safe assets are the same. Bond substitution elasticities reveal how shocks to the return of different safe bonds spill over via portfolio rebalancing to the rest of international bond markets. Surprisingly, substitutability is not limited to a small pool of highly-rated sovereign bonds with funds mostly substituting e.g. US Treasuries with German Bunds. Instead, when US Treasury returns increase, funds decrease their exposure to risky (with a low credit rating) and emerging market bonds the most in order to accommodate greater holdings of that safe asset. In contrast, a rise in German government bond returns triggers sales of primarily euro area bonds, issued by sovereigns with a high credit rating. Hence, one safe asset plays a global role in international portfolios – US Treasuries are the safe asset of choice across funds with diverse investment universes. The other safe asset is regional – German Bunds provide a safe or liquid component in portfolios of primarily euro area sovereign bonds. These substitution patterns point to substantial segmentation in fund portfolios consistent with an important role for preferred habitat investors (Vayanos and Vila, 2021) in international bond markets.

The estimated "specialness" of safe assets also varies over time. In periods of heightened market stress US Treasuries face an even lower demand elasticity and this is due to passive investors buying more of them despite low returns. This paper thus documents systemic "flights to safety" by investment funds and highlights that fund heterogeneity is key in understanding these episodes. In addition, the substitutability between safe and risky assets also deteriorates in times of stress. This pattern is particularly striking when it comes to the substitutability between US Treasuries and US BBB-rated corporate bonds.

But it also emerges when examining the substitutability of German Bunds with other euro area governments during the sovereign debt crisis. One consequence of these findings is that monetary policies that hope to affect broader funding conditions through changes in the interest rate on safe assets are not very effective during financial turmoil. At these times, the private sector substitutability between safe and risky assets is severely impaired. A back-of-the-envelope exercise tracing the substitution patterns following hypothetical Fed purchases of $100 billion US Treasuries highlights the stark difference in portfolio rebalancings under high substitutability of safe assets with risky bonds (low stress) versus low substitutability (high stress). In tranquil times funds invest $28 billion of the US Treasury proceeds in BBB-rated US corporate bonds, compared to only $14 billion during financial turmoil.

Finally, why study the bond demand of investment funds in the first place? Funds are not the only investors with a significant footprint in bond markets – banks, insurance companies and pension funds, official investors (central banks managing FX reserves, sovereign wealth funds and, due to unconventional monetary policies, domestic central banks) all hold significant portions of global debt securities. However, investment fund behaviour in international bond markets is particularly important for two reasons. First, even if individual funds are constrained by mandates and liquidity risk, the sector's objective is still to deliver returns and hence it is likely to more actively reallocate between bonds and drive aggregate bond substitution patterns.[3] Combined with funds' rapidly growing size as a share of global financial sector assets[4], this implies investment funds are likely to play a key role of 'deep-pockets' marginal investors in bond markets with important asset pricing implications. Second, investment funds are the leading vehicle for international portfolio diversification by advanced economies' residents and are thus key in understanding cross-border portfolio flows.[5] Understanding investment decisions by mutual funds is thus of primary importance for international portfolio capital allocation. Moreover, systemic evidence of cross-border capital flows documents that international investment is 'fickle', as international capital withdraws sharply during crises – especially debt investments in the form of cross-border bank lending and portfolio debt investment (Broner et al., 2013, Forbes and Warnock, 2012, 2021). Thus, more generally, mutual funds' investment in international bond markets is likely to play a key role in the cross-border transmission of shocks via financial markets.

Related literature. This paper provides detailed empirical evidence on the characteristics of safe asset demand by investment funds. Theoretically, such special demand for safe assets may have different origins. He, Krishnamurthy and Milbradt (2019) highlight the interaction between issuer safety or fundamentals and debt size or liquidity. The joint importance of safety and liquidity also plays a key role in safe asset determination and gives rise endogenously to convenience yields in Chahrour and Valchev (2022), Arvai and Coimbra (2023), Coppola, Krishnamurthy and Xu (2023). Safe assets should also provide

[3]Indeed, Fang, Hardy and Lewis (2022) find that mutual funds, especially foreign ones, have the highest demand elasticities for country-level sovereign debt.

[4]See Global Monitoring Report on Non-Bank Financial Intermediation 2022, *Financial Stability Board*: `https://www.fsb.org/wp-content/uploads/P201222.pdf`.

[5]Maggiori et al. (2018) show that country allocation of mutual fund portfolios reported to Morningstar aligns closely to aggregate external positions of the US (TIC) and the euro area (CPIS). For the euro area, Faia et al. (2022) document that only mutual funds take currency risk, other institutional sectors such as banks and insurers/pension funds do not.

investors with better insurance to bad states of the world due to a positive covariance between their returns and investors' stochastic discount factor (Coeurdacier and Rey, 2013, Gourinchas and Rey, 2022). In addition, safe assets are expected to pay their face value and thus require little production or acquisition of private information about their value Dang et al. (2009, 2012, 2017) – being traded under symmetric information enhances their liquidity. The role of safe assets and their supply and demand for international risk sharing and macroeconomic fluctuation are the focus of Caballero, Farhi and Gourinchas (2008, 2015, 2017), Gourinchas and Rey (2022, 2016). When global safe assets are in limited supply, investor demand shocks have profound effects on international imbalances and output volatility. In these models, the lack of suitable substitutes to safe assets issued only by a few countries is a key assumption. My paper brings direct evidence on the substitutability in international bond markets, emphasizing and quantifying the imperfect substitutability between bonds commonly perceived as safe assets and all others.

A related line of work measures the 'specialness' of safe assets in terms of convenience yields – a catch-all non-pecuniary benefit derived from holding safe assets that encompasses motives related to safety, liquidity, collateral and repo value, regulatory incentives, limited participation motives.[6] This approach hinges on comparing the yields of suspected safe assets (with US Treasury bonds and bills receiving particular attention) to other safe investments that do not provide the same liquidity or safety benefits. Common financial market spreads used in a US context include US corporate Aaa bond–Treasury (Krishnamurthy and Vissing-Jorgensen, 2012), general collateral repo–US T-bills (Nagel, 2016), US government-guaranteed agency debt (Refcorp)–Treasuries (Longstaff, 2004, Fleckenstein et al., 2014, Del Negro et al., 2017). In an international setting, Du, Im and Schreger (2018) calculate the covered interest parity deviations between the government bonds of major advanced economies and the US to measure relative convenience yields. My estimates take a different route to measuring the 'specialness' of US Treasuries that relies on investors' revealed preferences through observed bond holdings. In the process, I also flag bonds face a continuum of demand elasticities suggesting many assets may provide some 'safety' benefit to investors. I share this more agnostic view of the identity of safe assets with Van Binsbergen et al. (2022), Diamond and Van Tassel (2021) and Mota (2020). The former two papers calculate convenience yields versus a synthetic risk-free rate recovered from the put-call parity relationship for equity options. Their approach is only feasible for maturities of up to three years and for advanced countries with liquid derivatives markets. The demand elasticities studied here can be estimated across a much wider pool of assets – with different maturities and issued by emerging markets and advanced economies alike. In the same spirit, Mota (2020) recovers a range of safety premia across US non-financial corporate bonds using a credit-risk-adjusted corporate spread.

More broadly, the heterogeneity in demand elasticities and substitution patterns estimated here suggest international bond markets are segmented along multiple dimensions, including bond rating, issuer region and maturity. A growing literature on segmented markets assumes the presence of preferred-habitat investors in bond or currency markets.[7] It calibrates the footprint of preferred-habitat investors crudely by assuming that

[6] See *inter alia* Krishnamurthy and Vissing-Jorgensen (2012), Jiang, Krishnamurthy and Lustig (2018, 2020, 2021a), Krishnamurthy and Lustig (2019), Krishnamurthy and Li (2023), Engel (2020), Engel and Wu (2018), Valchev (2020), Nagel (2016).

[7] See Vayanos and Vila (2021), Gourinchas, Ray and Vayanos (2022), Ray et al. (2019), Costain, Nuño

one sector harbours a strong preference for a given market segment – for example, long-term bonds are the preferred habitat of insurance companies and pension funds. My demand elasticity estimates suggest that markets are segmented along many dimensions and that even within one sector – investment funds – there are both passive investors following a strict mandate and active arbitrageurs. This insight broadens the scope and applicability of this class of models to a wider range of issues.

The empirical results of this paper complement a diverse range of regularities uncovered using granular data on the role of foreign and non-bank investors for international portfolio diversification and portfolio rebalancing after quantitative easing programmes. Using sector-level bond holdings data for euro area investors, Faia, Salomao and Veghazy (2022) highlight the differential home currency bias across different investor sectors in the face of ECB bond purchases. Tabova and Warnock (2021) reveal that different investors in US Treasuries (domestic and foreign private versus foreign official) have different preferred habitats along the yield curve and earn different returns on their holdings as a result. Bergant, Fidora and Schmitz (2018), Joyce, Liu and Tonks (2014), Koijen, Koulischer, Nguyen and Yogo (2020a) build investor flows from security-level data to measure sectoral responses to asset purchases as part of quantitative easing programmes. Beck et al. (2023) unravel the ownership of euro area investment funds to trace the patterns of European financial integration.

Methodologically, my work builds on a rapidly growing characteristics-based asset demand literature. Koijen and Yogo (2019) estimate demand for US equities, while Koijen, Richmond and Yogo (2020b) extend their methodology to international demand for US and UK equity in a Nested Logit model. Of particular relevance to my research are the papers by Koijen and Yogo (2020) and Jiang, Richmond and Zhang (2021b) who estimate a demand system for international portfolio investment aggregated to three asset classes (equity, short- and long-term debt) at the country level. In addition, Koijen et al. (2020a) estimate demand for euro area sovereign debt again aggregated to the country level to examine the effects of the European Central Bank's quantitative easing programme. For bonds, in particular, Bretscher et al. (2020) estimate institutional demand for US corporate bonds at the security level using the methodology of Koijen and Yogo (2019), while Fang, Hardy and Lewis (2022) estimate sectoral demands for the aggregate government debt of advanced and emerging market economies. In a similar spirit, Eren, Schrimpf and Xia (2023) estimate sectoral demand for aggregate US Treasury debt[8]. Compared to these empirical studies, the demand estimation in this paper is based on much more granular and broad investor and bond data. On the bond side, I model demand for fine bond portfolios constructed bottom-up from security-level holdings and bond characteristics. The bonds are international, of all credit ratings and issued by governments, supranational agencies as well as corporates. On the investor side, the unit of my analysis is a single mutual fund matched to information related to its mandate such as the asset classes it can invest in, its investment area as well as the type of bonds (government or corporate) that it tends to invest in. In addition, I make substantial progress on the estimation

and Thomas (2022), Kekre, Lenel and Mainardi (2022).

[8]To obtain exogenous variation in US government bond yields over time, Eren, Schrimpf and Xia (2023) also use high-frequency Fed monetary policy shocks. The identification in my paper utilizes not only the time variation in monetary policy shocks around both Fed and ECB announcements but also the heterogeneous effects of these by bond maturity, country and currency as a way to obtain variation *across* a broad range of international bonds.

methodology in order to capture demand for this granular and broad set of assets and estimate flexible substitution patterns among them.

In the broader context of asset pricing, my demand estimates contribute to a long-standing literature using index additions and deletions as exogenous demand shocks to document downward-sloping demand curves for financial assets (Shleifer, 1986, Harris and Gurel, 1986, Chang et al., 2014, Chen et al., 2004, Petajisto, 2011). Recently, Gabaix and Koijen (2022) examine how the implied imperfect substitutability between financial assets can generate and exacerbate macroeconomic fluctuations.

Outline The remainder of the paper proceeds as follows. In Section 2 I give a brief overview of the dataset, its coverage and the main patterns of bond investment by mutual funds. Section 3 lays out the empirical demand model and implied demand elasticities, as well as the identification strategy. In Section 4, I present the main estimation results and summarize the demand elasticities. Section 5 discusses what estimated elasticities imply about the role of different safe assets in international bond markets. Section 6 concludes.

2 Data

I collect a dataset of security-level bond holdings by individual open-ended mutual funds and ETFs from Morningstar Direct – a platform providing end-investors with investment fund information and recommendations. The holdings information is based on fund reporting and verified by Morningstar against available regulatory reports.[9] I limit the fund universe studied in this paper to funds domiciled in the two largest currency areas – the US and euro area. Five domiciles within the euro area – Luxembourg, Ireland, Germany, France and Netherlands – suffice to cover 90% of overall debt securities held by euro area investment funds[10], so I focus on these largest euro area domiciles.

Notably, throughout the analysis the investor unit is an individual fund (e.g. "Vanguard Total International Bond Index Fund"), rather than the umbrella institution ("Vanguard"). This allows me to supplement the dataset with fund-specific characteristics relevant to the portfolio allocation decision – country of domicile, fund type (either fixed income, which invest solely in fixed income securities, or balanced, which invest in both bonds and equity), style (index fund, ETF or other), investment area, Morningstar fund category, with an institutional or retail investor base, size (assets under management or AUM), net fund flows, total fund returns. Portfolio holdings are most often reported at quarterly frequency[11] , while all other time-varying fund variables (size, returns, flows) are

[9]My own checks comparing the portfolios reported by US fixed income funds to Morningstar with their mandatory SEC reports suggests funds provide accurate security-level information. In an influential line of research using Morningstar security-level holdings, Maggiori, Neiman and Schreger (2018), Coppola, Maggiori, Neiman and Schreger (2020) and Beck et al. (2023) also confirm the accuracy of these. On the other hand, Chen, Cohen and Gurun (2021) find that some bond funds strategically misreport aggregated statistics such as overall bond portfolio risk in order to obtain a better risk-return rating from Morningstar. I therefore steer clear of using any aggregated portfolio statistics on fund style from Morningstar and solely use the security-level holdings information throughout the analysis.

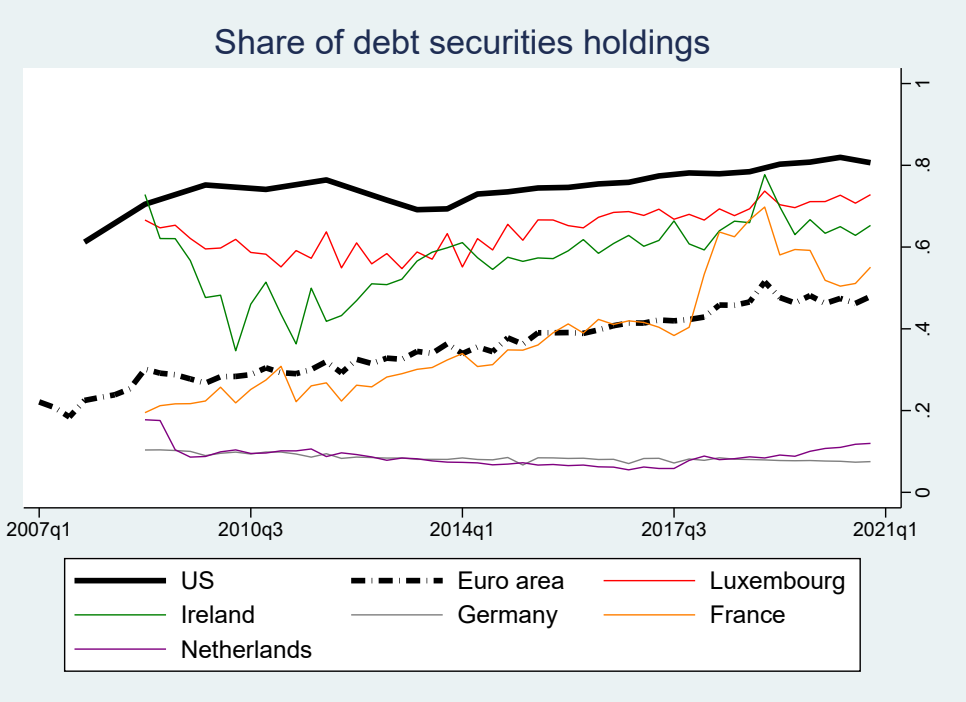
[10]Source: Security Holdings Statistics by Sector (SHSS), *European Central Bank*.

[11]Some larger investment funds report portfolio holdings at higher frequencies. Given the systematic differences in fund coverage in quarter-end versus within-quarter dates, the baseline empirical analysis is at quarterly frequency. Estimating bond demand on monthly fund holdings data yields similar results.

monthly. The estimation sample starts in 2007, when Morningstar fund portfolio holdings coverage becomes significant, and ends in December 2020.

Overall, the US and EA funds in the collected Morningstar data hold around $8.5 trillion worth of debt securities and manage a total of around $11 trillion assets as of end-2020. Comparing total security-level holdings to national financial accounts statistics from the Federal Reserve Board (FRB) for US funds and from the European Central Bank (ECB) for EA funds suggests the dataset covers a substantial portion of aggregate fund debt security holdings. For the three largest fund domiciles the coverage is very high – 80% for US funds by end-2020; over 70% for Luxembourg funds; and around 65% for Irish funds (Figure 1). Funds based in Germany, France and the Netherlands are less well-represented in the fund-security-level dataset, but the growing role of Luxembourg- and Ireland-domiciled funds in overall euro area bond investment makes this less of a concern in the latter part of the sample. Similarly, funds in my dataset account for around 90% of the total AUM of US fixed income and balanced funds and 40% of the respective euro area funds' AUM (Appendix Figure A.15).

Figure 1: Morningstar debt security holdings: representativeness vs financial accounts

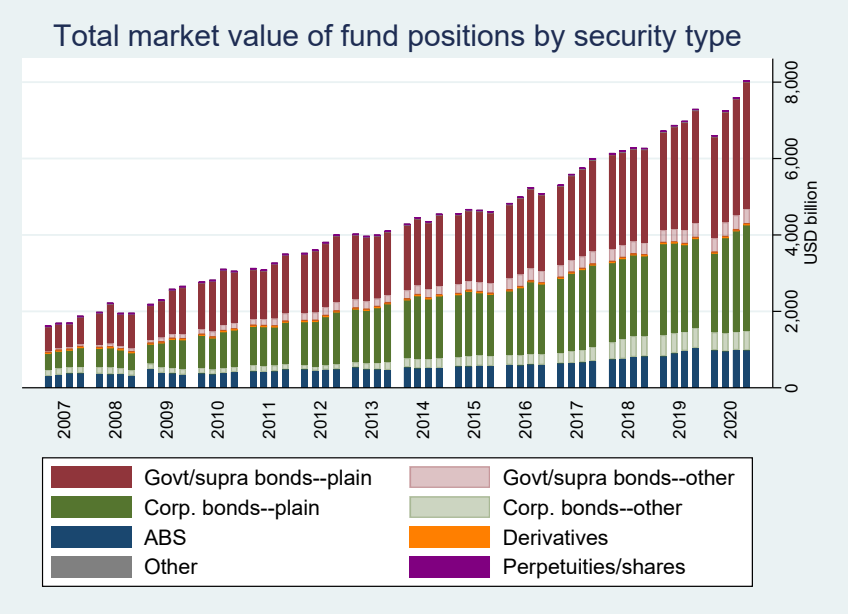


Next, I match the fund portfolio holdings from Morningstar using the reported security identifier (either ISIN or CUSIP) to extensive bond pricing and reference data. I start by classifying all securities using reference data from Refinitiv Eikon. I collect information on the instrument type (e.g. bonds, asset-backed securities, derivatives, etc.), as well as key characteristics such as the issuer type (e.g. government, municipal, corporate bonds), coupon type (e.g. floating vs fixed rate), whether a bond is inflation-protected, convertible, perpetual. Since my objective is to characterize the demand for safe assets through their substitutability with comparable assets, I limit the bond universe to relatively 'plain' bonds – government and corporate bonds excluding floating-rate notes, inflation-protected

bonds, convertible and perpetual securities, as well as US municipal bonds whose demand is heavily influenced by tax exemptions for local investors.

Figure 2 shows a breakdown of all funds' debt security holdings into the broad security types I use to define the bond universe of study. Government or supranational bonds together with corporate bonds account for the majority (80%) of mutual fund bond holdings. Each of these is split into 'plain' bonds as described above and all other bonds. Plain bonds clearly dominate, such that the exclusion of 'other' government and corporate bonds removes only 10% of mutual fund bond holdings from the analysis. Asset-backed securities (ABS) account for almost all the other debt securities intentionally excluded from the analysis, with around 20% of Morningstar funds' debt holdings. Data on ABS has somewhat worse coverage than 'plain' bonds and collecting these is left for future work. The share of other securities (derivatives, perpetuities, other – some of which misclassified by Morningstar as debt securities) is negligible.

Figure 2: Breakdown of fund debt security holdings by type



With this list of 'plain' government and corporate bonds in hand, I collect historical data on month-end bond prices, yields[12] and total returns from Refinitiv Datastream. Coverage of the pricing data is adequate given the diverse set of international bonds in fund portfolios, such that the priced bonds account for 60% of the raw reported Morningstar fund holdings (out of the 70% overall holdings of government and corporate 'plain' bonds). I supplement the pricing data with the following time-varying information about the bonds: amounts outstanding, credit ratings from three global rating agencies (Fitch, Moody's, DBRS), and exchange rates of their currency of denomination against the US dollar. Finally, several static variables complete the set of bond characteristic needed for the analysis: bond maturity date (used to calculate bond's residual maturity over time), currency of denomination, ultimate parent issuer type (government, supranational

[12]I use yield to maturity for bonds that are neither callable nor putable and yield to worst in the case of bonds with optionality

or corporate), issuer country & country of risk[13] , bond seniority (ranging from a top rank of "Senior Secured" to the lowest of "Junior Subordinated Unsecured").

The bond universe that this data collection procedure leaves me with consists of approx. 85,000 unique bonds with a total face value of $74.3 trillion as of end-2020. Thus the bonds included in the analysis in this paper account for 57% of total debt securities outstanding worldwide[14]. The coverage is even higher for securities issued by general government – 78% of the worldwide total. Of all debt securities issued by other entities (financial and non-financial companies, international organizations), the bond dataset collected here corresponds to 33%, which primarily reflects the intentional exclusion of asset-backed securities and other structured instruments from the analysis.

Bond buckets Estimating demand for individual bond ISINs is not desirable in this application for two key reasons. First, as time passes individual bonds approach maturity. Suppose a fund seeks a relatively stable weighted average maturity of its bond portfolio and the asset manager substitutes a bond nearing maturity for another bond of the same issuer, with the same credit or currency risk but closer to the fund's targeted maturity. This type of mechanical portfolio churn is not informative about the fund's economic motives but would require adding many zero portfolio weights for individual bonds that are simply being replaced by similar instruments. Second, I have a much broader set of assets than in any other asset demand system estimation so far. This is a paper describing the *global* bond market and the number of securities included reflects this ambitious scope. However, modelling the demand for over 85,000 individual bonds and calculating substitution elasticities between each pair poses a significant computational burden that is not warranted by the macro-financial research question addressed here. In addition, the elasticities estimated from portfolio allocations to single securities are likely to be much higher than the substitution elasticities between more aggregated bond portfolios, as it may be easier to find a substitute for e.g. a single corporate bond (another bond of the same company or of a similar company would presumably do) but much harder to find a good substitute for all US corporate bonds rated "BBB" (Chaudhary et al., 2022).

In keeping with a long asset pricing literature that groups individual securities into portfolios along key asset characteristics (Fama and French, 1993, He, Kelly and Manela, 2017), I group bonds into bond buckets that capture differences along five key risk dimensions most relevant for international investors. These include: (i) issuer country of risk – 140 countries; (ii) issuer type – three categories (sovereign, supranational or corporate); (iii) bond currency of denomination – around 60 currencies; (iv) credit rating – five bond rating scales ("AAA-AA", "A", "BBB", "BB","B-D")[15], and (v) residual maturity – four

[13]The two countries can be different especially for large multinational companies with financing subsidiaries located in small financial centres such as the Cayman Islands or Luxembourg. Whenever available, I use country of risk in the analysis as the country of the bond issuer.

[14]See Bank for International Settlements, Debt security statistics: https://www.bis.org/statistics/secstats.htm?m=202.

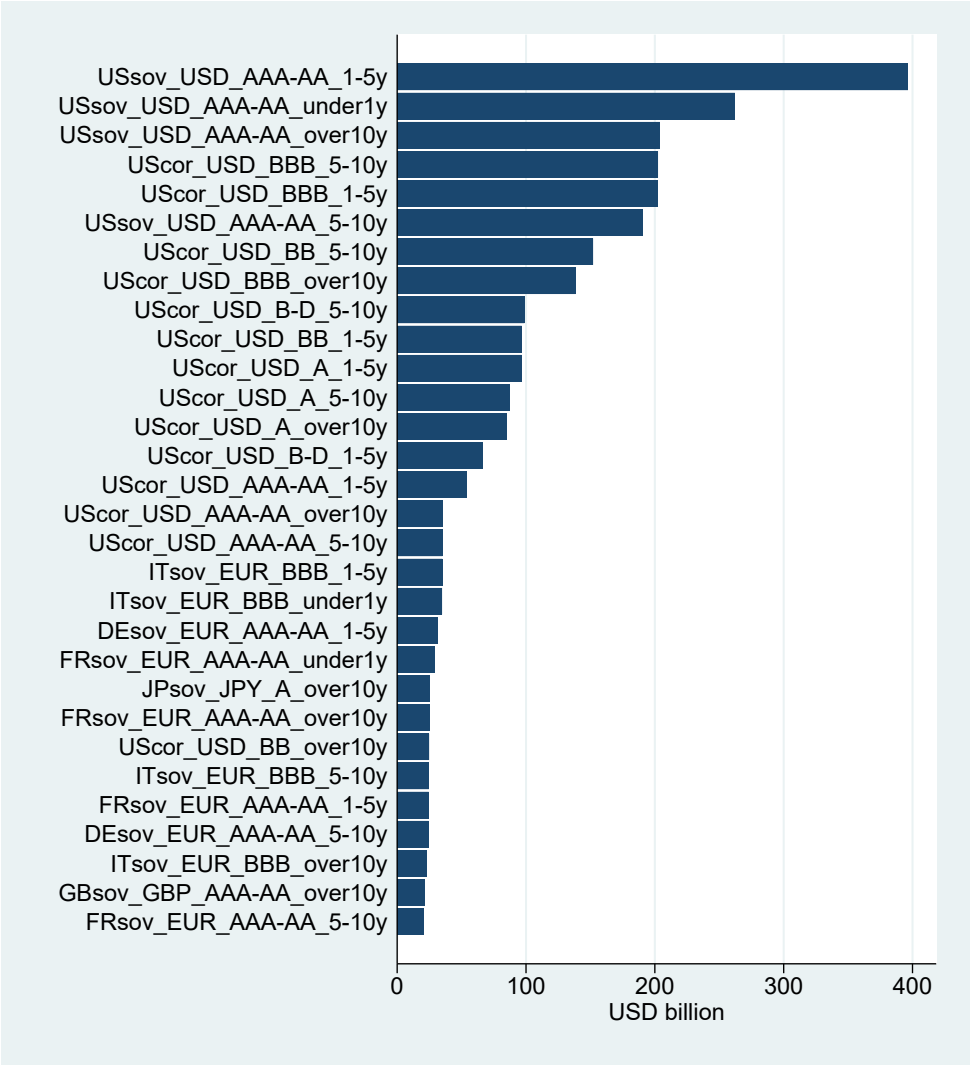
[15]Specifically, a bond is classified into the "AAA-AA" rating bucket if it has a maximum rating from the three rating agencies included in the analysis (Fitch, Moody's and DBRS) of AAA, A+, A, or A-. Similarly a "BBB" rating bucket contains bonds with a rating of BBB+, BBB, or BBB-. This grouping of bond ratings is closely aligned with regulators' credit assessment frameworks used to assess the credit quality of collateral used in monetary policy operations. For example, see the Eurosystem credit assessment framework (ECAF) at https://www.ecb.europa.eu/paym/coll/risk/ecaf/html/index.en.html.

categories (under 1 year, 1-5 years, 5-10 years, over 10 years).

This bucketing of bonds simplifies the portfolio allocation problem that I describe and estimate in the next sections, as I now model the choice among some 5,000 bond buckets rather than 85,000 bonds. At the same time, I still make the most of the security-level data that I have by building all variables describing a given bond bucket bottom-up (rather than, for example, using off-the-shelf bond indices) from the characteristics of individual bonds that enter the fund sectors' portfolios at any point during the estimation sample. As a concrete example, this means that there is no mismatch between the bonds used to calculate a given bucket's total return and the bonds actually held in fund portfolios. In particular, bond returns, yields, prices, residual maturity, bond seniority rank are the face-value-weighted averages of the respective individual security characteristic across bonds in a particular bond bucket; bucket-level amount outstanding is the sum of bond amounts outstanding converted into US dollars.

Figure 3 provides a snapshot of the 30 most important bond buckets in the dataset by the overall market value held by mutual funds as of end-2020. Unsurprisingly, given the size and importance of US Treasury markets, the three largest buckets consist of US Treasuries of various maturities. For instance, "USsov_USD_AAA-AA_1-5y" stands for US sovereign bonds, denominated in US dollars, rated in the broad rating scale of "AAA-AA", with a remaining maturity of 1 to 5 years. US corporate bonds of different maturities and credit ratings come next as single buckets with large fund holdings, followed by advanced economy sovereign bond buckets (issued by Italy, Germany, France, Japan and the UK). For the remainer of this paper, I use these bond buckets everywhere in the analysis and sometimes use "bond", "bond bucket" and "bucket" interchangeably in the discussion, unless explicitly stated otherwise.

Figure 3: Top bond buckets by market value of fund holdings as of end-2020



Fund types The second dimension of data granularity that deserves attention is at the level of the investor. The fund holdings dataset that I collect from Morningstar is more granular than previous work using demand system estimation. As flagged earlier, I observe the holdings of each individual fund rather than the umbrella institution as in Koijen and Yogo (2019), Koijen et al. (2020b).[16] This granularity allows me to control for fund characteristics (both observable and unobservable) in the estimation of the demand model and improve the precision of estimates. However, the smaller the investor unit, the smaller the number of bonds it holds on average in its portfolio. As Table 1 shows, the median fund holds around 20 bond buckets. This implies some pooling of funds will be required in the estimation but pooling over all funds is likely to overlook important differences across investors with heterogeneous bond demand.

[16] A list of the largest 30 funds by their overall bond holdings as of end-2020 is provided in Appendix Table A.8.

Table 1: Summary of funds

Fund Type	Number of Funds	%All-fund AUM	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th Percentile)	Number of Buckets Held (Median)	Number of Buckets Held (90th Percentile)
US bond passive	524	20	0.95	294	3,446	18	86
US bond active	676	29	1.35	384	4,404	27	76
EA bond passive	949	9	0.62	142	1,069	22	75
EA bond active	1,006	13	0.73	187	1,547	31	80
US balanced passive	135	8	0.10	316	3,876	8	85
US balanced active	203	13	0.25	350	4,013	20	103
EA balanced passive	375	2	0.05	62	516	9	47
EA balanced active	595	5	0.15	89	876	13	72

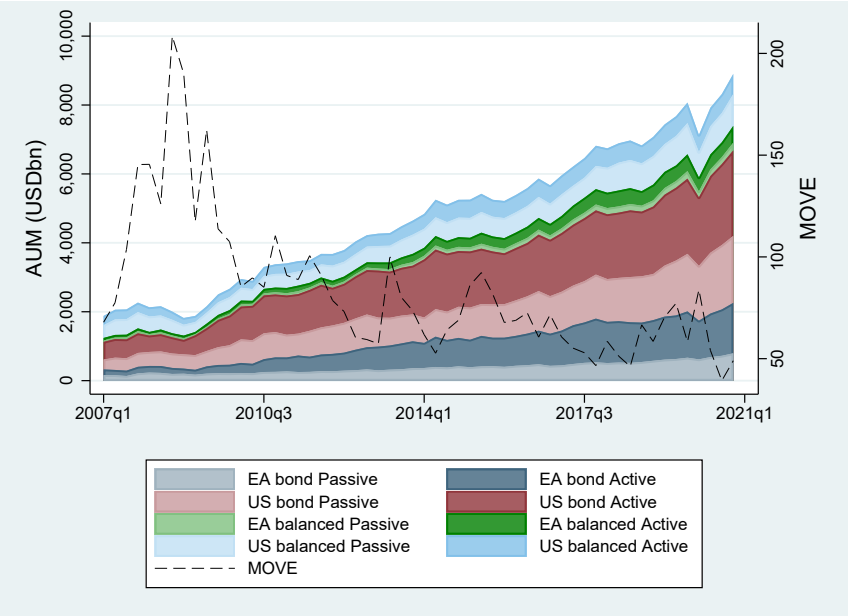
A close look at fund sector structure and portfolio allocation suggests at least two observable dimensions along which funds are very different from each other. First, Table 1 reveals that funds domiciled in the euro area (EA) are more numerous but much smaller in terms of assets under management (AUM) than their US counterparts. In addition, a long literature in international finance has documented a strong home and home currency bias in international bond portfolios (Coeurdacier and Rey, 2013, Maggiori, Neiman and Schreger, 2018). These two considerations imply that funds domiciled in each of the two currency areas included in the analysis – the US and euro area – might have different demand for bonds and the estimation should allow for this heterogeneity. Second, the summary statistics of the portfolio allocation of balanced versus fixed income funds in Appendix Table A.9 suggests the asset classes that funds are allowed to invest in are another differentiating feature. Balanced funds (especially in the EA), who have exposures to bonds and equity alike, seem to hold on average a safer portfolio of bonds than fixed income funds. This is evident in the higher portfolio weight of "AAA-AA" rated bonds, of short-term bonds with maturity under 1 year, as well as in their preference for sovereign over corporate issuers. Thus, at least four broad fund types emerge as a useful delineation: US fixed income, EA fixed income, US balanced and EA balanced funds.

The investment funds in the dataset also contain some index and ETF funds which track a particular bond index with little leeway to deviate from the portfolio shares implied by index weights. As the methodology section clarifies, a key object of interest in the estimation of bond demand is the sensitivity of funds to changes in relative bond returns. Index funds are by mandate not allowed to take advantage of such variation in returns and should therefore be modelled separately. In addition, recent literature emphasizes that even non-index funds are managed against a benchmark and may be dis-incentivised to deviate their portfolio allocation too far from the benchmark index weights (Brennan and Li, 2008, Cremers and Petajisto, 2009, Kashyap, Kovrijnykh, Li and Pavlova, 2021). To separate both *de jure* and *de facto* passive funds from more active ones, I therefore adapt the active share definition of Cremers and Petajisto (2009) to measure the extent to which funds' bond portfolios deviate from their benchmark. Since data on multiple benchmark indices and their historical compositional weights are difficult to obtain, I follow Koijen, Richmond and Yogo (2020b) and define a fund's benchmark based on the observed holdings. The benchmark weight of each bond bucket in a given fund's portfolio corresponds to the share of that bucket in the total market value of all bond buckets ever held by that investor (i.e. his benchmark). The Bond Active Share is then calculated at every quarter as the sum of absolute deviations of the observed portfolio shares from the benchmark weights, divided by 2. The distribution of the resulting active share measure (averaged over time) across funds of the four broad fund types in Appendix

Figure A.17 highlights considerable dispersion in the degree of activeness even within fund type. Therefore, I split each of the four broad fund types into active and passive funds – funds with above-median Bond Active Share, on average over time, are classified as Active; those with below-median Active Share are Passive.

Thus, I arrive at eight main fund types – US fixed income Passive & Active, EA fixed income Passive & Active, US balanced Passive & Active and EA balanced funds Passive & Active. Figure 4 plots the evolution of assets under management of the final set of funds for estimation, split into these eight fund types. US fixed income funds are the most sizeable, followed by EA fixed income funds, US balanced and finally EA balanced funds. The empirical methodology motivated and developed in the next section allows all fund preferences for bond characteristics to vary across these eight fund types. Within each fund type, granular fund-level variables also control for mandate-related sources of bond demand heterogeneity (controls for geographical mandates, home country bias, corporate/ government bond allocation rules) in order to precisely estimate the fund-type-specific preference parameters.

Figure 4: Total fund AUM by fund types



Passive / Active : Funds with below- / above-median Bond Active Share, on average over time.
Bond Active Share : Sum of absolute bond portfolio weight deviations from market-value-weighted fund bond universe weights, divided by 2 (Koijen, Richmond and Yogo, 2020b).

To recap, I build a state-of-the-art dataset of international bond holdings from granular yet comprehensive fund-security-level data. I aggregate bond holdings into fine buckets suited to study international finance questions about safe asset status and spillovers via bond market substitutions. I retain fund-level holdings data but group funds into eight economically meaningful types with potentially heterogeneous bond preferences. The next section develops the empirical methodology applied to this dataset to estimate the international bond demand of mutual funds.

3 Methodology

In this section I outline the bond demand specification, explain how this is implemented empirically and derive the demand elasticities which are used to characterize safe assets and describe bond substitution pattern. The methodology builds on two seminal contributions in the rapidly growing literature on demand-based asset pricing. Like Koijen and Yogo (2019), demand for bonds is a function of bond characteristics and depends on investor preferences, motivated by a standard mean-variance portfolio optimization problem. The international portfolio application implies that both bond local currency returns and exchange rate fluctuations enter the investor portfolio choice problem as in Koijen and Yogo (2020).

To account for the greater granularity of holdings and breath of assets modelled in this paper relative to previous research, I make four important methodological deviations from these papers. Here, I flag them briefly before proceeding to the detailed discussion of the bond demand methodology. First, I allow for fund-specific and time-varying risk aversion as a source of time variation in portfolio allocations. Second, I relax the Nested Logit restrictions imposed in Koijen and Yogo (2020) to model a diverse set of assets by including heterogenous investor preferences for all potential nest fixed effects. This is important in an international setting with granular assets, where multiple potential dimensions of market segmentation along country of issuance, currency, credit risk or maturity may exist. Third, I am able to control for a much broader and more granular set of both bond and fund characteristics in the estimation – especially when comparing the results to international portfolio investment demand aggregated at the country level as in Koijen and Yogo (2020) and Jiang et al. (2021b). Finally, I develop an alternative identification strategy using high-frequency monetary policy shocks to the entire yield curve in order to isolate exogenous variation in international bond returns in an application where the market clearing condition (as used for identification by Koijen and Yogo (2019, 2020)) is not a feasible source of identification due to the breadth of assets being modelled.

3.1 International bond portfolio allocation

I start by deriving the bond demand specification used for the empirical analysis of international bond demand. Like in Koijen and Yogo (2019), funds face a standard mean-variance optimization problem with a short-selling constraint to model the long-only bond holdings of investment funds. Given the international portfolio allocation application, investors value future wealth converted in their domestic currency such that bond local currency returns and exchange rate fluctuations enter their problem jointly as in Koijen and Yogo (2020).

Investment funds indexed by $i = 1, \ldots, I$ allocate their bond portfolio across $|\mathcal{N}_{i,t}|$ risky bonds (where $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$ and N denotes the number of all bonds modelled in the demand system) and one outside asset. Bonds can be denominated in different currencies and their gross returns between period t and $t+1$ in terms of investor i's home currency are stacked in the $|\mathcal{N}_{i,t}|$-dimensional vector $\mathbf{R}_{i,t+1}$. The return on the investor-currency-specific outside asset is $R_{i,t+1}(0)$ and for expositional simplicity is assumed to be risk-free.[17]

[17] In Appendix B I relax this assumption to allow for a risky outside asset whose returns may be correlated with bond returns. A similar empirical demand specification follows, only the interpretation

Portfolio choice is described by a two-period international capital asset pricing model (ICAPM). Investor risk preferences are described by more general constant relative risk aversion (CRRA) objective function than the log-utility specification in Koijen and Yogo (2019).[18] This means that investors may have different and time-varying risk aversion denoted by $\rho_{i,t}$. This modelling choice reflects extensive empirical evidence of time variation in aggregate risk aversion (Rey, 2013, Bauer, Bernanke and Milstein, 2023), while also allowing for heterogeneous risk preferences across funds. Fund i with risk aversion $\rho_{i,t}$ at time t maximizes expected utility from one-period-ahead wealth $A_{i,t+1}$ subject to budget and short-selling constraints by choosing portfolio weights vector $\mathbf{w}_{i,t}$ in terms of expected returns covariances and shadow prices:

$$\begin{aligned}
\max_{\mathbf{w}_{i,t}} \quad & \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big] \\
\text{s.t.} \quad & A_{i,t+1} = A_{i,t}[R_{i,t+1}(0) + \mathbf{w}_{i,t}'(\mathbf{R}_{i,t+1} - R_{i,t+1}(0)\mathbf{1})] && (1)\\
& \mathbf{w}_{i,t} \geq \mathbf{0} && (2)\\
& \mathbf{1}'\mathbf{w}_{i,t} \leq 1 && (3)
\end{aligned}$$

Following Koijen and Yogo (2019), I assume log-normal bond returns, approximate portfolio returns as in Campbell and Viceira (2002) and denote the Lagrange multipliers on the short-selling constraint (2) by the vector $\Lambda_{i,t}$ and the multiplier on constraint (3) by $\lambda_{i,t}$ to derive fund i's optimal portfolio weights:

$$\mathbf{w}_{i,t} = (\rho_{i,t}\mathbf{\Sigma}_{i,t})^{-1}\Big(\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{\sigma_{i,t}^2}{2} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}\Big) \tag{4}$$

which is exactly the same as equation (A4) in Koijen and Yogo (2019) apart from the addition of a time-varying risk-aversion parameter possibly different from one and returns being investor-specific due to funds measuring them in their home currencies.

Funds here differ in their optimal bond portfolio allocation for several reasons. First, different risk preferences $\rho_{i,t}$ affect the scale of fund i's entire risky bond portfolio but do not shift the allocation *across* risky bonds. Second, investors may base their allocation on different return expectations ($\mathbb{E}_{i,t}$), variance ($\sigma_{i,t}^2$) and covariance ($\mathbf{\Sigma}_{i,t}$) estimates. The model is ambiguous regarding the cause of the different evaluations of bond return moments across investors – they could be interpreted as different beliefs or unobserved investment constraints. Last, it is worth emphasising that the dimension of the optimal portfolio weights vector $\mathbf{w}_{i,t}$ (given by $|\mathcal{N}_{i,t}|$) also varies across investors but is exogenous to the demand system and comes from the observed fund investments.[19] The demand system can thus flexibly capture continuous belief and risk preference heterogeneity as well as discrete constraints on the investment universe of specialised funds.

of why investors value bond characteristics becomes broader and reflects the relation between bond characteristics and the return covariance of bonds and the outside asset.

[18] Koijen and Yogo (2019) instead start from a standard multi-period portfolio choice model with log-utility (i.e. homogeneous risk aversion of 1 across all investors, at all periods t) which simplifies to independent one-period-ahead portfolio allocation problems at each t. In both cases, the myopic portfolio choice modelling decision is well-suited to short-term investors such as investment funds, whose shareholders are sensitive to recent fund performance.

[19] My baseline specification assumes $|\mathcal{N}_{i,t}|$ equals the number of bond buckets in fund i's portfolio during the current quarter.

Bringing (4) directly to the data is a challenge since it requires estimates of 5,000 expected returns, all their variances and covariances. Koijen and Yogo (2019) show that assuming a fairly general factor structure in return beliefs and that observable and easy-to-measure asset characteristics determine asset loadings on common factors, one could instead model portfolio weights as a function of an asset's own characteristics.[20] In Appendix B, I follow closely Koijen and Yogo (2019) to derive the portfolio weights on any bond n in the investment universe of investor i ($w_{i,t}(n)$) and on the outside asset ($w_{i,t}(0)$) as logistic functions of bond characteristics and fund risk aversion:

$$w_{i,t}(n) = \frac{\frac{1}{\rho_{i,t}} \exp\left\{\hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_i\right\}}{1 + \sum_{m=1}^{\mathcal{N}_{i,t}} \frac{1}{\rho_{i,t}} \exp\left\{\hat{\mathbf{x}}_{i,t}(m)'\hat{\beta}_i\right\}} \tag{5}$$

$$w_{i,t}(0) = \frac{1}{1 + \sum_{m=1}^{\mathcal{N}_{i,t}} \frac{1}{\rho_{i,t}} \exp\left\{\hat{\mathbf{x}}_{i,t}(m)'\hat{\beta}_i\right\}} \tag{6}$$

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \frac{1}{\rho_{i,t}} \exp\left\{\hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_i\right\} \tag{7}$$

where $\hat{\mathbf{x}}_{i,t}(n)$ contains a comprehensive set of exogenous bond characteristics discussed in greater detail in the next subsection, as well as unobservable demand disturbances $\varepsilon_{i,t}(n)$. The coefficients on these characteristics $\hat{\beta}_i$ capture investor i's beliefs about how expected excess returns and bond factor loadings relate to the bond characteristics. Importantly, demand of all bonds depends on fund-specific risk aversion $\rho_{i,t}$. Note that one could simplify the expression (7) by including $-\log(\rho_{i,t})$ in the vector of time-varying investor and bond characteristics $\hat{\mathbf{x}}_{i,t}(n)$. A panel estimation then can account for heterogeneous, time-varying risk aversion using investor-time fixed effects, as the next section explains in greater detail.

The outside asset with portfolio weight $w_{i,t}(0)$ captures either bonds not reported by the fund or excluded from the estimation, or other assets in fund portfolios (e.g. equity for balanced funds and cash for fixed income ones). For estimation purposes, expressing bond demand as a ratio of each bond holding relative to an investor-specific outside asset weight is clearly more convenient, as it decreases the dimensionality of the empirical estimation problem from one where bond n's allocation depends on the characteristics of all bonds in investor i's choice set (equation 5) to one where demand is a function only of the characteristics of bond n (equation 7).

The specification in (7) is a simple Logit model but thanks to the heterogeneity in preference parameters $\hat{\beta}_i$ across investors and the rich bond characteristics included in $\hat{\mathbf{x}}_{i,t}(n)$, it implies more flexible substitution patterns than the Nested Logit model of international portfolio investment in Koijen and Yogo (2020). This flexibility is necessary in my setting studying global bond markets at a granular bond level as *ex ante* restrictions regarding the dimension along which bonds of different countries, currencies, issuers, ratings and maturities may be better or worse substitutes are hard to justify.[21] For the heterogeneous-

[20] There is a clear parallel from the empirical industrial organization (IO) literature starting with Lancaster (1971), where demand for products is modelled as a function of their own prices and characteristics rather than as a function of the prices and quantities demanded of all the products in the consumer choice set. The objective in both IO and asset pricing applications is to reduce the dimensionality of the empirical demand model.

[21] The Nested Logit specification in Koijen and Yogo (2020) assumes long-term bonds of all countries

investor Logit in equation (7) to be a generalization of a Nested Logit model of demand, the vector of bond characteristics $\hat{\mathbf{x}}_{i,t}(n)$ needs to contain fixed effects for all bond characteristics along which investors may perceive markets to be segmented (Berry, 1994). These could include bond country, currency, rating, maturity or issuer type (e.g. government vs corporate). I turn next to the empirical specification that allows me to flexibly estimate substitution patterns in global bond markets.

3.2 Empirical specification

This subsection clarifies how I translate the general characteristics-based demand function given by (7) to an empirical specification tailored to model international demand for bonds. This paper's primary objective is to estimate rich substitution patterns to describe empirically international bond market segmentation and study transmission of shocks from one market segment to all other segments where investment funds are active. All specification choices are made with this goal in mind.

I select a comprehensive set of bond characteristics $\hat{\mathbf{x}}_{i,t}(n)$ that capture exposure to key risk factors. The key time-varying return variable that investors care about is the predicted excess bond return of each bond n, h periods ahead, which I denote by $per^h_{\chi(i),t}(n)$. This variable captures in a single index time variation in the bond's local currency return as well as exchange rate fluctuations of the bond currency relative to investor i's home currency. The relevant bond returns are defined in terms of the currency of the investment fund – US dollar for US-domiciled funds, euro for euro area funds.[22]

Funds (indexed by i) are assumed to predict bond excess returns in their home currency $per^h_{\chi(i),t}(n)$ using a few key variables observable at time t. Following Koijen and Yogo (2020), I use predictive bond return regressions to obtain a proxy of $per^h_{\chi(i),t}(n)$. Specifically, I estimate two predictive panel regressions of returns h quarters ahead – one with realized bond excess return in US dollars $rx_{\$,t+h}(n)$ as the left-hand-side variable (relevant to US-based funds) and one with euro returns $rx_{€,t+h}(n)$ (relevant for euro area funds). The following predictive panel regression is estimated at monthly frequency over the sample period 2002-2020:

$$
\begin{aligned}
&rx_{\chi(i),t+h}(n) \equiv r_{\chi(i),t+h}(n) - y^h_{\chi(i),t} \\
&= A^h_\chi(i)\ y_t(n) + B^h_\chi(i)\ rer_{i,t}(n) + \sum_{f=1}^{3} C^h_{\chi(i),f}\ uspc_{f,t} + \sum_{f=1}^{3} D^h_{\chi(i),f}\ depc_{f,t} + F^h_{\chi(i),n} + E_{\chi(i),n,t+h}
\end{aligned}
\tag{8}
$$

where $r_{\chi(i),t+h}(n)$ is the total return on bond bucket n[23] between month t and $t+h$ in the investor's home currency $\chi(i)$; $y^h_{\chi(i),t}$ is the time-t risk-free rate with term h in the home

are perceived as equally good substitutes for each other, while different asset classes (e.g. short- and long-term debt may not be as substitutable).

[22] In practice, most shares of US funds are indeed denominated in US dollars and likely held by US investors. The majority of EA-based funds also report their holdings and denominate their shares in euros but with more exceptions, where at least some fund share classes are sold in other major currencies such as USD, GBP or JPY.

[23] This is calculated as the face-value weighted average of total returns on individual bond returns in bucket.

currency of investor i[24]; $y_t(n)$ is the yield-to-maturity[25] likely to predict the bond return in local currency; $uspc_{f,t}$ stands for principal components extracted from the US Treasury yield curve with $f = \{1, 2, 3\}$ capturing level, slope and curvature factors, respectively; $depc_{f,t}$ are the equivalent yield curve factors from German government bonds[26]; $rer_{\chi(i),t}(n)$ is the log real exchange rate defined as units of the home currency of each investor $\chi(i)$ (i.e. US dollars or euros) per bond n currency[27]; $F^h_{\chi(i),n}$ is a bond bucket fixed effect separately estimated for bond returns in terms of the home currency of investor i and of horizon h quarters; and $E_{\chi(i),n,t+h}$ is a forecasting error term.

This predictive regression improves on the one proposed in Koijen and Yogo (2020) in three ways: (i) the excess returns are at a much more granular bond-bucket level rather than at the aggregate country level, so I control for a bucket fixed effect rather than country fixed effect; (ii) I add yield curve factors to the predictive variables in line with a long-standing literature on bond return predictability (Fama and Bliss, 1987, Cochrane and Piazzesi, 2005) to improve the fit to my more granular bond data; (iii) I estimate (8) separately for each investor currency, whereas Koijen and Yogo (2020) predict returns only in US dollar terms. Unlike Koijen and Yogo (2020), I assume that the risk-free rate is given by the euro and dollar OIS rates, respectively, and obtain bond predicted excess returns relative to these from independent predictive regression in terms of different currencies. This approach is more flexible, as it effectively allows investors to have different predictive models of returns in different currencies.

Thus, the bond return variable that enters the demand system's bond characteristics $\hat{\mathbf{x}}_{i,t}(n)$ is the fitted bond excess return from predictive regressions (8):

$$per^h_{\chi(i),t}(n) = \widehat{A^h}_{\chi(i)}\ y_t(n) + \widehat{B^h}_{\chi(i)}\ rer_{\chi(i),t}(n) + \sum_{f=1}^{3} \widehat{C^h}_{\chi(i),f}\ uspc_{f,t} + \sum_{f=1}^{3} \widehat{D^h}_{\chi(i),f}\ depc_{f,t} \tag{9}$$

The horizon h that is most relevant to investment funds in my dataset turns out to be 3 months ahead, which aligns well with their predominantly quarterly portfolio reporting practices. In Section 4, I also report predictive regression results for bond returns 12 and 1 month ahead. Results are robust to these different return horizons.

In addition to predicted excess returns, the bond demand equation controls for a number

[24] This correspond to the USD or EUR OIS rates, respectively, with term h.

[25] Or yield-to-worst if bond is callable or putable.

[26] The bond asset pricing literature has emphasized the predictive power of yield curve factors for excess returns on Treasuries in particular (Fama and Bliss, 1987, Cochrane and Piazzesi, 2005). Adding a factor extracted from forward rates as in Cochrane and Piazzesi (2005) does not increase the predictive power in this bond sample.

[27] Real exchange rates fluctuations tend to mean-revert as their equilibrium value is relatively stable. Thus an appreciated currency can be expected to depreciate in future and thereby reduce the bond return received by the foreign investor, implying the coefficient F^h_i should be negative.

of other bond and fund characteristics, which are included in the vector $\hat{\mathbf{x}}_{i,t}(n)$ as follows:

$$\hat{\mathbf{x}}_{i,t}(n) = \begin{bmatrix} per^{h}_{\chi(i),t}(n) \\ \mathbf{x}^{1}_{t}(n) \\ \mathbf{x}^{2}(n) \\ \mathbf{b}_{i}(n) \\ \zeta_{i,t} \\ \log(\varepsilon_{i,t}(n)) \end{bmatrix} \tag{10}$$

First, vector $\mathbf{x}^{1}_{t}(n)$ includes bond characteristics with some time variation - the face-value-weighted average residual maturity and seniority rank of all bonds in bucket n, as well as the total face value of all bonds in the bucket capturing the relative liquidity of that bucket[28]. Second, a vector of static bond characteristics $\mathbf{x}^{2}(n)$ contains categorical variables already used to define bond buckets – broad credit rating scale dummies, bond country (of risk) and currency (of denomination) fixed effects. In addition, I control for time-invariant bilateral (fund-bond) dummies collected in vector $\mathbf{b}_{i}(n)$ which capture aspects of the fund mandate and whether each bond complies with them. These include: (i) a home bias dummy, which equals one if a bond's country of risk is the same as the fund's domicile; (ii) a home currency bias dummy, which equals one if a bond is denominated in the fund's home currency; (iii) a binary variable that equals one if a bond's country of risk is within the fund investment area (as reported to Morningstar); (iv) three dummies that capture the correspondence between a fund being government or corporate bond-focused and a government or corporate bond indicator – one that equals one if a government bond fund is holding a government bond, another that equals one if a corporate bond fund holds a corporate bond, and a third that equals one if a mixed or total bond fund holds a government bond[29].

Importantly, the control variables include investor-time fixed effects $\zeta_{i,t}$ which capture time-varying changes in investor-specific risk appetite. This adds more structure to the interpretation of the residual demand for bonds and helps isolate systemic changes in investor behaviour from their relative portfolio allocation across bonds. The residual of this demand system $\log(\varepsilon_{i,t}(n))$ now corresponds to unexplained variation in the investor-specific bond allocation at every period t.

The general demand equation (7) allows for all coefficients to be investor-specific. Implementing this is not feasible in most empirical settings where the presence of many small investors with a limited number of investments makes estimating individual preferences

[28] To make face value comparable across bonds with different denomination currencies, this needs to be converted into a common currency - that of the funds whose portfolio decision it enters. To avoid introducing endogeneity in the face value control variable, the conversion is done using the bilateral exchange rate lagged by a year, i.e. at quarter $t-4$.

[29] To classify funds as government, corporate or mixed/total bond funds, I calculate the average share they hold of corporate versus government bonds for the full sample. If a fund holds less than 20% of corporate bonds, it is classified as a government bond fund; if it holds more than 80% in corporate bonds, it is a corporate fund; and anything in the middle is a mixed or total bond fund. I use this custom classification rather than the Morningstar fund category, as the latter provides a fine split of US fixed income funds into government and corporate but neither separates international bond funds into government versus corporate ones nor gives an indication what type of bonds balanced funds are allowed to invest in.

for many bond characteristics imprecise. For instance, while Koijen and Yogo (2019) and Koijen, Richmond and Yogo (2020b) estimate individual demand functions only for the largest institutional investors in equity markets, they supplement them with pooled demand estimates for smaller investors with an insufficient number of portfolio holdings. In this particular study, the number of cross-sectional observations for individual funds is more limited for two reasons: (i) bond holdings are summed over individual securities to form bond buckets informative about the type of risk exposures, and (ii) the investor unit is much more granular than in asset demand papers using institutional holdings such as Koijen and Yogo (2019), Koijen, Richmond and Yogo (2020b).[30]

In addition, modelling the demand of individual investors separately is not desirable when the objective is to estimate how the return on one bond affects the portfolio allocation to many others. Intuitively, such estimates are based on the covariance of returns on one bond with the holdings of all other bonds, conditional on their returns and other characteristics. This implies using the only available source of variation in returns on internationally traded bonds – time variation[31] – and calls for a panel specification. And to obtain a broad set of substitution elasticities, the estimation sample needs to also cover a considerable portion of the cross-section of bonds. At the same time, heterogeneity in preferences is both likely closer to reality (funds have different mandates and risk profiles) and helps to recover richer market-wide substitution elasticities, as emphasized by the IO literature (Berry, 1994, Berry, Levinsohn and Pakes, 1995) and explained in greater detail in the next subsection.

I strike a balance between the need for granularity in investor preferences and the estimation benefits from a broader, longer panel of bonds. I estimate the demand equation using the full time period with observed holdings – 2007:Q1–2020:Q4 – but separately for eight types of funds. As discussed in Section 2, I split funds by the currency area of their domicile (US or euro area), depending on whether they invest in a single asset class (fixed income funds) or in both bonds and equity (balanced funds) and into active or passive funds according to their bond portfolio's Active Share. This corresponds to estimating the demand of eight separate panel demand models: for US active and passive bond funds, for EA active and passive bond funds, for US active and passive balanced funds, and for EA active and passive balanced funds.[32]

Expanding on the general demand specification in (7) by plugging in the specific bond characteristics given by (10) delivers a demand specification that can be estimated on this

[30]The latter consideration is at the same time a key advantage of using the Morningstar holdings dataset, where security holdings are observed for the individual funds rather than for the holding company which may manage hundreds of funds. Greater granularity of holdings allows to take funds' mandates and constraints into account when estimating their bond preferences, e.g. by splitting funds by type, controlling for aspects of their mandate with $\mathbf{b}_i(n)$, and allowing for fund-specific variation in aggregate bond market exposure by including fund-time fixed effects $\zeta_{i,t}$.

[31]If bond purchase prices vary across investors – for instance, because they buy at different dates within the same quarter or have access to different brokers – there may be some variation in returns on the same bond across different investors. Such sources of return variation can only be explored in detailed transactional data rather than in the portfolio holdings data used in this project.

[32]In robustness checks reported in Appendix C, I compare my main results to a split of funds by size instead of active share.

data:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{\alpha_{T(i)} per^{h}_{\chi(i),t}(n) + \mathbf{x}^{1}_{t}(n)'\beta^{1}_{T(i)} + \mathbf{x}^{2}(n)'\beta^{2}_{T(i)} + \mathbf{b}_{i}(n)'\theta_{T(i)} + \zeta_{i,t} + \varepsilon_{i,t}(n)\right\} \tag{11}$$

where the coefficients on characteristics ($\alpha_{T(i)}$, $\beta^{1}_{T(i)}$, $\beta^{2}_{T(i)}$, $\theta_{T(i)}$) are specific to the fund type T to which fund i belongs, whereas fund-time fixed effects $\zeta_{i,t}$ and residual demand disturbances $\varepsilon_{i,t}(n)$ are specific to investor i.

Finally, I turn to the choice of fund investment universe $|\mathcal{N}_{i,t}|$ which determines the bonds that enter the portfolio weights vector $\mathbf{w_{i,t}}$. Clearly, the holdings reported by each fund for a given quarter are part of their investment universe. The question is whether zero holdings should be added for bonds that are not held in a given quarter but could have been.[33] Appendix Table A.12 shows that aggregated to bucket level, funds' bond universe is very persistent with over 90% of current holdings remaining in an investor's portfolio from one quarter to the other. Thus, for the demand estimation I take a fund's current-quarter holdings as its investment universe and do not include any zero positions.[34] This means that I can take the logarithm of equation (11), which only takes positive values, and re-write the estimation equation as a fund-type-level panel Logit model:

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = \alpha_{T(i)} per^{h}_{\chi(i),t}(n) + \mathbf{x}^{1}_{t}(n)'\beta^{1}_{T(i)} + \mathbf{x}^{2}(n)'\beta^{2}_{T(i)} + \mathbf{b}_{i}(n)'\theta_{T(i)} + \zeta_{i,t} + \varepsilon_{i,t}(n) \tag{12}$$

which can be estimated by linear methods such as OLS or two-stage least squares. This relatively simple estimation equation delivers the key ingredients underpinning flexible substitution or cross-elasticities: (i) heterogeneity in investor preferences for *all* bond characteristics; (ii) categorical control variables in $\hat{\mathbf{x}}_{i,t}(n)$ that capture most plausible segments of international bond markets (country, currency, issuer type, credit risk, maturity) such that the estimated degree of substitutability can vary flexibly along all these dimensions; and (iii) a broad and long sample of granular bond buckets in each fund type panel regression – providing enough data to estimate substitution patters between a large number of bonds. The next subsection discussed the functional form of the associated substitution elasticities and how they compare to those implied by existing asset demand literature.

[33] In the Morningstar holdings data, few funds directly report zero holdings at the individual bond level, and once I sum the bond holdings to bucket level, the observations with zero holdings disappear. So this information cannot be directly taken from portfolio reports.

[34] Koijen and Yogo (2019) define the investment universe as the set of stocks a given investor has held in the current or preceding 11 quarters and emphasize that omitting these zero holdings can bias results for small investors. However, the panel set-up here mitigates this bias since estimates are disproportionately influenced by large funds with many bond positions.

3.3 Demand elasticities

From equation (11) fund i's demand for a given bond bucket n is given by the following portfolio weight:

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m=1}^{\mathcal{N}_{i,t}} \delta_{i,t}(m)} = \frac{\exp\left\{\alpha_{T(i)} per^h_{\chi(i),t}(n) + \mathbf{x}^1_t(n)'\beta^1_{T(i)} + \mathbf{x}^2(n)'\beta^2_{T(i)} + \mathbf{b}_i(n)'\theta_{T(i)} + \zeta_{i,t} + \varepsilon_{i,t}(n)\right\}}{1 + \sum_{m=1}^{\mathcal{N}_{i,t}} \exp\left\{\alpha_{T(i)} per^h_{\chi(i),t}(m) + \mathbf{x}^1_t(m)'\beta^1_{T(i)} + \mathbf{x}^2(n)'\beta^2_{T(i)} + \mathbf{b}_i(m)'\theta_{T(i)} + \zeta_{i,t} + \varepsilon_{i,t}(m)\right\}} \tag{13}$$

where $\delta_{i,t}(n) \equiv \frac{w_{i,t}(n)}{w_{i,t}(0)}$.

I focus on the following definition of demand elasticity that can be analytically derived from this logistic portfolio weight function by taking the partial derivative of (13) with respect to the predicted excess return on any given bond k, $per_{\chi(i),t}(k)$[35]:

$$\eta_{i,t}(jk) \equiv \frac{\partial \log(w_{i,t}(j)) * 100}{\partial per_{\chi(i),t}(k)} = \begin{cases} \alpha_{T(i)}\ (1 - w_{i,t}(j)) * 100 & \text{if } j = k, \\ -\alpha_{T(i)}\ w_{i,t}(k) * 100 & \text{otherwise.} \end{cases} \tag{14}$$

which describes the percent change in the weight of bond j in investor i's portfolio in response to 1 *percentage point* change in the predicted excess return on bond k.[36] This elasticity with respect to returns is particularly relevant to understanding the degree of segmentation in international bond markets among safe and risky assets, as it highlights the degree to which investment funds step in to arbitrage away dispersion in bond returns. For other questions, such as the optimal issuance of new bonds, researchers might prefer to study the elasticity of demand to other bond characteristics such as maturity, credit risk or currency of denomination and the demand model here is flexible enough for these alternative applications.

The first case in (14) of $j = k$ describes the response of portfolio weight of a bond to fluctuations in its own return, which I refer to as *own elasticity*. The parameter $\alpha_{T(i)}$ determines if the bond demand curve of investor i is flat ($\alpha_{T(i)} = 0$), downward-sloping in prices ($\alpha_{T(i)} > 0$, since bond yields and returns are negatively related to prices) or potentially upward-sloping ($\alpha_{T(i)} < 0$). Estimating this parameter with equation (12) for different types of funds is the focus of the empirical exercise and is discussed in detail in the next section. The logistic demand specification in (13) calls for this parameter to be scaled by $1 - w_{i,t}(j)$ or the share of investor i's portfolio not allocated to bond j. Mechanically, this reflects the underlying logistic functional form whose slope changes with the value of $w_{i,t}(j)$. Intuitively, if a fund allocates a very high portfolio weight to

[35] An elasticity definition directly applied from Koijen and Yogo (2019) as the percent change in quantity held per percent change in price ($-\frac{\log(Q_{i,t}(n))}{\log(P_t(n))}$) requires additional assumptions on the relationship between predicted excess bond returns and bond price, which I spell out in Appendix B along with the relationship between these different elasticity definitions.

[36] Given that returns are expressed in percentage points, this semi-elasticity of demand is easier to compare across bonds with different yield levels than a demand elasticity with respect to *percent* changes in returns. In addition, a percentage point higher interest rate cost can be related directly to the overall debt servicing cost of the borrower.

bond j, it either chooses from a limited investment universe or perceives other bonds as very imperfect substitutes for bond j – implying it has less elastic demand for that bond.

To gain further intuition about this definition of own elasticity, I consider three extreme hypothetical cases. First, suppose an investor follows simple allocation rules in terms of % of portfolio in particular bond buckets. Since he aims to keep his portfolio weights constant, by the definition in (14) this investor's elasticity would be zero. Alternatively, suppose we observe an index fund that simply holds bonds in proportion to their market value, i.e. has inelastic demand in the sense of $-\frac{\partial \log(Q_{i,t}(j))}{\partial \log(P_{i,t}(j))} = 0$. The elasticity measure given by (14) would also be close to zero but with a negative sign.[37] At the other extreme, an unconstrained representative-agent CAPM model would imply a nearly-infinite demand elasticity (see calibration in Petajisto, 2009).

I next turn to the second case in (14) of $j \neq k$, which describes the response of other bonds' portfolio weights when bond j's return changes – the *cross* or *substitution elasticities*. These too depend on the crucial return sensitivity parameter $\alpha_{T(i)}$, as only funds that adjust their portfolio share of j in response to a change in bond j's own return, will need to adjust all the other weights in their portfolio. In addition, cross-elasticities depend on the portfolio weight of the bond whose return changes ($w_{i,t}(k)$), as greater exposure implies greater need for rebalancing. The cross-elasticity has the opposite sign to the own elasticity, as the sum of all changes to portfolio weights should sum to 0 such that the sum of portfolio weights (including that of the ouside asset) remains equal to 1. If demand is downward-sloping ($\alpha_{T(i)} > 0$), all other bonds are substitutes for investor i and their cross-elasticity is negative. And *vice versa*, for bonds to be complements, investor i would need to have an upward-sloping bond demand curve ($\alpha_{T(i)} < 0$).

Note that, at the individual fund level, substitution elasticities from a fixed bond k are homogenous across bonds. This follows from expressing individual fund demand as a logistic function of predicted excess returns and other bond characteristics (equation 11). Hence, there is no meaningful variation in *individual* fund substitution elasticities. The specification used in this paper, however, delivers flexible substitution elasticities once aggregated to the fund sector – which I turn to next.

To describe the demand of the entire fund industry in my dataset, I define the fund sector aggregate demand elasticity as the percent change in the weight of bond j *in the aggregate fund sector portfolio* in response to a 1 percentage point change in bond k's predicted excess return. This can be derived from funds' individual elasticities weighted

[37] The exact magnitude depends on the bond maturity as shown in Appendix equation B.24. In particular, $\eta_{i,t}(jj) = (-\frac{\partial \log(Q_{i,t}(j))}{\partial \log(P_{i,t}(j))} - 1) \times \frac{mat_t(j)}{\widehat{A}_i^h} = (-1) \times \frac{mat_t(j)}{\widehat{A}_i^h}$, where $\widehat{A}_i^h$ is the estimated relationship between bond excess returns and yields given by (9) and $mat_t(j)$ is the remaining years until maturity of bond j. For a 10-year bond and an estimated $\widehat{A}_i^h$ of around 2.3, the elasticity would be around minus 4%, so negative but also very close to zero.

by the footprint of each fund in the overall fund holdings of a given bond j[38]:

$$\eta_t(jk) \equiv \frac{\partial \log(w_t(j)) * 100}{\partial per_t(k)} = \begin{cases} \sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))} \alpha_{T(i)} \left(1 - w_{i,t}(j)\right) * 100 & \text{if } j = k, \\ -\sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))} \alpha_{T(i)} \, w_{i,t}(k) * 100 & \text{otherwise.} \end{cases} \tag{15}$$

where $w_t(j) = \frac{\sum_i AUM_{i,t} \, w_{i,t}(j)}{\sum_i AUM_{i,t}}$ is the share of bond j in the total assets under management ($\sum_i AUM_{i,t}$) of all investment funds in my dataset (US and EA fixed income and balanced funds). These aggregated elasticities form the basis of my empirical results, where I describe the variation in own and cross-elasticities by different bond characteristics as well as over time. There are three interacted sources of variation in (15): (i) the composition of investors holding bond j; (ii) investor sensitivities to bond returns $\alpha_{T(i)}$; and (iii) the portfolio allocation of different investors (either to bond j in the own elasticity or to the remaining bonds k in the cross-elasticity expression). Since the portfolio weights on individual bond buckets are relatively small (as discussed in section 2), the variation in elasticities would also be small in the absence of heterogeneity in $\alpha_{T(i)}$ across investors. Thus, compositional effects are a key driver of variation in fund sector elasticities across different bonds and over time.

Substitution or cross-elasticities have so far received relatively little attention in the asset demand literature due to a primary focus on the slope of demand curves.[39] While individual fund substitution elasticities here are homogenous with respect to a given bond k's return, the fund sector aggregate substitution elasticities (equation 15) can vary flexibly across all bonds $j \neq k$.[40] In effect, variation in substitutability comes from covariances between the estimated return sensitivities $\alpha_{T(i)}$ and the distribution of bond holdings across investors. Put differently, the closest substitutes are those which are held simultaneously and in larger quantities by the funds with the highest return sensitivities.

3.4 Identification

The empirical specification in equation (12) overcomes the dimensionality challenge posed by estimating a demand system over a large number of bonds by modelling the demand for each bond as a function of a parsimonious set of characteristics. However, a second identification challenge needs to be tackled before taking the model to the data – endogeneity of bond returns is likely to bias estimates of $\alpha_{T(i)}$ downwards. A positive demand shock for a given bond relative to other bonds in investors' portfolios could both increase bond holdings by funds in the dataset and raise bond prices (lower returns). Note that all demand shocks that affects all bond holdings of a given investor (or of multiple funds) are already captured by the fund-time fixed effects $\zeta_{i,t}$, so the only potential bias could

[38] See Appendix B for derivation.

[39] An important exception is Chaudhary et al. (2022) who flag that the prices of bonds with close substitutes are less affected by arguably exogenous demand shocks. They do not, however, directly estimate substitution elasticities between pairs of bonds and instead *assume* that the only relevant substitutes to a given corporate bond are other corporate bonds with the same rating.

[40] As discussed in the previous subsections, including fixed effects for all potential dimensions of bond market segmentation (issuer country and type, currency, rating, maturity) in the bond characteristics vector $\hat{\mathbf{x}}_{i,t}(n)$ *and* allowing for heterogeneity in investor preferences for these is a more general approach to capture market segmentation than nested Logit demand (as used in Koijen and Yogo, 2020, Jiang et al., 2021b, Koijen et al., 2020b). See McFadden (1978), Cardell (1997), Berry (1994) for derivations.

come from *relative* demand shocks within a given investor's portfolio. This section tackles the threat of correlation between the unobserved investor-specific relative demand shock and predicted excess bond returns which may arise either due to omitted variable bias or reverse causality:

$$\mathbb{E}_t\left[\varepsilon_{i,t}(n)\ per^h_{\chi(i),t}(n) \;\middle|\; \mathbf{x}^1_t(n),\ \mathbf{x}^2(n),\ \mathbf{b}_i(n),\ \zeta_{i,t}\right] \neq 0 \tag{16}$$

To address this identification challenge, I need an instrument that is exogenous to fund demand shocks (controlling for all bond characteristics) but strongly affects bonds' predicted returns. Previous asset demand literature (Koijen and Yogo, 2019, 2020, Gabaix and Koijen, 2022) relies on idiosyncratic shocks to the demand of investors other than i, which jointly with the market clearing condition for each asset in the demand system identifies variation in asset prices that is arguably orthogonal to investor i's demand shocks $\varepsilon_{i,t}(n)$. In contrast, I model only the bond demand of investment funds, who as described in section 2 hold only part of the bonds' outstanding value. I thus develop an alternative identification strategy that can identify exogenous variation in the returns on a wide range of international bonds – both cross-sectionally and over time.

A highly relevant source of variation in bond market prices comes from surprises to investors' expectations of monetary policy.[41] High-frequency measures of monetary policy shocks derived from changes in interest rates in a short intraday window around monetary policy announcements have been shown to materially affect domestic financial market and real economic conditions (Gürkaynak, Sack and Swanson, 2005, Gertler and Karadi, 2015). And monetary policy, especially since the global financial crisis of 2008-9, acts along the entire yield curve by informing investor expectations about future monetary policy as well as by affecting risk premia though extensive asset purchase programmes (Swanson, 2021, Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa, 2019). Moreover, monetary policy shocks influence financial conditions across borders as documented by e.g. Miranda-Agrippino and Rey (2020b) for the Fed and by Miranda-Agrippino and Nenova (2022) for both the Fed and ECB. And the international spillovers of monetary policies are heterogeneous depending on the segment of the domestic yield curve affected (Miranda-Agrippino and Rey, 2020a, Miranda-Agrippino and Nenova, 2022). Another practical benefit is that monetary policy announcements are made by the major central banks around once a month (both following planned and exceptional meetings) and can thus be used to extract monthly exogenous variation in bond returns.

These findings make the monetary policy shocks extracted from both Fed and ECB announcements good candidates for instrumenting the bond returns of the broad set of internationally-traded government and corporate bonds observed in my fund holdings dataset. I construct two monetary policy shocks for *each bond bucket* held by investment funds – one Fed, one ECB shock. Raw high-frequency surprises for the two central banks come from two publicly available datasets: Gürkaynak et al. (2022) for the Fed (which updates Gürkaynak et al. (2005) until June 2019) and the continuously updated dataset

[41] Monetary policy shocks are relevant instruments since they can shift the risk-free yield curve – a starting point for pricing all risky bonds. They also affect the borrowing costs and risk-taking behaviour of leveraged intermediaries such as global banks (Coimbra and Rey, 2023) and, through market clearing, the risk premia of the risky assets these intermediaries invest in.

of Altavilla et al. (2019) for the ECB. Both datasets contain the intraday changes in domestic interest rates of different maturities as well as in a few other assets such as equity indices and exchange rates around policy announcements. For each central bank I use the first principal component of surprises to domestic short-term interest rates, as well as to 2-, 5- and 10-year government bond yields.[42] The raw announcement surprises contain information both regarding monetary policy and the economic outlook (Nakamura and Steinsson, 2018, Miranda-Agrippino and Ricco, 2021, Jarociński and Karadi, 2018). To make the interpretation of instruments more straightforward, I clean the monetary policy shocks from central bank information components following the "poor man's" approach of Jarociński and Karadi (2018) applied to each interest rate maturity as in Miranda-Agrippino and Nenova (2022)[43]. In total, that procedure yields 17 shocks: Fed shocks to US interest rates of 4 different maturities; one ECB shock to short euro OIS rates; and twelve ECB shocks to longer-term euro area sovereign yield curves (four governments, each with three interest rate maturities). I take one final step to match these 17 shocks to the bond buckets in the fund demand dataset. While Fed and ECB shocks are of four discrete maturities, I observe bonds along a continuum of residual maturities between less than a month to 100 years. For shocks emanating from each central bank in turn, I interpolate between the two monetary policy shocks with closest maturities to approximate a shock of maturity equal to each bond bucket's weighted average maturity.[44]

This procedure results in two instruments for each bond bucket n (one for Fed shocks denoted by $FEDiv_t(n)$ and one for ECB shocks – $ECBiv_t(n)$) which vary over time as well as across bond maturity:

$$Z_t(n) = [FEDiv_t(n),\ ECBiv_t(n)]'$$

Within the euro area, the instruments also vary by bond issuer country thanks to the data availability of high-frequency surprises to the yield curves of Germany, France, Italy and Spain (Altavilla et al., 2019). It is worth noting that the instrumented bond returns $per^h_{i,t}(n)$ do not vary by the investor who holds the bond within the fund-type-specific panel demand regression specified in (12).[45] Therefore, to avoid including multiple ob-

[42]For the Fed, the relevant futures contracts with maturity of up to a year are MP1, MP2, ED2, ED3, ED4; while for longer maturities I use surprises to on-the-run Treasury yields. For the ECB, the short-run surprises are those to the EONIA OIS curve. Altavilla et al. (2019) provide surprises to the government yield curves of the largest euro area sovereign issuers: Germany, France, Italy and Spain, so I use each of these curves for instrumenting the domestic bonds of each of these countries. For all other bond-issuing countries in my dataset, I take the surprise to the German yield curve as the relevant instrument.

[43]Under this procedure, each interest rate surprise is used as a monetary policy shock only if it was accompanied by an intraday change in the respective equity index (S&P 500 for the Fed, Eurostoxx 50 for the ECB) of the opposite sign. Otherwise the surprise was not a monetary policy shock and the instrument value is set to zero.

[44]To be precise, if a given German bond bucket (corporate or government) has a maturity of 3.5 years, I construct a single ECB monetary policy instrument for it by linearly interpolating between the shock to the 2-year and 5-year German government yields. For the same bond, I construct a Fed monetary policy shock of 3.5-year maturity by interpolating between the shocks to the 2- and 5-year Treasury bond yields. If the bucket instead contains Italian bonds again with weighted average maturity of 3.5 years, I interpolate between the ECB shocks to the 2- and 5-year Italian government yields to obtain a single ECB monetary policy instrument; the Fed monetary policy instrument is the same as for the German bonds bucket.

[45]The endogenous predicted excess return $per^h_{i,t}(n)$ only varies across investors if they are domiciled in different currency areas and, thus, choose bond allocation based on expected returns in different

servations with identical endogenous and instrumental variables in the identification and overstating the strength of instruments, I estimate the demand system in two stages. The first stage is estimated on unique bond return observations within a month – separately for bond returns converted into US dollars and into euros. While the second stage regresses all bond holdings of a given fund type on the fitted returns from the first stage, at quarterly frequency.

To allow for heterogeneous spillovers across bonds from the monetary policies of each of the two major central banks, I estimate separate first-stage regressions by unique country-currency pair (indexed by cx) for all pairs with at least 1,000 bucket-month observations:

$$\begin{aligned} per^{h}_{\chi(i),t}(n) = \mathbb{a}^{Fed}_{\chi(i),cx}\, FEDiv_t(n) \;+\; \mathbb{a}^{ECB}_{\chi(i),cx}\, ECBiv_t(n) \\ +\; \mathbb{b}_{\chi(i),cx}\, \mathbf{x}_t(n) \;+\; \mathbb{c}_{\chi(i),cx}\, Risk_t \;+\; \mathbb{d}_{\chi(i),t}(n) \end{aligned} \tag{17}$$

Bond return sensitivities to Fed $\mathbb{a}^{Fed}_{\chi(i),cx}$ and ECB shocks $\mathbb{a}^{ECB}_{\chi(i),cx}$ are specific to bonds issued by entities in country c *and* denominated in currency x. All coefficients are also specific to the currency in which bond returns are calculated (indexed by $\chi(i) \in \{\$, €\}$), since each currency-pair panel regression (17) is estimated twice – once with predicted returns in terms of US dollars and once with returns in euros.

The first stage regression also controls for the demand system bond characteristics that are unique to each bond in $\mathbf{x}_t(n)$ – this combines the vectors $\mathbf{x}^1_t(n)$ and $\mathbf{x}^2(n)$ with bond maturity, face value, credit rating, seniority plus a corporate dummy that is the bond-level equivalent of the corporate fund-bond binary variables in $\mathbf{b}_{\chi(i)}(n)$ of the main demand specification in (B.17). The investor-bond interactions $\mathbf{b}_{\chi(i)}(n)$ in the demand specification (12) become redundant, as only unique bond return observations are used in the first stage. The second-stage estimation equation in (12) also controls for an investor-time fixed effect $\zeta_{i,t}$ to capture investor-specific shifts in preferences for bonds overall. At the bond level of the first-stage regression, the closest feasible equivalent would be to control for aggregate market risk aversion which should affect the relative allocation between bonds and other asset classes such as equity.[46] The baseline first-stage specification in (17) controls for the most commonly used proxy of aggregate risk – the *VIX* index of option-implied US equity market volatility. Robustness checks using only the risk aversion component of market risk, as proposed by either Bekaert, Hoerova and Lo Duca (2013) (*BHL*) or Bekaert, Engstrom and Xu (2022) (*BEX*), result in similar estimates. Similarly, using risk aversion proxies specific to bond markets such as the US excess bond premium (*EBP*) by Gilchrist and Zakrajšek (2012) or the euro area Composite Indicator of Systemic Stress bond market subindex (*CISSEAbond*) by Holló, Kremer and Lo Duca (2012).

Exogeneity of instruments: The key identifying assumption here is that the heterogeneous effects of monetary policy shocks across bond country, currency and maturity are orthogonal to the unobserved fund demand shocks $\varepsilon_{i,t}(n)$. Note that this is condi-

currencies. As I estimate panel demand by fund types which are defined over funds in the same domicile, multiple holdings of the same bond n within a quarter t are always characterized by the same $per^{h}_{i,t}(n)$.

[46] A direct application of control variables from the second stage would imply including a time fixed effect in the first stage regression (17). This approach, however, absorbs all time variation in the monetary policy instruments.

tional on all other control variables in the vector $\hat{\mathbf{x}}_{i,t}(n)$ which includes both bond-specific characteristics and time-varying aggregate investor risk aversion proxies. The first stage estimation approach can be thought of as a parsimonious approximation to including the entire yield curve of monetary policy shocks $\int_{\tau=0}^{100} Z_t(\tau)d\tau$ (with $Z_t(\tau)$ denoting the 2-dimensional vector of the time-t Fed and ECB monetary policy shocks at maturity τ), interacted with a dummy variable that equals one when the maturity of bond n is equal to the maturity of the shock $\mathbb{1}_{mat(n)=\tau}$ as well as country-currency fixed effects $\mathbb{1}_{n\in|cx|}$:

$$\mathbb{E}_t\left[\varepsilon_{i,t}(n)\left(\int_{\tau=0}^{100} Z_t(\tau)d\tau \times \mathbb{1}_{mat(n)=\tau} \times \mathbb{1}_{n\in|cx|}\right) \middle| \mathbf{x}_t^1(n),\ \mathbf{x}^2(n),\ \mathbf{b}_i(n),\ \zeta_{i,t}\right] = 0 \quad (18)$$

The instruments $Z_t(\tau)$ vary only across bonds and time but not across investors, so that by construction there can be no correlation between the monetary policy instruments and $\varepsilon_{i,t}(n)$ variation *across* funds (i.e. along dimension i). Thus, identification comes from heterogeneous monetary policy spillovers in the *cross-section of bonds*.

A growing body of evidence suggests that monetary policy decisions by the Fed in particular but also by the ECB (Bauer et al., 2023, Miranda-Agrippino and Rey, 2020b, Miranda-Agrippino and Nenova, 2022) can affect aggregate risk appetite. To the extent this prompts investors to rebalance between broad asset classes such as equity and bonds, in the demand system its effects would be captured in the investor-time fixed effect $\zeta_{i,t}$ and would not enter the unobserved demand shocks $\varepsilon_{i,t}(n)$. Similarly, in the first stage regression aggregate investor risk aversion is controlled for via widely-used proxies such as the VIX, Bekaert, Hoerova and Lo Duca (2013) or Bekaert, Engstrom and Xu (2022) risk aversion indices, or bond market risk premia (Gilchrist and Zakrajšek, 2012, Holló et al., 2012). Thus, for the identifying assumption to hold, only fund demand shock dispersion away from the aggregate time variation in risk premia and within funds' bond portfolio (rather than between bonds and other assets) need to be uncorrelated with the high-frequency shocks to yield curves around Fed and ECB announcements. This is a much weaker and more realistic assumption than claiming that fund demand shocks and monetary policy shocks are uncorrelated – monetary policy may well be (causally or endogenously) correlated with aggregate fluctuations in investor risk appetite as well as with cross-asset-class portfolio rebalancing[47].

Moreover, the stark difference in frequencies between instruments and unobserved demand shocks – with the former based on intraday price fluctuations on monetary policy announcement days and the latter reflecting quarter-end portfolio positions – implies the two are based on different underlying information sets. Moreover, high-frequency shocks isolate only the component of monetary policy that is unexpected by market participants, whereas asset manager expectations about asset returns are likely to incorporate a broader set of information, including the stance of monetary policy (expected and unexpected), macroeconomic and political conditions.

Finally, the construction of monetary policy instruments for different bonds solely from euro and dollar short-term money market interest rates and the yield curves of five gov-

[47] See Lu and Wu (2023) for evidence of fund-driven reallocation across asset classes in response to monetary policy shocks.

ernment issuers is well-suited to satisfy the identifying assumption. To see this, suppose monetary policy shocks do trigger an increase in risk appetite that causes mutual funds to rebalance their portfolios towards risky bonds and away from safer bonds. The proposed instrument is not be correlated with such a reallocation since by construction it varies only over time, across bond maturity, country and currency but not across credit risk, bond seniority or liquidity. Indeed, I find that the magnitude of monetary policy shocks across different bonds are not correlated with their rating or maturity. In additions, the monetary policy spillover coefficients estimated in the first stage IV regression (17) – $\mathbb{a}^{Fed}_{\chi(i),cx}$ and $\mathbb{a}^{ECB}_{\chi(i),cx}$ – are also uncorrelated with bond riskiness. When I discuss the results from the first stage regressions in the next section, I find that the bonds whose predicted dollar returns react most to Fed shocks are those denominated in dollars or in currencies to some extent anchored to the dollar[48] and not those of the riskiest issuers. I conclude that the threat to identification from the exogeneity condition in (18) being violated due to greater spillovers of the monetary policy instruments to risky versus safe bonds is small.

Strength of instruments: To improve the precision of estimates and utilize the full time variation in monetary policy shocks, the first stage is estimated on monthly data since all bond demand system variables other than fund holdings are easily available at monthly frequency. The sample period is also longer, reflecting the data availability of monetary policy surprises from January 2002 to June 2019.[49]

The strength of instruments used in (17) is formally tested in the next section using effective F-statistics and critical values proposed by Olea and Pflueger (2013). There is a trade-off between instrument strength and allowing for heterogeneous monetary policy spillovers. For country-currency pairs where the instruments' effective F-statistic is below the critical values or I have less than 1,000 bond-month observations, I pool the panel estimation by bond issuer country only and add a bond currency fixed effect to the first stage specification in (17). If the instruments turn out to be insignificant in any of these panels too, I pool the remaining bond return observations by bond currency and repeat the estimation this time adding a bond issuer country fixed effect to the first stage specification in (17). Finally, if any bond panels with low instrument F-stats remain, they are pooled in a single rest-of-the-world (RoW) panel where I control for both bond country and currency fixed effects. In all these steps, I retain only bond return fitted values for the second stage from panel estimates with high F-statistics to reduce any weak instrument bias in the final demand estimates. The results of these first stage regressions are summarized in the next section.

Exclusion restriction: Instrument validity requires monetary policy to only affect fund bond holdings through expected bond returns. Since the demand model controls for an investor-time fixed effect likely to capture a range of alternative ways through which monetary policy could affect mutual funds (e.g. through their end-investor wealth and

[48] As expected, countries who choose to stabilize their currencies *vis-a-vis* the dollar import US financial conditions via global bond markets.

[49] Some of the ECB surprises (e.g. to the German yield curve) are also published for the period 1999-2001 but not all used here to construct monetary policy instruments. In addition, the ECB Governing Council switched from bi-monthly to monthly meetings in 2002, so I use only the period when announcements were at relatively stable frequency, consistent with monthly bond returns.

inflows, general market liquidity, the overall macroeconomic outlook), the identification strategy seems to adequately meet this requirement.

Finally, all other observable variables in the bond characteristics vector $\hat{\mathbf{x}}_{\mathbf{i,t}}(n)$ are assumed to be uncorrelated with fund demand shocks $\varepsilon_{i,t}(n)$. This assumption is strongest with regards to the bond supply control variable (face value). Governments usually plan their debt issuance as part of an annual budget such that the amount outstanding at quarterly frequency is very likely exogenous. Corporations may be more responsive to market conditions but even they need time to market their debt to investors, so endogeneity is unlikely to be a major concern at high frequencies.[50] In addition, the face value of each bond bucket is converted into a common currency for the estimation using exchange rates lagged by a year again with the objective to maintain the exogenous supply assumption. Bond fundamentals such as maturity, seniority and credit rating are also unlikely to respond to investor demand shocks within the same quarter. Turning to the remaining explanatory variables, a couple (residual maturity and bond seniority rank) are aggregated to bond bucket level from individual bond characteristics – these are constructed as weighted averages using face value weights rather than bond market values to avoid price fluctuations affecting them through changes in bond weights. Hence, the assumption that bond characteristics other than returns are exogenous seem appropriate as well.

Estimation procedure To summarize, the estimation of the empirical bond demand model proceeds in three steps:

1. Obtain predicted excess returns $per^h_{\chi(i),t}(n)$ across bond buckets as the fitted values of bond return predictive regressions described by (8);

2. Estimate first-stage instrumental variable regressions of $per^h_{\chi(i),t}(n)$ on Fed and ECB monetary policy shocks given by (17);

3. Estimate the panel bond demand model in (12) using two-stage least squares separately for each of eight fund types: EA and US bond-only active and passive funds, EA and US balanced active and passive funds.

Following these steps, I obtain estimates of $\alpha_{T(i)}$ by fund type. These return sensitivities are then combined with the portfolio weights and holdings data to calculate demand elasticities of individual funds and of the aggregate fund sector, given by expressions (14) and (15) respectively. The next section first describes the intermediate results from each of these three estimation steps. It then calculates and summarizes the magnitude of the implied demand elasticities.

[50] To verify the validity of this assumption, I also estimate the demand model with monthly holdings data to increase the frequency of observations further. The coefficient on bond amount outstanding remains unchanged.

4 Estimation results

4.1 Step 1: Predictive bond return regressions

As detailed in the methodology section 3.2, to operationalize the demand system I first obtain an estimate of funds' predicted excess bond returns in their home currency. To that end, I regress realized excess returns at alternative horizons ($h = 3, 12$ months ahead) on data as of the base period of returns (time t if return is calculated as the change between $t + h$ and t). The explanatory variables include bond yield, the first three principal components from the US and German government yield curves (labelled below as US & DE Level, Slope and Curvature), the log real exchange rate between the respective bond's currency of denomination and fund i's home currency, as well as bond-bucket fixed effects. The estimates of regression equation (8) are shown in Tables 2 and 3, with results of predictive regressions for excess returns in dollar terms ($rx_{\$,t+h}$) on the left-hand side, and results for excess returns in euro terms ($rx_{€,t+h}$) in the left-hand-side table.

Table 2: USD excess returns

	(1) $rx_{\$,t+3}(n)$	(2) $rx_{\$,t+12}(n)$
$y_t(n)$	2.314***	1.976***
	(0.285)	(0.082)
$rer_{\$,t}(n)$	-0.614***	-0.449***
	(0.068)	(0.024)
US Level	-0.046**	-0.045***
	(0.020)	(0.006)
US Slope	-0.242***	-0.136***
	(0.083)	(0.026)
US Curvature	0.436	-0.146
	(0.417)	(0.137)
DE Level	0.002	0.017***
	(0.017)	(0.005)
DE Slope	0.476***	0.296***
	(0.128)	(0.038)
DE Curvature	0.145	-0.134
	(0.603)	(0.185)
Obs	405,449	406,279
Adj. Rsq.	0.11	0.39
Within Rsq.	0.09	0.32

Table 3: EUR excess returns

	(1) $rx_{€,t+3}(n)$	(2) $rx_{€,t+12}(n)$
$y_t(n)$	2.295***	1.898***
	(0.226)	(0.085)
$rer_{€,t}(n)$	-0.473***	-0.412***
	(0.054)	(0.024)
US Level	0.006	0.008
	(0.014)	(0.007)
US Slope	0.221**	0.166***
	(0.090)	(0.032)
US Curvature	-0.214	0.348***
	(0.320)	(0.134)
DE Level	-0.053***	-0.049***
	(0.011)	(0.005)
DE Slope	0.067	0.062*
	(0.092)	(0.035)
DE Curvature	-0.729	-0.543***
	(0.448)	(0.166)
Obs	405,450	406,279
Adj. Rsq.	0.09	0.37
Within Rsq.	0.07	0.30

Note: Estimation sample from Jan-2002 to Dec-2020, month-end. $y_t(n)$ denotes yield to maturity/worst on bond n at the end of month t; $rer_{\$,t}(n)$ is the logarithm of the real exchange rate of bond currency n relative to the US dollar (US dollars per unit of currency n); $rer_{€,t}(n)$ – the logarithm of the real exchange rate of bond currency n relative to the euro (euros per unit of currency n); US Level, Slope and Curvature correspond to the first three principal components extracted from the US government bond yield curve; US Level, Slope and Curvature are the first three principal components of the German government yield curve. All predictive panel regressions also include bond bucket fixed effects. Standard errors clustered at bond bucket and month level.

First, bond yield-to-maturity[51] in month t has a strong predictive power for all bond return horizons and currencies. The yield importance is somewhat greater at the shorter horizon of 3 months compared to 12 months ahead but very similar across returns converted into euros or dollars.

Second, a high log real exchange rate at time t (i.e. an appreciated bond currency vis-à-vis the dollar or euro) implies lower future bond returns in the investor currency if the bond currency depreciates back to its slow-moving equilibrium value over the forecast horizon h. That is indeed the case on average in this panel of bond returns as suggested by the significant negative coefficients on the log real exchange rate.

Third, the six factors extracted from safe US Treasury and German Bund yield curves also add power to the regressions. For bond returns converted into US dollars (first two columns), the level of the US yield curve lowers the excess return of international bonds. The same holds for the level of the German yield curve with regards to the excess returns converted into euros. At the longer end, a higher US slope factor also predicts lower USD bond returns (columns 1 and 2) and a higher German curvature factor is associated with lower bond returns in euros (columns 3 and 4). These findings are consistent with how safe

[51] Or, respectively, yield-to-worst for callable/putable bonds.

yield curves might predict excess returns on risky assets via different mechanisms. Firstly, the US and German level factors are highly correlated with the respective short-term safe rates subtracted from bond returns to construct the excess returns on the left-hand-side of these regressions.[52] If safe rates are persistent, their level could be informative about future safe rates and, in turn, excess returns. Second, higher interest rates could increase aggregate risk aversion and, perhaps with some delay due to slow portfolio rebalancing, lower risky asset returns (Stavrakeva and Tang, 2021, Miranda-Agrippino and Rey, 2020a, Miranda-Agrippino and Nenova, 2022).

On the other hand, the level of foreign yield curves (i.e. not in the currency into which bond returns are converted) has limited predictability for both dollar and euro returns. For example, the US level factor is not a strong predictor of euro bond returns. And the German level factor predicts dollar bond returns only 12-months ahead and with lower magnitude than the US level factor. Changes further along the foreign government yield curves, captured by the slope and to a lesser extent by the curvature factor also predict bond returns. Most significant coefficients on factors extracted from the respective foreign yield curve have the opposite sign to the domestic yield curve. For instance, a higher German yield curve slope is associated with higher dollar returns in the panel of international bonds. This is consistent with Lustig, Stathopoulos and Verdelhan (2019), who find that a higher yield curve slope relative to the US predicts higher dollar excess government bond returns in a panel of advanced economies. They show this result combines two components – the higher-slope bonds are, on the one hand, likely to yield a lower currency excess return (lowering dollar bond returns), but, on the other hand, their local currency returns are higher and the latter effect dominates. My results confirm their finding in a panel of corporate and government bonds issued by a wider range of countries and of diverse maturities and currencies of denomination. In addition, in Table 3 I confirm that this result holds when bond returns are converted into another major currency. When the euro is the reference currency, one can think of US bonds as the foreign asset and as before a higher US slope predicts higher euro returns on foreign bonds.

Overall, the predictive regressions account for around 30% of the variation in 12-month-ahead bond returns (excluding the contribution from bucket fixed effects) and around 8% of the variation of the more volatile 3-month bond returns. Given the relatively parsimonious predictive regression and the broad set of international corporate and government bond returns modelled, this fit is considerable. I save the fitted values from the regressions in Tables 2 and 3 to use as proxies of expected bond returns in the next steps of the estimation. These fitted values are referred to as predicted excess returns and denoted by $per^{12}_{\chi(i),t}(n), per^{3}_{\chi(i),t}(n)$, respectively.

4.2 Step 2: First-stage IV regression

With these predictions of excess returns in hand, I proceed to the first-stage regressions in order to obtain exogenous variation in excess returns. In the main text of the paper I will focus on results using the predicted excess returns at 3-month horizons and control

[52] USD excess returns are calculated by subtracting the 12-month or 3-month USD OIS interest rates from bond returns of the respective horizon. EUR excess returns subtract the respective horizon EUR OIS rates.

for time-variation in risk attitudes with the VIX index. Similar results are obtained if I use 12-month-ahead returns instead. Results are also robust to replacing the VIX index with alternative measures of aggregate risk aversion. All first-stage results and robustness checks can be found in Appendix C, Figures C.18 – C.26.

As described in the previous Section, I form panel subsets from the full monthly bond dataset defined by the country of risk and currency of denomination of bonds. The units of observation are unique bucket-month data points of which there are over 350,000 in total for the period Jan 2002 – Jun 2019, covering 5,269 unique buckets. For each unique country-currency sub-panel, I estimate the specification in (17) and save the results if the effective F-statistic is at least above the 30% critical value of Olea and Pflueger (2013). Estimates from these panel regressions are denoted by the ISO 2-letter country code and 3-letter currency code in the reported results, such that for instance "JP_JPY" stands for results based on the panel formed from bonds issued by Japanese entities and denominated in yen. Country-currency panels for which I obtain too low F-stats are then pooled further into a country panel, denoted by for instance "JPothfx" for all remaining bonds by Japanese issuers. Again, the first-stage algorithm only saves those country panels where instruments are strong and pools the rest of the bonds into currency panels. Saved currency panels with high F-stats from this step are denoted for example "JPYrest" for the pooled bonds denominated in yen. The final rest-of-the-world (RoW) panel is formed by bond sub-panels with either too few observations or too low F-stats from the finer sub-panels in the previous steps.

The first panel of Appendix Figure C.18 shows the effective F-statistics from all panel regressions estimated following this algorithm for predicted bond dollar returns $per^3_{\$,t}(n)$. The algorithm estimates 76 unique regressions for $per^3_{\$,t}(n)$ with an F-statistic greater or equal to the critical value (red diamond). The first stage provides a fitted value for 4,777 out of 5,269 bond buckets (or 99% of the face value of bonds in the dataset), which will be used in the estimation of bond demand by US funds. The majority of bond panels with sufficiently high F-stats for the instruments are at the country-currency level but fitted values from a few more aggregated panels (with labels ending in "othfx" or "rest") are also saved. The final catch-all "RoW" panel estimates are not saved due to an F-stat just below the critical value (see third-to-last bar of the graph).

The second panel of Appendix Figure C.18 shows the F-statistics from a total of 64 regressions ran for $per^3_{€,t}(n)$ using the same algorithm. The bonds with sufficiently-high F-stat account for around 99% of the amount outstanding of bonds (or a total of 4,667 unique buckets) in the dataset for EA funds' bond demand estimation.

The first stage instrument F-stats presented so far establish that monetary policy shocks are strong instruments for bond returns. They also have heterogeneous effects on bond returns depending on the country and currency of the bonds as shown in Figures C.19 and C.20. For the Fed, predicted dollar returns 3 months ahead (panel (a) of Figure C.19) vary between positive and negative 0.4 percentage points per 1 percentage point shock to the relevant segment of the US yield curve at time t. As the predictive bond return regressions made clear, several forces determine international bond returns converted back into dollars. First, a higher US yield curve may drive up local currency yields across the globe as countries import US financial conditions either due to a fixed or semi-flexible

exchange rate regime or through other channels, e.g. global financial intermediaries. Second, the dollar appreciates after a Fed tightening and this may or may not reverse in the months following the shock. If the dollar appreciation on impact (at time t) reverses by the end of the 3-month horizon, foreign currency bonds may have higher returns in the depreciated dollar. On the other hand, if the dollar appreciation is persistent, foreign currency bond returns may fall.

How spillovers play out and which channel dominates for a given set of bonds depends on its fundamentals. For instance, the bonds whose returns increase the most in response to a Fed tightening (to the left of panel (a) of Figure C.19) are either denominated in dollars or currencies closely linked to the dollar (like the Hong Kong dollar HKD or the Chinese yuan CNY) or, interestingly, in Swiss francs (CHF). For dollar and dollar-pegged currency bonds, the first two international transmission channels dominate – their bond yields comove with US ones and the lagged dollar depreciation might help drive up future returns too. On the other hand, the dollar appreciation affects more strongly bonds denominated in e.g. euros, British pounds, Japanese yen, Canadian and Australian dollars such that the Fed shock lowers their returns in dollar terms at 3-month horizons. The effects of Fed monetary policy shocks on bond returns converted into euros (panel (b) of Figures C.19) resemble those for dollar returns but are somewhat weaker in absolute terms. Again, dollar, pegged currency and Swiss franc bonds are on the left-hand side with positive spillovers and other currency bonds are on the right with lower excess returns after a Fed hike.

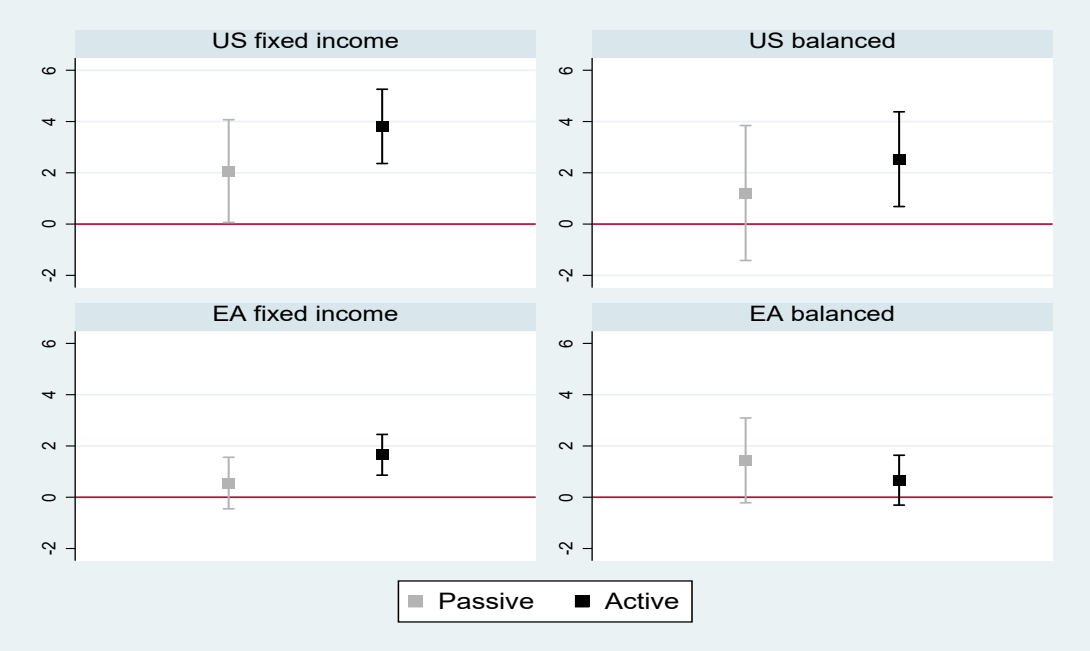
Turning to the effects of ECB monetary policy shocks on bond returns (Figure C.20) flags how different international bond market spillovers from these two central banks are. Starting with the effects of ECB tightening on returns converted into its own currency, the euro, in panel (b) of Figure C.20, what is most striking is the smaller magnitude of bond return impacts and the greater estimation uncertainty around those. This may be because fewer countries with fixed exchange rate regimes use the euro as their anchor currency (Ilzetzki, Reinhart and Rogoff, 2019). That would mean euro area financial conditions are not directly 'exported' to as many peggers as US interest rates. It is also certainly true both in the bond dataset analysed here and in overall debt issuance that fewer international bonds are denominated in euros than in dollars (ECB, 2020). When the ECB hikes, the euro likely appreciates – if the appreciation persists past the month of the initial shock, it could reduce the euro return of non-euro-denominated bonds. Indeed, examining the estimated responses of predicted dollar returns to ECB policy announcements (panel (a) of Figure C.20), the first thing to note is that responses are on average greater and more precisely estimated. Intuitively, that fact is especially true for euro-denominated bonds such as ones issued by Italy and Spain (IT_EUR, ES_EUR). This suggests that an important channel of monetary policy spillovers of ECB policy to international bond markets is through the shift in the euro-dollar exchange rate.

4.3 Step 3: Panel bond demand by fund types

For the last step of the estimation procedure, I report the results from the panel bond demand regressions in (12) by fund type. The resulting point estimates of $\widehat{\alpha}_{T(i)}$ or the fund sensitivity to bond predicted excess returns are of particular interest. These are combined with data on fund holdings to construct estimates of funds' demand elasticities

according to equation (15). Figure 5 summarizes the estimated $\widehat{\alpha}_{T(i)}$ for the baseline fund types by domicile, asset class and active share rankings.

Figure 5: Estimated coefficients $\widehat{\alpha}_{T(i)}$ on instrumented $per^3_{\chi(i),t}$ by fund type



Note: Each square indicates a point estimate of $\alpha_{T(i)}$ and the ranges around it show the corresponding 90% confidence bands. Subplots are by fund domicile and asset class. Within each subplot, the dark-grey estimate is for all respective funds, while the light-grey denotes the estimate for passive funds only and the black denotes active funds only. Active and passive funds are defined relative to the median bond active share of each fund (averaged over time). Full regression output reported in Appendix Table C.14.

Starting with the top-left plot of the estimated sensitivities, we see that US fixed income funds have relatively high estimated sensitivities. Active US bond funds are considerably more responsive to changes in predicted bond returns than passive ones. For passive funds the estimated $\widehat{\alpha}_{T(i)}$ is around 2, whereas for active it rises to 4. A similar pattern holds for US balanced funds (top-right panel), albeit with somewhat lower point estimates across both passive and active funds and somewhat wider confidence bands.

Euro area funds in general are less sensitive to predicted bond return fluctuations – both within the fixed income and balanced fund types. The bottom-left panel shows that the sensitivity of active EA fixed income funds is significantly higher than zero but with a point estimate of just under 2 is only half as high as that of their US counterparts. The sensitivity of passive EA fixed income funds is only slightly above zero and not to a statistically significant degree. EA balanced funds, like US balanced funds, are less sensitive to changes in predicted bond returns compared to their fixed income counterparts in the same currency area. The structural estimate is consistent with the summary portfolio allocation statistics discussed in Section 2, which flagged that EA balanced funds have the highest average allocation to safe and sovereign bonds of all fund types discussed here.

Overall, the patterns revealed by the heterogeneous fund sensitivities to bond returns

make intuitive sense – active funds react more to return fluctuations than passive ones, especially for fixed income funds; and funds who invest exclusively in bonds (fixed income) are more sensitive to their returns than funds who hold multiple asset classes (balanced). The systematically higher sensitivity to returns of US funds compared to EA funds is potentially consistent with differences between the fund sector market structure, where the US industry's assets under management are more concentrated in fewer large funds compared to their euro area counterparts. In the next subsection I use the point estimates of $\alpha_{T(i)}$ for the eight fund types of interest to construct demand elasticities across different bonds and discuss in detail what the magnitudes of these point estimates imply for the slope of funds' demand curves.

The full regression tables with estimated coefficients on the other exogenous bond characteristics can be found in Appendix C, Table C.14. The remaining coefficients are consistent with the discussed estimates of fund sensitivities to bond returns as well as with the summary statistics on portfolio allocation presented in Section 2. Bond maturity is not independently an attractive bond feature for investment fund beyond its relation to higher predicted bond returns (incorporated into the first-stage regressions). Some of the balanced funds seem to even prefer bonds of shorter maturities perhaps due to liquidity risk management demands. For all fund domiciles and fund styles by asset class, passive funds have a strong preference for investment-grade bonds (with a credit rating of BBB- or higher) and active funds rarely do. Within the investment-grade category, EA funds place greater weight on top-notch bonds with a rating of AA- or higher, whereas US funds are just as keen on the lowest investment-grade notches (BBB). All funds prefer bonds with a higher amount outstanding but within each fund domicile and style, the passive funds are consistently estimated to place greater weight on the quantity available from each bond. For instance, the coefficient on amount outstanding is estimated at 0.46 for US passive fixed income funds (column 2) and 0.33 for their active peers (column 3). The seniority of bonds is not an important determinant of fund portfolios beyond its association with bond returns established in the first-stage regressions (where more senior bonds are associated with lower returns).

The home bias coefficient can only be estimated within the euro area fund types (although preferences for any country can be recovered from the country fixed effects) and there it only appears to significantly bias the holdings of fixed income funds towards home bonds. Geographical fund mandates are clearly followed in portfolio allocation decisions, especially for fixed income funds where more of the portfolio holdings are in bonds. A government bond funds is significantly more likely to gold bonds issued by governments across the board. Funds that hold a mix of government and corporate bonds also have a (weaker) preference for government bonds, likely reflecting a higher average portfolio weight of government bonds in the fund sector as a whole. Only active corporate bond funds have an additional preference for corporate bonds once all other bond characteristics are taken into account. All panel regressions include fund-quarter fixed effects as well as bond currency and issuer country fixed effects, which aid considerably to fit the observed holdings data with on average 50% of the overall variation in holdings data explained by these fixed effects (as evident from the differences between the overall R-squared and the Within R-squared statistics).

Overall, the bond demand model fits the portfolio allocation by funds in the sample

very well. The overall R-squared is at least 80% for most fund types, ranging between 71% for active US fixed income funds and 94% for EA passive fixed income funds. The bond demand model describes particularly well the portfolio allocation by passive fixed income funds, where it likely benefits from a large portfolio portion being observable as well as from mandates being well-described by the broad categorical bond characteristics. The Appendix reports results for alternative fund type splits, definitions of the endogenous bond return variable (predicted excess bond returns 12 months ahead) and different choices of the aggregate risk aversion control in the first stage. These all confirm that the baseline results provide robust foundations for the description of fund demand elasticities.

4.4 Estimated demand elasticities

I proceed to calculate the elasticities implied by the bond demand model and estimated sensitivities of funds to predicted excess returns $\widehat{\alpha}_{T(i)}$ from the last subsection. Here, I summarize broad patterns of demand elasticities across all bonds and fund types and compare magnitudes to existing literature. In the next section, I explore how the demand elasticities vary across safe versus risky bonds as well as how safe bond elasticities (own demand elasticities as well as substitution elasticities) change over time.

Own elasticities Own demand elasticities of the fund sector – i.e. the percent change in portfolio weight of a given bond in response to a 1 percentage point change in own predicted excess return – are a natural starting point for examining the estimated elasticities. *Own* elasticities have been the focus of much of the recent literature on downward sloping asset demand, providing a useful benchmark for my results. Here, I summarize results for bond-specific elasticities aggregated to the fund sector level. Table 4 provides an overview of the distribution of own demand elasticities $\eta_t(jj)$ across different bond buckets j over the sample period $t = \{2007Q1, \ldots, 2020Q4\}$[53]:

Table 4: Summary statistics for own bond elasticities of aggregate fund sector $\eta_t(jj)$

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US fixed income	311.98	64.17	333.16	204.31	380.98	75,938
EA fixed income	133.66	32.07	144.21	54.51	165.43	105,945
US balanced	199.82	52.51	218.25	120.07	253.15	43,041
EA balanced	78.54	20.62	67.62	64.23	143.66	77,109
Total Fund Sector	180.40	75.41	164.84	55.01	378.96	110,529

Note: Elasticities $\eta_t(jj)$ aggregated for the entire fund sector or by four broad fund types. Each summary statistic is calculated across two dimensions: bonds (j) and quarters with holdings data (t).

On average, the fund sector changes the portfolio weight of a bond by 180% in response to a 1 percentage point change in its predicted excess return. This number can easily be related back to the estimates of fund return sensitivities $\alpha_{T(i)}$ shown in Figure 5 of the previous subsection. Suppose a single fund i's estimated $\alpha_{T(i)}$ is 2 and its bond portfolio weight of a given bond j is 1%[54], then its elasticity by this measure would equal $2 \times (1 - 0.01) \times 100 = 198$. The main source of variation in the own elasticity comes from

[53] As shown in (15), these are holdings-weighted averages of the fund-specific demand elasticities. And a summary of the underlying individual own demand elasticities can be found in Appendix Table C.15.

[54] 1% portfolio weight corresponds to the 75th percentile of observed bond weights $w_{i,t}(j)$ in the dataset.

the estimated heterogeneous sensitivities $\alpha_{T(i)}$, since funds are diversified and $w_{i,t}(j)$ are small such that the $(1 - w_{i,t}(j))$ component of the elasticity formula (14) is close to 1. This is evident if one compares the elasticities aggregated at the level of four broad fund types (rows 1-4 of Table 4). The funds with highest estimated $\alpha_{T(i)}$ as shown in Figure 5 are US fixed income funds and their average elasticity is above 300%. At the other end of the spectrum, the low-sensitivity EA balanced funds have the lowest elasticities – on average, 79%.

Consistent with existing literature on demand elasticities[55], my estimates confirm a downward-sloping demand curve in prices. They suggest that investment funds on average have fairly elastic demand for international bonds but are still far less elastic than implied by workhorse finance models of portfolio allocation (with elasticities of approx. 20,000, according to Petajisto, 2009). There is no directly comparable work modelling demand for international bonds issued by both corporates and sovereigns at this level of granularity both at the holdings side (bond buckets defined by country, currency, issuer type, rating and maturity segments) and at the investor side (individual mutual funds). Studies based on investor bond holdings aggregated at country level or broad country-sector level report demand elasticities with respect to prices. To make like-for-like comparisons with these studies, in Table 5, I use the relationship between my baseline elasticity definition in (14) and the elasticity of demand with respect to prices derived in equation (B.24) of Appendix B.3:

Table 5: Summary statistics for own bond elasticities of aggregate fund sector, *w.r.t.* price: $-\frac{\partial \log(Q_t(j))}{\partial \log(P_t(j))}$

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US fixed income	355.15	530.78	152.88	23.56	1,915.53	75,938
EA fixed income	170.77	232.70	77.25	9.12	826.25	105,945
US balanced	179.44	286.97	81.22	13.37	1,194.77	43,041
EA balanced	91.96	129.13	46.20	7.07	603.31	77,109
Total Fund Sector	230.11	357.15	91.80	11.90	1,571.52	110,529

Note: Elasticities $-\frac{\partial \log(Q_t(j))}{\partial \log(P_t(j))}$ aggregated for the entire fund sector or by four broad fund types. Each summary statistic is calculated across two dimensions: bonds (j) and quarters with holdings data (t).

This conversion simply scales each elasticity by the relationship between bond returns and prices (dividing by bond maturity and multiplying by the effect of bond yield on returns). By this definition, mean elasticities are higher than the baseline (as for very short-term bonds the elasticity with respect to prices divides by their maturity of less than 1 year), while the median elasticity is lower across the sample of bonds here. A median elasticity of around 90 is higher than most existing elasticities estimated for long-term debt from aggregate country-level data (both at the investor and asset side). Consistent with this literature's estimates, elasticities for short-term debt are calculated to be higher than for long-term debt. For instance, Koijen and Yogo (2020) estimate an elasticity of 4.2 for long-term debt and of 42 for short-term debt based on aggregate international portfolio

[55]This includes both a long string of papers documenting a persistent price effect of stock index additions and exclusions (e.g. Shleifer, 1986, Chang, Hong and Liskovich, 2015, Pavlova and Sikorskaya, 2022, among many others), as well as more recent attempts to estimate demand systems for financial assets following the methodology of Koijen and Yogo (2019).

investment. Using a similar estimation methodology and aggregated holdings data, Jiang, Richmond and Zhang (2021b) report an elasticity of 229 for short- and 2 for long-term debt. Koijen, Koulischer, Nguyen and Yogo (2020a) estimate a total market elasticity of 3.21 for the aggregated debt of euro area sovereigns[56], with significant variation by the holder sector. Their results suggest that mutual-fund-specific demand elasticity faced by euro area sovereigns is on average 2.93. Consistent with my finding that US funds have more elastic demand, Koijen, Koulischer, Nguyen and Yogo (2020a) estimate that foreign investors in euro area sovereign debt have a much higher demand elasticity (7.19) than any euro area investors. Similarly, estimating demand based on the aggregated international government debt holdings of six broad investor sectors (domestic and foreign banks, non-banks and official sectors) (Fang, Hardy and Lewis, 2022) find private non-banks (which include mutual funds as well as insurers, pension funds, hedge funds, households and other non-bank financial companies) are the most elastic ones – with an elasticity of 1.5 for domestic and 3.5 for foreign investors.

Broadly, the more granular elasticities estimated in this paper are higher than those from previous literature based on country-level debt holdings. This might reflect a general tendency of demand elasticities to decrease as the definition of an asset becomes more aggregated. In essence, the broader the asset definition, the harder it would be for an investor to find a suitable substitute and, hence, the lower the demand elasticity. In a finance application to US corporate bonds, this feature is nicely illustrated by Chaudhary, Fu and Li (2022) but it is commonly observed across industrial organisation and international trade studies at different levels of product aggregation (Goldberg and Pavcnik, 2016, Fontagné et al., 2022, Boehm et al., 2023).

More specifically to bond demand elasticities, meaningful comparisons between granular elasticity estimates from different studies or even between bonds of different maturities within the same study are severely impaired when the elasticity is defined in terms of bond prices as in equation (B.24) and shown in 5. To make this clear, suppose I observe a 6-month bond and a 10-year bond. Again, let's take an investor with estimated return sensitivity of $\alpha_{T(i)} = 2$ and bond portfolio weights of 1% for each of the two bonds. Now recall that the estimated effect of bond yields on predicted excess returns $A^h_{\chi(i)}$ was 2.3 (see e.g. Table 2). The same investor's elasticity with respect to the price of the bond with six months (or 0.5 years) until maturity will be $2 \times (1 - 0.01) \times 100 \times 2.3/0.5 + 1 = 912$, while his elasticity with respect to the price of the bond with 10 years until maturity will be $2 \times (1 - 0.01) \times 100 \times 2.3/10 + 1 = 46.5$. To see how much dispersion in elasticities across bonds the maturity generates, compare the standard deviations of bond elasticities of the total funds sector (bottom row) under the baseline elasticity definition reported in Table 4 to the standard deviation of the elasticity with respect to bond prices in Table 5. Maturity entering this calculation increases the standard deviation five-fold – from 75 to 357. This example highlights a key consideration for focusing throughout this paper on the elasticity definition in (14) to compare demand elasticities across different bonds with heterogeneous characteristics.[57]

[56]The Koijen, Koulischer, Nguyen and Yogo (2020a) elasticity calculation is based on the weighted average maturity of aggregate sovereign debt – on average 7 years – so is most comparable to long-term debt elasticities reported elsewhere.

[57]An alternative definition sometimes used in this literature calculates the elasticity as the change in quantity of bonds held with respect to the bond yield (Koijen and Yogo, 2020, Jiang et al., 2021b, Fang et

Another application-specific reason for the elasticity definition chosen by this paper is conceptual – understanding safe asset behaviour relative to risky assets calls for a definition in terms of portfolio rebalancing rather than absolute quantities of bonds. Other important applications – such as the effects of purchases or sales of a given stock of assets by central banks or of the change in the debt stock issued by governments or corporates – might call for an estimate of changes to the quantity of bonds held in response to bond price or yield fluctuations. These alternative definitions of demand elasticity can easily be implemented with the methodology developed here and are indeed summarized in Appendix Tables 5 and C.16.

The next section explores the rich variation in fund sector demand elasticities flagged in Table 4. Before that, however, I summarize another contribution of this study – estimates of substitution or cross-elasticities in global bond markets.

Substitution elasticities Next, I summarize what the demand model estimates imply for bond substitution elasticities or the change in portfolio weight of a given bond j in response to a percentage point change in the return of another bond k ($\eta_t(jk)$). Like own elasticities, I construct cross-elasticities by plugging in the estimated point estimates of bond return sensitivities by fund type $\widehat{\alpha}_{T(i)}$ into the second line of equation (14), along with portfolio holdings data. This cross-elasticity measure suggests that bonds j and k are close substitutes if: (i) as with own elasticities, the investors who hold them are highly sensitive to return fluctuations such that they respond to the return of k (i.e. have high $\widehat{\alpha}_{T(i)}$); (ii) investors with high holdings of bond j (captured in the investor i weight $\sum_i \frac{AUM_{i,t}w_{i,t}(j)}{\sum_i(AUM_{i,t}w_{i,t}(j))}$) also hold a significant portfolio weight of the bond whose return experiences the shock ($w_{i,t}(k)$). Thus, if no investor universe includes a given pair of bonds, then complete market segmentation arises (at least concerning the fund sector) between them according to the bond demand model.

With over 5,000 bonds included in the estimation, the model could potentially produce around 25 million substitution elasticities.[58] This paper's goal is to characterize the behaviour of safe assets, so I focus on the substitution patterns that follow an increase in the predicted excess return on the safest bond buckets – highly-rated liquid sovereign bonds with a short maturity. The sovereign bonds with residual maturity of less than a year issued by the US or Germany are of particular interest since they are the leading safe assets of the two currency areas where funds studied in this paper are domiciled – US and the euro area.[59] In the Appendix (section C), I also report the cross-elasticities from shocks to other segments of the US and German government yield curves.[60]

al., 2022), i.e. $\frac{\partial \log(Q_t(n))*100}{\partial y_t(n)}$. This is also a function of bond maturity, as derived in Appendix equation (B.25). Thus, it also generates greater dispersion in bond-specific elasticities as evident in the standard deviation of this elasticity definition reported in Appendix Table C.16.

[58]The substitution matrix is not symmetric, as the formula for $\eta_t(jk)$ in equation (15) shows. In the bond pair for which I study the substitution elasticities in the next section, I generally find high correlation between the mirror substitution elasticities (i.e. $\eta_t(jk)$ and $\eta_t(kj)$) over time but their magnitudes can differ as a shock emanating from a bond with a high portfolio weight spills over more to other bond allocations.

[59]I sometimes use "T-bills" as a short-hand for these buckets (although the term technically applies to bonds with an *issue* maturity of a year or less, rather than a *residual* maturity of under a year).

[60]The estimated bond demand system offers a wealth of other substitution patterns that are worth exploring in future work too. For instance, one could dig into the shocks to financial and non-financial

Table 6 reports the mean and standard deviations of elasticities $\eta_t(jk)$ with respect to returns changes in the T-bills issued by the US, Germany, Switzerland and Japan. Substitution elasticities are less than or equal to zero, implying that the bonds modelled here are substitutes in fund portfolio allocation decisions. This follows from the empirical estimates of $\widehat{\alpha}_{T(i)}$ all being greater or equal to zero (Figure 5). The number of observations is smaller than own elasticities, as cross-elasticities are only constructed from portfolios which hold e.g. US T-bills (for the first row) and other bonds at the same time.

Table 6: Summary statistics for estimated cross-elasticities $\eta_t(jk)$ *w.r.t.* changes in US, German, Swiss, Japanese T-bill returns

Bond k	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US sov <1y	-1.15	2.83	-0.35	-12.80	-0.00	77,243
DE sov <1y	-0.25	1.17	-0.03	-3.91	-0.00	61,952
CH sov <1y	-0.01	0.17	-0.00	-0.11	-0.00	17,242
JP sov <1y	-0.31	1.73	-0.03	-5.26	-0.00	54,345

Note: Elasticities $\eta_t(jk)$ aggregated for the entire fund sector. Each summary statistic is calculated across two dimensions: bonds (j) and quarters with holdings data (t), while keeping bond k (source of the return shock) constant.

Starting with the substitution elasticities from US T-bills in the first row, these vary between close to zero and 13%, with a median of around 1%. Digging further into this range of percentages can reveal which bonds are sold by the fund sector the most in order to accommodate an increase in the portfolio weight of US T-bills when the latter's return goes up. As may be expected by the smaller footprint of the German, Swiss and Japanese T-bill markets, the substitutions following changes to their returns are smaller.

Sources of variation in elasticities The next section explores variation in own as well as substitution elasticities to characterize safe assets though the prism of investor demands. To recap on this section, estimated demand elasticities from this model can vary both across bonds and over time. The main source of this variation is the composition of investors with different return sensitivity $\alpha_{T(i)}$ as well as with different portfolio composition. Investor composition is especially important in driving the dispersion of own elasticities, accounting for almost all variation in elasticities across bonds and, on average, around 86% of time variation in elasticities for a given bond. Portfolio exposure to particular bonds interacts more significantly with investor return sensitivity when it comes to the substitution elasticities, as substitution is facilitated by funds who invest in a multitude of bonds.

5 Safe asset features

5.1 Safety and low demand elasticity

How do *own* demand elasticities vary across bonds with different characteristics? Much of the previous finance literature on asset demand has focussed primarily on the average

corporates which spill over more widely and increase global systemic risk. Or map how policies aimed at bond portfolio flows into and out of one emerging market (capital flow management measures or FX interventions) spill over to other countries through international investors' portfolio reallocation.

slope of demand curves across a certain set of assets.[61] The heterogeneous international bond dataset allows me to also explore how demand elasticities vary by bond. I can answer questions such as: (i) Do safe assets face lower demand elasticities than riskier bonds? (ii) Does 'safety' relate to the credit risk of a bond, its maturity (i.e. low duration risk), the identity of the issuer or the currency of denomination?

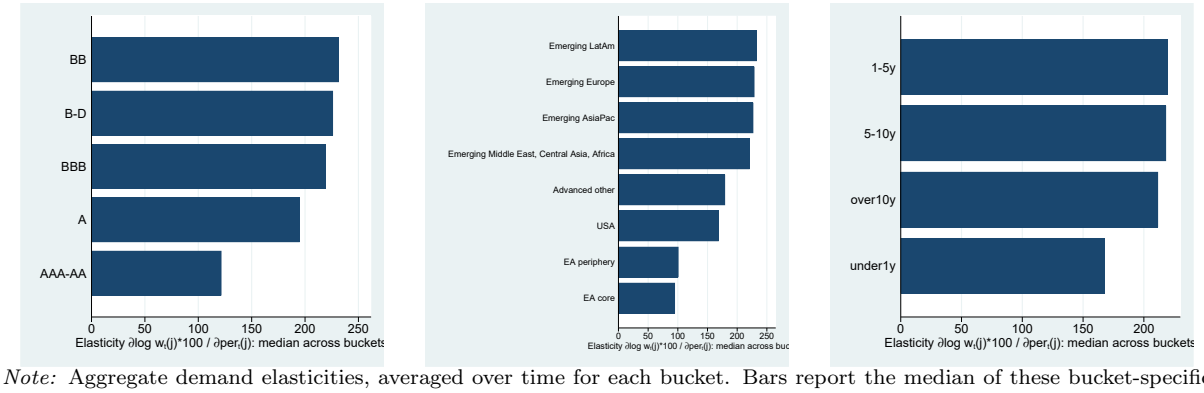
Figure 6 addresses these questions by comparing the median elasticities across sovereign bonds along three bond characteristics: credit rating, issuer region and bond maturity. The fist panel suggests a very striking ranking of demand elasticities. The bonds with lowest credit risk (rated AAA or AA) face the lowest demand elasticities from investment funds. Demand elasticities then progressively increase as the credit rating deteriorates, with the largest drop in elasticities between the top-rated bonds and bonds in the next-best "A" rating scale. This suggests that top-rated sovereign bonds play a special role in the portfolios of investment funds – even when returns fall, investors refrain from selling these bonds to the same degree as they would sell junk bonds. This finding is consistent with models which assign US Treasuries, for instance, a special status due to the non-pecuniary 'convenience yield' offered by these assets (Krishnamurthy and Vissing-Jorgensen, 2012, Jiang, Krishnamurthy and Lustig, 2021a). The underlying investor motivation to hold more tightly on to these safe bonds could come from multiple sources such as greater liquidity, collateral pledgeability, simplicity or regulatory requirements. It is worth noting that in textbook CAPM models, the opposite is usually true – the demand elasticity of risky assets should be lower. There, an investor requires a larger shift in risky asset returns because increasing their portfolio share increases the overall portfolio risk by more.

But my empirical results flag this safe asset 'specialness' is not merely a US phenomenon. The second panel of Figure 6 ranks sovereign bond elasticities by the issuer region. Euro area and other advanced issuers also face lower demand elasticities than emerging market bond issuers. Surprisingly, euro area issuers face even lower demand elasticities than US Treasuries. This is, of course, related to the investor base of euro area sovereign bonds and becomes clear when comparing the ranking of demand elasticities by issuer region only for US funds – in the second panel of Figure 7. For US funds, which hold a greater share of the bond market value, US Treasuries are indeed the safe asset of choice. This highlights that safe asset 'specialness' interacts materially with the home bias of less return-sensitive euro area funds. Indeed, Figure 8 shows that EA funds are both less sensitive to the returns on bonds overall and least sensitive to their safest regional asset – top-rated sovereign bonds issued by the euro area core countries.

[61] E.g. US equities in Koijen and Yogo (2019), US and UK stocks in Koijen et al. (2020b), euro area bonds in Koijen et al. (2020a), government bonds in Fang et al. (2022), long-term / short-term debt / equity in Koijen and Yogo (2020), Jiang et al. (2021b), exchange rates in (Camanho et al., 2022).

Figure 6: Own elasticities $\bar{\eta}(jj)$ by bond characteristics – Sovereign bonds

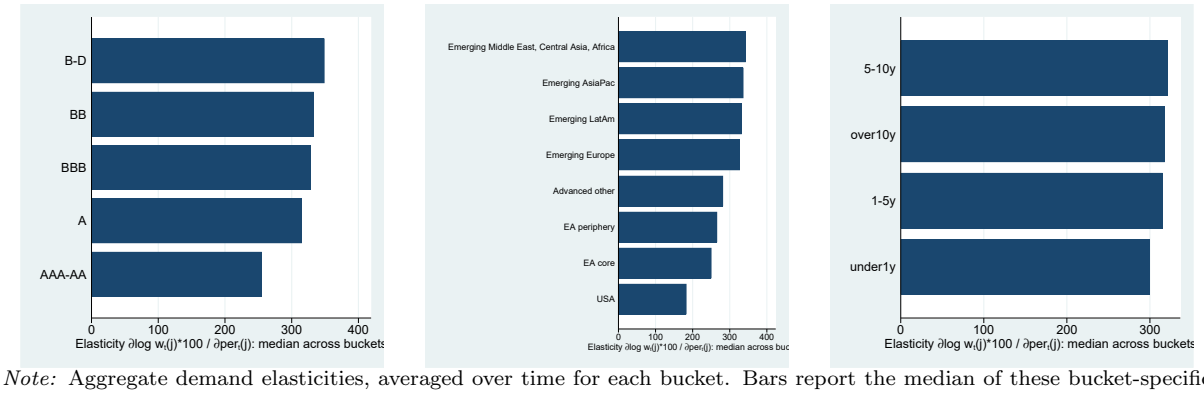
(a) Credit rating **(b)** Issuer region **(c)** Bond maturity



Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure 7: Own elasticities $\bar{\eta}(jj)$ by bond characteristics – Sovereign bonds, US funds

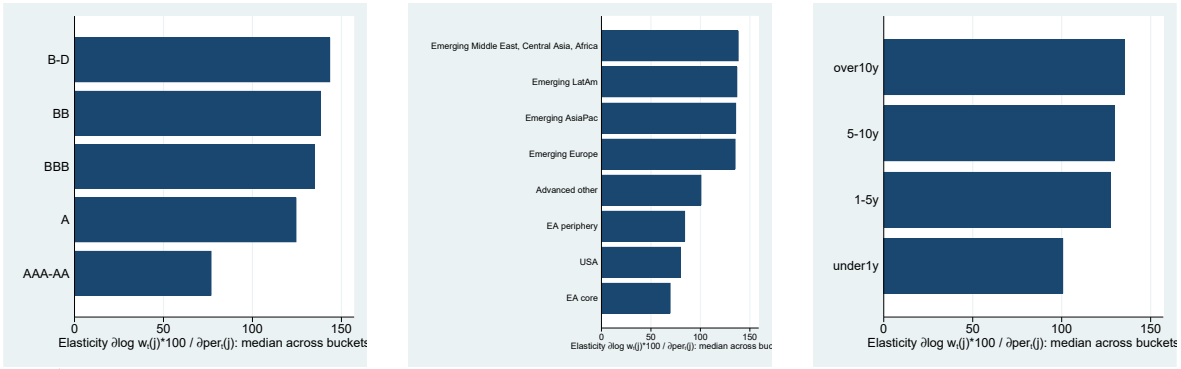
(a) Credit rating **(b)** Issuer region **(c)** Bond maturity



Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure 8: Own elasticities $\bar{\eta}(jj)$ by bond characteristics – Sovereign bonds, EA funds

(a) Credit rating **(b)** Issuer region **(c)** Bond maturity



Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

The third panel of Figure 6 reveals another feature of safe assets – sovereign bonds with maturity under a year face the lowest demand elasticity. The low duration risk is a feature

particularly salient for EA funds as evident in Figure 8. Thus, safe assets face low demand elasticities by investment funds and the most salient features of safe sovereign bonds are their top-notch credit rating and the government backing them. Short maturity also plays a role. And there is room for more than one safe asset (US Treasuries) because regional investors have a home bias toward their regional safe asset.

To fully characterize safe assets through a comparison of elasticities across bonds, Appendix Figures D.29 and D.30 perform the same rankings for corporate bonds only as well as for all bonds in the dataset (sovereign, corporate and supranational). For corporate bonds, elasticities are highest for those below investment grade (rated "BB" or "B-D") but special role is attached to the credit-worthiest bonds (rated "AAA-AA"). The maturity of corporate bonds is also not an important aspect of differentiation in terms of funds' demand elasticity. EA corporate issuers still face low demand elasticities (partly due to the home bias of less elastic EA funds) but US corporate bonds are not 'special' like their government counterparts in the eyes of investment funds.

Finally, demand elasticities also vary a lot by bond currency but less systematically (Appendix Figure D.31). The euro faces the lowest demand elasticity and not only because of EA funds' home (currency) bias. The US dollar, on the other hand, faces a relatively high demand elasticity and has little 'special' value compared to other currencies unless the issuer identity is taken into account. Many emerging market governments issue in dollars and their funding currency mismatch makes them especially risky, which dominates the median dollar-bond elasticity reported in Figure D.31.

In summary, the variation in own demand elasticities across bonds offers a new classification of safe assets based on the estimated demand elasticity of private international investors. Low demand elasticities for what are usually perceived as safe assets reinforce the need to understand the non-pecuniary value that investors derive from holding these. Thanks to the granular bond data, this paper is in a unique position to clarify the features of safe assets that make them special in investors' eyes. These are primarily the low credit risk, the issuing government, and short bond maturity (closer substitutability with cash). Having a less elastic and home-biased investor base (potentially in conjunction with a limited supply of safe bonds) – as in the case of the euro area – might help cement a regional safe asset's status too.

5.2 Global and regional safe assets: a bond substitution view

The next key aspect of safe assets I characterize is how changes in their returns spill over to different segments of international bond markets. To that end, I examine the variation in substitution elasticities with respect to a percentage point change in the expected excess return on two key safe assets in the demand system in turn – US and German sovereign bonds with maturity of less than 1 year. Which bonds do investors sell the most when making room for a higher safe asset portfolio weight in response to that safe asset's return increase?

First, Figure 9 summarizes how portfolio spillovers (captured by funds' substitution elasticities) from US T-bills vary by key bond characteristics. A surprising ranking of substitution elasticities by credit rating emerges from the first panel. Bonds that see greatest

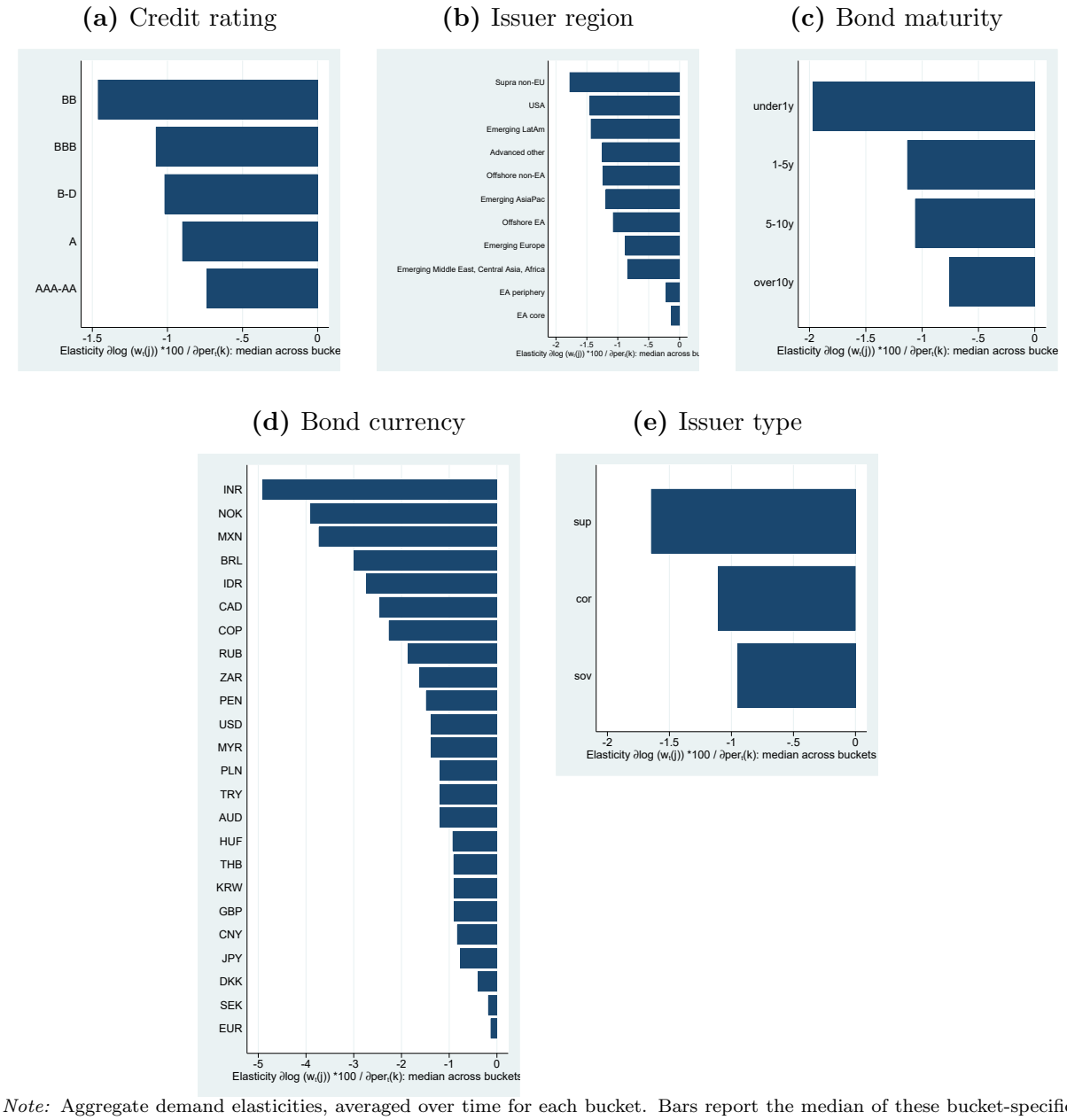
portfolio reallocations after a change in US T-bill returns are the riskiest bonds with ratings of BB+ and lower. Bonds in the same broad rating bucket as US T-bills ("AAA-AA") still see rebalancing flows but only half of the magnitude experienced by risky bonds. These results suggest that a higher return on the safest US Treasuries induces funds to de-risk rather than sell bonds with a similar risk profile and keep the riskiness of their own portfolio constant. If the source of the shock to US T-bill returns is US monetary policy tightening, this ranking along bond credit ratings is consistent with a risk-taking channel of monetary policy operating through investment fund holdings. Tracing the origins of these aggregate substitution pattern to the portfolio rebalancing by US and EA funds in Appendix Figures D.32 and D.33 confirms that riskier bonds see the greatest rebalancing regardless of the identity of the US T-bills investor.

The second panel of Figure 9 highlights the issuer regions most and least affected by US T-bill return shocks. Bonds issued by all regions other than euro area are significantly affected. Supranational issuers other than the European Union (mostly development banks that fund projects in developing countries), other US mostly corporate issuers and Latin American bonds are the bonds experiencing the most significant spillovers. A similar ranking of bond substitutions from US T-bills can be found when examining the cross-elasticities of US and EA funds in Appendix Figures D.32 and D.33. EA funds are particularly unlikely to substitute between US T-bills and euro area bonds. Consistent with the substitutes' ranking by issuer, substitutions by bond currency in the fourth panel of Figure 9 are greatest for emerging market currencies such as the Indian rupee (INR), Norwegian krona (NOK) and Mexican peso (MXN), and weakest for bonds denominated in euros and the closely-linked currencies of Denmark (DKK) and Sweden (SEK).

Interestingly, the spillovers from US T-bill return changes are greatest for bonds of the same short maturity (third panel of Figure 9) and this finding holds across funds domiciled in the US and euro area alike. Thus, portfolio rebalancing by mutual funds across the credit risk spectrum seems stronger than their rebalancing along the yield curve. In terms of the issuer type (last panel of Figure 9), substitutions to corporate and sovereign bonds are similar yet weaker than substitutions to the smaller pool of supranational bonds – consistent with the elasticity ranking by issuer region discussed above.

These substitution patterns help understand the global role of US Treasuries as a safe asset. Shocks to their returns spill over globally, across bonds with different credit ratings, issuer types, regions and bond currencies. Surprisingly, the only regional segmentation of these US return spillovers are to euro area bonds, which to some degree reflects the composition of EA fund portfolios. The patterns discussed here are not an isolated feature of the shortest-dated US Treasuries either – they also hold for the substitution patterns observed in response to shifts to the returns of Treasuries with maturities greater than a year (Appendix Figures D.36-D.38).

Figure 9: Substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds with maturity of less than 1 year by bond characteristics

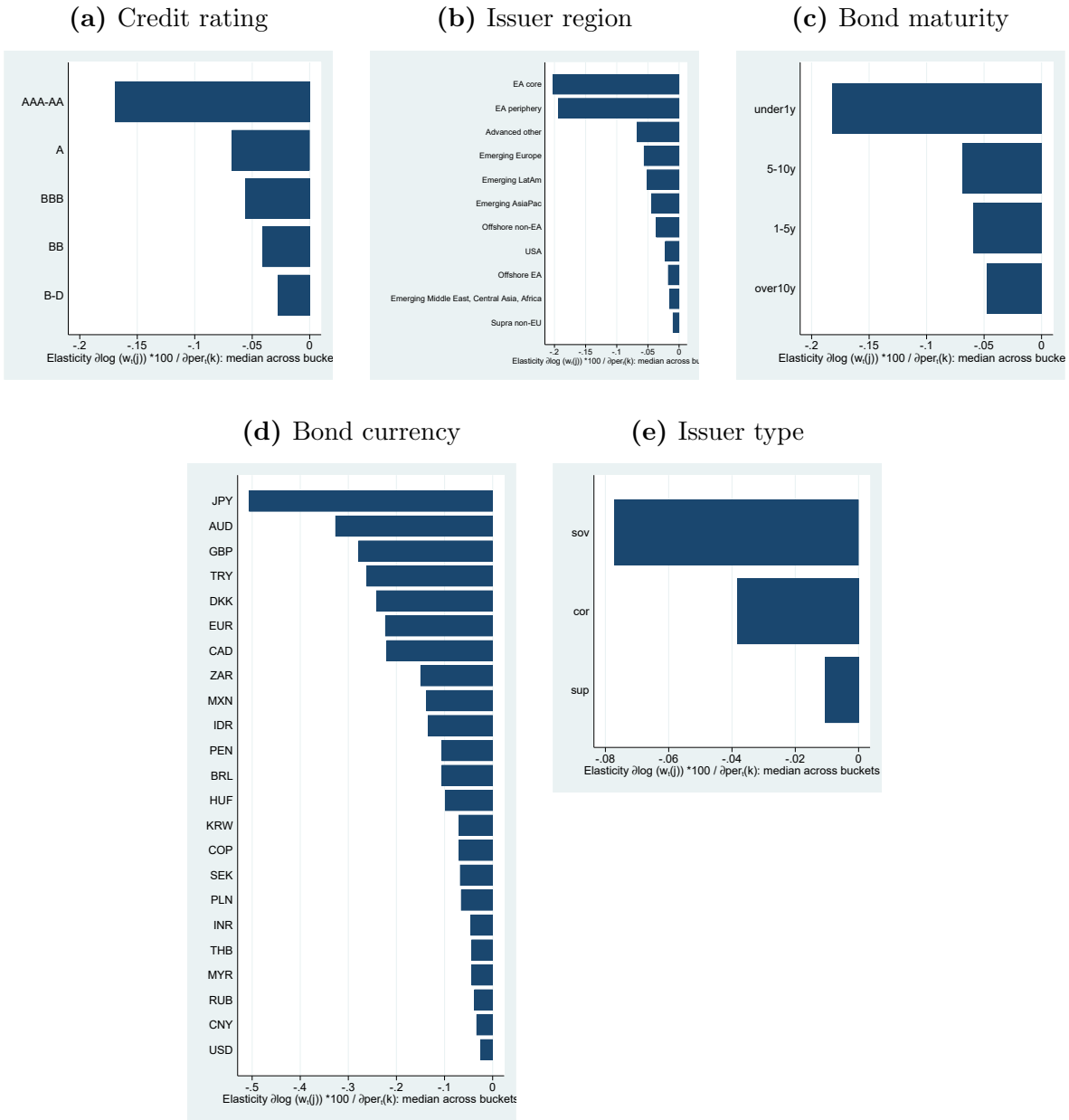


Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

I next turn to the substitution elasticities following a shock to the predicted returns on the safest asset in the euro currency area – German government bonds with residual maturity of less than one year (Figure 10). For the sake of brevity, I continue to abuse the shorthand "T-bills" when describing these bonds. The portfolio spillovers across international bonds from the safest euro area asset could not be more different to those from the safest US asset. Investment funds that hold German T-bills react to that asset's predicted return increase by mostly reducing their exposure to similar bonds – those rated "AA-" or higher (first panel), issued by euro area (second panel) sovereigns (last panel), with a maturity of under 1 year (third panel). The denomination of bonds with a highest substitutability to German bonds is either also the euro or currencies of advanced economies such as

the Japanese yen, Australian dollar, British pound, but not US dollars. Indeed, dollar-denominated bonds see the least portfolio rebalancing in response to German bond return shifts (fourth panel of Figure 10). This suggests that the leading safe assets of the dollar and euro currency area (US and German T-bills) are not substitutable in mutual fund portfolios.

Figure 10: Substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds with maturity of less than 1 year by bond characteristics



Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Most of these substitution patterns are shared among US (Appendix Figure D.34) and EA funds (Appendix Figure D.35). They do not simply reflect the home bias of local investors in euro area bond markets. The only substitution pattern that differs across US and EA funds is the preference for sovereign over corporate bonds as German T-bill substitutes. The latter pattern is driven by US funds' portfolios, where German bunds

are held in conjunction primarily with other sovereign bonds (Appendix Figure D.34). As for US Treasury substitutes, these patterns are also remarkably stable regardless of which segment of the German government yield curve I consider (Appendix Figures D.39-D.41).

These substitution patterns consistently suggest that the safest bonds of the dollar and euro currency areas trigger very different international portfolio adjustments. Investment funds reduce their portfolio allocation to bonds with high credit risk most to make room for more US Treasuries holdings when the latter returns increase. In contrast, they substitute safe, sovereign and euro area bonds for more German Bunds when the latter's return rises. These orthogonal portfolio spillovers of shocks to the two safe assets are consistent with German Bund owners having a much more concentrated bond portfolio – both geographically and in terms of risk exposures. The funds holdings US Treasuries, on the other hand, are more diverse – their bond substitutions thus affect a more diverse set of bonds. Hence, one safe asset plays a global role in international portfolios – US Treasuries are the safe asset of choice across funds with diverse investment universes. The other safe asset is regional – it provides a safe or liquid component in portfolios of primarily euro area sovereign bonds.

Furthermore, this evidence enriches the conclusion drawn from own elasticities that both US Treasuries and German Bunds are safe assets – as measured by their lower elasticity of demand than other bonds. The strikingly different substitution results revealed in this subsection emphasize that while both are safe assets, they are also *very different* safe assets. US Treasuries provide the safe asset component to global portfolios with different regional and risk profiles and thus their return changes spill over globally and across the risk spectrum. German Bunds build the safe asset component only of bond portfolios more concentrated on euro area safe assets. Shocks to German Bunds thus spill over more locally.

5.3 Flight to safety

Next, I use the elasticity estimates to address the question whether safe asset 'specialness' is stable or varies over time. Is funds' demand for safety sensitive to general market conditions and how? For instance, safe assets are often considered to be at the centre of 'flights to safety' during periods of heightened stress in financial markets. Do international investment funds contribute to this phenomenon and can we learn anything from their heterogeneous behaviours during market stress? To this end I again examine the estimated safe bonds' demand elasticities – both relative to all bonds in the demand system (as captured by their own elasticity) and relative to specific risky bonds (i.e. their cross-elasticities) – but now focus on the time variation in specific series.

Focussing on the global safe asset – US Treasuries – I first summarize how its own demand elasticity comoves with commonly-used measures of market risk. I remind the reader that, as discussed at the end of Section 4, there are two sources of time variation in the estimated safe asset elasticities given by equation (15): (ii) changes to the investor base of the bond of interest, $\sum_i \frac{AUM_{i,t}w_{i,t}(j)}{\sum_i(AUM_{i,t}w_{i,t}(j))}\widehat{\alpha}_{T(i)}$, and (ii) funds' portfolio exposure to the safe asset $w_{i,t}(k)$.[62] Across the four different maturity buckets of US Treasuries in particular,

[62] A reminder on subscripts: i indexes an individual fund; the bond whose predicted excess return changes is indexed by k; and the bond whose holdings change in response is indexed by j; quarterly time

investor composition changes account for at least 75% of variation in elasticities over time.

Table 7: Correlations between US sovereign bond elasticities and risk measures

	US sov <1y	US sov 1-5y	US sov 5-10y	US sov >10y
Elasticities				
US sov <1y	1.000			
US sov 1-5y	0.555***	1.000		
US sov 5-10y	0.375***	0.564***	1.000	
US sov >10y	0.294**	0.512***	0.453***	1.000
Risk				
VIX	-0.304**	-0.265**	-0.167	-0.245*
BEX risk aversion	-0.210	-0.215	-0.101	-0.222
BHL risk aversion	-0.319**	-0.195	-0.086	-0.187
MOVE	0.197	-0.013	-0.161	-0.187
EBP	-0.044	-0.303**	-0.269**	-0.255*
CISSEAbond	-0.064	-0.214	-0.067	-0.233*

Note: *** Significant at 1% level. ** Significant at 5% level. * Significant at 10% level.

Table 7 reports the pairwise correlations between the four buckets of US Treasuries in the upper panel, and between each bucket's elasticity and six different measures of market stress in the lower panel. Reassuringly, time variation in elasticities of US Treasuries of different maturity are significantly correlated with each other (top panel). They are also negatively correlated with all measures of market stress – when aggregate risk aversion is high, US Treasuries face the lowest demand elasticities. The pattern holds across different Treasury maturities and different measures of risk aversion (based on equity markets like VIX, on multiple asset classes – BEX and BHL, on Treasury markets – MOVE, on US corporate bond markets – EBP, as well as on EA bond markets – CISSEAbond). Investment funds value the safety of US Treasuries more in times of stress (have lower demand elasticity) and contribute to the overall flight to safety patterns observed in international financial markets.

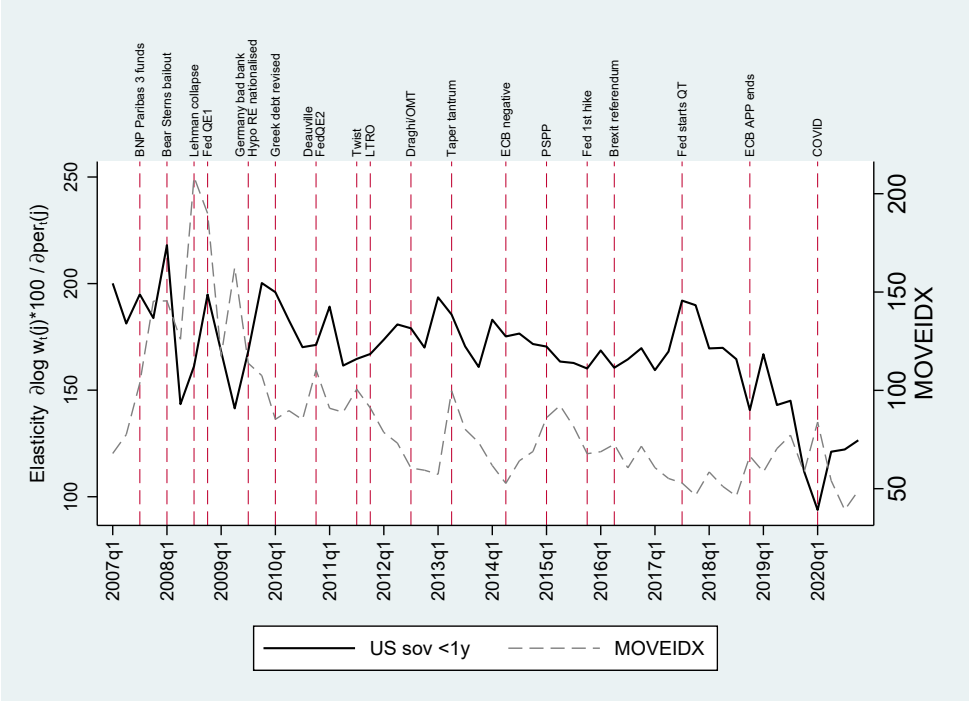
Appendix Tables D.17-D.19 report the same elasticity correlations over time for three other safe asset candidates – German, Swiss and Japanese sovereign bonds – and find they are less of a focal point for flight to safety episodes. German elasticity have little correlation with market stress and at long maturities even increase when risk aversion rises at odds with a flight to safety. Swiss bonds experience lower demand elasticities during market stress but predominantly at maturities of 5 years or longer, while the correlations of Japanese bond demand elasticities with risk aversion suggest a flight to safety only to the shortest-dated bonds.

So who are the funds that demand more US Treasuries than warranted by relative returns during financial stress? Figure 11 compares the fluctuations in the US T-bill elasticity (black line) to one of the risk aversion measures considered – the option-implied volatility of long-dated US Treasuries, i.e. the MOVE index. For better visibility, key market and policy events are marked with vertical red dashed lines. The Lehman Brothers collapse

periods are indexed by t.

at the pinnacle of market panic during the Global Financial Crisis (2008Q3) and the lead-up to it saw a marked drop in the elasticity of US T-bills (from 200% to about 150%). Examining the underlying holdings data suggests this decline in elasticity can be traced back to Treasuries buying by return-insensitive US passive balanced funds. In a similar fashion, the market turmoil in March 2020 at the onset of the global COVID pandemic coincides with a sharp fall in T-bills' elasticity. This time the compositional driver is buying by US passive fixed income funds – who were presumably channelling increased savings (in response to greater uncertainty and lockdown measures) to the safest assets. Interestingly, the same episode is associated with a much weaker decline in the elasticities of US Treasuries with maturities of 1-10 years and even an increase in the very long US Treasuries' elasticity (Appendix Figure D.42). This is consistent with the increased demand for cash and cash-like instruments (i.e. shorter-maturity bonds) and the temporary illiquidity in long-term Treasury markets during this episode (He et al., 2022). To sum up, return insensitive passive funds tend to buy the safe assets when risk aversion increases. This may be due to their desire to return their portfolios closer to a safe benchmark or to channel net inflows by end-investors to the least risky mutual funds. Whichever the source, US Treasuries benefit from an increase in their 'specialness' in bad times.

Figure 11: Own demand elasticities $\eta_t(jj)$ of US T-bills



Black line: Funds' demand elasticity for US Treasuries with maturity under 1 year to changes *w.r.t.* 1ppt change in its predicted excess returns.

The evidence on safe asset own elasticities showcases how the relative safety compared to all bonds in the demand system changes with time. I now turn to some of the key substitution elasticities of safe assets with risky bonds. Figure 12 tracks the substitutability between long-dated US Treasuries and "BBB"-rated US corporate bonds of comparable maturity. Now, when the black line (substitution elasticity) increases, the safe and risky bonds become worse substitutes. Strikingly, times of heightened market stress (high

MOVE index) coincide with low substitutability between US Treasuries and risky corporate bonds. At the height of the global financial crisis in 2008, the substitution elasticity of US corporate bonds in response to US Treasuries halves (from -12% to -6%) and only returns back to pre-crisis levels toards the end of 2013. The COVID market turmoil in March 2020 sees the elasticity tick up again (i.e. substitutability declines) but only marginally so perhaps thanks to the swift intervention of the Fed in US corporate bond markets (Gilchrist, Wei, Yue and Zakrajšek, 2020). Appendix Figure D.43 compares the US Treasury-BBB US corporate bond substitutability across all four maturity buckets and confirms that safe-risky bond substitution declines with market stress.

This relative aspect of flight to safety is particularly important for the transmission of monetary policy through portfolio rebalancing by private investors. The most commonly used monetary policy tools – conventional rate changes, forward guidance as well as government bond purchases – affect the rate of return on safe assets of different maturities. Textbook monetary policy transmission assumes the shift in the return on safe assets transmits to riskier assets and ultimately to broader borrowing costs partly through the rebalancing of private investors' portfolios away from (the lower yielding) safe assets and towards riskier (higher return) assets. My results suggest the effective transmission of monetary policy through substitution from safe to risky assets changes over time and, in particular, during periods of heightened stress.

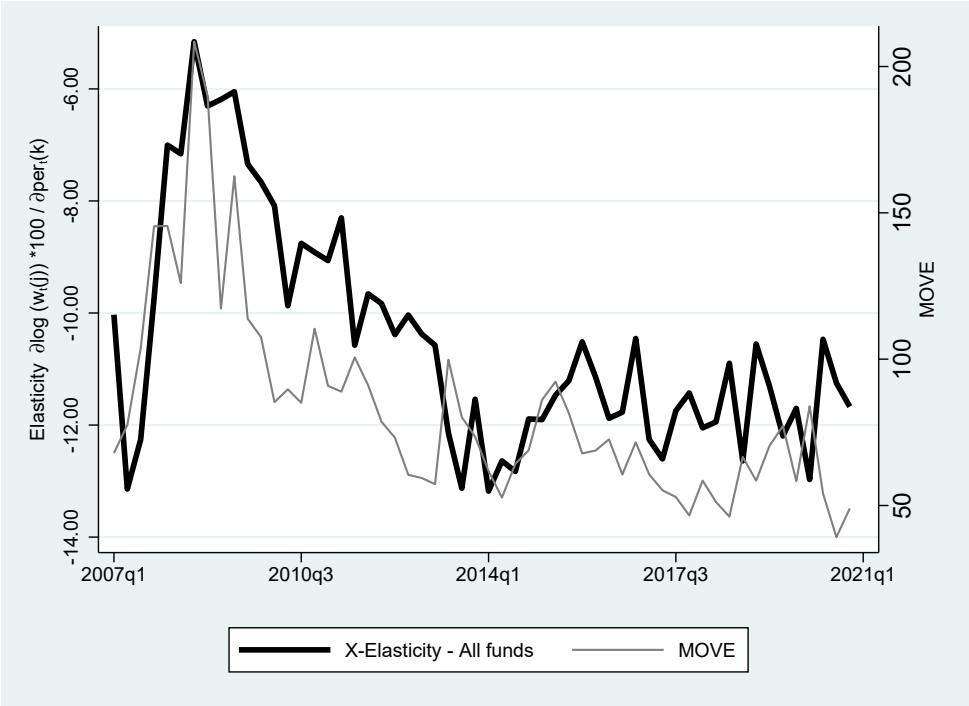
To give a sense of the economic significance of these changes to the substitutability between safe and risky assets, I perform a back-of-the-envelope calculation of the fund rebalancing to BBB corporate bonds following Fed purchases of US Treasuries under different bond demand elasticities. Suppose the Fed purchases $100 billion US Treasuries from the fund sector.[63] Let's assume the purchases are made during tranquil times to counter a recession, not a financial crisis. This implies that funds have a higher-than-average demand elasticity for US Treasuries of around 210%[64] and would need returns to decrease by 5-21 basis points to part with their Treasury holdings. As an example, let us also assume the purchases are spread along the four maturity buckets in the same way as they were during the Fed's QE2 programme announced in late 2011 (6% under 1 year, 43% 1-5 years, 44% 5-10 years, 7% over 10 years). I take into account all US BBB corporate bond substitutions (i.e. 16 in total – 4 substitution elasticities in response to each of the four US Treasury buckets) and calculate the implied overall increase in funds' corporate bond allocation is 5%. Fund holdings of US BBB-rated corporate bonds are $556 billion at the end of 2020, so this 5% increase corresponds to $28 billion corporate bond purchases. Of course, these calculations do not take into account changes to expected corporate bond returns required to clear markets after the increase in demand or the effects of channels other than portfolio rebalancing on corporate bond returns. I, therefore, find them useful primarily as a comparison to the numbers implied from the same partial equilibrium exercise but using demand elasticities from a different period.

[63] In reality the Fed purchases bonds from a variety of sectors but also the overall size of its QE programmes have been several times larger than $100 billion. For instance, the latest round of QE in response to the COVID pandemic outbreak in early 2020 saw the Fed purchase $2 trillion worth of US Treasuries.

[64] This figure corresponds to the average elasticity across the four maturity buckets of US Treasuries. The bucket-specific elasticities are 218% for bonds with less than a year until maturity, 195% for 1-5 year bonds, 219% for 5-10 year bonds, and 210% for bonds with maturity over 10 years.

Looking instead at the lower demand elasticities for US Treasuries and lesser substitutability with risky bonds during periods of financial stress implies much more limited portfolio rebalancing flows into US BBB corporate bonds from the same amount of US Treasury purchases. During periods of stress the average demand elasticity of US Treasuries is lower (130% average across the four maturity buckets) as investors are less willing to part with the safety or liquidity benefits yielded by these assets. Funds thus require a larger adjustment in US Treasury returns – a fall by 8-33 basis points depending on the maturity bucket – to induce them to sell to the Fed. Even so, the worse substitutability between risky BBB-rated corporate bonds and Treasuries at times of heightened risk implies only half of the portfolio rebalancing compared to normal times. Specifically, funds increase their corporate bond holdings by only 2.5% or $14 billion, according to end-2020 holdings. Albeit quite rough and partial, these calculations flag that the portfolio rebalancing channel of Treasury purchases may be severely impaired during financial crises when investors are less willing to substitute between safe and risky assets. This likely has broader implications for asset prices and the transmission of monetary policy, and ultimately affects the financing conditions for the real economy.

Figure 12: Substitutability of US corporate bonds (BBB-rated, over 10y maturity) with US Treasuries

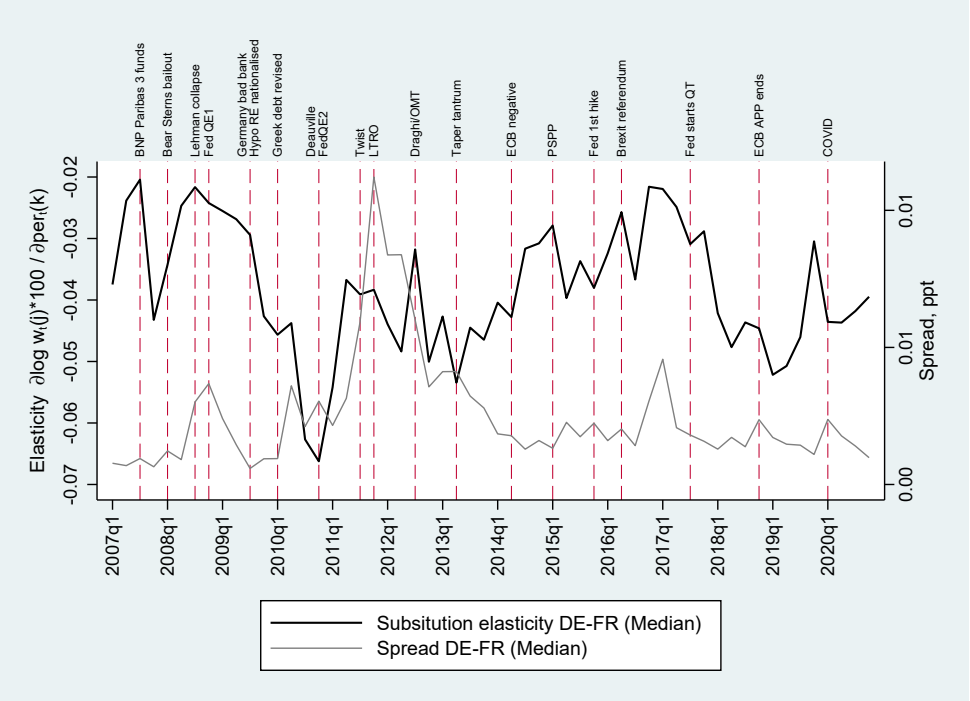


Black line: Substitution elasticity of BBB-rated US corporate bonds with maturity of over 10 years *w.r.t.* 1ppt change in predicted excess returns on US Treasury with maturity over 10 years.

Finally, I show that the decline in substitutability between safe and risky assets is not limited to one safe asset by examining the time variation in the substitutability of German Bunds with other riskier bonds. Consistent with the concentration of German Bund substitutes within euro area sovereigns and motivated by the euro area crisis that unfolded in the middle of my estimation sample (2010–2012), I differentiate between sovereigns perceived to be in the euro area 'core' and 'periphery'.

Figure 13 compares the substitutability of Germany with one of the 'core' euro area countries – France. The two governments' bonds are close to unsubstitutable at the height of the GFC in late-2008 but as market stress eases post-crisis France becomes a better substitute for Germany (substitution elasticity becomes more negative) by the end of 2009. At first, when Greek debt problems become clear in early 2010, substitutability between the euro area core countries improves. But by the end of 2010 when contagion spreads across the euro area[65] the status of French government bonds as substitutes for Germany sharply deteriorates (the elasticity jumps towards zero). French substitutability with German Bunds only partly recovers towards the end of the sample – from 2018 onwards. The figure plots the substitutability against the French-German yield spread, highlighting that demand elasticities provide distinct information from observable market rates. The decline in substitutability and widening of French-German spreads at the end of 2010 broadly coincide but elasticities provide additional information on private investor behaviour during the later period when spreads remain very stable, partly supported by significant intervention by the European Central Bank in euro area sovereign bond markets. Appendix Figures D.44 and D.45 document similar dynamics of the substitutability of two other euro area core countries – Belgium and Netherlands – with safe German Bunds.

Figure 13: Substitutability of German and French sovereign bonds



Black line: Substitution elasticity of French sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

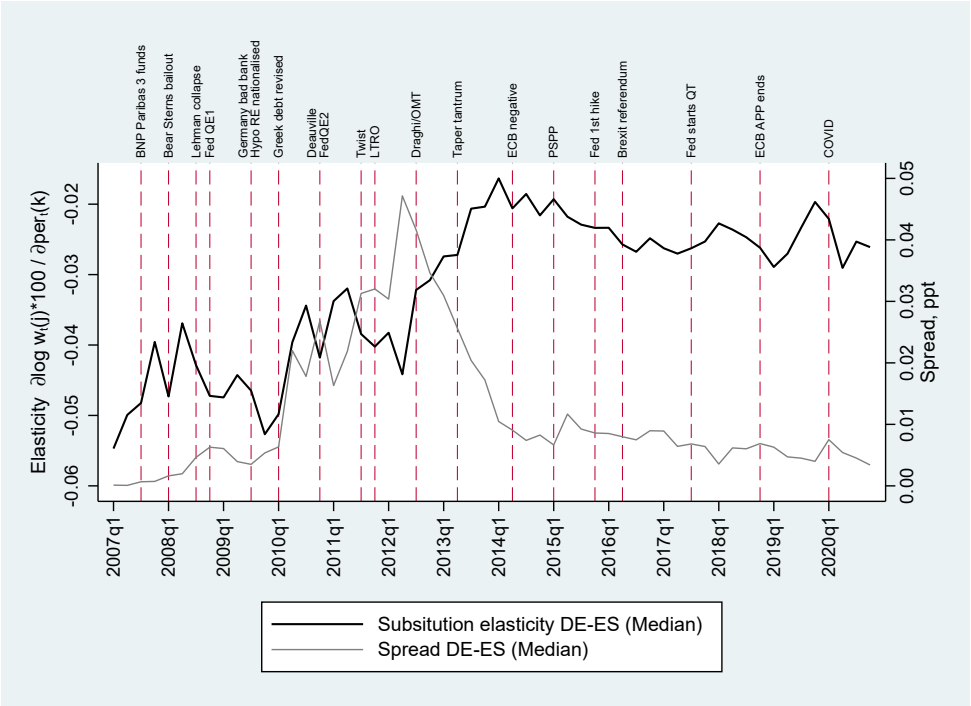
I next turn to the euro area 'periphery' and examine the substitutability of Spanish government debt with German Bunds in Figure 14. In line with the widening of Spanish-

[65]The Deauville summit in October 2010, where French and German leaders Sarkozy and Merkel agree that future euro area sovereign bailouts would involve private investor participation, is widely considered a trigger of wider contagion within the euro area.

German spreads, the substitution elasticity between euro area core and periphery deteriorates (jumps towards zero) already in early 2010 with the revision of Greek debt statistics. Contagion from Greece to the euro area periphery happens instantaneously rather than with a lag like to euro area core countries. What is most striking, however, is that while Spanish-German spreads eventually compress after extensive policy interventions (by fiscal and monetary authorities alike), the substitutability of German and Spanish bonds in mutual fund portfolios remains suppressed. A similar pattern of declining substitutability between German Bunds and Italian government debt is shown in Appendix Figure D.46.

This persistent decline in the substitutability between euro area periphery and core could have significant implications for the transmission of the euro area's single monetary policy. In particular, policies that only affect safe euro rates may have limited effects on borrowing costs of the periphery. Unlike the time variation of risky asset substitutability with US Treasuries, the euro area market segmentation seems worryingly more persistent and not limited to short-lived market turmoil.

Figure 14: Substitutability of German and Spanish sovereign bonds



Black line: Substitution elasticity of Spanish sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

In summary, the time variation in bond elasticities reveals three important patterns: (i) safe asset 'specialness' increases in times of stress in line with flight to safety by mutual funds; (ii) this implies substitutability between safe and risky assets is especially impaired during market turmoil with significant implications for the effectiveness of monetary policies that rely on transmission from safe asset interest rates to riskier borrowers' costs; (iii) a persistent decline in the substitutability between German and peripheral euro area sovereign debt indicates continuing market segmentation within the euro area even after extensive sovereign bond purchases by the European Central Bank.

6 Conclusions

This paper estimates international bond demand by mutual funds using a rich and granular dataset of security-level holdings. Investor heterogeneity in bond preferences combined with a rich set of fund and bond controls allows the estimation of demand elasticities across international bonds of various credit quality and maturity, issued by different countries and sectors, in many currencies. Demand elasticities for highly-rated sovereign bonds with short maturities are estimated to be lowest, while risky, corporate or emerging market bonds face roughly double the elasticities. Estimated low bond demand elasticities offer a new measure of safe asset 'specialness' rooted in observed investor behaviour.

In addition, substitution elasticities with respect to safe asset returns reveal no two safe assets are the same in investors' eyes. US Treasuries are a global safe asset and any shock to their returns trickles globally via international portfolio allocations. Risky and emerging market bonds experience the greatest spillovers. German Bunds, on the other hand, play a regional safe asset role and shocks to their returns affect primarily the portfolio allocations to other highly-rated euro area sovereign bonds. Strikingly, safe asset 'specialness' increases in times of market stress and the substitutability between safe and risky assets deteriorates. This implies a major impairment in the effectiveness of monetary policies that rely on private investors to intermediate impulses from safe interest rates to riskier parts of bond markets during times of stress.

More broadly, the dataset and methodology developed in this paper deliver a detailed mapping of demand elasticities in global bond markets that can be used to evaluate the international financial transmission of a range of risk or policy shocks. Heterogeneous bond substitutability across borders implies variable degrees of international financial integration across different segments of the bond market. Such heterogeneous market segmentation can have profound implication for the cross-border transmission of shocks as well as long-term economic outcomes (Kleinman, Liu, Redding and Yogo, 2023).

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A Dataset

Figure A.15: Morningstar debt security holdings: representativeness vs financial accounts

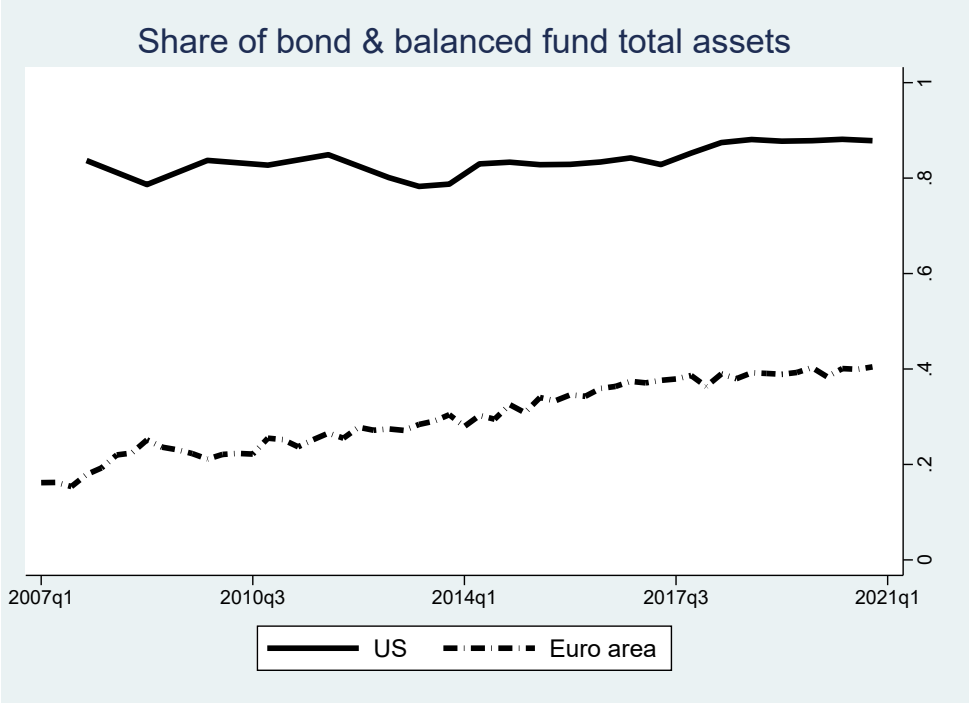


Figure A.16: Refinitiv debt security types – by pricing data availability

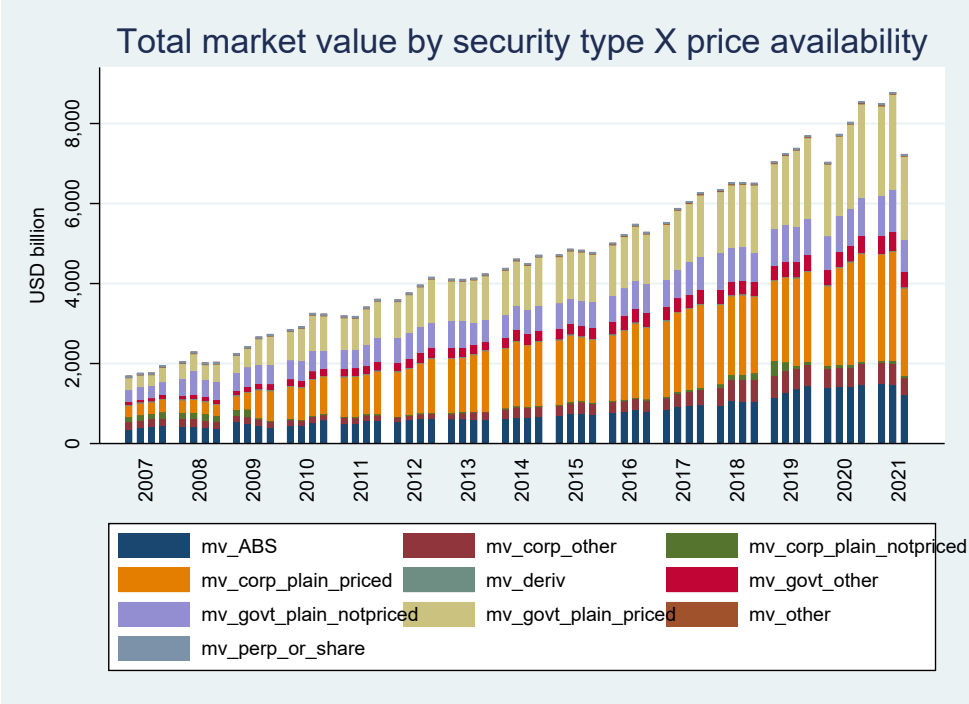


Table A.8: Top 30 funds by bond holdings, MV as of end-2020

Fund	Firm	Category	Domicile	Rank	BondMV_USDbn
Vanguard Total Intl Bd Idx Institutional	Vanguard	Fixed Income	US	1	149.4
Vanguard Short-Term Bond Index Inv	Vanguard	Fixed Income	US	2	57.67
iShares Core US Aggregate Bond ETF	iShares	Fixed Income	US	3	57.04
Metropolitan West Total Return Bd M	Metropolitan West Funds	Fixed Income	US	4	54.74
Vanguard Short-Term Investment-Grade Inv	Vanguard	Fixed Income	US	5	48.71
iShares iBoxx $ Invmt Grade Corp Bd ETF	iShares	Fixed Income	US	6	47.34
GS USD Treasury Liq Res Pref Acc	Goldman Sachs Asset Management Fund Services Ltd	Money Market	IE	7	41.61
Fidelity US Bond Index	Fidelity Investments	Fixed Income	US	8	38.48
Vanguard Interm-Term Corp Bd Idx Instl	Vanguard	Fixed Income	US	9	37.82
Vanguard Interm-Term Bond Index Inv	Vanguard	Fixed Income	US	10	37.14
American Funds Bond Fund of Amer A	American Funds	Fixed Income	US	11	36.94
PIMCO Income Instl	PIMCO	Fixed Income	US	12	36.91
Vanguard Short-Term Corp Bd Idx I	Vanguard	Fixed Income	US	13	36.15
American Funds American Balanced A	American Funds	Allocation	US	14	32.71
PIMCO Total Return Instl	PIMCO	Fixed Income	US	15	31.00
JPM USD Treasury CNAV Ins (dist.)	JPMorgan Asset Management (Europe) S.Ã r.l.	Money Market	LU	16	30.69
PGIM Total Return Bond A	PGIM Funds (Prudential)	Fixed Income	US	17	29.62
Dodge & Cox Income	Dodge & Cox	Fixed Income	US	18	29.46
Vanguard Wellesley Income Inv	Vanguard	Allocation	US	19	28.73
Vanguard Interm-Term Invmt-Grade Inv	Vanguard	Fixed Income	US	20	28.58
Vanguard Wellington Inv	Vanguard	Allocation	US	21	27.89
Lord Abbett Short Duration Income A	Lord Abbett	Fixed Income	US	22	25.91
Vanguard High-Yield Corporate Inv	Vanguard	Fixed Income	US	23	23.40
iShares iBoxx $ High Yield Corp Bd ETF	iShares	Fixed Income	US	24	23.33
Western Asset Core Plus Bond I	Franklin Templeton Investments	Fixed Income	US	25	21.40
Fidelity Series Investment Grade Bond	Fidelity Investments	Fixed Income	US	26	20.80
AB American Income C Inc	AllianceBernstein (Luxembourg) S.Ã r.l.	Fixed Income	LU	27	20.71
BlackRock High Yield Bond K	BlackRock	Fixed Income	US	28	19.77
iShares 1-3 Year Treasury Bond ETF	iShares	Fixed Income	US	29	19.11
iShares 20+ Year Treasury Bond ETF	iShares	Fixed Income	US	30	19.08

Table A.9: Summary of funds' bond portfolios

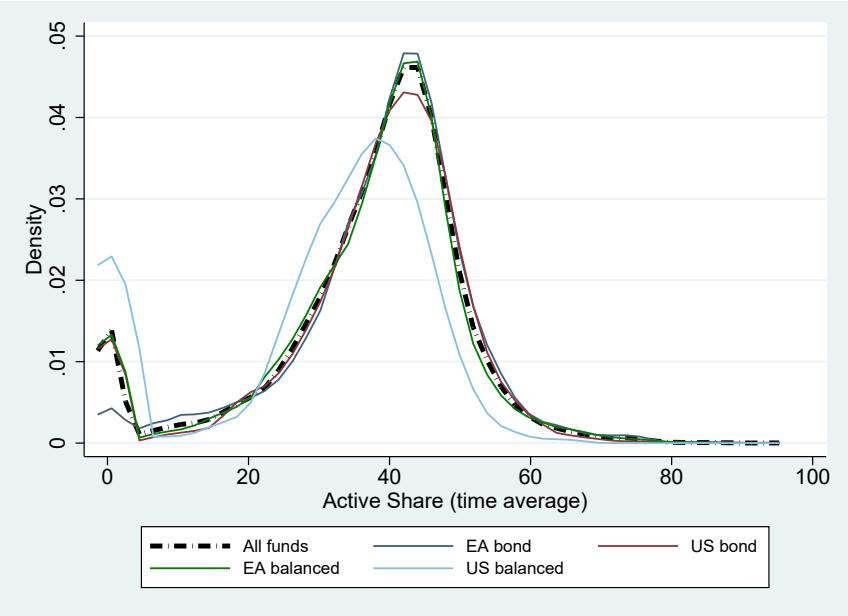
Portfolio of:	All funds mean	EA bond mean	US bond mean	EA allocation mean	US allocation mean	EA MMFs mean
Mat. bucket under1y	0.20	0.08	0.07	0.11	0.07	0.85
Mat. bucket 1-5y	0.39	0.41	0.39	0.43	0.38	0.33
Mat. bucket 5-10y	0.36	0.39	0.39	0.37	0.38	0.26
Mat. bucket over10y	0.21	0.21	0.21	0.18	0.20	0.31
Weighted maturity	6.51	7.41	8.01	6.58	8.09	1.01
Rating bucket AAA-AA	0.44	0.37	0.38	0.50	0.42	0.53
Rating bucket A	0.22	0.22	0.18	0.20	0.19	0.33
Rating bucket BBB	0.27	0.30	0.28	0.25	0.25	0.29
Rating bucket BB	0.10	0.11	0.14	0.08	0.10	0.06
Rating bucket B-D	0.07	0.10	0.10	0.06	0.07	0.03
Asset type cor	0.57	0.55	0.61	0.47	0.59	0.68
Asset type sov	0.46	0.48	0.42	0.54	0.43	0.40
Asset type sup	0.04	0.05	0.02	0.06	0.01	0.09
USD bonds	0.63	0.51	0.88	0.27	0.89	0.64
EUR bonds	0.47	0.63	0.15	0.69	0.10	0.87
CHF bonds	0.30	0.30	0.03	0.42	0.04	0.79
JPY bonds	0.15	0.14	0.11	0.08	0.11	0.36
GBP bonds	0.14	0.12	0.05	0.06	0.04	0.60
US bonds	0.42	0.25	0.68	0.18	0.75	0.18
DE bonds	0.11	0.12	0.04	0.18	0.03	0.15
FR bonds	0.10	0.12	0.02	0.14	0.02	0.21
IT bonds	0.09	0.10	0.02	0.11	0.02	0.21
ES bonds	0.06	0.07	0.02	0.08	0.01	0.14

Table A.10: Summary of funds, with Active Share

Fund Type	Number of Funds	%All-fund AUM	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th Percentile)	Active Share % (Median)	Active Share % (90th Percentile)
US bond passive	524	20	0.95	294	3,446	33	45
US bond active	676	29	1.35	384	4,404	45	56
EA bond passive	949	9	0.62	142	1,069	35	44
EA bond active	1,006	13	0.73	187	1,547	45	53
US balanced passive	135	8	0.10	316	3,876	27	41
US balanced active	203	13	0.25	350	4,013	41	51
EA balanced passive	375	2	0.05	62	516	35	45
EA balanced active	595	5	0.15	89	876	45	51

Bond Active Share : Sum of absolute bond portfolio weight deviations from market-value-weighted fund bond universe weights, divided by 2 (Koijen, Richmond and Yogo, 2020b). Passive / Active : funds with below- / above-median Bond Active Share, on average over time.

Figure A.17: Distribution of Bond Active Share by 4 broad fund types



Bond Active Share : Sum of absolute bond portfolio weight deviations from market-value-weighted fund bond universe weights, divided by 2 (Koijen, Richmond and Yogo, 2020b).

Table A.11: Summary of funds over time

Year	Number of Funds	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th Percentile)	Active Share % (Median)	Active Share % (90th Percentile)
2007	2,086	2.31	184	1,686	40	49
2008	2,487	2.29	162	1,463	40	49
2009	2,903	2.80	143	1,237	40	50
2010	3,236	3.58	169	1,530	40	50
2011	3,603	3.47	159	1,558	41	50
2012	3,950	3.80	160	1,690	41	50
2013	4,253	3.95	172	1,854	41	50
2014	4,660	4.33	172	1,987	41	50
2015	5,078	4.81	164	1,918	41	50
2016	5,429	5.05	164	1,937	41	51
2017	5,726	5.45	178	2,042	41	50
2018	6,018	5.36	178	2,130	41	51
2019	6,471	5.85	182	2,097	41	53
2020	6,586	5.68	192	2,188	42	56

Table A.12: Persistence of bond holdings

	Previous Quarters										
Fund Type	1	2	3	4	5	6	7	8	9	10	11
US bond passive	92	93	93	94	94	95	95	95	95	95	95
US bond active	90	91	92	92	93	93	94	94	94	94	94
EA bond passive	91	92	93	93	94	94	94	95	95	95	95
EA bond active	89	90	91	92	93	93	93	93	94	94	94
US balanced passive	93	94	94	95	95	95	95	95	95	95	96
US balanced active	90	91	92	92	93	93	93	93	94	94	94
EA balanced passive	91	92	93	93	94	94	94	94	94	95	95
EA balanced active	89	90	91	91	92	92	92	93	93	93	93

B Derivation of bond demand model

B.1 Baseline international CAPM with risk-free outside asset

Investment fund i ($i = 1, \ldots, I$) chooses allocation across $|\mathcal{N}_{i,t}|$ risky assets ($\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$) and one outside asset. Gross returns are expressed in investor i's currency and stacked in $|\mathcal{N}_{i,t}|$-dimensional vector $\mathbf{R}_{i,t+1}$. The return on the outside asset is $R_{i,t+1}(0)$ and assumed to be risk-free (as implicitly imposed by Koijen and Yogo (2019) by choosing log-utility). There are two periods t and $t+1$, with investors allocating initial wealth $A_{i,t}$ and deriving utility from net-period wealth $A_{i,t+1}$. Risk preferences are characterized by constant relative risk aversion (CRRA) parameter $\rho_{i,t}$ which is investor- and time-specific. I do not make any assumption about the data-generating process behind $\rho_{i,t}$.

Investor i chooses a vector $\mathbf{w}_{i,t}$ of portfolio weights across bonds in his universe to maximize expected utility from period $t+1$ wealth subject to budges and short-selling constraints:

$$\begin{aligned} \max_{\mathbf{w}_{i,t}} \quad & \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big] \\ \text{s.t.} \quad & A_{i,t+1} = A_{i,t}[R_{i,t+1}(0) + \mathbf{w}_{i,t}'(\mathbf{R}_{i,t+1} - R_{i,t+1}(0)\mathbf{1})] && \text{(B.1)} \\ & \mathbf{w}_{i,t} \geq \mathbf{0} && \text{(B.2)} \\ & \mathbf{1}'\mathbf{w}_{i,t} \leq 1 && \text{(B.3)} \end{aligned}$$

Assuming $A_{i,t+1}$ is lognormal, the objective function and budget constraint can be rewritten in logs. This gives a standard mean-variance optimization problem:

$$\begin{aligned} \max_{\mathbf{w}_{i,t}} \quad & \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big] = \max_{\mathbf{w}_{i,t}} \quad \ln \mathbb{E}_{i,t}\big[A_{i,t+1}^{1-\rho_{i,t}}\big] = \max_{\mathbf{w}_{i,t}} \quad (1-\rho_{i,t})\mathbb{E}_{i,t}a_{i,t+1} + \frac{1}{2}(1-\rho_{i,t})^2\sigma_{a_{i,t}}^2 \\ \text{s.t.} \quad & a_{i,t+1} = a_{i,t} + r_{p,i,t+1} \qquad \text{where} \quad r_{p,i,t+1} = \ln(R_{p,i,t+1}) \end{aligned}$$

where small-case letters denote natural logarithms of level variables, e.g. $a_{i,t} = \ln(A_{i,t})$, and $R_{p,i,t+1}$ is the gross portfolio return of investor i.

Divide the above by $(1-\rho_{i,t})$ and substitute in the log-budget constraint for $a_{i,t+1}$:

$$\max_{\mathbf{w}_{i,t}} \quad \mathbb{E}_{i,t}r_{p,i,t+1} + \frac{1}{2}(1-\rho_{i,t})\sigma_{r_p,i,t}^2 \tag{B.4}$$

where $\sigma_{r_p,i,t}^2$ denotes the conditional variance of log portfolio returns.

To proceed, the log portfolio returns need to be related to log returns on individual bonds. This is done using the approximation of the portfolio return from Campbell and Viceira (2002, equation 2.23):

$$r_{p,i,t+1} - r_{i,t+1}(0) = \mathbf{w}_{i,t}'(\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}) + \frac{1}{2}\mathbf{w}_{i,t}'\sigma_{i,t}^2 - \frac{1}{2}\mathbf{w}_{i,t}'\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} \tag{B.5}$$

where $\mathbf{\Sigma}_{i,t}$ is the conditional covariance matrix of individual excess bond returns $\mathbf{r}_{i,t+1}$,

and $\sigma^2_{i,t}$ is a vector containing their variances (the diagonal elements of $\mathbf{\Sigma}_{i,t}$):

$$\mathbf{\Sigma}_{i,t} \equiv \mathbb{E}_{i,t}\Big[\big(\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1} - \mathbb{E}_{i,t}(\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1})\big)\ \big(\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big)'\Big]$$

To arrive at the optimization in terms of mean and variance of returns, we note these are given by:

$$\begin{aligned}\mathbb{E}_{i,t}\big[r_{p,i,t+1} - r_{i,t+1}(0)\big] &= \mathbf{w}'_{i,t}\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t}\\ \sigma^2_{r_p,i,t} &= \mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t}\end{aligned}$$

The investor then chooses portfolio weights to maximize the objective:

$$\begin{aligned}&\max_{\mathbf{w}_{i,t}} \quad \mathbb{E}_{i,t}r_{p,i,t+1} + \frac{1}{2}(1-\rho_{i,t})\sigma^2_{r_p,i,t}\\ =&\max_{\mathbf{w}_{i,t}} \quad \mathbf{w}'_{i,t}\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} + \frac{1}{2}(1-\rho_{i,t})\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t}\\ =&\max_{\mathbf{w}_{i,t}} \quad \mathbf{w}'_{i,t}\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\rho_{i,t}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t}\end{aligned}$$

This re-arrangement of the constrained problem gives the Lagrangian:

$$L_{i,t} = \mathbf{w}'_{i,t}\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\rho_{i,t}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} + \Lambda'_{i,t}\mathbf{w}_{i,t} + \lambda_{i,t}(1 - \mathbf{1}'\mathbf{w}_{i,t}) \tag{B.6}$$

with first-order condition:

$$\frac{\partial L_{i,t}}{\partial \mathbf{w}_{i,t}} = \mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{\sigma^2_{i,t}}{2} - \rho_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1} = \mathbf{0} \tag{B.7}$$

implying optimal portfolio weight:

$$\begin{aligned}\rho_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} &= \mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{\sigma^2_{i,t}}{2} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}\\ \mathbf{w}_{i,t} &= (\rho_{i,t}\mathbf{\Sigma}_{i,t})^{-1}\Big(\underbrace{\mathbb{E}_{i,t}\big[\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}\big] + \frac{\sigma^2_{i,t}}{2}}_{\equiv\mu_{i,t}} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}\Big)\end{aligned} \tag{B.8}$$

which is exactly the same as equation (A4) in Koijen and Yogo (2019) apart from the risk-aversion parameter $\rho_{i,t}$ being different from one and allowed to vary over time.

Next, to derive an expression for the Lagrange multipliers, partition the bonds into two groups – those for which the short-sale constraint is not binding and those for which it

binds:

$$\Lambda_{i,t} = \begin{bmatrix} \mathbf{0} \\ \Lambda_{i,t}^{(2)} \end{bmatrix}; \qquad \mathbf{w}_{i,t} = \begin{bmatrix} \mathbf{w}_{i,t}^{(1)} \\ \mathbf{0} \end{bmatrix}; \qquad \mu_{i,t} = \begin{bmatrix} \mu_{i,t}^{(1)} \\ \mu_{i,t}^{(2)} \end{bmatrix}; \qquad \mathbf{\Sigma}_{i,t} = \begin{bmatrix} \mathbf{\Sigma}_{i,t}^{(1,1)} & \mathbf{\Sigma}_{i,t}^{(1,2)} \\ \mathbf{\Sigma}_{i,t}^{(2,1)} & \mathbf{\Sigma}_{i,t}^{(2,2)} \end{bmatrix}.$$

The inverse return covariance matrix is:

$$\mathbf{\Sigma}_{i,t}^{-1} = \begin{bmatrix} \mathbf{\Omega}_{i,t}^{(1)} & -\mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Omega}_{i,t}^{(2)} \\ -\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\mathbf{\Omega}_{i,t}^{(1)} & \mathbf{\Omega}_{i,t}^{(2)} \end{bmatrix}.$$

where

$$\begin{aligned} \mathbf{\Omega}_{i,t}^{(1)} &= \left(\mathbf{\Sigma}_{i,t}^{(1,1)} - \mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\right)^{-1} \\ \mathbf{\Omega}_{i,t}^{(2)} &= \left(\mathbf{\Sigma}_{i,t}^{(2,2)} - \mathbf{\Sigma}_{i,t}^{(2,1)}\mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\right)^{-1} \end{aligned}$$

Then re-write the optimal portfolio allocation:

$$\begin{aligned} \mathbf{w}_{i,t} &= (\rho_{i,t}\mathbf{\Sigma}_{i,t})^{-1}\Big(\mu_{i,t} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}\Big) \\ \begin{bmatrix} \mathbf{w}_{i,t}^{(1)} \\ \mathbf{0} \end{bmatrix} &= \begin{bmatrix} \frac{1}{\rho_{i,t}}\Big[\mathbf{\Omega}_{i,t}^{(1)}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) - \mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Omega}_{i,t}^{(2)}(\mu_{i,t}^{(2)} + \Lambda_{i,t}^{(2)} - \lambda_{i,t}\mathbf{1})\Big] \\ \frac{1}{\rho_{i,t}}\Big[-\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\mathbf{\Omega}_{i,t}^{(1)}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) + \mathbf{\Omega}_{i,t}^{(2)}(\mu_{i,t}^{(2)} + \Lambda_{i,t}^{(2)} - \lambda_{i,t}\mathbf{1})\Big] \end{bmatrix} \end{aligned} \tag{B.9}$$

Multiplying the second block by $\mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}$ and adding the two blocks, simplifies the positive portfolio weights expression:

$$\begin{aligned} \mathbf{w}_{i,t}^{(1)} &= \frac{1}{\rho_{i,t}}\Big[\big(\mathbf{\Omega}_{i,t}^{(1)} - \mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\mathbf{\Omega}_{i,t}^{(1)}\big)(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1})\Big] \\ &= \frac{1}{\rho_{i,t}}\Big[\big(\mathbf{I} - \mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\big)\mathbf{\Omega}_{i,t}^{(1)}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1})\Big] \\ &= \frac{1}{\rho_{i,t}}\Big[\mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,1)}\big(\mathbf{I} - \mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Sigma}_{i,t}^{(1,2)}\mathbf{\Sigma}_{i,t}^{(2,2)-1}\mathbf{\Sigma}_{i,t}^{(2,1)}\big)\mathbf{\Omega}_{i,t}^{(1)}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1})\Big] \\ &= \frac{1}{\rho_{i,t}}\Big[\mathbf{\Sigma}_{i,t}^{(1,1)-1}\mathbf{\Omega}_{i,t}^{(1)-1}\mathbf{\Omega}_{i,t}^{(1)}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1})\Big] \\ &= \frac{1}{\rho_{i,t}}\Big(\mathbf{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \end{aligned}$$

By definition, the portfolio weight on the outside asset is then:

$$\begin{aligned} w_{i,t}(0) &= 1 - \mathbf{1}'\mathbf{w}_{i,t}^{(1)} \\ &= 1 - \mathbf{1}'\Big(\rho_{i,t}\mathbf{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \end{aligned} \tag{B.10}$$

We examine the case when constraint $\mathbf{1}'\mathbf{w}_{i,t} \leq 1$ binds (i.e. zero investment in outside asset) to obtain the expression for its Lagrange multiplier:

$$\begin{aligned}
\mathbf{1}'\mathbf{w}_{i,t}^{(1)} = \mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) &= 1 \\
\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mu_{i,t}^{(1)} - \mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mathbf{1}\lambda_{i,t} &= 1 \\
\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mathbf{1}\lambda_{i,t} &= \mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mu_{i,t}^{(1)} - 1 \\
\lambda_{i,t} &= \frac{\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mu_{i,t}^{(1)} - 1}{\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mathbf{1}} \\
\Rightarrow \lambda_{i,t} &= \max\left\{\frac{\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mu_{i,t}^{(1)} - 1}{\mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}_{i,t}^{(1,1)}\Big)^{-1}\mathbf{1}}, \quad 0\right\}
\end{aligned} \tag{B.11}$$

Characteristics-based demand We let $\mathbf{x}_{i,t}(n)$ denote a K-dimensional vector of observed characteristics of bond n and let investors form heterogeneous beliefs about asset returns based on both these observable characteristics and unobservable (to the econometrician) $\log(\epsilon_{i,t}(n))$. Investor i's information set for asset n is collected in vector $\hat{\mathbf{x}}_{\mathbf{i,t}}(n)$, where I separate the endogenous predicted excess returns from other observable characteristics, in keeping with Koijen and Yogo (2019):

$$\hat{\mathbf{x}}_{i,t}(n) = \begin{bmatrix} per_{\chi(i),t}(n) \\ \mathbf{x}_{i,t}(n) \\ \log(\epsilon_{i,t}(n)) \end{bmatrix} \tag{B.12}$$

From these, we form an Mth-order polynomial of characteristics as the following $\sum_{m=1}^{M}(K+2)^m$-dimensional vector $\mathbf{y}_{i,t}(n)$:

$$\mathbf{y}_{i,t}(n) = \begin{bmatrix} \hat{\mathbf{x}}_{i,t}(n) \\ \mathbf{vec}[\hat{\mathbf{x}}_{i,t}(n)\hat{\mathbf{x}}_{i,t}(n)'] \\ \vdots \end{bmatrix} \tag{B.13}$$

Assumption: Returns have a one-factor structure, with *both* expected returns and factor loadings a function of the asset characteristics:

$$\begin{aligned}
\mu_{i,t}(n) &= \mathbf{y_{i,t}}(n)'\boldsymbol{\Phi}_i + \phi_{i,t} \\
\Gamma_{i,t}(n) &= \mathbf{y_{i,t}}(n)'\boldsymbol{\Psi}_i + \psi_{i,t} \\
\boldsymbol{\Sigma}_{i,t} &= \boldsymbol{\Gamma}_{i,t}\boldsymbol{\Gamma}_{i,t}' + \gamma_{i,t}\mathbf{I}, \qquad \gamma_{i,t} > 0
\end{aligned}$$

where to map into the panel estimation specification of this paper, I keep the coefficients that relate bond characteristics to return expectations $\boldsymbol{\Phi}_i$ and factor loadings $\boldsymbol{\Psi}_i$ constant over time (but heterogeneous across investors).

For the subset of assets for which the short-sale constraint is not binding, we have:

$$
\begin{aligned}
\mu_{i,t}^{(1)} &= \mathbf{y_{i,t}^{(1)}}'\mathbf{\Phi}_i + \phi_{i,t}\mathbf{1} \\
\mathbf{\Gamma}_{i,t}^{(1)} &= \mathbf{y_{i,t}^{(1)}}'\mathbf{\Psi}_i + \psi_{i,t}\mathbf{1} \\
\mathbf{w}_{i,t}^{(1)} &= \left(\rho_{i,t}\mathbf{\Sigma}_{i,t}^{(1,1)}\right)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \\
&= \frac{1}{\rho_{i,t}}\left(\mathbf{\Gamma}_{i,t}^{(1)}\mathbf{\Gamma}_{i,t}^{(1)'} + \gamma_{i,t}\mathbf{I}\right)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mathbf{I} + \frac{\mathbf{\Gamma}_{i,t}^{(1)}\mathbf{\Gamma}_{i,t}^{(1)'}}{\gamma_{i,t}}\right)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \\
&\qquad\qquad \mathbf{\Gamma}_{i,t}^{(1)}(\mathbf{I} + \underbrace{\frac{\mathbf{\Gamma}_{i,t}^{(1)'}\mathbf{\Gamma}_{i,t}^{(1)}}{\gamma_{i,t}}}_{\text{scalar}})^{-1}\mathbf{\Gamma}_{i,t}^{(1)'} \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mathbf{I} - \frac{}{\gamma_{i,t}}\right)(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mathbf{I} - \frac{\mathbf{\Gamma}_{i,t}^{(1)}\mathbf{\Gamma}_{i,t}^{(1)'}}{\gamma_{i,t} + \mathbf{\Gamma}_{i,t}^{(1)'}\mathbf{\Gamma}_{i,t}^{(1)}}\right)(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1}) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1} - \mathbf{\Gamma}_{i,t}^{(1)}\underbrace{\frac{\mathbf{\Gamma}_{i,t}^{(1)'}}{\gamma_{i,t} + \mathbf{\Gamma}_{i,t}^{(1)'}\mathbf{\Gamma}_{i,t}^{(1)}}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1})}_{\kappa_{i,t}=\text{scalar}}\right) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1} - \mathbf{\Gamma}_{i,t}^{(1)}\kappa_{i,t}\right) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mathbf{y_{i,t}^{(1)}}'\mathbf{\Phi}_i + \phi_{i,t}\mathbf{1} - \lambda_{i,t}\mathbf{1} - (\mathbf{y_{i,t}^{(1)}}'\mathbf{\Psi}_i + \psi_{i,t}\mathbf{1})\kappa_{i,t}\right) \\
&= \frac{1}{\rho_{i,t}\gamma_{i,t}}\left(\mathbf{y_{i,t}^{(1)}}'(\mathbf{\Phi}_i - \mathbf{\Psi}_i) + (\phi_{i,t} - \lambda_{i,t} - \psi_{i,t}\kappa_{i,t})\mathbf{1}\right) \\
\mathbf{w}_{i,t}^{(1)} &= \frac{1}{\rho_{i,t}}\left(\mathbf{y_{i,t}^{(1)}}'\mathbf{\Pi}_{i,t} + \pi_{i,t}\mathbf{1}\right)
\end{aligned}
\tag{B.14}
$$

where $\mathbf{\Pi}_{i,t} \equiv \frac{\mathbf{\Phi}_i - \mathbf{\Psi}_i}{\gamma_{i,t}}$; $\pi_{i,t} \equiv \frac{\phi_{i,t} - \lambda_{i,t} - \psi_{i,t}\kappa_{i,t}}{\gamma_{i,t}}$ – exactly as in Koijen and Yogo (2019) apart from the constant structural parameters $\mathbf{\Phi}_i$, $\mathbf{\Psi}_i$ and the heterogeneous, time-varying risk aversion $\rho_{i,t}$.

Under the following parameter restrictions on $\mathbf{\Pi}_{i,t}$ and $\pi_{i,t}$:

$$
\frac{\mathbf{\Pi}_{i,t}}{w_{i,t}(0)} = \begin{bmatrix} \hat{\beta}_i \\ vec(\hat{\beta}_i\hat{\beta}_i') \\ \vdots \end{bmatrix}; \qquad \text{and} \qquad \pi_{i,t} = w_{i,t}(0), \tag{B.15}
$$

bond demand can be expressed as an exponential function of characteristics:

$$\begin{aligned}\frac{w_{i,t}(n)}{w_{i,t}(0)} &= \frac{1}{\rho_{i,t}}\left(\mathbf{y}_{i,t}(n)'\frac{\mathbf{\Pi}_{i,t}}{w_{i,t}(0)} + \frac{\pi_{i,t}}{w_{i,t}(0)}\mathbf{1}\right) \\ &= \frac{1}{\rho_{i,t}}\left(1 + \mathbf{y}_{i,t}(n)'\hat{\beta}_i\right) \\ &= \frac{1}{\rho_{i,t}}\left(1 + \hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_i + \frac{\text{vec}(\hat{\mathbf{x}}_{i,t}(n)\hat{\mathbf{x}}_{i,t}(n)')'\ \text{vec}(\hat{\beta}_i\hat{\beta}_i')}{2} + \dots\right) \\ &= \frac{1}{\rho_{i,t}}\sum_{m=0}^{M}\frac{\left(\hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_i\right)^m}{m!} \xrightarrow[M\to\infty]{} \frac{1}{\rho_{i,t}}\exp\left\{\hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_i\right\} \end{aligned} \tag{B.16}$$

Plugging this expression into the constraint $\sum_{n=1}^{|\mathcal{N}_{i,t}|} w_{i,t}(n) + w_{i,t}(0) = 1$, we can write the portfolio weights as functions of characteristics as follows:

$$w_{i,t}(0) = \frac{1}{1 + \sum_{m=1}^{|\mathcal{N}_{i,t}|}\frac{1}{\rho_{i,t}}\exp\left\{\hat{\mathbf{x}}_{i,t}(m)'\hat{\beta}_{i,t}\right\}}; \qquad w_{i,t}(n) = \frac{\frac{1}{\rho_{i,t}}\exp\left\{\hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_{i,t}\right\}}{1 + \sum_{m=1}^{|\mathcal{N}_{i,t}|}\frac{1}{\rho_{i,t}}\exp\left\{\hat{\mathbf{x}}_{i,t}(m)'\hat{\beta}_{i,t}\right\}};$$

Taking the ratio of the weight on any bond n and the outside asset, and then taking logarithm of the ratio yields an empirical Logit estimation consistent with (12):

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = \hat{\mathbf{x}}_{i,t}(n)'\hat{\beta}_{i,t} - \log(\rho_{i,t}) \tag{B.17}$$

where the vector of relevant characteristics $\hat{\mathbf{x}}_{i,t}(n)$ is described in Section **??** and investor-specific changes in risk preferences $\rho_{i,t}$ (as well as other unobservable changes to investor i's overall reported bond portfolio) are captured by investor-time fixed effect $\zeta_{i,t}$.

B.2 Allowing for a risky outside asset

A natural extension of the model above involves relaxing the assumption that the outside asset $R_{i,t+1}(0)$ is risk-free.[66] This may be interpreted literally, as the non-bond investments of some of the funds in the Morningstar dataset are indeed in risky equity. But it also corresponds to situations where the outside investment opportunities change with time, e.g. as a result of financial innovation or due to constraints on the fund investment universe coming from regulation or internal (to the financial institution offering a given fund) risk management requirements. In addition, a portfolio optimisation problem with a risky outside asset is isomorphic to one where asset managers are compensated depending on their portfolio performance relative to a benchmark index as in Kashyap et al. (2021) or Pavlova and Sikorskaya (2022). In that case, the interpretation of fund preferences for bond characteristics also reflects their relation to bond return comovement with the benchmark index.

As in the baseline model (Section B.1) investor i chooses bond portfolio weights to max-

[66] A risk-free outside asset is implicitly assumed also in Koijen and Yogo (2019) by choosing log-utility investor preferences.

imize one-period-ahead wealth. The approximated portfolio return is the same function of individual portfolio returns and their variance and covariances:

$$r_{p,i,t+1} - r_{i,t+1}(0) = \mathbf{w}'_{i,t}(\mathbf{r}_{i,t+1} - r_{i,t+1}(0)\mathbf{1}) + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t} \tag{B.18}$$

but now greater care is required as this only holds if the return covariance matrix $\mathbf{\Sigma}_{i,t}$ and its diagonal elements $\sigma^2_{i,t}$ are defined based on the excess returns over the risky outside asset.

The expected excess portfolio return is unchanged, while portfolio variance is now also affected by the variance of the outside asset return $\sigma^2_{i,t}(0)$ and its covariance with the individual bond excess returns $\sigma_{i,t}(\mathbf{rx}, 0)$ (highlighted in red below):

$$\mathbb{E}_{i,t}\left[r_{p,i,t+1} - r_{t+1}(0)\right] = \mathbf{w}'_{i,t}\mathbb{E}_{i,t}\left[\mathbf{r}_{t+1} - r_{t+1}(0)\mathbf{1}\right] + \frac{1}{2}\mathbf{w}'_{i,t}\sigma^2_{i,t} - \frac{1}{2}\mathbf{w}'_{i,t}\mathbf{\Sigma}_{i,t}\mathbf{w}_{i,t}$$

$$\begin{aligned}\sigma^2_{r_p,i,t} &= \mathbb{V}\mathrm{ar}_{i,t}[r_{t+1}(0)] + \mathbf{w}'_{i,t}\mathbf{\Sigma}_{\mathbf{i,t}}\mathbf{w}_{i,t} + 2\mathbf{w}'_{i,t}\mathbb{C}\mathrm{ov}_{i,t}[(\mathbf{r}_{t+1} - r_{t+1}(0)\mathbf{1}), r_{t+1}(0)] \\ &= \sigma^2_{i,t}(0) + \mathbf{w}'_{i,t}\mathbf{\Sigma}_{\mathbf{i,t}}\mathbf{w}_{i,t} + 2\mathbf{w}'_{i,t}\sigma_{i,t}(\mathbf{rx}, 0)\end{aligned} \tag{B.19}$$

Following the same steps as before, the optimal portfolio weight now takes into account the covariance of the outside asset return with each bond return:

$$\mathbf{w}_{i,t} = (\rho_{i,t}\mathbf{\Sigma}_{i,t})^{-1}\Big(\underbrace{\mathbb{E}_{i,t}\left[\mathbf{r}_{t+1} - r_{t+1}(0)\mathbf{1}\right] + \frac{\sigma^2_{i,t}}{2}}_{\equiv\mu_{i,t}} + \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}\Big) + \Big(1 - \frac{1}{\rho_{i,t}}\Big)\big(-\mathbf{\Sigma}^{-1}_{i,t}\sigma_{i,t}(\mathbf{rx}, 0)\big) \tag{B.20}$$

Two opposing effects arise from the risk associated with the outside asset: (i) the investor favours assets with a positive covariance with the outside asset, as (for a given return) that increases the expected simple return on the portfolio; (ii) this is traded off against the increase in portfolio risk associated with this covariance.[67]

Moving on to characterize the allocation to bonds with non-binding short-sale constraint, this again extends to account for covariances with the outside asset:

$$\mathbf{w}^{(1)}_{i,t} = \frac{1}{\rho_{i,t}}\Big(\mathbf{\Sigma}^{(1,1)}_{i,t}\Big)^{-1}(\mu^{(1)}_{i,t} - \lambda_{i,t}\mathbf{1} + (1 - \rho_i)\sigma^{(1)}_{i,t}(\mathbf{rx}, 0))$$

where, as before, $\sigma^{(1)}_{i,t}(\mathbf{rx}, 0)$ denotes the sub-vector of bond-outside asset covariances ($\sigma_{i,t}(\mathbf{rx}, 0) = [\sigma^{(1)}_{i,t}(\mathbf{rx}, 0), \sigma^{(2)}_{i,t}(\mathbf{rx}, 0)]'$).

And this implies the portfolio weight on the outside asset now also accounts for the additional risk-return trade-off associated with the covariance between bonds and the

[67] For the case of log-utility ($\rho_{i,t} = 1$), these two considerations offset each other exactly. Then the only difference from the riskless outside asset case is that excess returns (as well as their expectations, variances and covariances) are different from total returns, so care is required with $\mathbb{E}_{i,t}\left[\mathbf{r}_{t+1} - r_{t+1}(0)\mathbf{1}\right], \mathbf{\Sigma}_{i,t}, \sigma^2_{i,t}$. See discussion in Campbell & Viceira, ch.2.1.3, pp.24-25.

outside asset:

$$w_{i,t}(0) = 1 - \mathbf{1}'\left(\rho_{i,t}\mathbf{\Sigma}_{i,t}^{(1,1)}\right)^{-1}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1} + (1-\rho_i)\sigma_{i,t}^{(1)}(\mathbf{rx}, 0)) \tag{B.21}$$

This trade-off is also reflected in the value of the Lagrange multiplier on the constraint on the sum of portfolio weights on bonds and the outside asset (3):

$$\lambda_{i,t} = \max\left\{\frac{\mathbf{1}'\left(\rho_{i,t}\mathbf{\Sigma}_{i,t}^{(1,1)}\right)^{-1}(\mu_{i,t}^{(1)} + (1-\rho_i)\sigma_{i,t}^{(1)}(\mathbf{rx}, 0)) - 1}{\mathbf{1}'\left(\rho_{i,t}\mathbf{\Sigma}_{i,t}^{(1,1)}\right)^{-1}\mathbf{1}}, \quad 0\right\} \tag{B.22}$$

Characteristics-based demand The baseline assumptions in B.1 about a factor structure in excess returns and return expectations and factor loadings being functions of bond characteristics are unchanged. In addition, I assume the risky asset return is lognormally distributed, $r_{i,t}(0) \sim N(\mu_{i,t}(0), \sigma_{i,t}^2(0))$. And the covariance of the (risky) outside asset with the assets in the demand system is a function of their characteristics:

$$\sigma_{i,t}(rx(n), 0) = \mathbf{y_{i,t}}(n)'\mathbf{\Xi}_i + \xi_{i,t}$$

The implied weights have the same form as in the baseline riskless outside asset case (B.14), $\mathbf{w}_{i,t}^{(1)} = \frac{1}{\rho_{i,t}}\left(\mathbf{y_{i,t}^{(1)}}'\mathbf{\Pi}_{i,t} + \pi_{i,t}\mathbf{1}\right)$, but with a broader definition of coefficients on bond characteristics and investor-specific residuals:

$$\mathbf{\Pi}_{i,t} \equiv \frac{\mathbf{\Phi}_i - \mathbf{\Psi}_i + (1-\rho_{i,t})\mathbf{\Xi}_i}{\gamma_{i,t}}; \qquad \pi_{i,t} \equiv \frac{\phi_{i,t} - \lambda_{i,t} + (1-\rho_{i,t})\xi_{i,t} - \psi_{i,t}\kappa_{i,t}}{\gamma_{i,t}}.$$

$$\kappa_{i,t} \equiv \frac{\mathbf{\Gamma}_{i,t}^{(1)'}}{\gamma_{i,t} + \mathbf{\Gamma}_{i,t}^{(1)'}\mathbf{\Gamma}_{i,t}^{(1)}}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1} + (1-\rho_{i,t})\sigma_{i,t}^{(1)}(\mathbf{rx}, 0))$$

Investor demand for bond characteristics (captured by $\Pi_{i,t}$) now emerges not only because characteristics are useful to predict bond returns and gain exposure to common factors, but also because they capture the covariance of each bond with the outside asset return. The parameter restrictions necessary to express demand as a exponential function of bond characteristics are unchanged, and only the interpretation of coefficients $\hat{\beta}_i$ is now broader. For instance, if a given asset characteristic is associated with higher covariance with the outside asset ($\mathbf{\Xi}_i > 0$), the degree of risk aversion determines whether the investor increases or decreases the portfolio weight on the respective asset. Holding more of the correlated asset increases both portfolio returns and risk, with the latter becoming a more prominent consideration as risk aversion increases.

B.3 Demand elasticity derivation

Individual demand elasticity $\eta_{i,t}(jk)$: The starting point for deriving demand elasticities is the empirical expression for optimal portfolio weight of investor i (13):

$$\begin{aligned} w_{i,t}(n) &= \frac{\delta_{i,t}(n)}{1+\sum_{m=1}^{\mathcal{N}_{i,t}}\delta_{i,t}(m)} \\ &= \frac{\exp\left\{\alpha_{T(i)} per^h_{\chi(i),t}(n) + \mathbf{x}^1_t(n)'\beta^1_{T(i)} + \mathbf{x}^2(n)'\beta^2_{T(i)} + \mathbf{b}_i(n)'\theta_{T(i)} + \zeta_{i,t} + \epsilon_{i,t}(n)\right\}}{1+\sum_{m=1}^{\mathcal{N}_{i,t}}\exp\left\{\alpha_{T(i)} per^h_{\chi(i),t}(m) + \mathbf{x}^1_t(m)'\beta^1_{T(i)} + \mathbf{x}^2(n)'\beta^2_{T(i)} + \mathbf{b}_i(m)'\theta_{T(i)} + \zeta_{i,t} + \epsilon_{i,t}(m)\right\}} \end{aligned} \tag{B.23}$$

where $\delta_{i,t}(n) \equiv \frac{w_{i,t}(n)}{w_{i,t}(0)}$.

Here, I derive the semi-elasticity of this weight allocated to a given bond j with respect to a change in the predicted excess return on bond k as the following partial derivative:

$$\begin{aligned} \eta_{i,t}(jk) &\equiv \frac{\partial \log(w_{i,t}(j)) * 100}{\partial per_{\chi(i),t}(k)} \\ &= \begin{cases} \frac{1}{w_{i,t}(j)} \frac{\delta_{i,t}(j)\alpha_{T(i)}\left(1+\sum_{m=1}^{\mathcal{N}_{i,t}}\delta_{i,t}(m)\right) - \delta_{i,t}(j)^2\alpha_{T(i)}}{\left(1+\sum_{m=1}^{\mathcal{N}_{i,t}}\delta_{i,t}(m)\right)^2} * 100 & \text{if } j=k, \\ \frac{1}{w_{i,t}(j)} \frac{-\delta_{i,t}(j)\delta_{i,t}(k)\alpha_{T(i)}}{\left(1+\sum_{m=1}^{\mathcal{N}_{i,t}}\delta_{i,t}(m)\right)^2} * 100 & \text{otherwise.} \end{cases} \\ &= \begin{cases} \frac{1}{w_{i,t}(j)}\left(w_{i,t}(j)\alpha_{T(i)} - w_{i,t}(j)^2\alpha_{T(i)}\right) * 100 & \text{if } j=k, \\ \frac{1}{w_{i,t}(j)}\left(-w_{i,t}(j)w_{i,t}(k)\alpha_{T(i)}\right) * 100 & \text{otherwise.} \end{cases} \\ &= \begin{cases} \alpha_{T(i)}\left(1-w_{i,t}(j)\right) * 100 & \text{if } j=k, \\ -\alpha_{T(i)}\, w_{i,t}(k) * 100 & \text{otherwise.} \end{cases} \end{aligned}$$

If alternatively, I adapt the elasticity definition in Koijen and Yogo (2019) and consider the own demand elasticity:

$$\begin{aligned} \eta^{*p}_{i,t}(jj) \equiv -\frac{\partial \log(Q_{i,t}(j))}{\partial \log(P_{i,t}(j))} &= -\frac{\partial\left[\log(A_{it}w_{i,t}(j)) - p_{i,t}(j)\right]}{\partial p_{i,t}(j)} \\ &= -\frac{\partial \log(w_{i,t}(j))}{\partial \log(P_{i,t}(j))} + 1 \\ &= -\frac{\partial \log(w_{i,t}(j))}{\partial per_{\chi(i),t}(j)} \times \frac{\partial per_{\chi(i),t}(j)}{\partial \log(P_{i,t}(j))} + 1 \\ &= -\frac{\partial \log(w_{i,t}(j))}{\partial per_{\chi(i),t}(j)} \times \frac{\partial per_{\chi(i),t}(j)}{\partial (p_{j,t}(j) - s_{i/j,t})} + 1 \end{aligned}$$

where $\log(Q_{ijt}) = \log(A_{it}w_{ijt}) - p_{jt}$. The relevant bond price to investor i is that defined in

his home currency as the ratio of the bond price in local currency j and the spot nominal exchange rate of currency i per unit of currency j: $P_{i,t}(j) = P_{j,t}(j)/S_{i/j,t}$. Equivalently, in log terms: $p_{i,t}(j) = p_{j,t}(j) - s_{i/j,t}$. The relationship between the excess return is not modelled explicitly in this paper but I can use the estimated relation between predicted excess returns and the local currency yield, use the approximate relation between local-currency bond yield $y_{j,t}(j)$ and price ($p_{j,t}(j) = -mat_t(j) \times \frac{y_{j,t}(j)}{100}$), and for now abstract from joint dynamics between yields and exchange rates. This implies

$$\begin{aligned}
\frac{\partial per_{\chi(i),t}(j)}{\partial(p_{j,t}(j) - s_{i/j,t})} &\approx \frac{\partial per_{\chi(i),t}(j)}{\partial p_{j,t}(j)} \\
&\approx \frac{\partial per_{\chi(i),t}(j)}{\partial(-mat_t(j) \times \frac{y_{j,t}(j)}{100})} \\
&\approx -\frac{100}{mat_t(j)} \frac{\partial per_{\chi(i),t}(j)}{\partial y_{j,t}(j)} \\
&\approx -\frac{100}{mat_t(j)} \widehat{A}_i^h
\end{aligned}$$

where the last line uses the estimated coefficient $\widehat{A}_i^h$ from the predictive bond regression (8) as an approximation of the last partial derivative term above. Under these assumptions, the alternative demand elasticity definition is related to the semi-elasticity discussed in this paper as follows:

$$\eta_{i,t}^{*p}(jj) \equiv -\frac{\partial \log(Q_{i,t}(j))}{\partial \log(P_{i,t}(j))} = \eta_{i,t}(jj) \times \frac{\widehat{A}_i^h}{mat_t(j)} + 1 \tag{B.24}$$

where $mat_t(j)$ is the residual maturity of bond j at time t. It is worth considering the case where the semi-elasticity of portfolio weights $\eta_{i,t}(jj)$ is zero, which implies the face value of holdings increases one-to-one with bond prices. When the price increases, funds that keep their portfolio weight on bond j unchanged need to sell some of their holdings.

Finally, we may be interested in the related notion of the percent change in demand per 1 percentage point change in the local currency yield. This also has a simple relationship to the other two definitions of demand elasticity:

$$\begin{aligned}
\eta_{i,t}^{*y}(jj) &\equiv \frac{\partial \log(Q_{i,t}(j)) * 100}{\partial y_{i,t}(j)} = \frac{\partial \log(Q_{i,t}(j))}{\partial \frac{\log(P_{i,t}(j))}{-mat_t(j)}} = -\frac{\partial \log(Q_{i,t}(j))}{\partial \log(P_{i,t}(j))} \times mat_t(j) \\
&= \eta_{i,t}^{*p}(jj) \times mat_t(j) = \eta_{i,t}(jj) \times \widehat{A}_i^h + mat_t(j)
\end{aligned} \tag{B.25}$$

It is clear from (B.24) and (B.25) that these alternative elasticity definitions vary with the maturity of bond j, while the baseline definition discussed in this paper does not. This paper focuses on heterogeneity in investor elasticity to returns instead in order to facilitate comparisons between the elasticities on bonds with different maturities. I report and discuss summary statistics for the other two definitions for comparability with other literature on asset demand curve slopes.

Aggregate demand elasticity $\eta_t(jk)$: Below I show that aggregate elasticities of the fund sector as a whole can be calculated simply by weighing individual demand elasticities by the total fund AUM invested in the relevant bond. Defining the aggregate share of bond j in the fund sector's AUM at time t as $w_t(j) = \frac{\sum_i AUM_{i,t}\ w_{i,t}(j)}{\sum_i AUM_{i,t}}$ and taking its partial derivative with respect to predicted excess returns of any other bond k gives an expression for aggregate fund sector demand elasticities:

$$\begin{aligned}
\eta_t(jk) \equiv \frac{\partial \log(w_t(j)) * 100}{\partial per_t(k)} &= \frac{\partial \log(\frac{\sum_i AUM_{i,t}\ w_{i,t}(j)}{\sum_i AUM_{i,t}}) * 100}{\partial per_t(k)} \\
&= \frac{\partial \log(\sum_i AUM_{i,t}\ w_{i,t}(j))}{\partial per_t(k)} * 100 \\
&= \frac{1}{\sum_i AUM_{i,t}\ w_{i,t}(j)} \frac{\partial(\sum_i AUM_{i,t}\ w_{i,t}(j))}{\partial per_t(k)} * 100 \\
&= \sum_i \left(\frac{AUM_{i,t}}{\sum_i AUM_{i,t}\ w_{i,t}(j)} \frac{\partial w_{i,t}(j)}{\partial per_t(k)} \right) * 100 \\
&= \sum_i \left(\frac{AUM_{i,t} w_{i,t}(j)}{\sum_i AUM_{i,t}\ w_{i,t}(j)} \frac{\partial \log(w_{i,t}(j))}{\partial per_t(k)} \right) * 100 \\
&= \begin{cases} \sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))}\ \alpha_{T(i)}\ (1 - w_{i,t}(j)) * 100 & \text{if } j = k, \\ -\sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))}\ \alpha_{T(i)}\ w_{i,t}(k) * 100 & \text{otherwise.} \end{cases}
\end{aligned}$$

This expression can also be calculated for any subset of funds of particular interest. For instance, in some of the results I report elasticities aggregated by fund domicile, i.e. all euro area funds versus all US funds.

C Additional estimation results

C.1 First stage: monetary policy instruments

Table C.13: Correlation matrix between Fed and ECB monetary policy shocks

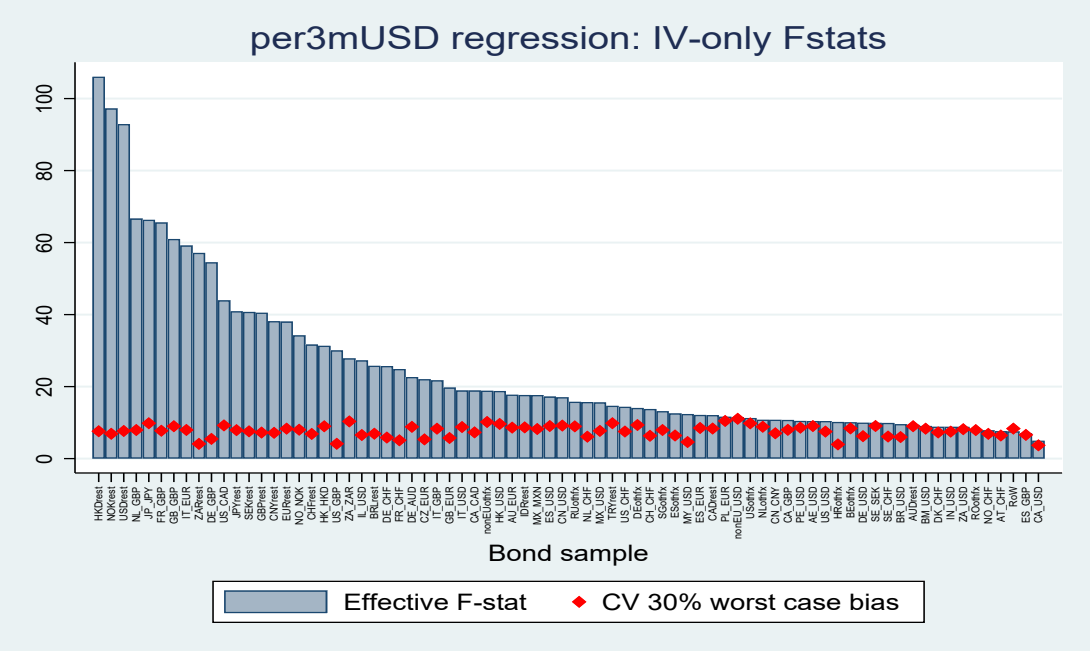
	fed_ff4_MP	fed_uspc1_MP	fed_us2y_MP	fed_us5y_MP	fed_us10y_MP	ecb_eon3m_MP	ecb_eonpc1_MP	ecb_eon2y_MP	ecb_eon5y_MP	ecb_eon10y_MP
fed_ff4_MP	1.000									
fed_uspc1_MP	0.930***	1.000								
fed_us2y_MP	0.746***	0.883***	1.000							
fed_us5y_MP	0.461***	0.671***	0.866***	1.000						
fed_us10y_MP	0.232***	0.425***	0.609***	0.876***	1.000					
ecb_eon3m_MP	0.079	-0.004	0.051	0.006	-0.029	1.000				
ecb_eonpc1_MP	0.070	-0.012	0.028	-0.009	-0.037	0.978***	1.000			
ecb_eon2y_MP	0.019	-0.049	-0.047	-0.041	-0.034	0.776***	0.862***	1.000		
ecb_eon5y_MP	-0.096	-0.125	-0.122	-0.048	-0.024	0.565***	0.635***	0.880***	1.000	
ecb_eon10y_MP	-0.041	-0.068	-0.072	-0.019	-0.015	0.321***	0.395***	0.682***	0.891***	1.000
N	276									

Note: Monthly shocks constructed as the sum of announcement days shocks if multiple announcements are made by each central bank within a month. Sample period: 1999M1:2021M12 (unbalanced with only ECB shocks data post-2019M6). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

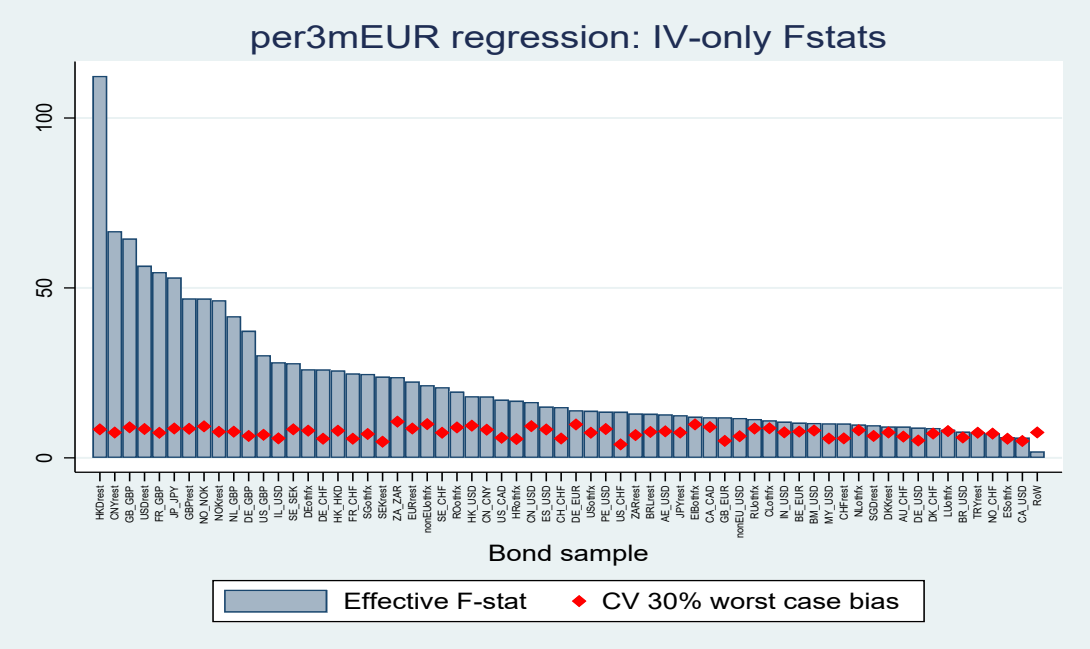
C.1.1 First stage results: baseline

Figure C.18: First stage F-statistics

(a) US dollar returns: $per^3_{\$,t}(n)$



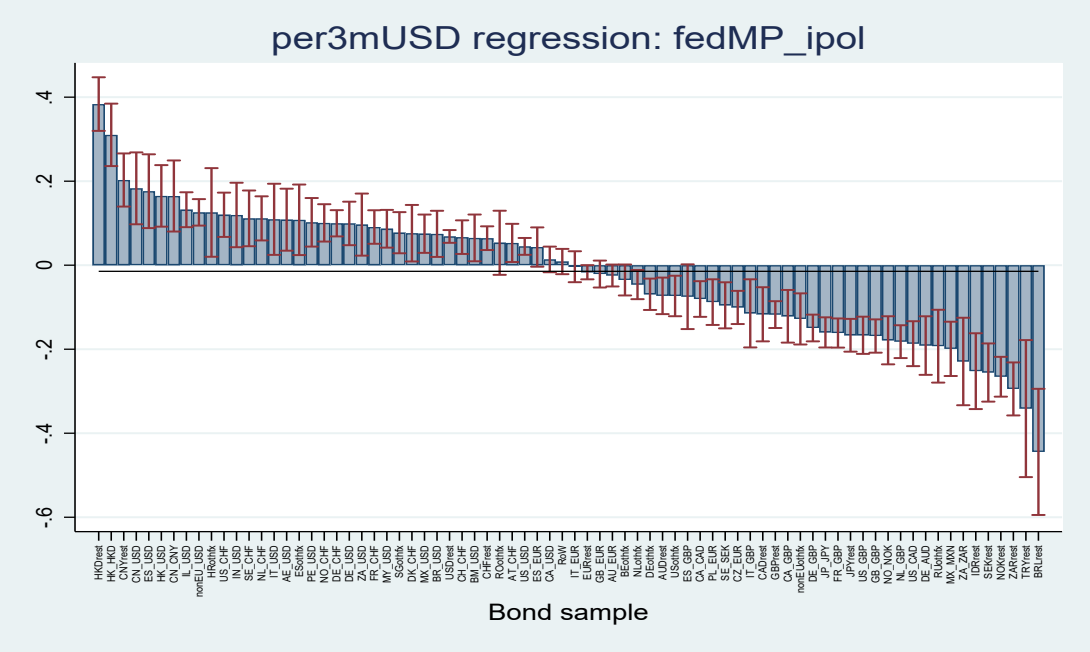
(b) Euro returns: $per^3_{€,t}(n)$



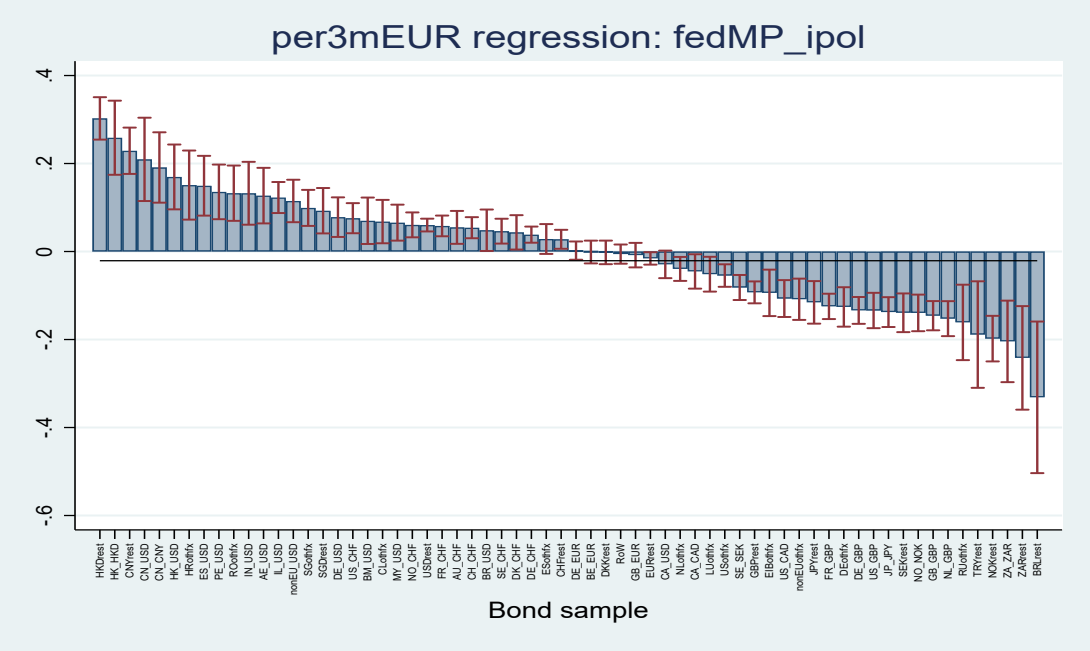
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective F-statistic associated with the monetary policy instruments, while the red diamonds plot the critical value associated with 30% of the worst case bias of Olea and Pflueger (2013) and implemented through the Stata package WEAKIVTEST by Pflueger and Wang (2013).

Figure C.19: Estimated coefficients on Fed monetary policy shock

(a) US dollar returns: $per^3_{\$,t}(n)$



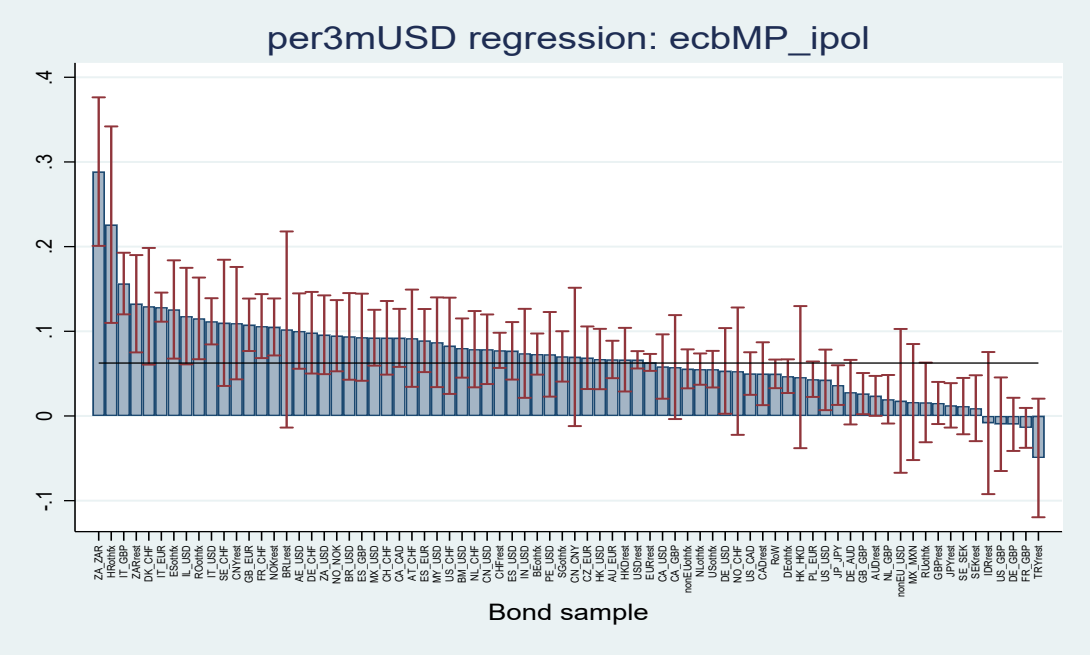
(b) Euro returns: $per^3_{€,t}(n)$



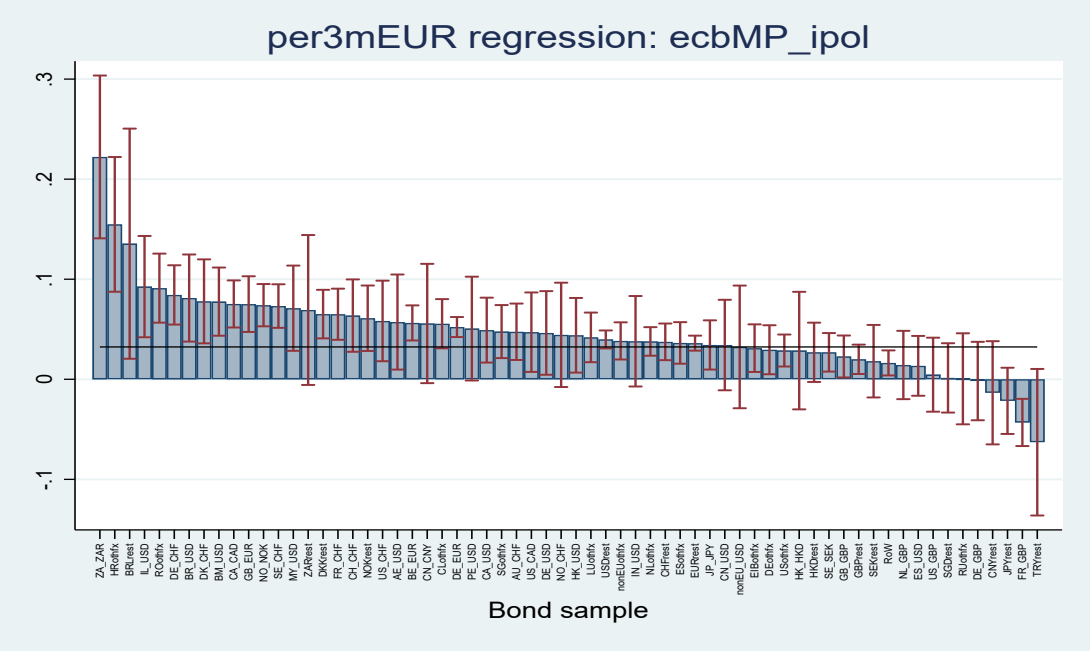
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the Fed monetary policy instrument and the red ranges plot 95% confidence bands.

Figure C.20: Estimated coefficients on ECB monetary policy shock

(a) US dollar returns: $per^3_{\$,t}(n)$



(b) Euro returns: $per^3_{€,t}(n)$

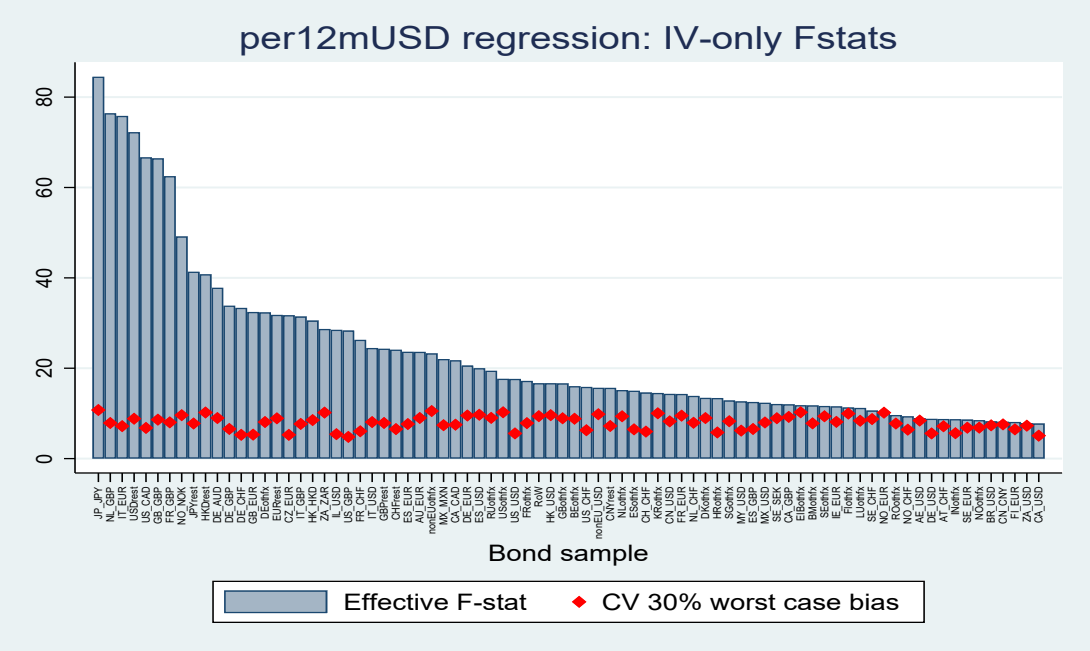


Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the ECB monetary policy instrument and the red ranges plot 95% confidence bands.

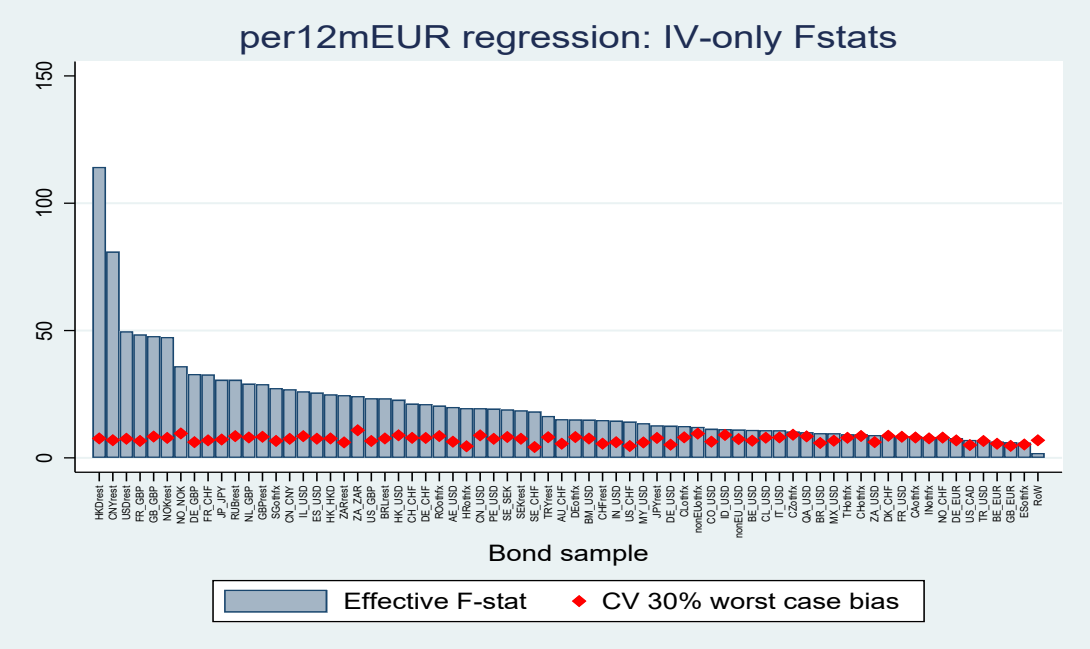
C.1.2 First stage results: robustness

Figure C.21: First stage F-statistics: 12-month returns

(a) US dollar returns: $per^{12}_{\$,t}(n)$



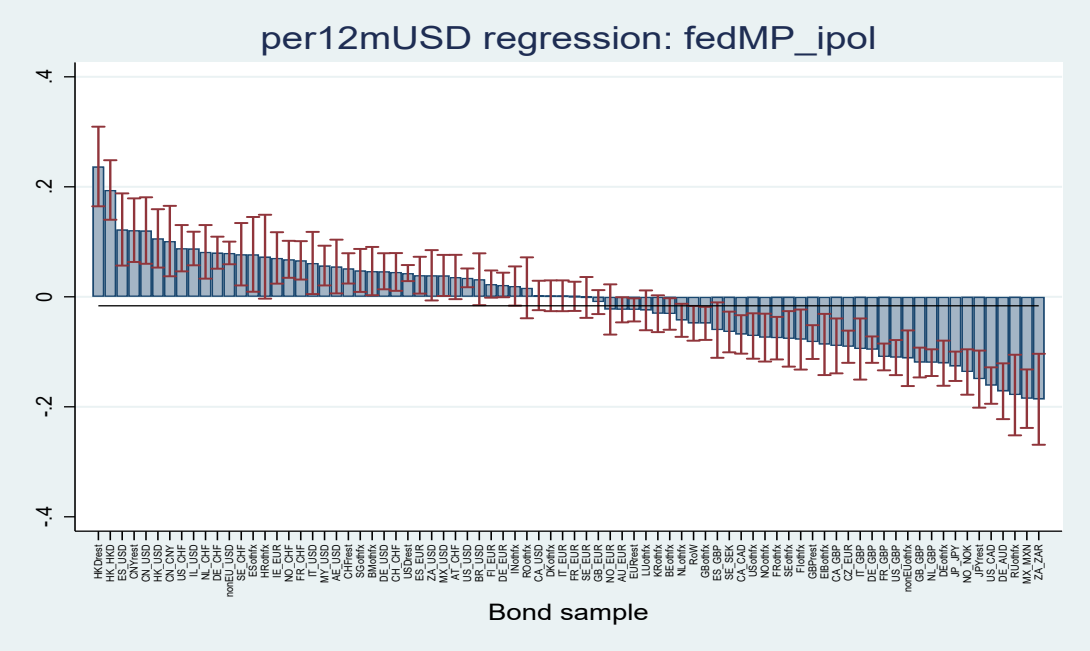
(b) Euro returns: $per^{12}_{€,t}(n)$



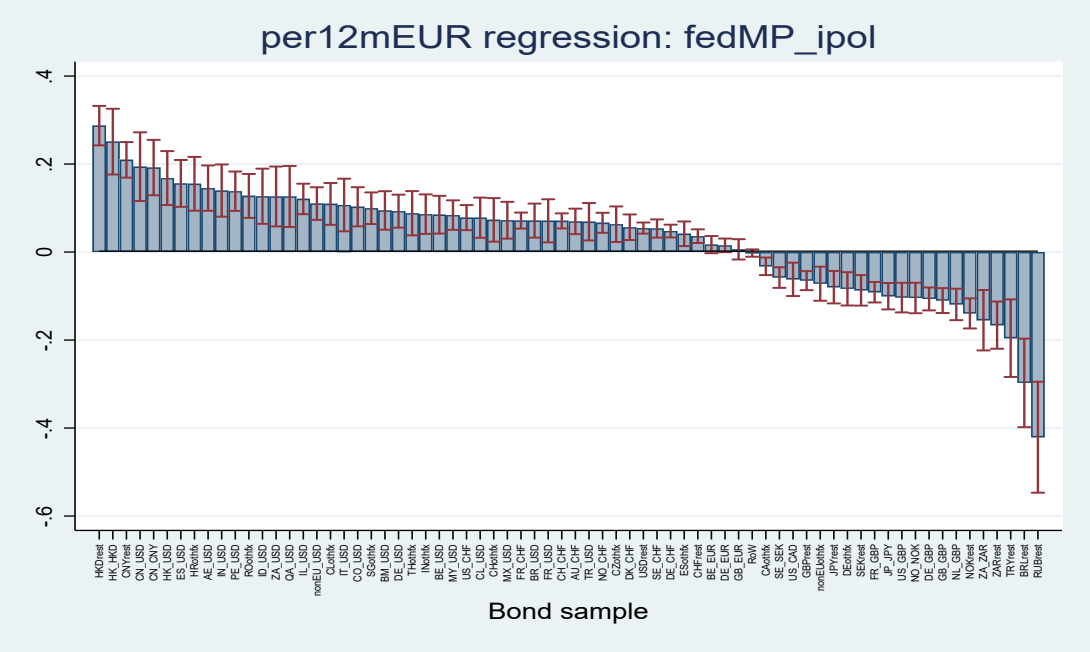
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective F-statistic associated with the monetary policy instruments, while the red diamonds plot the critical value associated with 30% of the worst case bias of Olea and Pflueger (2013) and implemented through the Stata package WEAKIVTEST by Pflueger and Wang (2013).

Figure C.22: Estimated coefficients on Fed monetary policy shock: 12-month returns

(a) US dollar returns: $per^{12}_{\$,t}(n)$



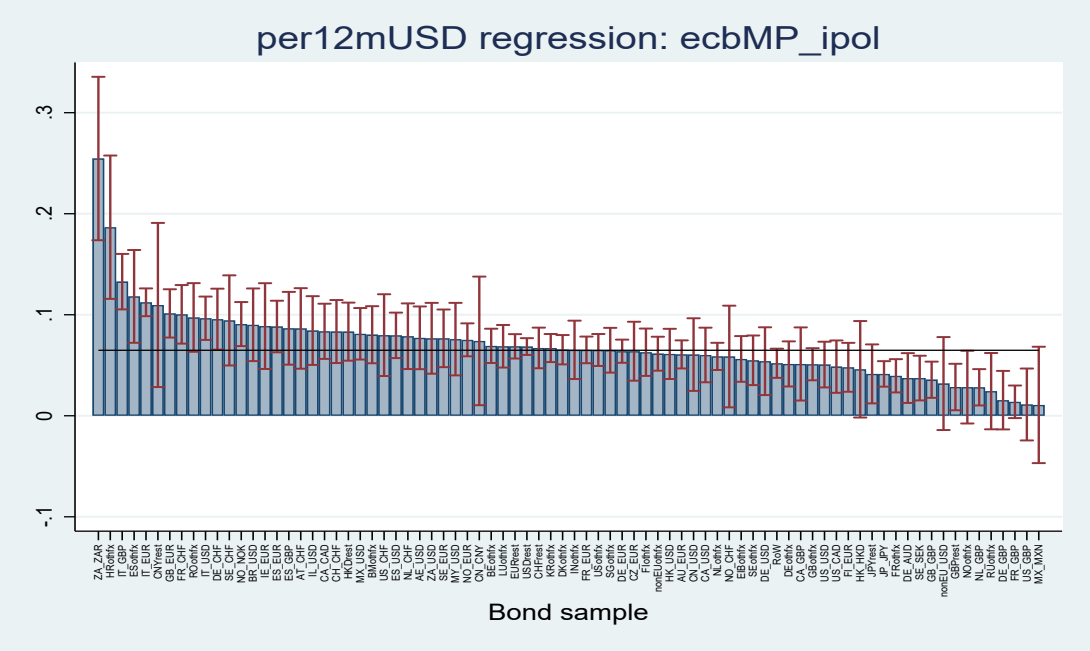
(b) Euro returns: $per^{12}_{€,t}(n)$



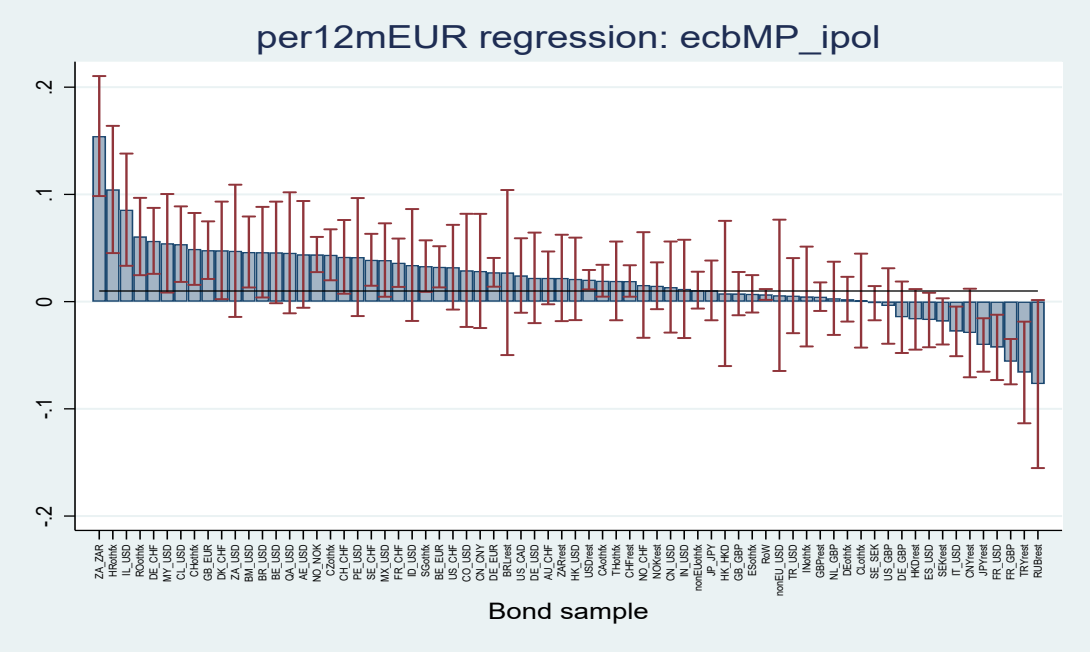
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the Fed monetary policy instrument and the red ranges plot 95% confidence bands.

Figure C.23: Estimated coefficients on ECB monetary policy shock: 12-month returns

(a) US dollar returns: $per^{12}_{\$,t}(n)$



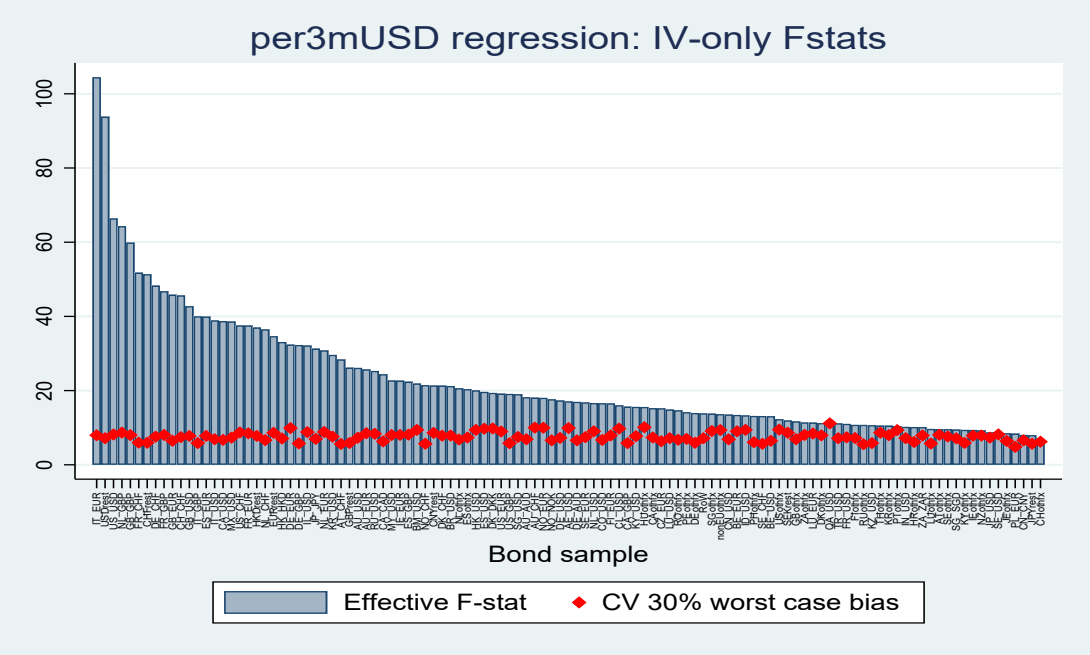
(b) Euro returns: $per^{12}_{€,t}(n)$



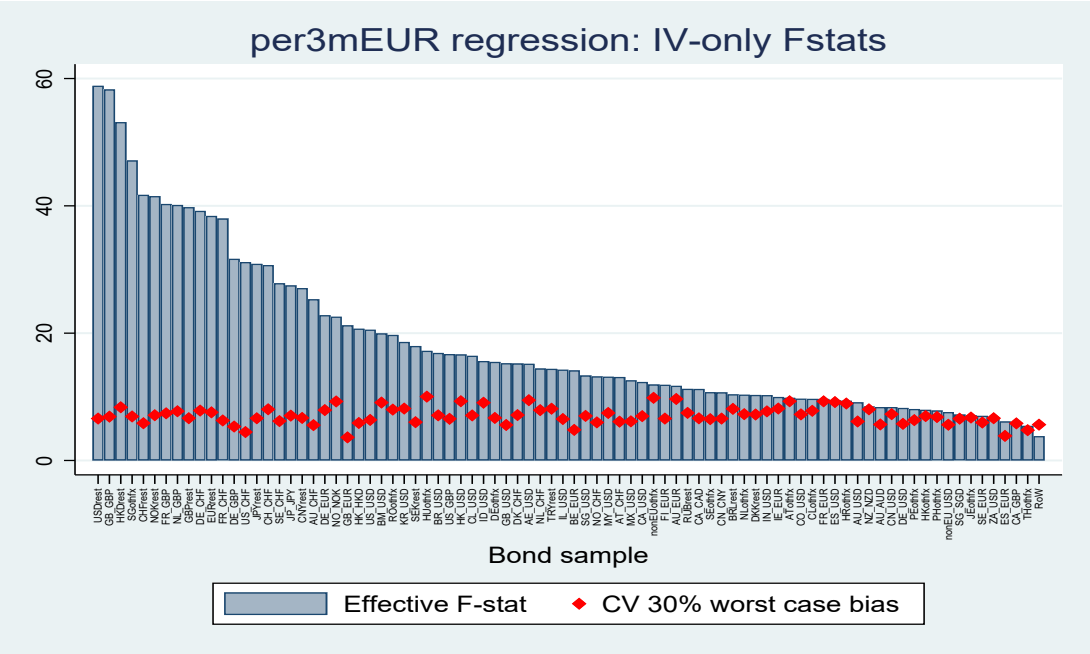
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the ECB monetary policy instrument and the red ranges plot 95% confidence bands.

Figure C.24: First stage F-statistics, controlling for EBP

(a) US dollar returns: $per^3_{\$,t}(n)$



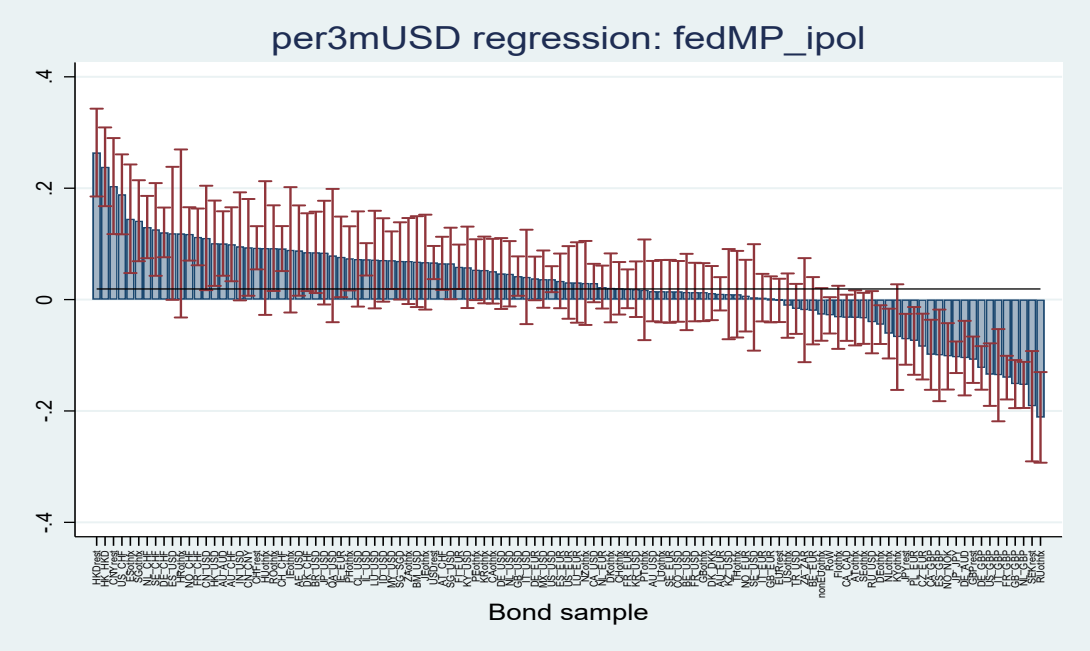
(b) Euro returns: $per^3_{€,t}(n)$



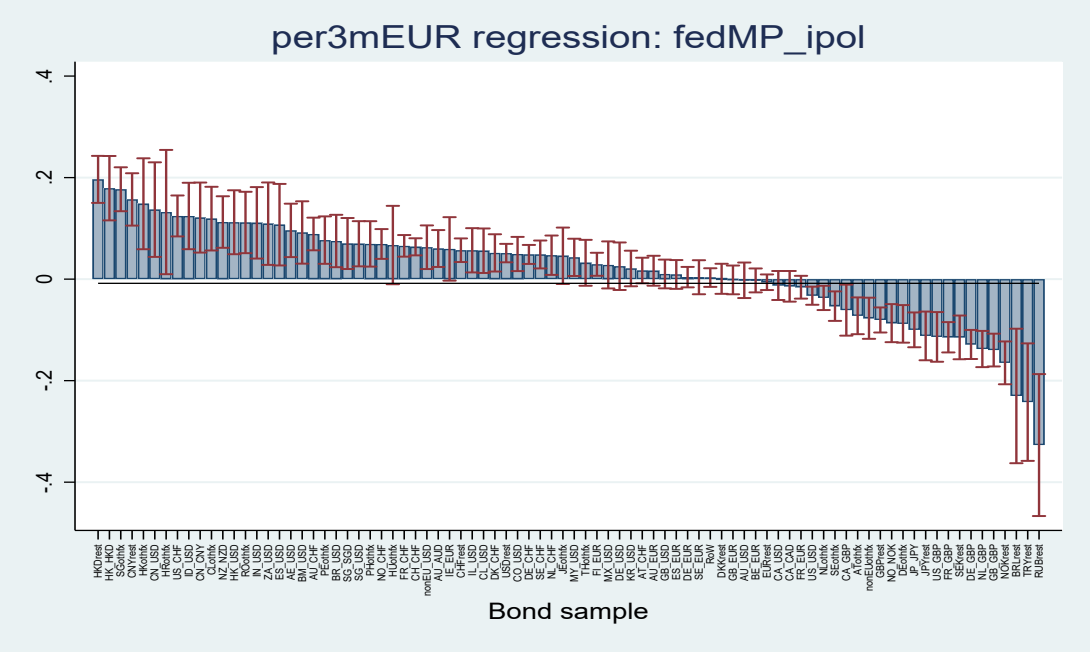
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective F-statistic associated with the monetary policy instruments, while the red diamonds plot the critical value associated with 30% of the worst case bias of Olea and Pflueger (2013) and implemented through the Stata package WEAKIVTEST by Pflueger and Wang (2013).

Figure C.25: Estimated coefficients on Fed monetary policy shock, controlling for EBP

(a) US dollar returns: $per^3_{\$,t}(n)$



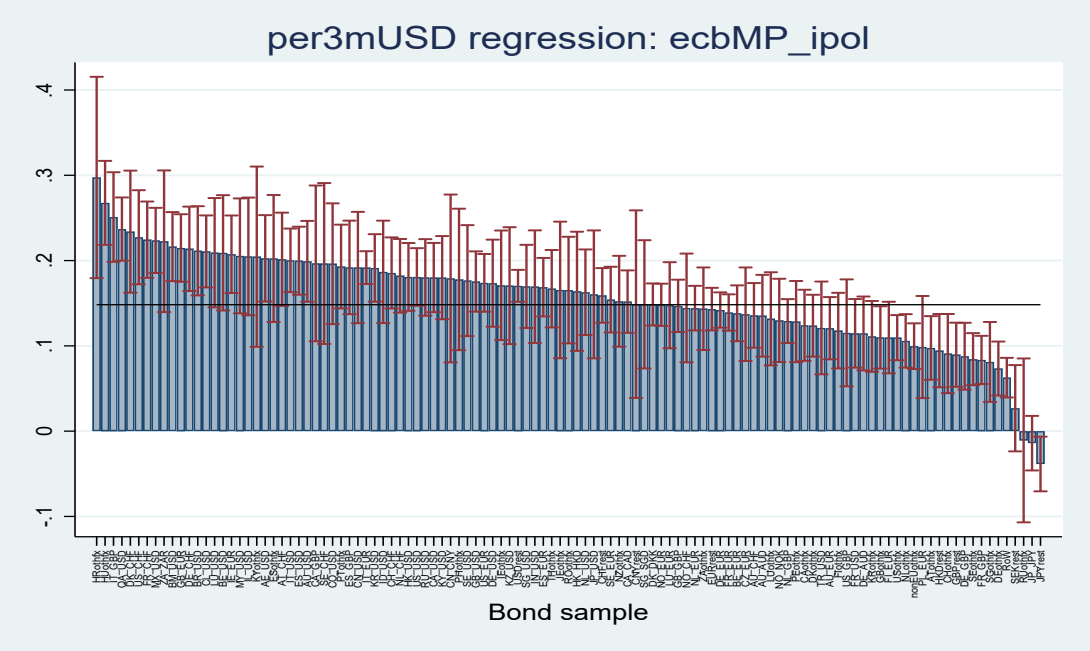
(b) Euro returns: $per^3_{€,t}(n)$



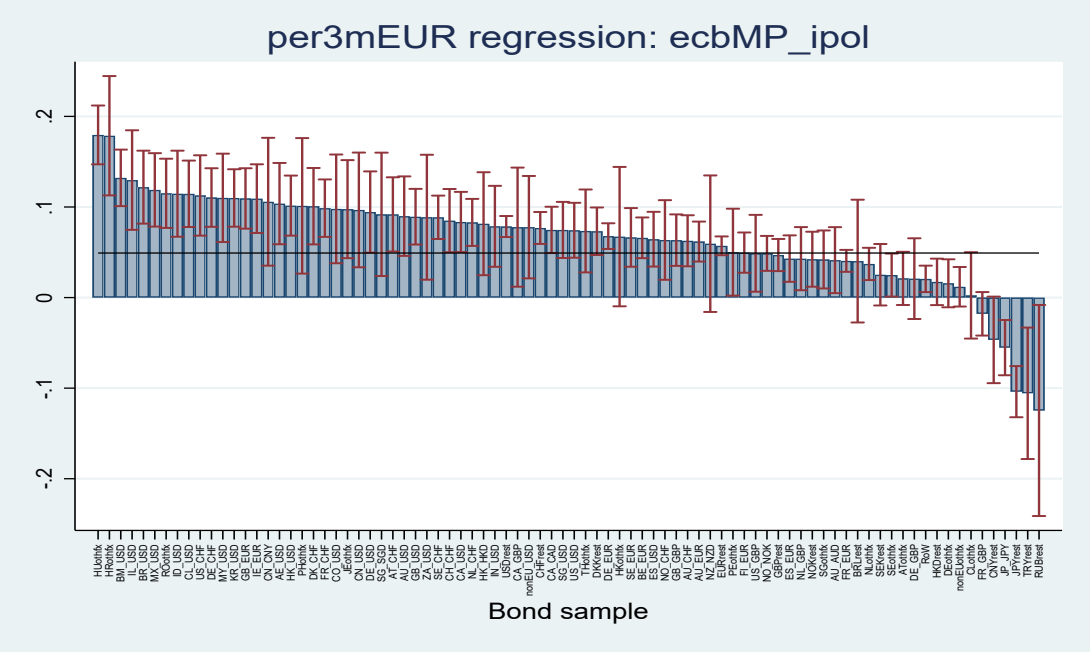
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the Fed monetary policy instrument and the red ranges plot 95% confidence bands.

Figure C.26: Estimated coefficients on ECB monetary policy shock, controlling for EBP

(a) US dollar returns: $per^3_{\$,t}(n)$



(b) Euro returns: $per^3_{€,t}(n)$



Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated coefficient on the ECB monetary policy instrument and the red ranges plot 95% confidence bands.

C.2 Second stage: bond demand panel Logits

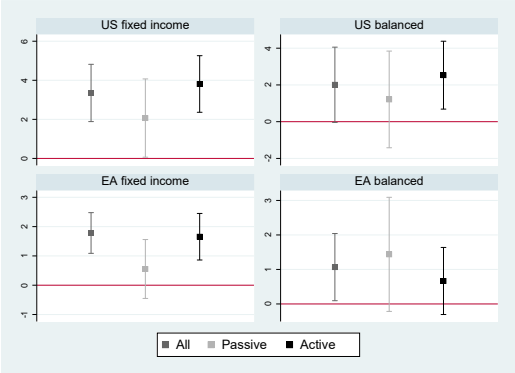
Table C.14: Panel Logit models by fund type

	(1) **US fixed inc.:**	(2) Passive	(3) Active	(4) **EA fixed inc.:**	(5) Passive	(6) Active	(7) **US balanced:**	(8) Passive	(9) Active	(10) **EA balanced:**	(11) Passive	(12) Active
$per^3_{i,t}$	3.3517***	2.0661*	3.8106***	1.7823***	0.5537	1.6549***	2.0080	1.2114	2.5316**	1.0679*	1.4376	0.6656
	(0.8911)	(1.2166)	(0.8799)	(0.4221)	(0.6108)	(0.4829)	(1.2432)	(1.5947)	(1.1180)	(0.5918)	(1.0042)	(0.5906)
Maturity	-0.0089**	-0.0073	-0.0078	-0.0022	-0.0005	-0.0019	-0.0065	-0.0037	-0.0084*	-0.0081***	-0.0104***	-0.0062**
	(0.0045)	(0.0051)	(0.0052)	(0.0016)	(0.0022)	(0.0019)	(0.0049)	(0.0059)	(0.0046)	(0.0026)	(0.0036)	(0.0026)
AAA-AA=1	0.2587**	0.6261***	-0.0054	0.1181*	0.2677***	0.0236	0.2130	0.3670**	0.0044	0.2997***	0.4977***	0.2278***
	(0.1116)	(0.1583)	(0.1323)	(0.0626)	(0.0870)	(0.0801)	(0.1348)	(0.1651)	(0.1448)	(0.0852)	(0.1424)	(0.0863)
A=1	0.2390**	0.6335***	0.0325	0.0390	0.1681**	0.0013	0.3286**	0.5546***	0.0686	0.1299	0.3473***	0.0574
	(0.1006)	(0.1641)	(0.1198)	(0.0579)	(0.0803)	(0.0760)	(0.1290)	(0.1550)	(0.1366)	(0.0793)	(0.1301)	(0.0815)
BBB=1	0.2247*	0.5949***	0.0846	0.0545	0.1820**	0.0273	0.2735*	0.5038***	0.0681	0.1311*	0.3297***	0.0710
	(0.1152)	(0.1717)	(0.1297)	(0.0544)	(0.0758)	(0.0714)	(0.1427)	(0.1679)	(0.1485)	(0.0723)	(0.1231)	(0.0734)
BB=1	0.1191	0.2917**	0.0906	0.0260	-0.0043	0.0435	0.1458	0.2543***	0.0839	0.0731	0.2008*	0.0327
	(0.0889)	(0.1308)	(0.1330)	(0.0552)	(0.0666)	(0.0762)	(0.0953)	(0.0949)	(0.1359)	(0.0653)	(0.1046)	(0.0627)
Amt. Outstanding	0.3774***	0.4646***	0.3293***	0.3063***	0.3776***	0.2613***	0.4384***	0.4876***	0.3468***	0.2518***	0.3187***	0.2239***
	(0.0236)	(0.0294)	(0.0262)	(0.0091)	(0.0142)	(0.0103)	(0.0293)	(0.0306)	(0.0321)	(0.0119)	(0.0180)	(0.0135)
Bond Seniority	-0.0172	-0.0057	-0.0063	-0.0063	-0.0063	-0.0022	0.0126	0.0472	0.0029	-0.0181*	-0.0267*	-0.0155
	(0.0141)	(0.0174)	(0.0148)	(0.0066)	(0.0101)	(0.0064)	(0.0215)	(0.0328)	(0.0164)	(0.0098)	(0.0148)	(0.0102)
Home Bond	0.0000	0.0000	0.0000	0.0651***	0.0689**	0.0730***	0.0000	0.0000	0.0000	-0.0021	-0.0220	0.0618
	(.)	(.)	(.)	(0.0235)	(0.0298)	(0.0270)	(.)	(.)	(.)	(0.0401)	(0.0471)	(0.0482)
Bond in Fund Investment Area	0.3224***	0.1459*	0.3249***	0.2373***	0.1472***	0.2658***	0.1569	0.0134	0.3437**	0.1301**	0.0947*	0.1442
	(0.0612)	(0.0820)	(0.0595)	(0.0343)	(0.0359)	(0.0401)	(0.1203)	(0.1481)	(0.1400)	(0.0632)	(0.0504)	(0.1020)
Govt Bond=1 X Govt Fund=1	0.6442***	0.5432***	0.6678***	0.6976***	0.6342***	0.6875***	1.3049***	1.2810***	0.9791***	0.9272***	0.8639***	0.9585***
	(0.0854)	(0.1309)	(0.1067)	(0.0420)	(0.0564)	(0.0536)	(0.1462)	(0.1882)	(0.2972)	(0.0838)	(0.1062)	(0.1083)
Govt Bond=1 X Mixed Fund=1	0.2150***	0.2198***	0.1904***	0.2927***	0.3476***	0.1992***	0.3460***	0.3750***	0.2319***	0.3428***	0.3930***	0.3205***
	(0.0651)	(0.0730)	(0.0610)	(0.0296)	(0.0367)	(0.0306)	(0.0685)	(0.0833)	(0.0672)	(0.0327)	(0.0453)	(0.0337)
Corp Bond=1 X Corp Fund=1	0.3062***	-0.1492	0.3671***	0.2150***	0.0384	0.2552***	-0.1101	-0.4955***	0.1354	0.0804	-0.2476***	0.1435*
	(0.1138)	(0.1078)	(0.0939)	(0.0394)	(0.0455)	(0.0374)	(0.1384)	(0.1257)	(0.1289)	(0.0686)	(0.0557)	(0.0757)
Obs	1,933,880	807,205	1,098,618	3,204,199	1,239,624	1,929,587	533,547	326,818	197,813	1,020,864	328,895	686,874
DoF	1,933,701	807,038	1,098,444	3,204,005	1,239,447	1,929,394	533,389	326,670	197,659	1,020,689	328,738	686,699
Adj. Rsq.–Within	0.16	0.26	0.11	0.17	0.28	0.12	0.22	0.27	0.14	0.15	0.24	0.12
Adj. Rsq.	0.82	0.89	0.71	0.91	0.94	0.88	0.81	0.85	0.72	0.80	0.84	0.78
Fund X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

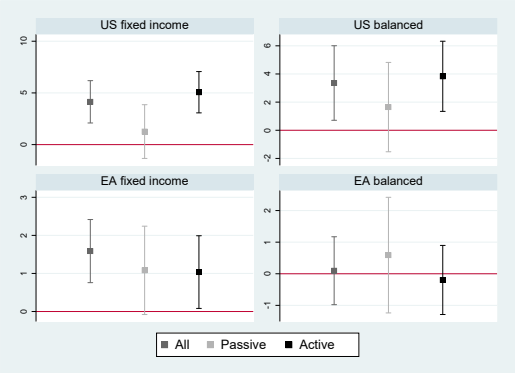
Note: Each column corresponds to a separate panel regression for a subset of funds: (1) all US fixed income funds, (2) passive US fixed income funds, (3) active US fixed income funds, etc. The dependent variable is the log ratio of bond bucket portfolio weight over the outside asset weight $\log\left(w_{i,t}(n)/w_{i,t}(0)\right)$. $per^{12}_{i,t}$ is the fitted value for the 12-month-horizon predicted excess return (using only information as of time t) on bond buckets in terms of investor i's currency from the first-stage instrumental variables regressions. Exogenous explanatory variables include bucket face-value-weighted average bond residial maturity (*Maturity*), broad credit rating dummies (*AAA-AA, A, BBB, BB*), total amount outstanding of bonds in bucket converted into fund currency ($ or €) at exchange rates lagged by one year (*Amt. Outstanding*), *Corporate Bond* dummy, *Bond Seniority* rank raging from 1 (Senior Secured) to 9 (Junior Subordinated Unsecured), a *Home Bond* dummy which equals one if the bond country of risk and the fund domicile country coincide (fund domicile only varies within EA funds), and a *Bond in Fund Investment Area* dummy which equals one if the bond country of risk coincides with the fund investment area as reported to Morningstar. In addition, all panel regressions include fund-time, bond country and bond currency fixed effects. Standard errors (in parentheses) clustered at fund and bucket level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.27: Estimates of $\alpha_{T(i)}$: compare fund splits

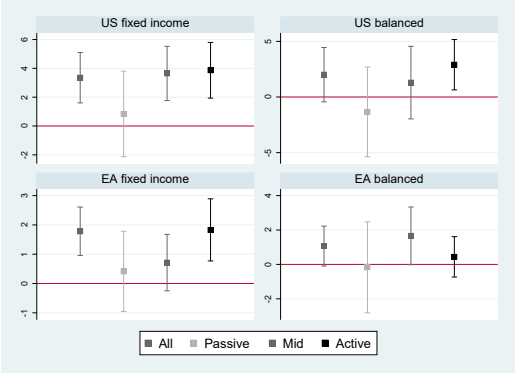
(a) Baseline: Above / Below Median Active Share, $per^{3}_{i,t}(n)$



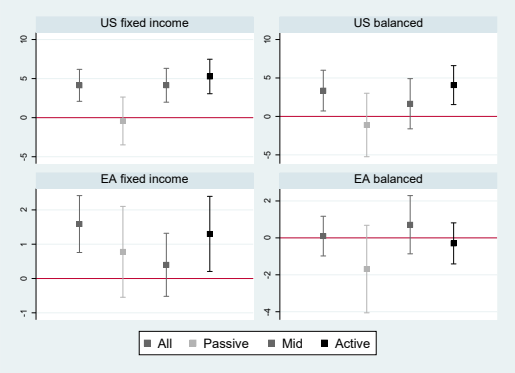
(b) Above / Below Median Active Share, $per^{12}_{i,t}(n)$



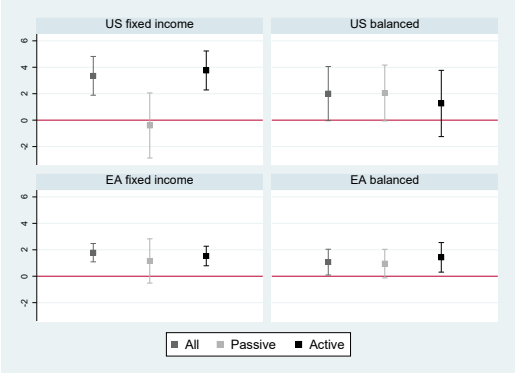
(c) By Active Share quartiles, $per^{3}_{i,t}(n)$



(d) By Active Share quartiles, $per^{12}_{i,t}(n)$



(e) Index funds vs other, $per^{3}_{i,t}(n)$



(f) Index funds vs other, $per^{12}_{i,t}(n)$

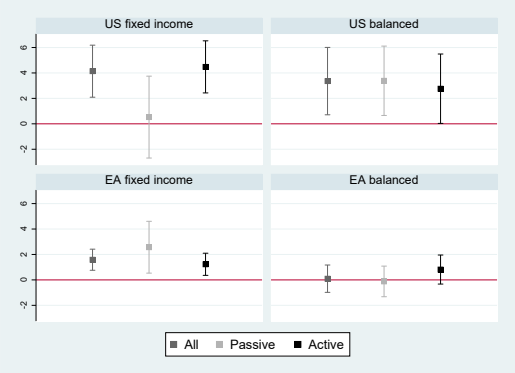
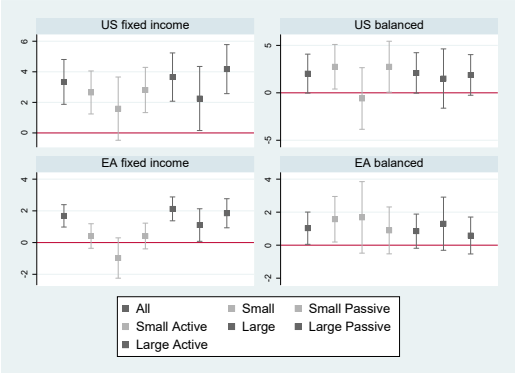
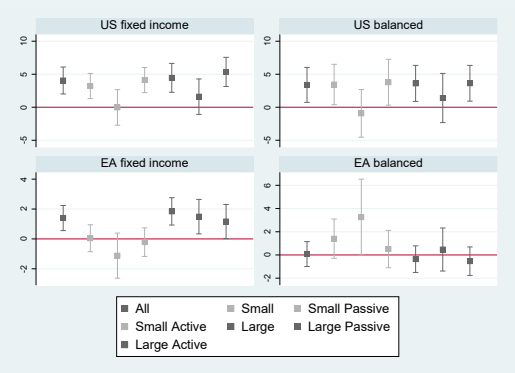


Figure C.28: Estimates of $\alpha_{T(i)}$ by both Active Share and AUM

(a) Small/Large × Active/Passive, $per_{i,t}^{12}(n)$



(b) Small/Large × Active/Passive, $per_{i,t}^{12}(n)$



C.3 Demand elasticity estimates

Table C.15: Summary statistics for estimated own bond elasticities of individual funds $\eta_{i,t}(jj)$, by four broad fund type

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US fixed income	304.05	85.95	373.58	183.48	381.03	2,446,056
EA fixed income	121.26	53.29	162.64	48.52	165.48	4,471,108
US balanced	171.66	64.14	121.13	114.60	253.15	629,621
EA balanced	89.69	35.29	66.49	62.09	143.75	1,396,971
Total	169.87	105.04	163.94	51.14	380.96	8,943,756

Note: Individual elasticities $\eta_{i,t}(jj)$ for broad fund types. Each summary statistic is calculated across three dimensions: funds of each type (i), bonds held by these funds (j) and quarters with holdings data (t).

Table C.16: Summary statistics for own bond elasticities of aggregate fund sector, $w.r.t.$ yield: $\frac{\partial \log(Q_t(n))*100}{\partial y_t(n)}$

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US fixed income	729.04	148.13	778.89	476.16	897.02	75,938
EA fixed income	312.96	73.86	337.65	126.85	396.84	105,945
US balanced	470.27	121.71	513.26	280.47	608.53	43,041
EA balanced	186.65	47.96	165.08	149.67	337.36	77,109
Total Fund Sector	422.03	175.81	381.59	129.09	880.53	110,529

Note: Elasticities $\frac{\partial \log(Q_t(j))*100}{\partial y_t(j)}$ aggregated for the entire fund sector or by four broad fund types. Each summary statistic is calculated across two dimensions: bonds (j) and quarters with holdings data (t).

D Additional elasticities

D.1 Safety and low demand elasticity

Figure D.29: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond characteristics – Corporate bonds

(a) Credit rating **(b)** Issuer region **(c)** Bond maturity

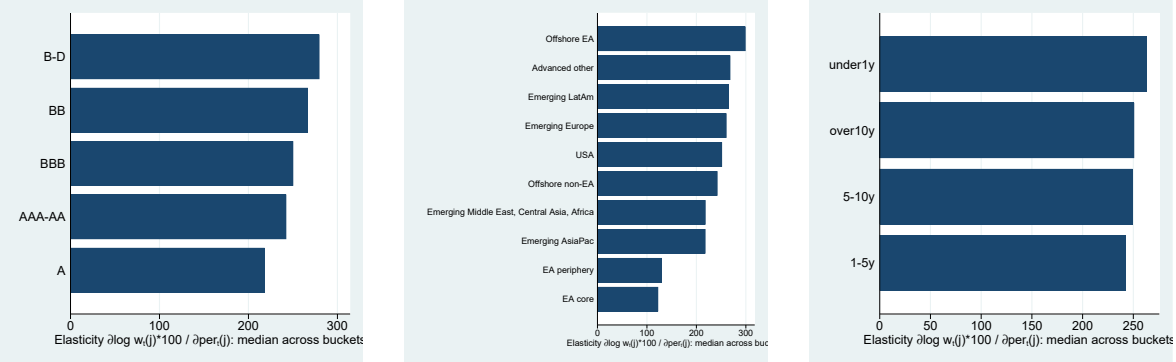


Figure D.30: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond characteristics – All bonds

(a) Credit rating **(b)** Issuer region **(c)** Bond maturity

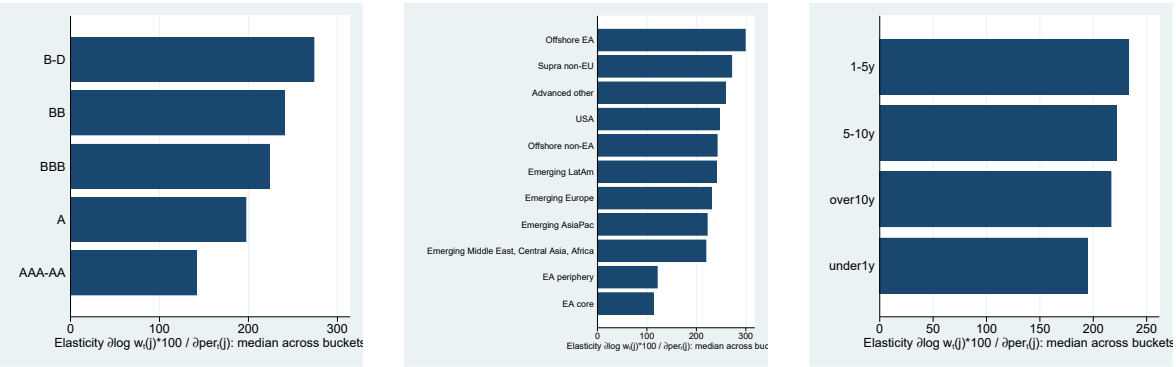
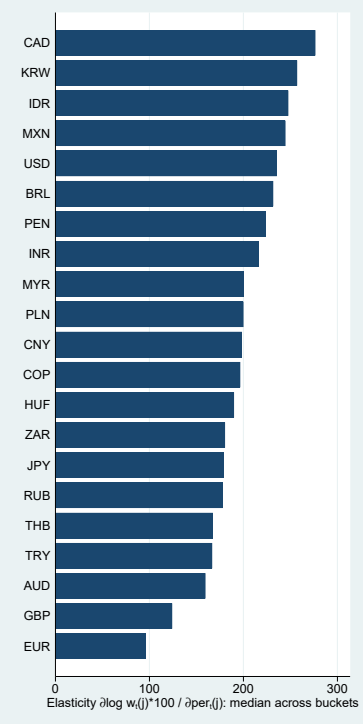
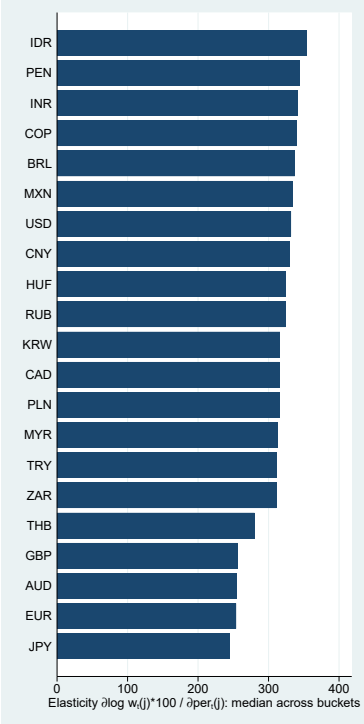


Figure D.31: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond currency – Sovereign bonds

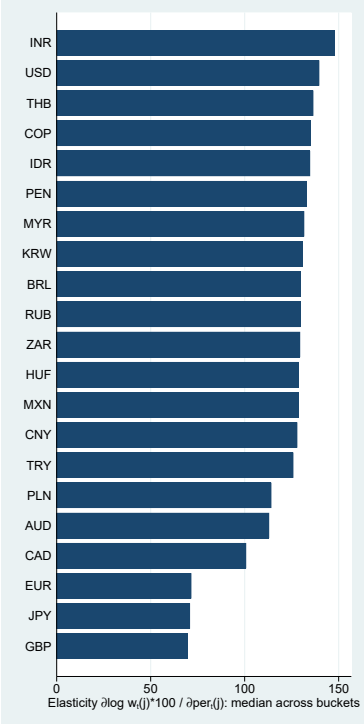
(a) All funds



(b) US funds



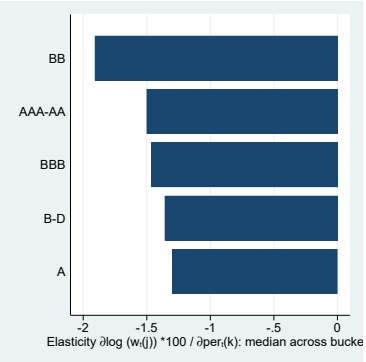
(c) EA funds



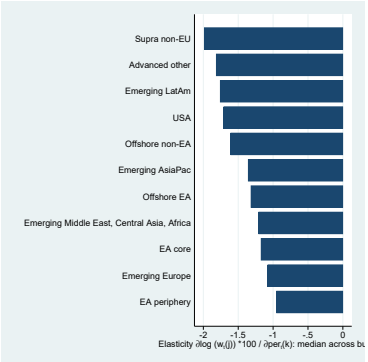
D.2 Global and regional safe assets: a bond substitution view

Figure D.32: Substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds with maturity of less than 1 year by bond characteristics – US funds

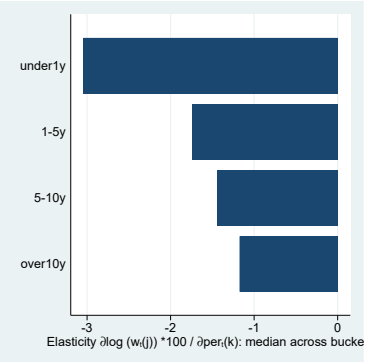
(a) Credit rating



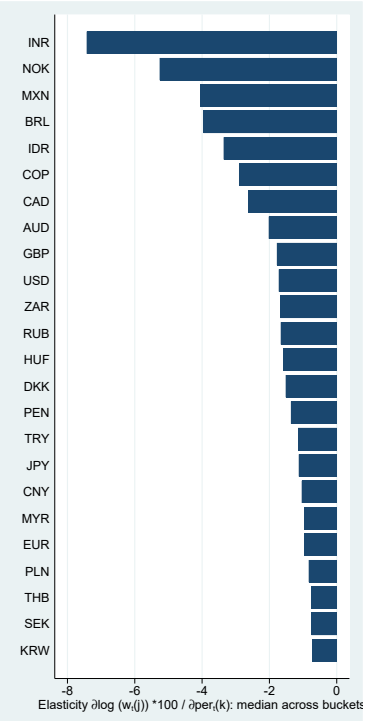
(b) Issuer region



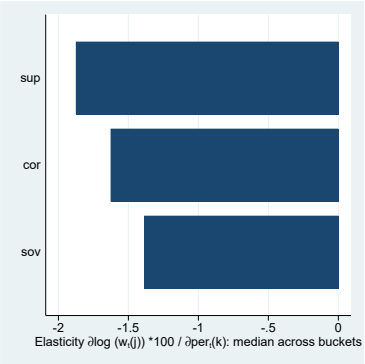
(c) Bond maturity



(d) Bond currency



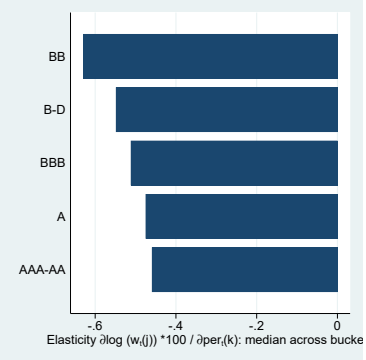
(e) Issuer type



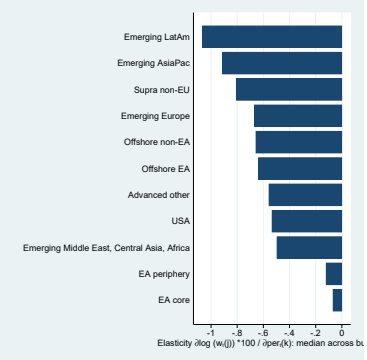
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure D.33: Substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds with maturity of less than 1 year by bond characteristics – EA funds

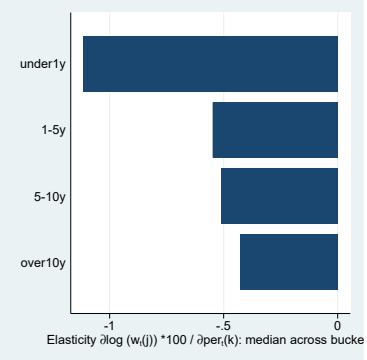
(a) Credit rating



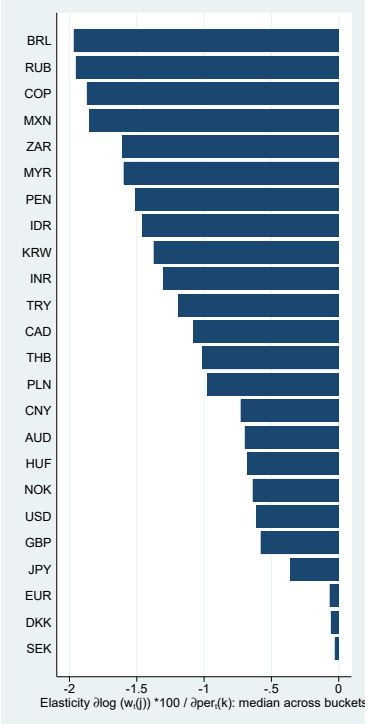
(b) Issuer region



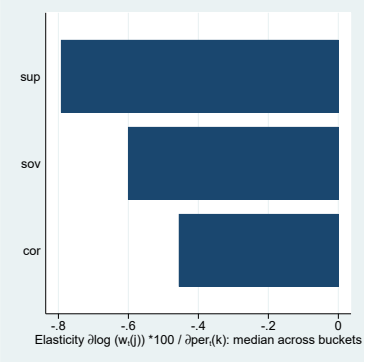
(c) Bond maturity



(d) Bond currency



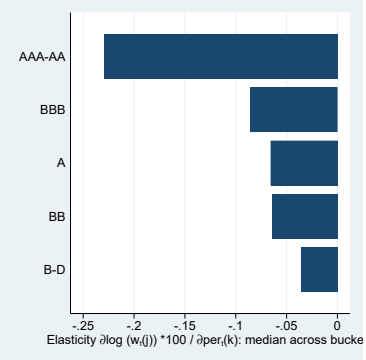
(e) Issuer type



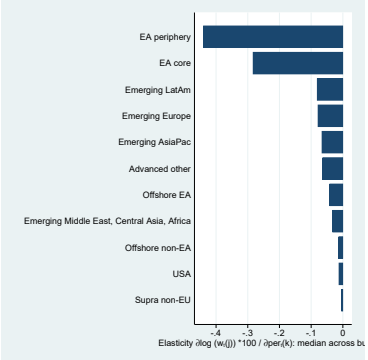
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure D.34: Substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds with maturity of less than 1 year by bond characteristics – US funds

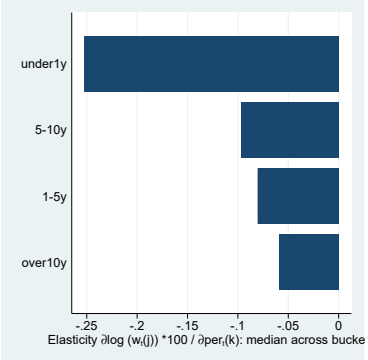
(a) Credit rating



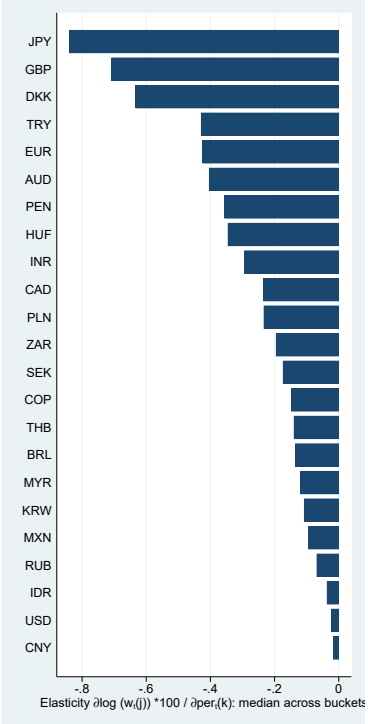
(b) Issuer region



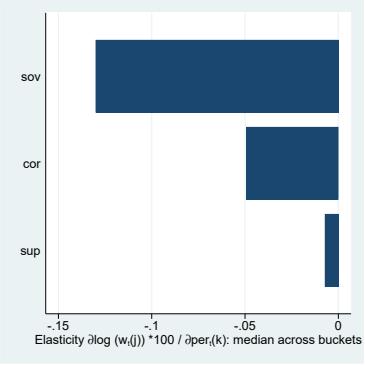
(c) Bond maturity



(d) Bond currency



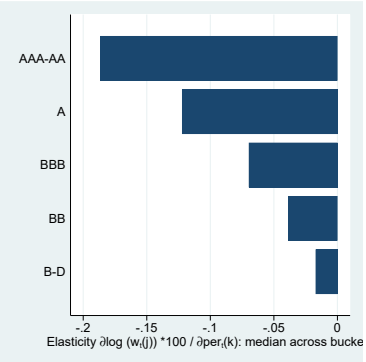
(e) Issuer type



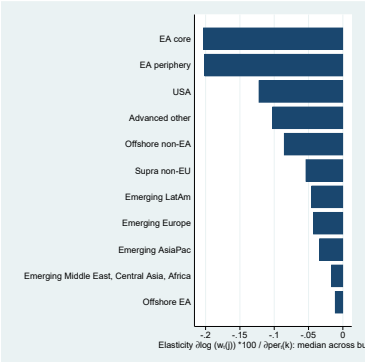
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure D.35: Substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds with maturity of less than 1 year by bond characteristics – EA funds

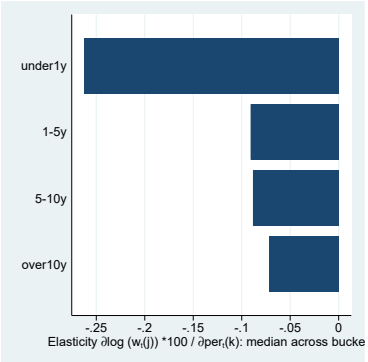
(a) Credit rating



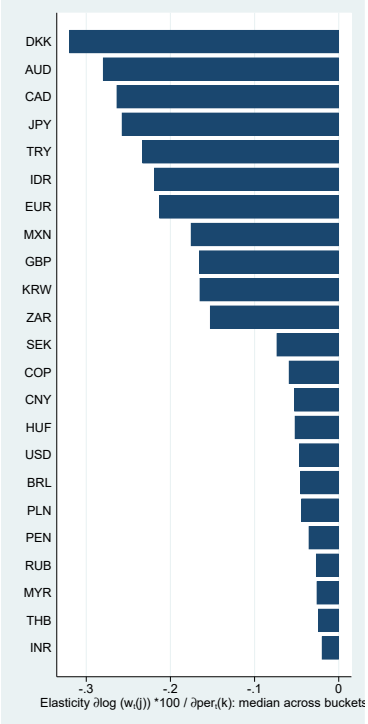
(b) Issuer region



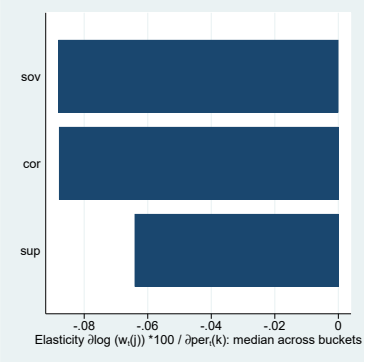
(c) Bond maturity



(d) Bond currency



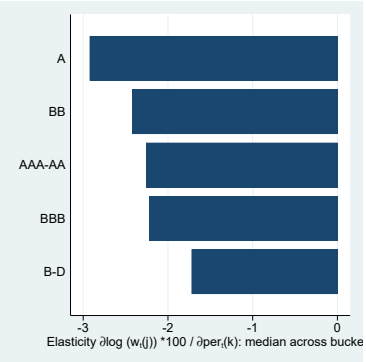
(e) Issuer type



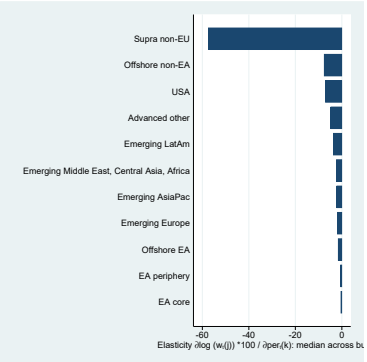
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure D.36: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of 1-5 year maturity by bond characteristics

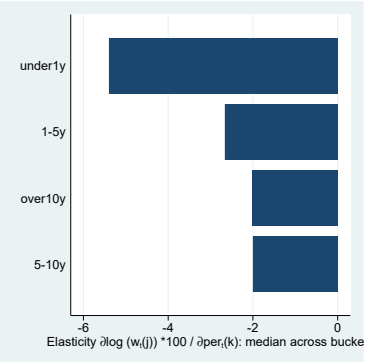
(a) Credit rating



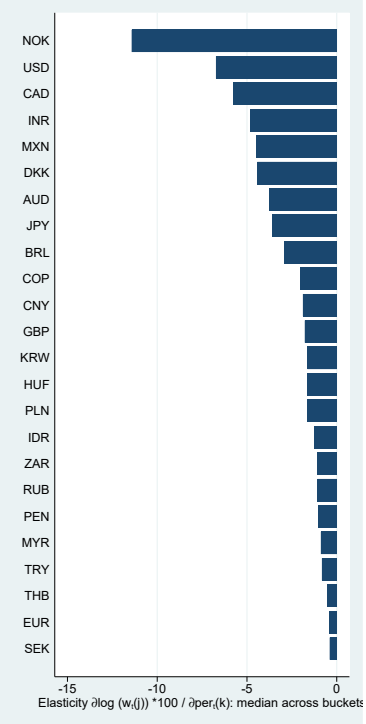
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

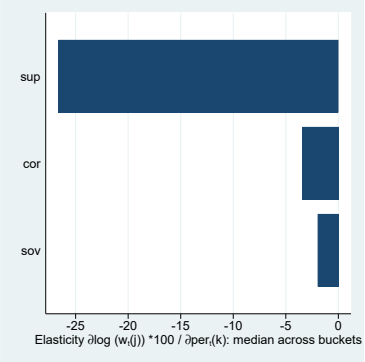
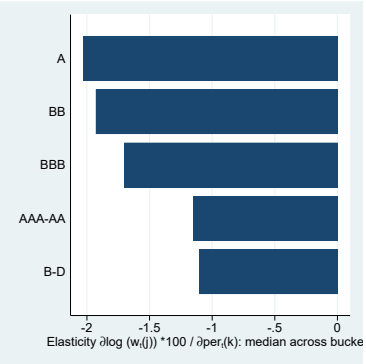
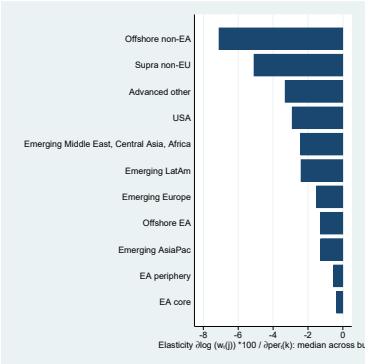


Figure D.37: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of 5-10 year maturity by bond characteristics

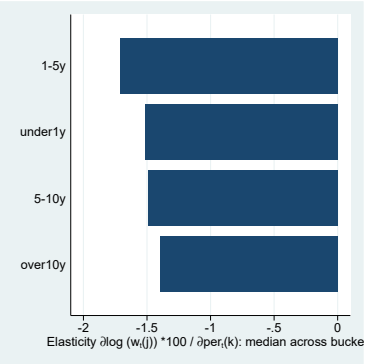
(a) Credit rating



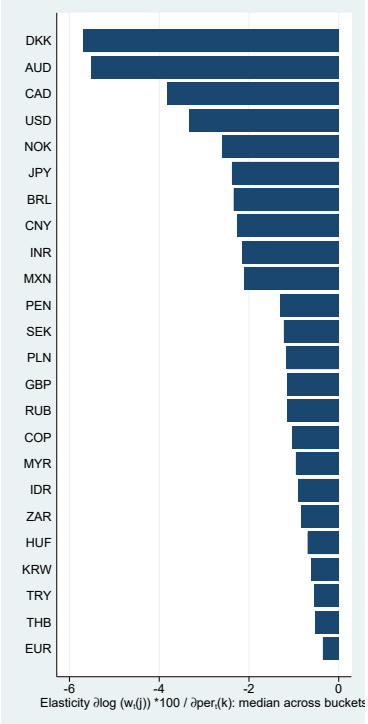
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

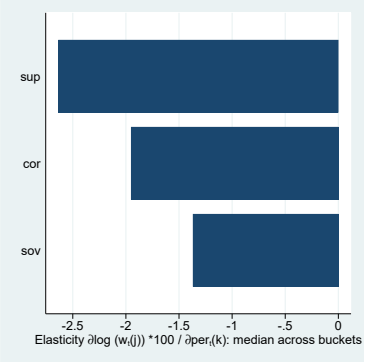
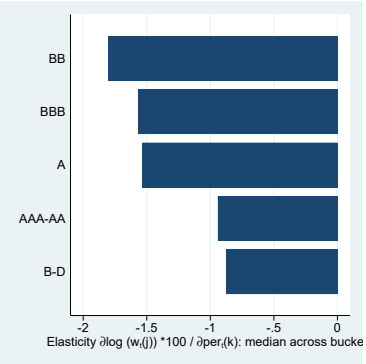
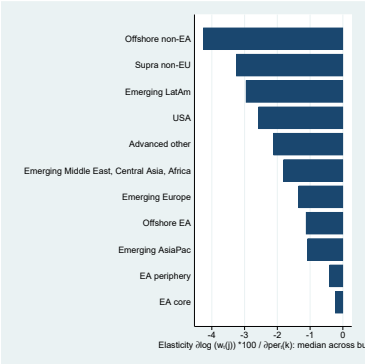


Figure D.38: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of over 10-year maturity by bond characteristics

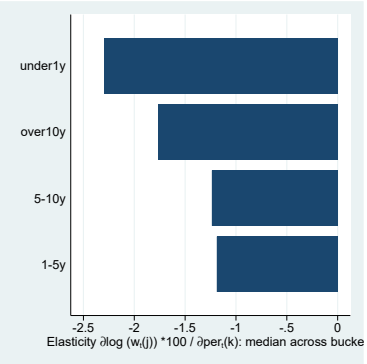
(a) Credit rating



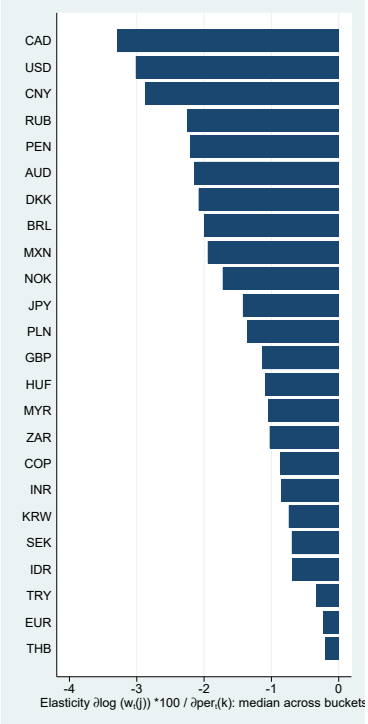
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

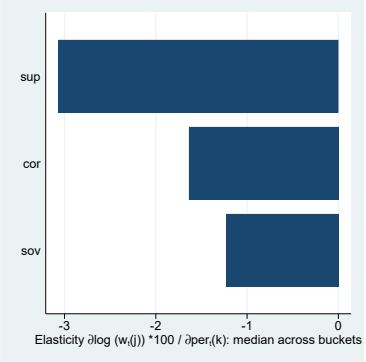
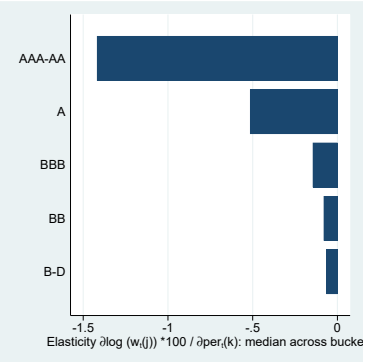
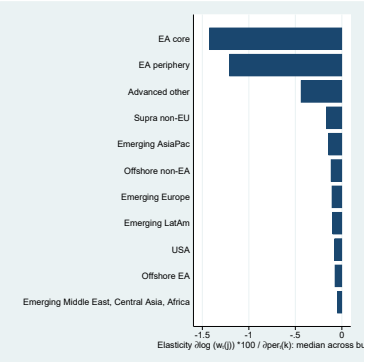


Figure D.39: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of 1-5 year maturity by bond characteristics

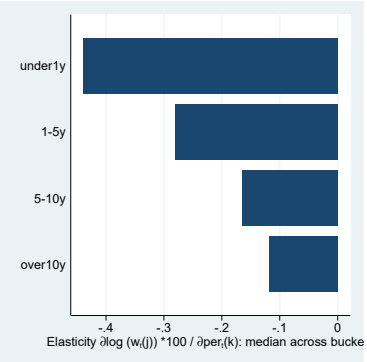
(a) Credit rating



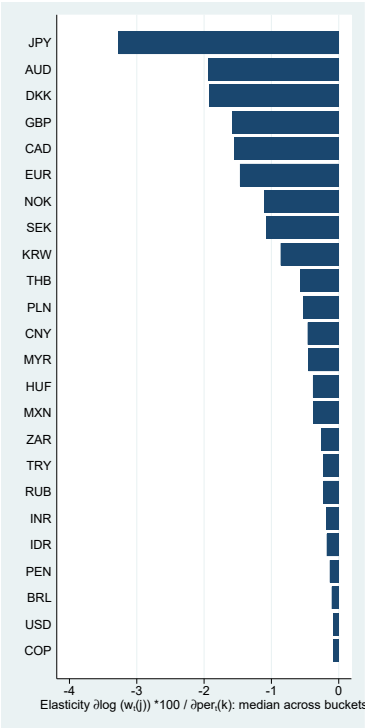
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

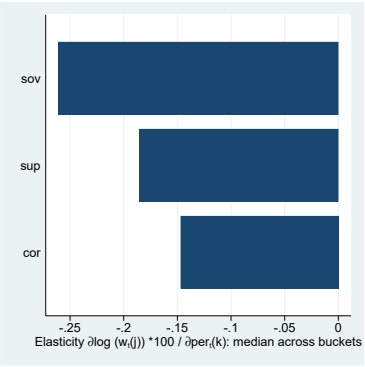
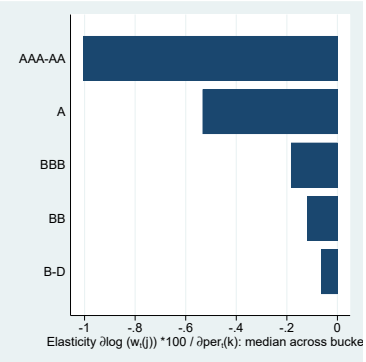
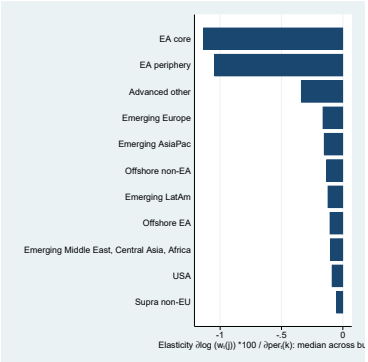


Figure D.40: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of 5-10 year maturity by bond characteristics

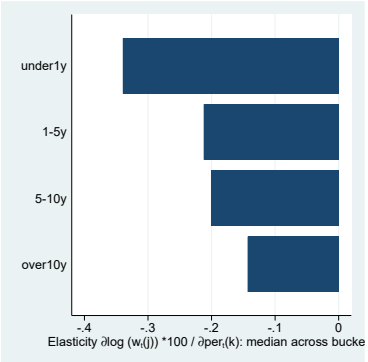
(a) Credit rating



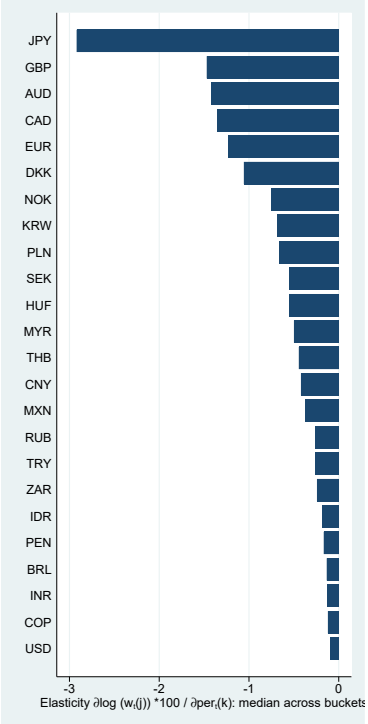
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

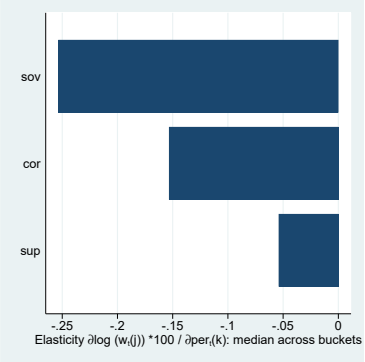
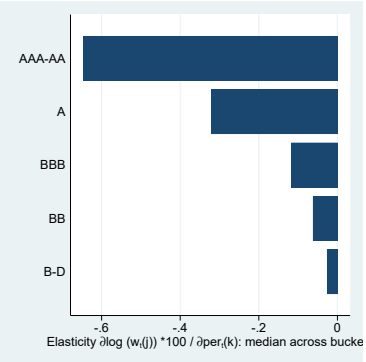
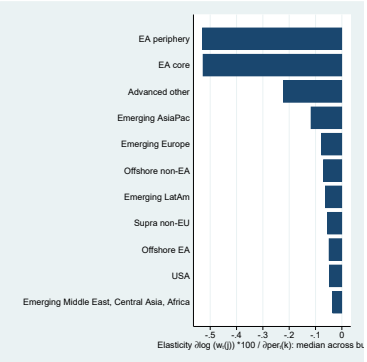


Figure D.41: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of over 10-year maturity by bond characteristics

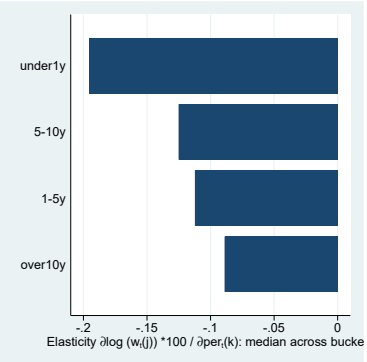
(a) Credit rating



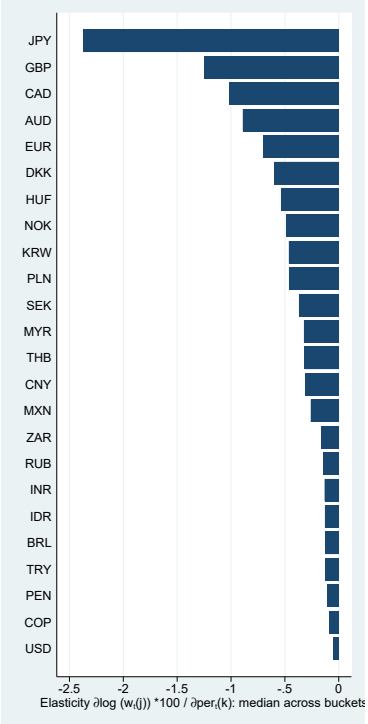
(b) Issuer region



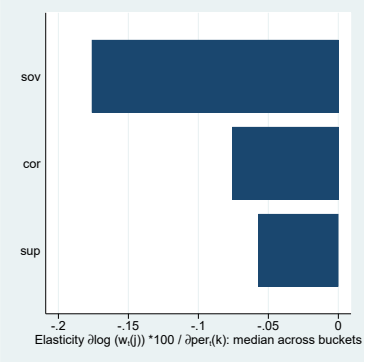
(c) Bond maturity



(d) Bond currency



(e) Issuer type



D.3 Flight to safety

Table D.17: Correlations between German sovereign bond elasticities and risk measures

	DE sov <1y	DE sov 1-5y	DE sov 5-10y	DE sov >10y
Elasticities				
DE sov <1y	1.000			
DE sov 1-5y	0.181	1.000		
DE sov 5-10y	0.178	0.601***	1.000	
DE sov >10y	0.355***	0.346***	0.514***	1.000
Risk				
VIX	0.152	0.200	0.206	0.366***
BEX risk aversion	0.117	0.141	0.151	0.316**
BHL risk aversion	0.161	0.185	0.196	0.354***
MOVE	0.383***	0.088	0.289**	0.520***
EBP	0.050	0.168	0.174	0.414***
CISSEAbond	0.149	0.168	0.333**	0.330**

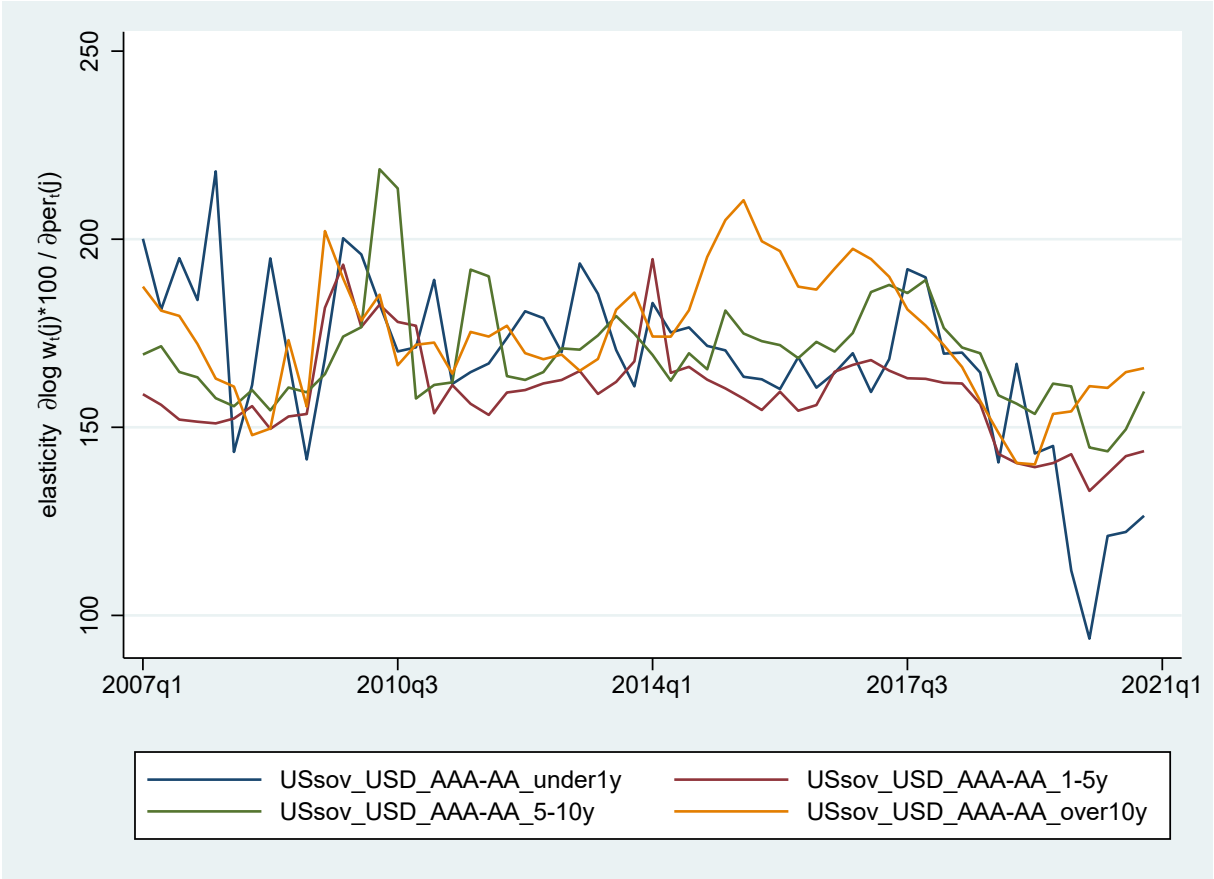
Table D.18: Correlations between Swiss sovereign bond elasticities and risk measures

	CH sov <1y	CH sov 1-5y	CH sov 5-10y	CH sov >10y
Elasticities				
CH sov <1y	1.000			
CH sov 1-5y	-0.035	1.000		
CH sov 5-10y	0.280*	0.306**	1.000	
CH sov >10y	-0.521***	0.638***	0.274**	1.000
Risk				
VIX	-0.076	-0.100	-0.302**	-0.394***
BEX risk aversion	0.101	-0.080	-0.248*	-0.402***
BHL risk aversion	-0.086	-0.100	-0.323**	-0.383***
MOVE	0.331**	-0.457***	-0.194	-0.723***
EBP	-0.033	-0.142	-0.032	-0.443***
CISSEAbond	0.210	-0.187	-0.090	-0.433***

Table D.19: Correlations between Japanese sovereign bond elasticities and risk measures

	JP sov <1y	JP sov 1-5y	JP sov 5-10y	JP sov >10y
Elasticities				
JP sov <1y	1.000			
JP sov 1-5y	-0.466***	1.000		
JP sov 5-10y	-0.352***	0.626***	1.000	
JP sov >10y	-0.173	0.617***	0.400***	1.000
Risk				
VIX	-0.286**	0.378***	0.191	0.079
BEX risk aversion	-0.338**	0.398***	0.216	0.029
BHL risk aversion	-0.324**	0.379***	0.215	0.080
MOVE	-0.398***	0.699***	0.289**	0.303**
EBP	-0.265**	0.398***	0.042	0.116
CISSEAbond	-0.142	0.424***	0.238*	-0.013

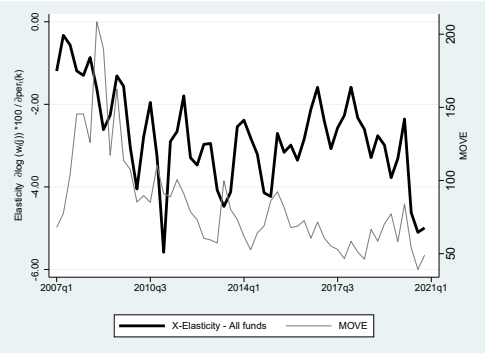
Figure D.42: Own demand elasticities $\eta_t(jj)$ of US sovereign bonds



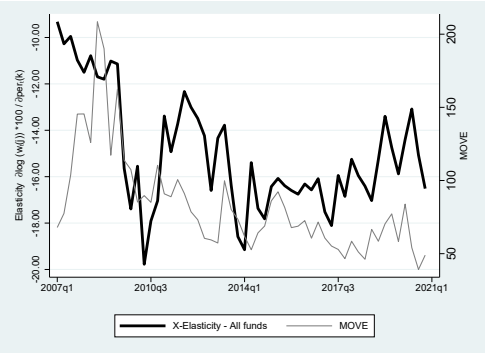
Black line: Funds' demand elasticity for US Treasuries with maturity under 1 year to changes *w.r.t.* 1ppt change in its predicted excess returns.

Figure D.43: Substitutability of US corporate bonds (BBB-BB) with US Treasuries of the same maturity

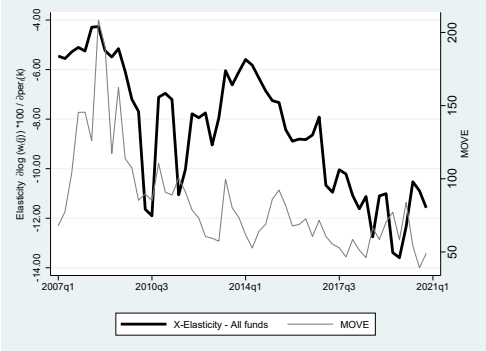
(a) US corporate BBB <1y bonds



(b) US corporate BBB 1-5y bonds



(c) US corporate BBB 5-10y bonds



(d) US corporate BBB >10y bonds

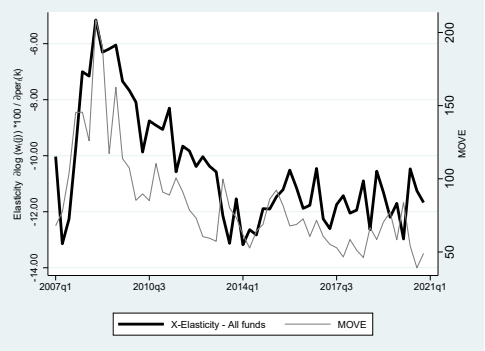
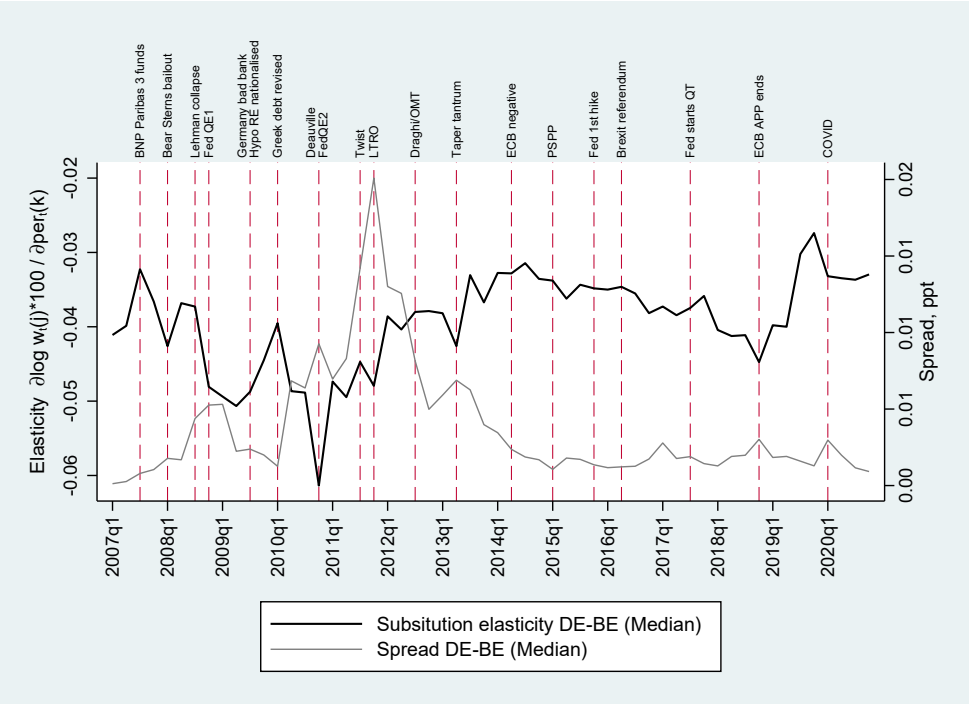
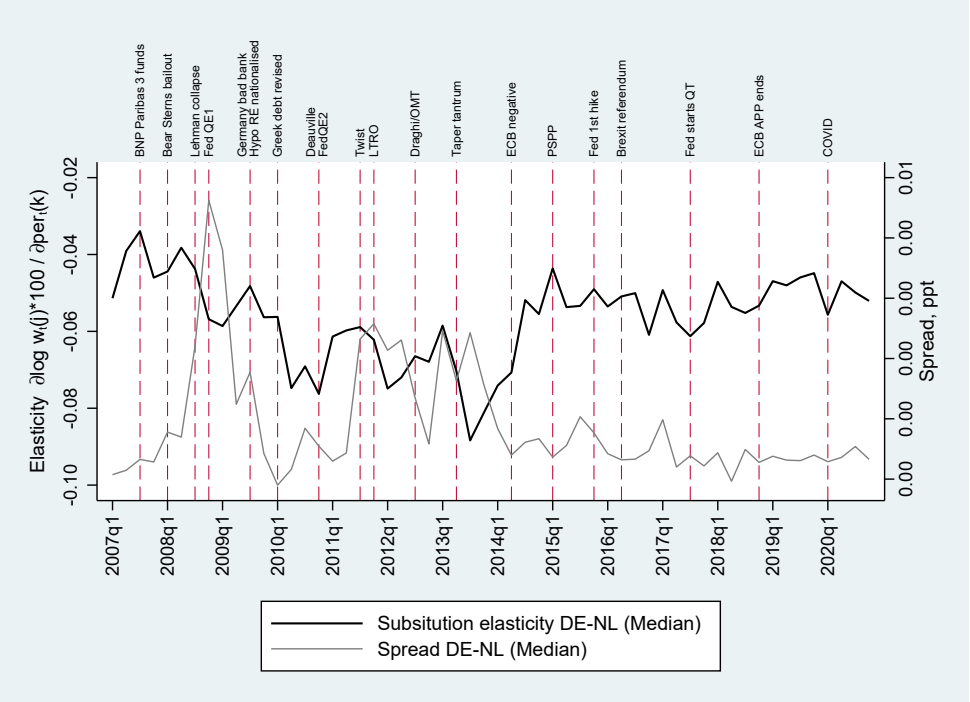


Figure D.44: Substitutability of German and Belgian sovereign bonds



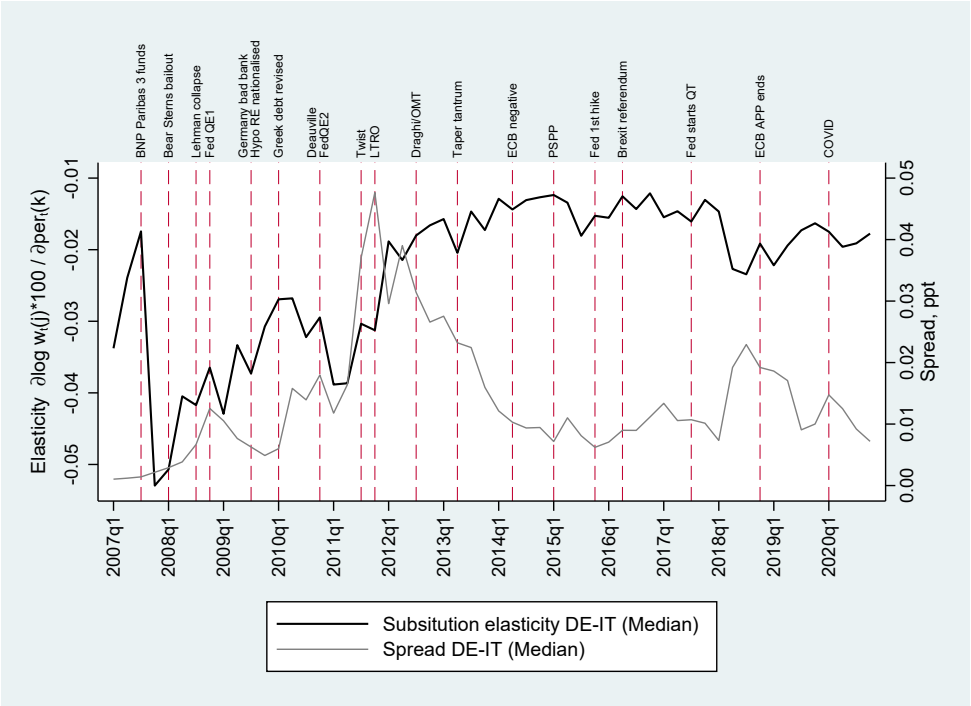
Black line: Substitution elasticity of Belgian sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

Figure D.45: Substitutability of German and Dutch sovereign bonds



Black line: Substitution elasticity of Dutch sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

Figure D.46: Substitutability of German and Italian sovereign bonds



Black line: Substitution elasticity of Italian sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).