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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 both domestically and internationally. That is not only due to their sheer size, being the largest securities market in the world[1], but also because they are home to many of the world's safe assets – the government bonds of advanced economies with low credit risk. The monetary policies of the world's largest economies such as the US and euro area can often directly affect the returns on their domestic safe assets (through short-term interest rate changes or direct asset purchases) but most of the time only indirectly influence the broader bond market, including domestic risky corporate bonds or foreign sovereign bonds. One important channel of global monetary policy transmission is the portfolio rebalancing of international investors between safe assets and the rest of the bond market. To systematically characterize this rebalacing, knowledge of the demand elasticities and substitutability of fixed income assets – especially, with respect to safe assets – is key for policy makers. However, both the literature on safe assets and that on monetary policy transmission 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 and portfolio rebalancing in international bond markets by directly estimating elasticities for global government and corporate bonds held by mutual funds 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. In other words, these elasticity estimates allow me to characterize not only the *degree* of portfolio rebalancing following shocks to the world's leading safe assets (via the *own* elasticities of safe assets) but also the *composition* of this rebalancing across the bond market (via bond-specific *substitution* elasticities with respect to the safe asset returns). These are the first estimates of substitution elasticities in global bond markets, at a granular bond level, and offer a new and more systematic approach to capturing portfolio rebalancing than traditional approaches of tracing flows to ineligible securities in the immediate aftermath of asset purchase programmes[2]. Furthermore, the demand elasticities captured with this paper's methodology can be estimated continuously rather that around specific events such as QE programme announcements. Thus, they offer a unique view of financial turmoil throughout a sample period spanning 2007 to 2020 – 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). To estimate an international bond demand model using a broader and more granular set of assets and investors than in any previous application and allow for more flexible bond-specific substitution elastici-

[1]See SIFMA Research Capital Markets Fact Book 2024: `https://www.sifma.org/wp-content/uploads/2023/07/2024-SIFMA-Capital-Markets-Factbook.pdf`.

[2]E.g. Bergant et al. (2020) for ECB asset purchases and Selgrad (2023) for Fed Treasury purchases.

ties, 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 et al., 2023). Second, I estimate flexible substitution elasticities across bonds by allowing both heterogeneous investor preferences (as in Koijen 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)[3] and brings insights from a long-standing empirical industrial organization literature on demand system estimation[4] to demand-based asset pricing. To identify more flexible substitution elasticities – a contribution that is key to characterizing the composition of portfolio rebalancing in global bond markets – the *combination* of granular data and empirical specification allowing for heterogeneous preferences along many bond dimensions is key.[5] 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.[6] 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 with different characteristics offers new insights on different dimensions of asset safety and confirms that bonds often perceived as safe assets are also estimated to face particularly low demand elasticity from international mutual funds.

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

[3]In contrast, Koijen and Yogo (2020), Koijen, Richmond and Yogo (2020b) allow heterogeneous substitution across asset classes but maintain uniform substitutability within a broad asset class, e.g. global long-term debt securities.

[4]Berry and Haile (2021), Gandhi and Nevo (2021) offer insightful overviews of decades of research in this area.

[5]Relaxing demand estimation restrictions on asset-specific cross-elasticities of demand is also crucial for addressing methodological criticisms raised in Fuchs et al. (2023).

[6]In addition to financial gain, safe assets may offer investors non-pecuniary benefits related to their liquidity, collateral pledgeability, simplicity or regulatory requirements (often summarized as an asset's "convenience yield"). 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, in particular.

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 and other (non-US) advanced economy 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. If such segmentation affects the overall rebalancing between these two safe assets and other international bonds, then the implications for monetary policy spillovers are stark. Shocks to US Treasuries' expected returns from Fed policy are likely to have global ramifications with asymmetric effects on risky bonds, whereas shocks to euro area safe asset returns from ECB policy may be more contained within advanced economy sovereign bond markets[7].

Both the degree and composition of portfolio rebalancing in bond markets with respect to safe assets – as captured by safe asset own and cross elasticities, respectively – vary meaningfully over time. In periods of heightened market stress US Treasuries face an even lower demand elasticity and this is due to passive investors rebalancing even less away from them despite low returns. This paper thus documents systemic "flights to safety" by investment funds and highlights that investor base effects are key to 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 by directly targeting 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 rebalancing under high substitutability of safe assets with risky bonds (low stress) versus low substitutability (high stress). In tranquil times funds invest $27 billion of the US Treasury proceeds in BBB-rated US corporate bonds, compared to only $12 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

[7] Descriptive evidence of the capital flows triggered by ECB sovereign bond purchases in Bergant et al. (2020) seem to support such patterns of ECB spillovers for all holders of euro area sovereign bonds – not just domestic and US mutual funds.

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.[8] Combined with funds' rapidly growing size as a share of global financial sector assets[9], 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.[10] 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, Zhou, 2024). Thus, more generally, mutual funds' portfolio rebalancing in international bond markets plays a first-order role in the cross-border transmission of shocks via financial markets and deserves the granular examination undertaken in this paper.

Related literature. This paper provides detailed empirical evidence on the characteristics of safe asset demand by investment funds. Theoretically, the special demand for safe assets corresponding to the low estimated *own* demand elasticities may have different origins. He et al. (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 et al. (2023). Safe assets should also provide 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 et al. (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 measurement of the premia priced into safe assets, i.e. their convenience yield – a catch-all non-pecuniary benefit derived from holding safe assets that encompasses motives related to safety, liquidity, collateral and repo value, regulatory incentives,

[8]Indeed, Fang et al. (2022) find that mutual funds, especially foreign ones, have the highest demand elasticities for country-level sovereign debt.

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

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

limited participation motives.[11] 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 et al. (2018) calculate the covered interest parity deviations between the government bonds of major advanced economies and the US to measure relative convenience yields. My bond-specific estimates of *own* demand elasticities directly capture investors' revealed preferences through observed bond holdings without *ex ante* assumptions about which bonds are safe assets. 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. 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. 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 – and offer a complementary tool to assess investors' perceived asset safety.

More broadly, the heterogeneity in demand elasticities and substitution patterns estimated here suggest international bond portfolios of mutual funds 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 (Vayanos and Vila, 2021, Gourinchas et al., 2022, Ray et al., 2019, Costain et al., 2022, Kekre et al., 2022). It calibrates the footprint of preferred-habitat investors crudely by assuming that 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 institutional investors' portfolios 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 also 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 et al. (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

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

returns on their holdings as a result. Bergant et al. (2020), Joyce et al. (2014), Koijen et al. (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. In contemporaneous work, Selgrad (2023) identifies quantitative easing shocks to US Treasuries and traces what rebalancing these trigger within US-based mutual fund portfolios across a few broad US asset classes. As in my substitution elasticities with respect to changes in the expected returns on US Treasuries, US corporate bonds receive a large share of the rebalancing – especially those with a similar residual maturity as the shocked Treasuries. Breckenfelder and De Falco (2024) instead focus on the rebalancing triggered by ECB sovereign bond purchases and estimate the average rebalancing to all ineligible securities held by mutual funds. My approach estimates international funds' rebalancing after *both* Fed and ECB shocks in the same framework and captures the broader and heterogeneous rebalancing across global bonds at a much more granular level. The broad international focus of this paper also highlights how different spillovers from purchases of different safe assets can be, with US Treasury shocks causing global rebalancing and German Bund shocks primarily affecting euro area and other non-US advanced economy sovereign bond portfolio allocations.

Methodologically, my work builds on a rapidly growing characteristics-based asset demand literature. Koijen and Yogo (2019) estimate demand for US equities, while Koijen et al. (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 et al. (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 et al. (2022) estimate sectoral demands for the aggregate government debt of advanced and emerging market economies. In a similar spirit, Eren et al. (2023) estimate sectoral demand for aggregate US Treasury debt[12].

Compared to these earlier empirical applications, the demand estimation in this paper is based on much more granular *and* broader 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 geographical investment area, the type of bonds (government or corporate) that it tends to invest in as well as time variation in its overall bond portfolio share. In parallel, I make substantial progress on the estimation methodology in order to capture demand for this granular and broad set of assets and estimate flexible substitution patterns among them. These advances

[12] Eren et al. (2023) also use high-frequency Fed monetary policy shocks but only to obtain exogenous variation in US government bond yields *over time*. 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.

through greater data granularity on both the fund and bond side (including more precisely controlling for fund-specific mandates) and flexible substitution patterns via a more flexible functional form than Nested Logit address important criticisms of the original demand estimation proposed by Koijen and Yogo (2019) – especially concerns relating to the endogeneity arising from failing to control for fund-specific mandates while using cross-sectional variation in portfolio allocations by other investors for identification (van der Beck, 2022, Fuchs et al., 2023), and to the unrealistically uniform substitution patterns implied by the Logit demand function (Fuchs et al., 2023).

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 and exchange-traded funds (ETFs) from Morningstar Direct – a platform providing end-investors with fund information and recommendations. The portfolio holdings data is based on fund reporting and verified by Morningstar against available regulatory reports.[13] 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[14], 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 fund's mandate and portfolio allocation constraints: country of domicile, fund type (either fixed income,

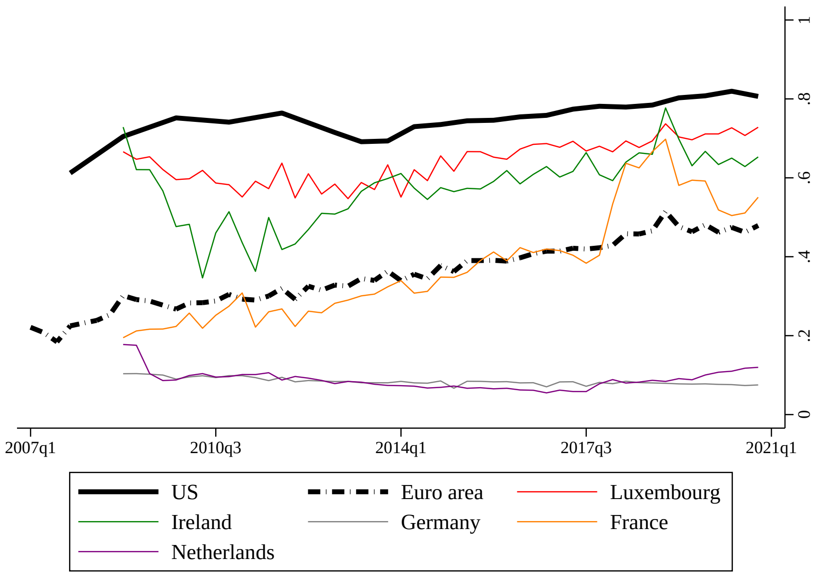
[13] My own checks comparing the portfolios reported by US fixed income funds to Morningstar with their mandatory SEC reports suggests funds provide accurate security-level information. In an influential line of research using Morningstar security-level holdings, Maggiori, Neiman and Schreger (2018), 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.

[14] Source: European Central Bank Investment Funds Balance Sheet Statistics (IVF).

which invest solely in fixed income securities, or balanced, which invest in both bonds and equity), style (index fund, ETF or other), geographic investment area as declared in the fund prospectus, Morningstar fund category, funds with an institutional or retail investor base, fund size (assets under management or AUM), net fund flows, total fund returns. Portfolio holdings are most often reported at quarterly frequency[15], while all other time-varying fund variables (size, returns, flows) are 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 subset of Morningstar data hold around \$8 trillion worth of debt securities and manage a total of around \$11.5 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 all US fixed income and balanced funds and 40% of the respective euro area funds' AUM (Appendix Figure A.16).

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



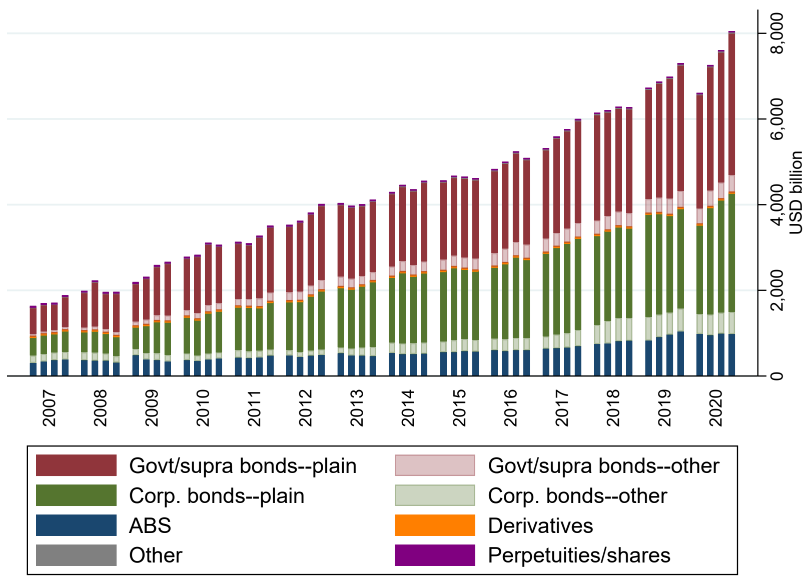
Notes: Each line corresponds to the total market value of debt securities held by funds in the Morningstar dataset collected for this paper as a share of the respective country of domicile's official statistics on its fund sector's total debt security holdings. For euro area countries, official statistics on the market value of debt security holdings of the fund industry are provided in the ECB's Investment Funds Balance Sheet Statistics (IVF). For the US, I sum the market value of debt security holdings of mutual funds and exchange-traded funds (ETFs) reported by the Federal Reserve as part of the Financial Accounts of the United States – Z.1.

[15]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.

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 assets with comparable payoff structure, 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 fund 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 left beyond the scope of this paper – corresponding to 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[16]) is negligible.

Figure 2: Breakdown of Morningstar funds' total debt security holdings by security type



Notes: Breakdown of Morningstar fund debt security holdings by security type. The security classification is based on Refinitiv Eikon reference data extracted using individual security identifiers reported in the portfolio holdings of Morningstar funds used in the dataset of this paper. 'Plain' bonds (government, supranational and corporate) exclude 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 and are the focus of the empirical analysis that follows.

[16]The reason these appear in my dataset in the first place is because Morningstar misclassifies some portfolio assets as bonds.

With this list of 'plain' government and corporate bonds in hand, I collect historical data on month-end bond prices, yields[17] 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 or corporate), issuer country & country of risk[18], 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[19]. 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. Further information on the dataset is provided in Appendix A.

Bond buckets While the collected data is at the security level, 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 which 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).

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

[18]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.

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

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")[20], and (v) residual maturity – four 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 have ever entered the observed fund portfolios between 2007 and 2020. 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. Specifically, bond returns, yields, prices, residual maturity, bond seniority rank are computed as 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.

Appendix Figure A.18 provides a snapshot of the 30 most important bond buckets in the dataset according to 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 remainder of this paper, all analysis is at the bond bucket level and I use "bond", "bond bucket" and "bucket" interchangeably in the discussion, unless explicitly stated otherwise.

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).[21] 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

[20]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.

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

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.

Table 1: Summary of funds

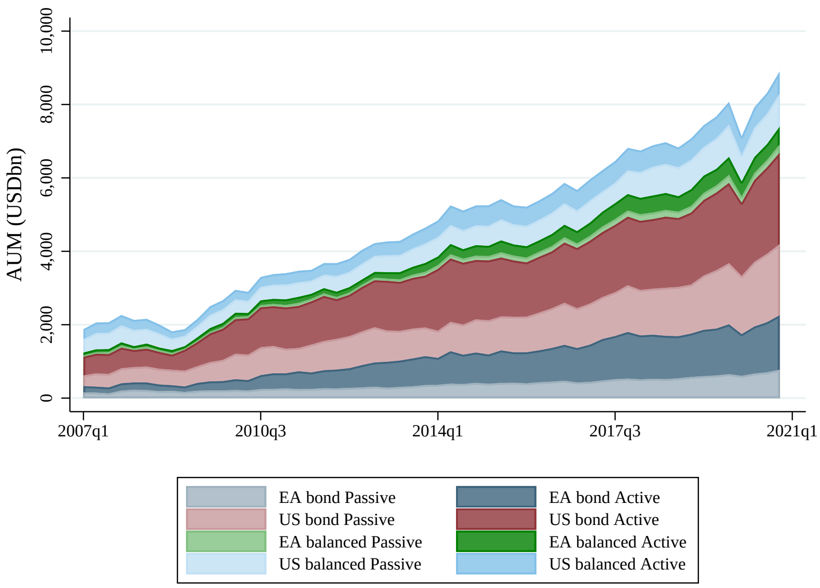
Fund Type	Number of Funds	%All-fund AUM	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th %ile)	Number of Buckets Held (Median)	Number of Buckets Held (90th %ile)
US bond passive	1,232	20	0.93	294	3,460	18	87
US bond active	1,231	29	1.27	385	4,356	27	76
EA bond passive	2,141	8	0.54	141	1,078	22	76
EA bond active	2,507	14	0.72	185	1,507	31	79
US balanced passive	518	12	0.16	353	3,931	12	94
US balanced active	221	9	0.18	311	3,727	20	92
EA balanced passive	1,560	2	0.05	62	513	9	47
EA balanced active	1,492	5	0.13	90	878	13	72

Notes: Number of Funds counts how many unique funds of each time exist suring the entire sample between 2007 and 2020. In total, the analysis uses 10,902 bond and balanced mutual funds and ETFs. *%All-fund AUM* describes the share of the total AUM of funds in the dataset managed by each fund type, on average during the sample period. *%Outstanding* reports the share that each fund type holds of the face value of all corporate and government bonds *ever* held by the funds in the dataset, on average during the sample period. The remaining statistics refer to simple averages within each fund type across the 56 quarterly observations between 2007 and 2020. E.g. *AUM USDmil (Median)* is the quarterly median AUM across the funds of each type, averaged over 2007–2020.

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 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.12 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 will next clarify, 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, Doshi et al., 2015, Kashyap et al., 2021). To separate both *de jure* and *de facto* passive funds from more active ones, I therefore apply the active weight definition of Doshi et al. (2015) to measure the extent to which funds' bond portfolios deviate from their benchmark. This measure of activeness is more feasible when data on multiple benchmark indices and their historical compositional weights are difficult to obtain and a variant of it has already been applied in an asset demand estimation setting by Koijen, Richmond and Yogo (2020b). The active weight defines a fund's benchmark based on the market value of 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 Weight* 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 weight measure (averaged over time) across funds of the four broad fund types is shown in Appendix Figure A.19 and reveals considerable dispersion in the degree of activeness. With this heterogeneity in mind, 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.

Figure 3: Total fund AUM by fund types



Notes: This figure tracks the total AUM only of funds retained after dropping any funds that hold debt securities that do not classify as 'plain' corporate, government and supranational bonds *or* hold 'plain' bonds for which no price data is available from Refinitiv Datastream. The proportion of bond holdings retained is depicted in Appendix Figure A.17. Without bond data on prices and amounts outstanding, it would not be possible to use *Bond Active Weight* to group funds by their activeness. The analysis thus retains funds with an AUM of $9 trillion out of the initial sample of $11.5 trillion (Appendix Figure A.15.
Passive / Active : Funds with below- / above-median Bond Active Weight, on average over time.
Bond Active Weight : Sum of absolute bond portfolio weight deviations from market-value-weighted fund bond universe weights, divided by 2. Doshi et al. (2015) propose this measure of activeness and relate it to fund performance; Koijen, Richmond and Yogo (2020b) apply it to group funds in an asset demand estimation setting.

Thereby, I arrive at eight main fund types along which I will pool the demand estimation described in the next section – US fixed income Passive & Active, EA fixed income Passive & Active, US balanced Passive & Active and EA balanced funds Passive & Active. Figure 3 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, I retain the data granularity by using fund-specific bond bucket holdings to construct the demand regressor of interest and by controlling for granular fund-level variables capturing mandate-related sources of bond demand heterogeneity (controls for geographical mandates, home country bias, corporate/ government bond allocation rules). This yields bond preference parameter estimates that are heterogeneous by fund type. As the next section explains in detail, this hetegogeneity is a crucial ingredient in the estimation of flexible substitution patterns among this varied universe of international bonds.

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 portfolio rebalancing. 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 breadth 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 heterogeneous 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) – and that permits richer heterogeneity in substitution between bonds along more characteristics. 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).[22]

Investment funds indexed by $i = 1, \ldots, I$ allocate their bond portfolio across $|\mathcal{N}_{i,t}|$ risky bonds (where $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$, with N denoting 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.[23]

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).[24] 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

[22] Assuming that fund managers maximize the local currency future value of wealth implies either they do not hedge their currency exposures or they make the hedging decision independently from their bond allocation decision. This modelling decision reflects the fact that Morningstar data contains sparse information on derivatives usage by mutual funds. Existing evidence from alternative sources suggests funds' bond investments are not fully hedged for currency fluctuations and considering local currency returns is a reasonable first approximation of their international portfolio allocation decision. Using data on US fixed income funds' FX forwards usage, Sialm and Zhu (2024) find FX derivatives are emplyed by funds but to varying degrees (only for G10 currencies but not Emerging Market ones) and not solely for hedging purposes but also with speculative motives. Du and Huber (2024) collect industry-level data on the hedging of US dollar exposures by foreign institutional investors and find mutual funds hedge around 21% of these. I, therefore, leave the joint estimation of the portfolio allocation and currency hedging decisions as a potentially fruitful avenue for future research.

[23] 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 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.

[24] 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.

vector $\mathbf{w}_{i,t}$ in terms of expected returns covariances and shadow prices:

$$\max_{\mathbf{w}_{i,t}} \quad \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big]$$

$$\text{s.t.} \quad A_{i,t+1} = A_{i,t}[R_{i,t+1}(0) + \mathbf{w}'_{i,t}(\mathbf{R}_{i,t+1} - R_{i,t+1}(0)\mathbf{1})] \tag{1}$$

$$\mathbf{w}_{i,t} \geq \mathbf{0} \tag{2}$$

$$\mathbf{1}'\mathbf{w}_{i,t} \leq 1 \tag{3}$$

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:

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

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 ($\sigma^2_{i,t}$) 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.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.

Bringing (4) directly to the data is a well-known challenge in a long strand of empirical optimal portfolio choice literature since it requires estimates of 5,000 expected returns, all their variances and covariances.[25] Koijen and Yogo (2019) show that assuming (i) a fairly general factor structure in return beliefs, and (ii) 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.[26] 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

[25]See Brandt (2010) for a review.

[26]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.

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). Conceptually, including the outside asset in the estimation incorporates the investor's budget constraint into the empirical specification[27] and allows the estimation of substitution elasticities between any pair of portfolio assets, as we will see in subsection 3.3.

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.[28] For the heterogeneous-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

[27] To see this, notice that in this setting investor wealth will always equal portfolio holdings including the outside asset. Or, put differently, the sum of portfolio weights is always 1. Without an outside asset in this demand setting, substitution between bonds and other asset classes (cash, equity, etc.) is assumed to always be zero.

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

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. What bond and fund characteristics $\hat{\mathbf{x}}_{i,t}(n)$ are needed to describe bond allocation decisions by mutual funds? Four broad groups of considerations are likely to play a key role for the funds' decision: (i) maximizing portfolio returns, as funds compete to attract end-investor flows; (ii) managing diverse risks (duration, credit, country, currency) associated with this broad range of international government and corporate bonds; (iii) behaving according to the mandate agreed with the end-investors (e.g., relating to asset class, geography, currency of the investment universe); and (iv) adhering to the advertised investment style in terms of degree of risk-taking. The bond and fund characteristics used to capture these fund objectives and constraints are included in the vector $\hat{\mathbf{x}}_{i,t}(n)$ as listed in definition (8). I proceed to explain the rationale and construction of each component in turn.

$$\hat{\mathbf{x}}_{i,t}(n) \equiv \begin{bmatrix} per^h_{\chi(i),t}(n) \\ \mathbf{x}^1_t(n) \\ \mathbf{x}^2(n) \\ \mathbf{b}_i(n) \\ \zeta_{i,t} \\ \varepsilon_{i,t}(n) \end{bmatrix} \tag{8}$$

First, to maximize expected portfolio returns a fund must presumably form a view about the **expected excess return** of the bonds in its investment universe. I build on Koijen and Yogo (2020) and construct a single index to proxy for each bond's expected excess return expressed in the home currency of the fund, and call this the 'predicted excess return' $per^h_{\chi(i),t}(n)$. This captures both the bond's local currency return as well as exchange rate fluctuations of the bond currency relative to the investor home currency $\chi(i)$.[29] Specifically, I obtain $per^h_{\chi(i),t}(n)$ as the fitted value from two predictive panel regressions of returns h quarters ahead in each fund currency – i.e. 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:

$$\begin{aligned} rx_{\chi(i),t+h}(n) &\equiv r_{\chi(i),t+h}(n) - y^h_{\chi(i),t} \\ &= A^h_\chi(i)\ y_t(n) + B^h_\chi(i)\ rer_{i,t}(n) + \sum_{f=1}^{3} C^h_{\chi(i),f}\ uspc_{f,t} + \sum_{f=1}^{3} D^h_{\chi(i),f}\ depc_{f,t} + F^h_{\chi(i),n} + E_{\chi(i),n,t+h} \end{aligned} \tag{9}$$

[29] 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.

where $r_{\chi(i),t+h}(n)$ is the total return on bond bucket n[30] 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 currency of investor i[31]; $y_t(n)$ is the yield-to-maturity[32] 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[33]; $rer_{\chi(i),t}(n)$ 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[34]; $F^h_{\chi(i),n}$ 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 builds 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 (9) separately for each investor currency, whereas Koijen and Yogo (2020) predict returns only in US dollar terms and convert them into the investor currency *ex post* by assuming that the return on each country's short-term debt liabilities is equivalent to its risk-free rate. In contrast, I assume that the risk-free rate is given by the euro and dollar OIS rates, respectively, (determined outside of the bond demand system) 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 (9):

$$per^h_{\chi(i),t}(n) = \widehat{A^h}_{\chi(i)}\ y_t(n) + \widehat{B^h}_{\chi(i)}\ rer_{\chi(i),t}(n) + \sum_{f=1}^{3} \widehat{C^h}_{\chi(i),f}\ uspc_{f,t} + \sum_{f=1}^{3} \widehat{D^h}_{\chi(i),f}\ depc_{f,t} \tag{10}$$

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 demand estimation results using predicted excess bond returns 12 months ahead and the main findings remain intact.

Second, vectors $\mathbf{x}^1_t(n)$ and $\mathbf{x}^2(n)$ include time-varying and static bond characteristics, respectively, which capture various **dimensions of risk** relevant to international bond investors. The

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

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

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

[33] 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.

[34] 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.

time-varying characteristics are the face-value-weighted average residual maturity and seniority rank of all bonds in bucket n as of the end of each quarter t, as well as the total face value of all bonds in the bucket expressed in the currency of fund i[35], which captures the relative supply or liquidity of that bucket.[36] In turn, the vector of static bond characteristics $\mathbf{x}^2(n)$ contains categorical variables already used to define bond buckets – broad credit rating scale dummies, bond issuer's country (of risk) and bond currency (of denomination) fixed effects. Including these rich bond characteristics which capture dimensions of risk – or, equivalently, dimensions along which global bond markets may be segmented – and (as later explained) allowing different fund types to place heterogenous weight on each characteristic allows the estimation of fund demand substitution elasticities to capture greater substitutability of bonds that are similar along any of the above characteristics.

Third, funds have to adhere to an investment mandate, which can specify the currency, issuer type (e.g., sovereign or corporate), or geographic region, when allocating investor resources across financial assets. To proxy for such constraints on each fund's specific investment universe, I control for time-invariant bilateral (fund-bond) dummies collected in vector $\mathbf{b}_i(n)$: (i) a home bias dummy, which equals one if a bond's country of risk is the same as the fund's domicile[37]; (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 by the fund 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[38]. Explicitly controlling for fund mandates based on granular fund-specific information is a major advantage of using granular fund-level data in demand estimation and alleviates methodological concerns raised in van der Beck (2022), Fuchs et al. (2023) regarding the threat of endogeneity arising from omitting to control for fund mandates, while using the cross-section of investor portfolio allocations as an instrument for asset prices or returns as in Koijen and Yogo (2019) and following papers that directly apply their demand estimation methodology.

[35] 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 (either the US dollar or the euro). 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 $t-4$.

[36] The values of these continuous explanatory variables are summarized in Appendix Table A.11, along with the portfolio weights that enter the left-hand side of the demand equation ($w_{i.t}(j)$; and $w_{i.t}(0)$ and the bond yields and 3-month excess bond returns entering the predictive bond returns proxy $per^3_{\chi(i),t}(n)$ as in equation (10).

[37] For funds domiciled in the euro area, I define the fund's home country as follows: German, French and Dutch funds consider respectively Germany, France and the Netherlands as their home; funds domiciled in Ireland or Luxembourg consider the entire euro area as their home. Funds domiciled in the US consider that to be their home country.

[38] 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.

Fourth, individual funds will often have a risk profile that guides their allocation across asset classes (e.g. an aggressive balanced fund will hold more equities and less bonds than a moderate-risk one; or a conservative fixed income fund may hold a bigger proportion of its portfolio in cash). In addition, this risk-taking capacity may change over time with changes in fund management and investment strategy or with external forces (e.g. due to realized or anticipated redemption flows by the end-investors in times of broad market turmoil or in response to the fund's performance. In the ICAPM model motivating this demand specification, this corresponds to the investor-specific time-varying risk aversion parameter $\rho_{i,t}$ in the optimal portfolio weight equation (7) which shifts the demand for all bonds relative to the outside asset. The empirical demand specification uses fund-time fixed effects $\zeta_{i,t}$ to capture such 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. As a result, all bond preferences and resulting demand elasticities are identified solely from the variation in each indivudual fund's portfolio weights *across bonds, over time*. Accordingly, the residual of this demand system $\varepsilon_{i,t}(n)$ now corresponds to the unexplained part of this variation in the investor-specific bond allocation at every period t.

With the characteristics entering $\hat{\mathbf{x}}_{i,t}(n)$ covered, I now turn to the demand coefficients of interest in the vector $\hat{\beta}_i$. 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 for a wide range of 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 the two papers mentioned above.[39]

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[40] – 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

[39] As discussed earlier, this fine granularity is also a key advantage of using the Morningstar holdings dataset, as it allows to take funds' mandates and constraints into account when estimating their bond preferences.

[40] 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.

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 holding – 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 Weight. 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.[41] Expanding on the general demand specification in (7) by plugging in the specific bond characteristics given by (8) delivers a demand specification that can be estimated on this data:

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

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 the individual fund i.

Finally, I turn to the choice of fund investment universe $|\mathcal{N}_{i,t}|$ which determines the bonds that enter the fund-specific 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.[42] Appendix Table A.15 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.[43] This definition of the investment universe means that I can take the logarithm of equation (11) (which takes only positive values) and re-write the estimation equation as a fund-type-level panel Logit model:

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

which can be estimated by linear methods such as OLS or two-stage least squares.[44]

[41] In robustness checks reported in Appendix D, I compare my main results to those using different splits of funds – by size or into index *vs* non-index fund categories instead of Active Weight.

[42] 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.

[43] 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.

[44] Summary statistics for all continuous control variables; the bond and outside asset weights on the left-hand side of (12) as well as the bond yields and realized excess returns used in obtaining the proxy for predicted excess returns are reported in Appendix Table A.11. Further detail on the bond portfolio weights of different types of funds is provided in Appendix Table A.9.

This relatively simple estimation equation delivers the key ingredients needed to estimate flexible bond substitution 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.

3.3 Demand elasticities

I focus on a demand elasticity definition that is particularly relevant for the question at hand – understanding the degree of portfolio rebalancing in international bond markets among safe and risky assets from the perspective of international investors that compare bond return prospects in the investor's home currency. Specifically, I calculate how much funds' portfolio allocation changes when the expected bond excess return converted into the currency of the investor changes. This demand elasticity can be analytically derived from the logistic portfolio weight function assumed in equation (5) by taking a partial derivative with respect to the predicted excess return on any given bond k, $per_{\chi(i),t}(k)$.[45] For an individual investment fund, the corresponding expressions for the *own* and *substitution* elasticities[46] are given by:

$$\eta_{i,t}(jk) \equiv \frac{\partial \log(w_{i,t}(j))}{\partial per_{\chi(i),t}(k)} = \begin{cases} \widehat{\alpha}_{T(i)} \ (1 - w_{i,t}(j)) & \text{if } j = k, \\ -\widehat{\alpha}_{T(i)} \ w_{i,t}(k) & \text{otherwise.} \end{cases} \tag{13}$$

An alternative definition relating the *quantity* or face value of bond demand to bond prices or returns may be better suited to research questions about the *domestic* 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. Such exercises are straightforward to implement with the methodology developed here; its relationship to the elasticity definition in equation (13) is derived in Appendix B.3.[47] [48]

[45] For detailed derivation steps see Appendix B.3.

[46] To be precise, this is a semi-elasticity of demand 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. 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.

[47] An elasticity defined as the percent change in quantity held per percent change in price ($-\frac{\log(Q_{i,t}(n))}{\log(P_t(n))}$) as in Koijen and Yogo (2019) or as change in quantity per percentage point change in the yield ($\frac{\log(Q_{i,t}(n))}{y_t(n)}$) as in Koijen et al. (2020a) require additional assumptions on the relationship between predicted excess bond returns and bond price, which I spell out in Appendix B.3 along with the relationship between all three elasticity definitions. This comparison of elasticity definitions also highlights that only the baseline definition in (13) does not vary mechanically with bond maturity – making it more appropriate for the granular bond demand analysis conducted in this paper.

[48] For other questions, such as the optimal issuance of new bonds, researchers might prefer to study the elasticity of demand to other bond characteristics other than returns such as maturity, credit risk or currency of denomination and the demand model proposed in this paper is flexible enough for these alternative applications.

The *own elasticity*, i.e. the response of fund i's portfolio weight to a given bond to fluctuations in that bond's own return, is given by the first case in (13). The parameter estimate $\widehat{\alpha}_{T(i)}$ determines if the bond demand curve of investor i is flat ($\widehat{\alpha}_{T(i)} = 0$), downward-sloping in prices ($\widehat{\alpha}_{T(i)} > 0$, since bond yields and returns are negatively related to prices) or potentially upward-sloping ($\widehat{\alpha}_{T(i)} < 0$). 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 (5) 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 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, 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 (13) 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 (13) would have a negative sign since the portfolio weight is expressed in market value terms, i.e. the portfolio weight will comove positively with the bond price or negatively with its yield/ expected return.[49] At the other extreme, an unconstrained representative-agent CAPM model would imply a nearly-infinite demand elasticity (see calibration in Petajisto, 2009).

This paper, however, focusses especially on the *cross* or *substitution elasticities*, given by the second case in (13) which describes the response of other bonds' portfolio weights when bond j's return changes. These too depend on the crucial return sensitivity parameter $\widehat{\alpha}_{T(i)}$, 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 too. 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 ($\widehat{\alpha}_{T(i)} > 0$), 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 ($\widehat{\alpha}_{T(i)} < 0$).

Note that, at the individual fund level, substitution elasticities from a fixed bond k are homogenous across bonds. This follows from assuming that individual fund demand is 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

[49]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 (10) 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 2.4, the elasticity as defined in (13) of an index fund would be around -4.

this paper, however, does deliver heterogeneous substitution elasticities once aggregated to the fund sector – which I turn to next.

To describe the demand of all funds 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 by the footprint of each fund in the overall fund holdings of a given bond j[50]:

$$\eta_t(jk) \equiv \frac{\partial \log(w_t(j))}{\partial per_t(k)} = \begin{cases} \sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))} \, \widehat{\alpha}_{T(i)} \, (1 - w_{i,t}(j)) & \text{if } j = k, \\ -\sum_i \frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))} \, \widehat{\alpha}_{T(i)} \, w_{i,t}(k) & \text{otherwise.} \end{cases} \tag{14}$$

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 (14): (i) the composition of investors holding bond j; (ii) estimated investor sensitivities to bond returns $\widehat{\alpha}_{T(i)}$; 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). This demand specification with heterogenous fund preferences thus implies that the closest substitutes are those which are held simultaneously and in larger quantities by the funds with the highest return sensitivities. For instance, suppose funds exposed to German Bund return shocks via a high $w_{i,t}(k)$ allocated to German Bunds also have a preference for holding euro-denominated bonds and thus have a greater weighting in other euro-denominated bonds' elasticities via $\frac{AUM_{i,t} w_{i,t}(j)}{\sum_i (AUM_{i,t} w_{i,t}(j))}$ (as indeed I find in the results described in the next section). If these exposed funds are also estimated to have a non-zero return sensitivity $\alpha_{T(i)}$, that would generate a high substitution elasticity (in absolute terms) of euro-denominated bonds (indexed by j) with respect to expected return shocks to German Bunds (k).[51]

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.[52] Substitution elasticities can in principle be derived from any Logit or Nested Logit estimated demand function. However, the

[50] See Appendix B.3 for elasticity derivations.

[51] 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 the derivation of a nested Logit demand function from a more general Logit with nest fixed effects. Intuitively, the source of heterogeneity in substitution elasticities in my application is the same as in mixed Logit demand models used in IO such as the BLP methodology of Berry et al. (1995). There, the heterogeneity in individual preferences is simulated as only market-level demand data is observed. Here, I observe individual-level demand for bonds and directly estimate the heterogeneous bond preferences which lead to heterogeneous elasticity of aggregate fund sector demand.

[52] 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.

main specification used so far in an international setting (Koijen and Yogo, 2020) imposes rigid structure on the substitution elasticities – these can differ across asset classes but not within broad global asset classes. In other words, investor *are not* equally likely to substitute between and short- and long-term bond; but they *are* equally likely to substitute between long-term bonds issued by different countries. To give a stark example, this implementation of a Nested Logit demand function implies that Canadian and Brazilian bonds are equally good substitutes for US Treasuries. The methodology discussed here results in much richer bond substitution patterns which I analyse in Section 5.

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 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:

$$\mathbb{E}_t\left[\varepsilon_{i,t}(n)\ per^h_{\chi(i),t}(n)\ \middle|\ \mathbf{x}^1_t(n),\ \mathbf{x}^2(n),\ \mathbf{b}_i(n),\ \zeta_{i,t}\right] \neq 0 \tag{15}$$

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[53]. High-frequency measures of monetary policy shocks, in particular, have been shown to materially affect domestic financial market and real economic conditions[54]. And identification using these surprises is not only possible through their variation

[53] 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.

[54] These shocks are derived from changes in interest rates in a short intraday window around monetary policy

over time (as official announcements happen on average once a month), but also across assets with different maturities due to monetary policy becoming more active along the entire yield curve in the aftermath of the global financial crisis of 2008-9.[55] Moreover, monetary policy shocks of the major central banks influence foreign financial conditions to different degrees 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.

Following this logic, I construct two monetary policy shocks for *each bond bucket* held by investment funds – one instrument for the Fed announcement, and one for the ECB announcement. I match the monetary policy surprises at different segments of the respective domestic yield curve to the maturity of each bond bucket – for instance, the two instruments for the return on a bond bucket with weighted average residual maturity of 2 years would be the surprise in the 2-year US interest rate following a Fed monetary policy announcement and the surprise in the 2-year euro interest rate following an ECB monetary policy announcement. In addition, I allow the effects of both shocks to vary by the country of issuance and currency of denomination of each bond by estimating the first-stage regression separately for buckets within each unique combination of bond country and currency. The exact procedure to build these high-frequency instruments for bond returns is described in detail in Appendix C. Appendix Figure C.20 also reports the effective F-statistics of the first-stage regressions for 3-month predicted excess returns, with only bonds with strong first-stage results[56] retained in the following analysis.

Exogeneity of instruments and threats to identification 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 $\varepsilon_{i,t}(n)$. 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 $\mathbb{1}_{n\in|cx|}$:

$$\mathbb{E}_t\left[\varepsilon_{i,t}(n)\left(\int_{\tau=0}^{100} Z_t(\tau)d\tau \times \mathbb{1}_{mat(n)=\tau} \times \mathbb{1}_{n\in|cx|}\right) \middle| \mathbf{x}_t^1(n),\ \mathbf{x}^2(n),\ \mathbf{b}_i(n),\ \zeta_{i,t}\right] = 0 \qquad (16)$$

Note that this is conditional 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. In addition, the two instruments for each bond $Z_t(n)$ 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.*

There are two mechanisms through which monetary policy shocks could affect relative bond

announcements which are argued to be orthogonal to economic conditions already in the investors information set immediately before the policy announcement (Gürkaynak, Sack and Swanson, 2005, Gertler and Karadi, 2015).

[55] Alongside conventional changes to policy rates, major central banks increasingly used both forward guidance to form investor expectations about future monetary policy as well as extensive asset purchase programmes to compress risk premia (Swanson, 2021, Altavilla et al., 2019).

[56] Based on the critical values reported in Olea and Pflueger (2013).

returns but not residual fund bond demand in a way that satisfies this restriction. First, to the extent that some bonds are directly purchased by the Fed and ECB as part of quantitative easing programmes during this sample period, this central bank demand would lower the purchased bond returns more. From the funds' perspective, this corresponds lower returns due to a reduction in the residual bond supply of these bonds and is consistent with the restriction. Of course, I do not focus exclusively on the USD- and EUR-denominated bonds purchased by these two central banks in the analysis and for other international bonds or higher-risk corporate bonds, this argument does not apply. For the restriction to hold for these bonds too, other investors must be more exposed to the funding shocks caused by the monetary policy surprises such that their relative demand for some bonds changes (which again corresponds to a expected return change due to a shift in bonds' residual supply from the funds' perspective). Existing evidence indeed suggests monetary policy causes such shifts in risk-taking especially for more leveraged bond investors such as banks (Crosignani et al., 2020).

The most serious threat to this assumption is that a monetary policy tightening (loosening) surprise by the Fed or ECB, as measured by the intraday response of US or euro area interest rates, induces funds to hold less (more) risky bonds, and that change in funds' relative demand is what leads to a change in relative bond returns used here for identification. This would violate the exclusion restriction that such monetary policy shocks only affect funds' relative demand for bonds due to shifts in bonds' relative expected returns. One reason this may happen is if monetary policy shocks affect the time-varying risk of each bond differently and this is not captured in the bond controls (e.g. bond credit rating). To assess this potential threat, I including additional measures of bond-specific risk and test whether these are affected by the monetary policy shocks. Specifically, two bond time-varying risk measures feasible in this cross-section of bonds could be constructed by interacting a common proxy for investors' time-varying aggregate risk appetite – the *VIX* – with slower-moving proxies of bond-specific risk like (i) the median excess return on the bond over the full sample period; or (ii) the bond credit rating converted into a numerical score (ranging from 0 for D to 20 for AAA). Each of these two proxies is included in the bond demand specification (12) as an endogenous variable alongside predicted excess returns and instrumented with the bond-specific Fed and ECB monetary policy shocks[57]. I find that monetary policy shocks remain strong instruments for bond predicted excess returns but not for bond-specific time-varying risk, as measured by the interaction between the *VIX* and bond rating (Appendix Figure D.33) or by the interaction between the *VIX* and bond median return (Appendix Figure D.32). This does not necessarily imply that monetary policy has no effect on risk taking which would be at odds with macro evidence (Miranda-Agrippino and Rey, 2020b, Bauer et al., 2023). Instead, it likely suggests that this effect is either not fully captured by the interest rate surprises used as instruments here[58] or that it is already controlled for by including a measure of aggregate risk aversion in the first-stage estimation by bond country and currency (*VIX* in the baseline, bond market stress proxies like *EBP* and the euro area *CISSEAbond* in robustness checks) and fund-time fixed effects in the second-stage estimation.

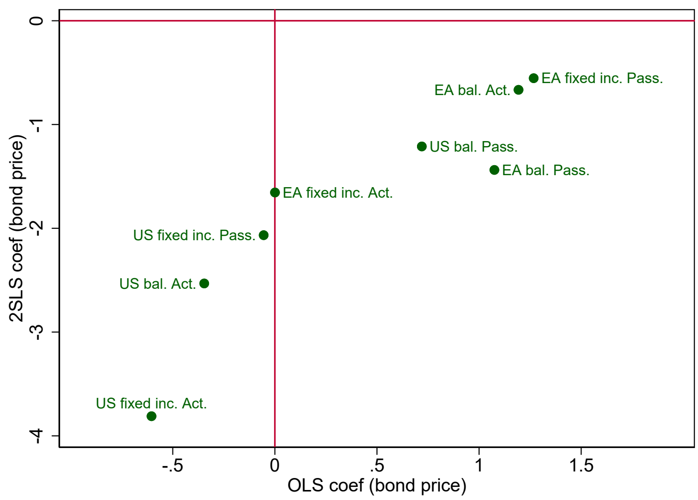
[57]Since the baseline model is overidentified (two shocks for a single endogenous variable, I can add up to one extra endogenous variable at a time.

[58]E.g. Cieslak and Schrimpf (2019) find most of the effect of monetary policy announcements on risky asset prices is not spanned by high-frequency interest rate reactions, and one needs to turn directly to the intra-day movements in risky asset prices to capture these risk shifts. In this sense, the monetary policy shocks used here can be thought of as primarily interest rate shocks.

To the extent that the interest rate surprises used here for identification affect investor risk appetite, this seems to happen primarily via end-investor rebalancing between funds or funds rebalancing between broad asset classes such as equities vs bonds, not via funds rebalancing their portfolios of bond included in the estimation here[59].

Another way to evaluate the threat from fund demand reacting to the monetary policy shocks and violating restriction (16) is to compare the estimated fund demand curve slope parameter $\widehat{\alpha}_{T(i)}$ using OLS versus two-stage least squares with monetary policy instruments. OLS results are likely to capture the unconditional relationship between relative bond demand and bond returns and reflect both supply and demand shocks. Indeed, most estimated OLS coefficients suggest a positive relationship between fund holdings and bond prices as plotted along the x-axis of the scatterplot in Figure 4. Unconditionally, demand shocks dominate and lead to a positive correlation between fund holdings and bond prices (or, equivalently, negative relationship between fund holdings and bond returns $\widehat{\alpha}^{OLS}_{T(i)}$). For all fund types, the IV estimate of this relationship becomes smaller or even flips sign to a negative relationship between holdings and prices, consistent with a downward-sloping demand curve in bond prices (or, equivalently, a positive relationship between holdings and returns). This shift from the OLS estimate implying an upward-sloping demand curve to the IV estimate implying a downward-sloping one is only possible if the monetary policy shocks used in the 2SLS estimation capture predominantly news about bond *supply* from the perspective of funds. This sign flip lends strong support to the identifying restriction in (16).

Figure 4: ESTIMATED COEFFICIENTS $\widehat{\alpha}_{T(i)}$ ON $per^3_{\chi(i),t}$ FROM OLS VERSUS TWO-STAGE LEAST SQUARES REGRESSIONS



Note: The scatter plot compares the coefficient on predicted excess bond returns $per^3_{\chi(i),t}(n)$ estimated using OLS on the horizontal axis with those estimated using two-stage least squares with Fed and ECB monetary policy instruments on the vertical axis. Each dot corresponds to the estimate for one of the eight fund types. All coefficient signs are intentionally flipped in this representation to more easily relate to the inverse relationship between prices and quantities (the original coefficients are estimated on bond returns, which have an inverse relationship with bond prices). Full regression output reported in Appendix Table C.17.

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

Finally, looking beyond the expected returns and their likely endogeneity, all other observable variables in the bond characteristics vector $\hat{\mathbf{x}}_{\mathbf{i},\mathbf{t}}(n)$ 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.[60] 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 excess return predictive regressions described by (9);

2. Estimate first-stage instrumental variable regressions of $per^h_{\chi(i),t}(n)$ on Fed and ECB monetary policy shocks given by (C.26);

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 (13) and (14) respectively. The next section first describes the intermediate results from each of these three estimation steps. It then briefly discusses the interpretation and magnitude of the implied demand elasticities.

4 Estimation results

4.1 Step 1: Predictive bond return regressions

As detailed in the methodology section 3.2, I start the estimation by obtaining a proxy of funds' expectations of 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

[60] 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.

(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 (9) 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. Since this are in-sample predictive regressions, they should be thought of a way of extracting a common signal about bond returns from local currency return factors as well as foreign factors such as exchange rate movements and foreign spillovers, rather than a formal forecasting exercise.

Table 2: USD excess returns

	(1) $\mathrm{rx}_{\$,t+3}(n)$	(2) $\mathrm{rx}_{\$,t+12}(n)$
$\mathrm{y}_t(n)$	2.388***	2.009***
	(0.211)	(0.086)
$\mathrm{rer}_{\$,t}(n)$	-0.582***	-0.451***
	(0.062)	(0.024)
US Level	-0.052***	-0.044***
	(0.018)	(0.005)
US Slope	-0.209***	-0.135***
	(0.071)	(0.026)
US Curvature	0.327	-0.140
	(0.361)	(0.137)
DE Level	0.016	0.017***
	(0.013)	(0.005)
DE Slope	0.379***	0.291***
	(0.094)	(0.039)
DE Curvature	0.034	-0.137
	(0.524)	(0.185)
Obs	400,769	400,769
Adj. Rsq.	0.13	0.38
Within Rsq.	0.11	0.31

Table 3: EUR excess returns

	(1) $\mathrm{rx}_{€,t+3}(n)$	(2) $\mathrm{rx}_{€,t+12}(n)$
$\mathrm{y}_t(n)$	2.324***	1.909***
	(0.170)	(0.087)
$\mathrm{rer}_{€,t}(n)$	-0.451***	-0.414***
	(0.053)	(0.025)
US Level	0.003	0.009
	(0.014)	(0.007)
US Slope	0.228**	0.167***
	(0.089)	(0.032)
US Curvature	-0.181	0.358***
	(0.309)	(0.133)
DE Level	-0.047***	-0.049***
	(0.011)	(0.005)
DE Slope	0.032	0.058*
	(0.095)	(0.035)
DE Curvature	-0.873**	-0.545***
	(0.406)	(0.166)
Obs	400,769	400,769
Adj. Rsq.	0.11	0.36
Within Rsq.	0.09	0.30

NOTES: Estimation sample from Jan-2002 to Dec-2020, month-end. $\mathrm{y}_t(n)$ denotes the continuously compounded yield to maturity or to worst on bond n at the end of month t; $\mathrm{rer}_{\$,t}(n)$ is the logarithm of the real exchange rate of bond currency n relative to the US dollar (US dollars per unit of currency n); $\mathrm{rer}_{€,t}(n)$ – 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.

Starting with the two variables which I include following Koijen and Yogo (2020) – the bond yield and real exchange rates – I confirm they are statistically strong predictors of bond-specific excess returns too. Bond yields in month t have strong predictive power across both return horizons and investor currencies of interest. For example, a 1 percentage point higher yield today predicts almost 2.4 percentage point higher returns on the same bond in dollar terms 3 months ahead. Also, an appreciated bond currency vis-à-vis the dollar or euro (i.e. high log real exchange rate at time t) implies lower future bond returns in the investor currency h months ahead. This finding is consistent with some real exchange mean reversion over the horizon.

The six factors extracted from safe US Treasury and German Bund yield curves improve the fit of the in-sample predictive regressions, consistent with considerable foreign spillovers from US and European yield curve movements. Starting with the level factors, these only play a significant role for the bond returns in the respective currency: the US Level factor is negatively correlated with future returns in dollars, while the German Level factor is negatively correlated with future returns in euros. Most likely, this relationship captures the fact that 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.[61] If safe rates are persistent, their level could be informative about future safe rates and, in turn, excess returns. Less mechanically, it is also possible that higher interest rates 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). But this channel seems somewhat at odds with the finding that the level of foreign yield curves – especially of US rates in the euro returns regressions (Table 3) – has limited predictability for bond returns.

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). The opposite signs of coefficients on factors extracted from the respective foreign yield curve versus from the same-currency yield curve 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 10% 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 $per^{3}_{\chi(i),t}(n)$ and $per^{12}_{\chi(i),t}(n)$, respectively.

[61] 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.

4.2 Step 2: First-stage IV regression

I next proceed to the first-stage regressions in order to obtain exogenous variation in these predicted excess returns.[62] The discussion on identification in the previous section already covered in detail the approach used to map monetary policy shocks around Fed and ECB announcements to the returns of bonds of different maturities, countries and currencies. In the course of defending the identification strategy, it also summarizes the strength of instruments (as depicted in the effective F-stat bar plots in Appendix Figure C.20) for the baseline specification using predicted excess returns at 3-month horizons and controlling for time-variation in risk attitudes with the VIX index. Appendix C also confirms a lack of correlation between Fed and ECB shocks across jurisdictions and reports the estimated first stage coefficients on the two instruments (Figures C.21 and C.22). Robustness of these baseline first stage results to changes in the predicted returns horizon (to 12 months), to alternative time series proxies of aggregate risk aversion, and to including a second endogenous variable capturing bond time-varying risk are provided in Appendix D, Figures D.23 – D.33. Here, I briefly discuss what the baseline estimates imply for Fed and ECB monetary spillovers in the cross-section of international bonds studied in this paper.

For the Fed, predicted dollar returns 3 months ahead (panel (a) of Figure C.21) 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. *De facto* dollar-pegged (HKD and CNY) and safe-haven-currency-denominated bonds (CHF), predicted excess returns rise after a US tightening (to the left of panel (a), Figure C.21). Presumably, the driver of this result is a comovement of these local currency yields with US ones, since the exchange rates vis-a-vis the USD should be fixed, or at least more stable (CHF) than other currencies. On the other hand, predicted excess returns of bonds denominated in other advanced and emerging market economy currencies decline following the Fed tightening. This may be due either to expectations of domestic loosening in response to the adverse external demand shock associated with the Fed tightening or an incomplete reversal of the initial depreciation of these currencies against the dollar within 3 months. The effects of Fed monetary policy shocks on bond returns converted into euros (panel (b) of Figures C.21) 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 in Figure C.22, it is most noticeable that the effects are generally smaller (averaging less than 0.1ppt effect per 1ppt tightening by the ECB) – consistent with somewhat weaker financial spillovers from the ECB than the Fed. This may be because fewer countries with fixed exchange rate regimes use the euro as their anchor currency (Ilzetzki, Reinhart and Rogoff, 2019) and, thus, euro area financial conditions are not directly 'exported' to as many peggers as US interest rates. It is also the case 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). The spillovers to predicted excess returns in dollar terms from ECB tightening shocks have a greater European focus, with bonds

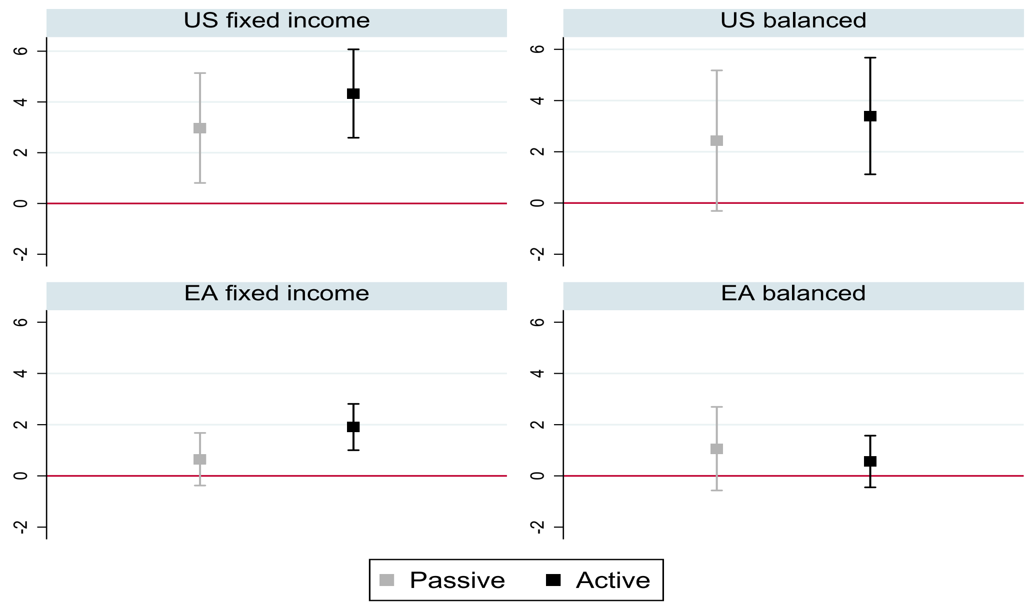
[62] The main variable of interest for bond demand is generated from the predictive regression in (9). Other than dealing with the endogeneity of returns and demand, instrumenting this variable has the additional benefit of better accounting for the noise associated with a generated explanatory variable.

of many European countries such as Denmark, Norway, France, Italy, Germany, Switzerland, Sweden, Spain and the United Kingdom being significantly affected (panel (a) of Appendix Figure C.22). Returns converted into euros of these European bonds are less affected by the ECB shock – presumably this reflects the fact that ECB monetary policy spill over to international bond returns to a large degree through its effect on the euro-dollar exchange rate (panel (b) of Appendix Figure C.22).

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, as these are combined with data on fund holdings to construct estimates of funds' demand elasticities. Figure 5 summarizes the estimated $\widehat{\alpha}_{T(i)}$ for the baseline fund types by domicile, asset class and fund activeness.

Figure 5: ESTIMATED COEFFICIENTS $\widehat{\alpha}_{T(i)}$ ON INSTRUMENTED $per^3_{\chi(i),t}$ BY FUND TYPE



NOTES: 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, light-grey squares and ranges report the estimate for passive funds, while the black correspond to active funds. Active and passive funds are defined relative to the median bond active weight of each fund (averaged over time). Full regression output reported in Appendix Table D.18.

Starting with the top-left plot, we see that US fixed income funds have relatively high estimated sensitivities. Active US bond funds are also more responsive to changes in predicted bond returns than passive ones. 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 2 for active ones 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 latter finding 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 specialize 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. Appendix Figure D.34 confirms these estimates of $\alpha_{T(i)}$ are robust, in turn, to an alternative bond return horizon (12 months), alternative controls for aggregate risk appetite in the first-stage regressions (EBP rather than the VIX), classifying passive funds more narrowly based on their index / ETF status for fixed income funds and a Morningstar categorization of active balanced funds (classified as 'aggressive' or 'flexible'). I also document that large[63] fixed income funds are more return-sensitive than small ones (panel e), but that variation in the sensitivities within small or large funds by activeness is more pronounced (panel f).

The full regression tables with estimated coefficients on the other exogenous bond and fund-bond characteristics can be found in Appendix D, Table D.18. 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. 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 absorbed country fixed effects) and there it only appears to significantly bias the holdings of fixed income funds towards home bonds.

[63]Based on having an AUM above the median fund in most quarters of their presense in the estimation sample.

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 hold bonds issued by governments across the board. Consistent with their mandates, 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. This high explanatory power of the demand model gives a firm foundation on our interpretation of the estimated return sensitivities $\widehat{\alpha}_{T(i)}$ as a response to divergences in bond expected returns, holding most relevant bond characteristics and fund constraints constant.

4.4 Estimated demand elasticities

I proceed to calculate the elasticities implied by the bond demand model (equation 14) using the estimated fund sensitivities to predicted excess returns $\widehat{\alpha}_{T(i)}$. For now, I only summarize estimated demand elasticities across all bonds and fund types and discuss how to interpret their magnitudes in relation to existing literature. In the next section, I explore the variation of demand elasticities across safe versus risky bonds as well as over time to shed light on the international portfolio rabalancing behaviour of mutual funds.

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	3.47	0.70	3.68	2.32	4.25	75,905
EA fixed income	1.27	0.47	1.43	0.09	1.72	105,895
US balanced	2.68	0.73	2.93	1.56	3.43	43,030
EA balanced	0.42	0.10	0.37	0.35	0.73	77,086
Total Fund Sector	1.84	0.96	1.72	0.09	4.23	110,477

NOTES: 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).

Own 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. Table 4 summarizes the distribution of own demand elasticities $\eta_t(jj)$ across *all* bond buckets j over the sample period $t = \{2007Q1, \dots, 2020Q4\}$.[64]

As discussed earlier, the elasticities that different bonds face from the fund sector can vary if they are held by funds with heterogeneous preferences (including return sensitivity $\alpha_{T(i)}$). On average, the fund sector changes the portfolio weight of a bond by 1.84 percent in response to a 1 percentage point change in its predicted excess return (bottom row of Table 4). But the elasticity magnitude can vary considerably (between around 0 and 4) depending on the bond. The main source of this variation comes from the estimated heterogeneous sensitivities by fund type $\widehat{\alpha}_{T(i)}$.[65] 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 around 3.5. At the other end of the spectrum, the low-sensitivity EA balanced funds have the lowest average elasticity of 0.4. In the aggregated fund-sector demand elasticities (bottom row of Table 4), bonds held disproportionately by active US fixed income funds will have a high demand elasticity, while those held by EA balanced funds will have a low demand elasticity.

Where do these elasticity numbers come from and what do they mean? Take the average demand elasticity of 1.84. Mechanically, this primarily reflects the weighted average return sensitivity based on the fund-type-specific estimates of $\widehat{\alpha}_{T(i)}$ in Figure 5.[66] Economically, a comparison with the three extreme cases described in Section 3.3 of a completely sticky portfolio (elasticity of 0), a passive fund (elasticity of -4 for a 10-year bond) and a CAPM-consistent near-perfectly-elastic bond demand (elasticity of several thousand), the estimated average elasticity of 1.84 implies mutual funds have a downward-sloping bond demand – more elastic than a passive investor but a lot less responsive to return differences than CAPM investors. Converting the elasticities to dollar values also helps to put the numbers in context.[67] The average bond bucket holding in the overall fund sector bond portfolio amounts to \$1.75 billion at the end of the sample period (December 2020), so an elasticity of 1.84 implies that a 1 percentage point higher expected return would induce mutual funds to increase their portfolio allocation by 32 million. These dollar values associated with each elasticity, of course, vary considerably by bucket. At the higher end, US Treasuries held by mutual funds in the dataset amount to 1,053 billion US dollars at the end of 2020, where the same elasticity would imply a portfolio reshuffle by 19 billion US dollars.

Existing literature on demand elasticities also finds demand for a range of financial assets is downward-sloping with respect to prices.[68] There is no directly comparable work modelling

[64] As shown in (14), these are holdings-weighted averages of the fund-specific demand elasticities for each bond bucket.

[65] In principle, another source of variation in the investor base of different bonds comes from the $(1 - w_{i,t}(j))$ component of the elasticity formula (14). In practice, funds hold diversified portfolios (i.e. $w_{i,t}(j)$ are small, see Appendix Table A.9) such that this component is close to 1 and varies little by bond.

[66] Suppose the portfolio weight of a given bond j is 1% across all investors (corresponding to the 75th percentile of observed bond weights $w_{i,t}(j)$ in the dataset). The weighted average of the $\widehat{\alpha}_{T(i)}$ estimates for bond j can be backed out from the elasticity as 1.84/ (1-0.01) = 1.86.

[67] If instead one is interested in converting the elasticity magnitudes into percentage point changes of the fund sector's portfolio weight allocated to specific buckets, Appendix Table A.10 provides a summary of the overall fund sector portfolio weight allocated to selected groups of bonds of interest.

[68] 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

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, holding the bond maturity fixed. I apply the same assumption as Koijen and Yogo (2020) that the maturity of long-term debt investment is 5 years and that of short-term debt is 3 months to the relationship between my baseline elasticity definition in (13) and the elasticity of demand with respect to prices derived in equation (B.24) of Appendix B.3. Table 5 reports the resulting bond demand elasticities defined as the percent change in quantity held to a percent change in the bond price. Reflecting the mechanical relationship between bond maturity and bond elasticity in equation (B.24), elasticities for short-term debt are calculated to be higher than for long-term debt. For comparison, Koijen and Yogo (2020) estimate a mean elasticity of 3.1 for long-term debt and of 25.2 for short-term debt based on aggregate international portfolio 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[69], with significant variation by the holder sector. 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 et al. (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 between 1 for domestic and 3.5 for foreign investors in long-term sovereign debt. Broadly, the magnitudes of the demand elasticity estimated in this paper are in the same ballpark as existing studies based on international bond investment.

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

Bond Maturity	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
Long-term (≥1y)	1.87	0.45	1.80	1.04	3.01	88,970
Short-term (<1y)	18.08	10.21	16.76	1.85	41.50	21,507

NOTES: Elasticities $-\frac{\partial \log(Q_t(j))}{\partial \log(P_t(j))}$ aggregated for the entire fund sector. For long-term bonds, maturity is fixed at 5 years to make the elasticities comparable across bonds; for short-term bonds, maturity is 3 months, following Koijen and Yogo (2020). Each summary statistic is calculated across two dimensions: bonds (j) and quarters with holdings data (t).

Unlike previous literature, however, the granular data and estimation methodology of this paper allows these demand elasticities to be bond-specific, reflecting heterogeneous substitution with the rest of international bond markets. I next turn to a brief overview of the estimated heterogeneity in substitution (or cross-) elasticities in global bond markets.

of Koijen and Yogo (2019).

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

Substitution elasticities The magnitudes of estimated bond substitution elasticities, defined as the change in portfolio weight of a given bond j in response to a percentage point change in the return of another bond k ($\eta_t(jk)$), are closely linked to the magnitudes of own elasticities discussed above. If the own elasticity faced by bond k is high, then changes to its return trigger considerable portfolio rebalancing or substitution with other bonds. This substitution elasticity expression in the second line of equation (14) suggests that a given bond j may be a closer substitute for bond k if: (i) the investors who hold j 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 accounting for a large share of the funds' holdings of bond j (captured in the weight $\sum_i \frac{AUM_{i,t}w_{i,t}(j)}{\sum_i(AUM_{i,t}w_{i,t}(j))}$) are also more exposed to the bond whose return experiences the shock (i.e. allocate a large portfolio weight to $w_{i,t}(k)$). In contrast, 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.[70] Since the goal of this paper is to characterize the behaviour of safe assets in particular, 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 of major advanced economies with a short residual maturity.[71] Table 6 summarizes the cross-elasticities with respect to returns changes in the T-bills[72] by four 'safe haven' bond issuers – the US, Germany, Switzerland and Japan. Substitution elasticities are less than or equal to zero, implying that the bond buckets in this dataset are substitutes in fund portfolio allocation decisions. This follows from the empirical estimates of $\widehat{\alpha}_{T(i)}$ all being greater than or equal to zero (Figure 5). The number of observations is smaller than for 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 substitution 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	-0.0121	0.0311	-0.0034	-0.1400	-0.0000	77,221
DE sov <1y	-0.0021	0.0096	-0.0002	-0.0340	-0.0000	61,946
CH sov <1y	-0.0001	0.0018	-0.0000	-0.0012	-0.0000	17,239
JP sov <1y	-0.0033	0.0190	-0.0003	-0.0571	-0.0000	54,335

NOTES: 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.

[70] The substitution matrix is not symmetric, as the formula for $\eta_t(jk)$ in equation (14) 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.

[71] 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 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.

[72] "T-bills" is used 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).

Starting with the substitution elasticities from US T-bills in the first row, these vary between close to zero and -0.14, with a mean of around -0.012. These numbers may seem small but the mutual fund sector is diversified and can substitute to around 1,400 out of the total 5,000 bond buckets following a change in US T-bills' expected return. In aggregate, the cross-elasticities with respect to a given bond return *must* correspond to the overall rebalancing captured in the *own* elasticity of that bond – the cross-elasticities give us additional information only on the composition of this portfolio rebalancing. The smaller cross-elasticities with respect to German, Swiss and Japanese T-bill returns simply reflect the smaller fund sector exposure via the portfolio weight $w_{i,t}(k)$ in the elasticity definition given by (14). The analysis of heterogeneity across substitution elasticities that follows, therefore, conditions on a shock coming from one single bucket and how this spills over to the rest of the bond portfolio via fund rebalancing.

The next section explores variation in own as well as substitution elasticities to characterize safe assets though the prism of investor demands. To recap, estimated demand elasticities from this model can vary both across bonds and over time, with the composition of investors with different return sensitivity $\alpha_{T(i)}$ as well as with different portfolio composition playing a key role in this heterogeneity. 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 a given bond elasticity. 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 (through the interaction between the fund footprint in the bond of interest $\sum_i \frac{AUM_{i,t}w_{i,t}(j)}{\sum_i (AUM_{i,t}w_{i,t}(j))}$ and the portfolio weight of the shocked bond $w_{i,t}(k)$ in formula (14)).

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 slope of demand curves across a certain set of assets.[73] 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

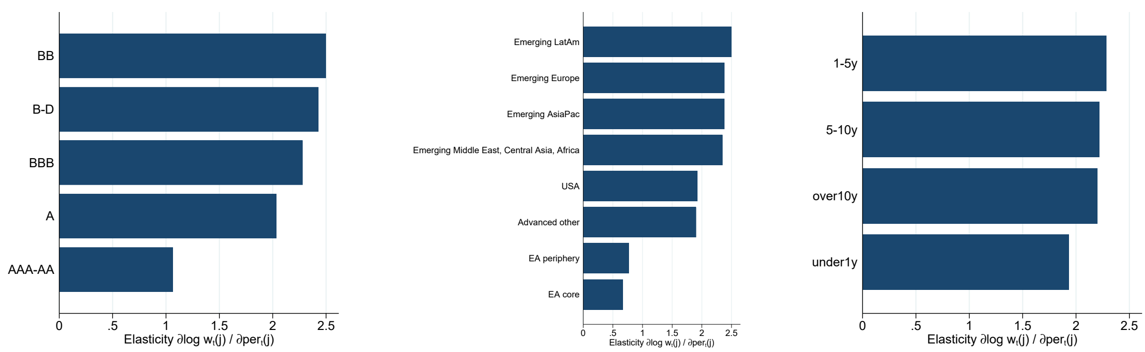
[73] E.g. US equities in Koijen and Yogo (2019), US and UK stocks in Koijen et al. (2020b), euro area bonds in Koijen et al. (2020a), government bonds in Fang et al. (2022), long-term / short-term debt / equity in Koijen and Yogo (2020), Jiang et al. (2021b), exchange rates in Camanho et al. (2022).

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 relatively low elasticity of safe asset demand 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 attractiveness *per se* 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.

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

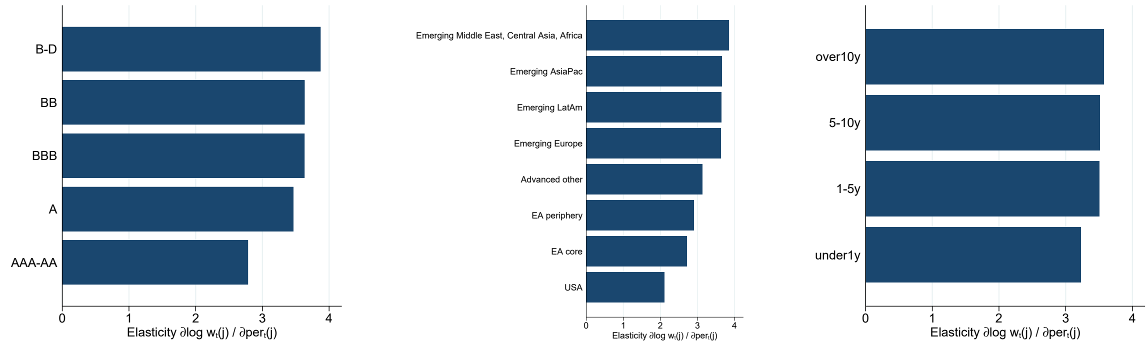
(a) Credit rating **(b)** Issuer region **(c)** Bond maturity



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

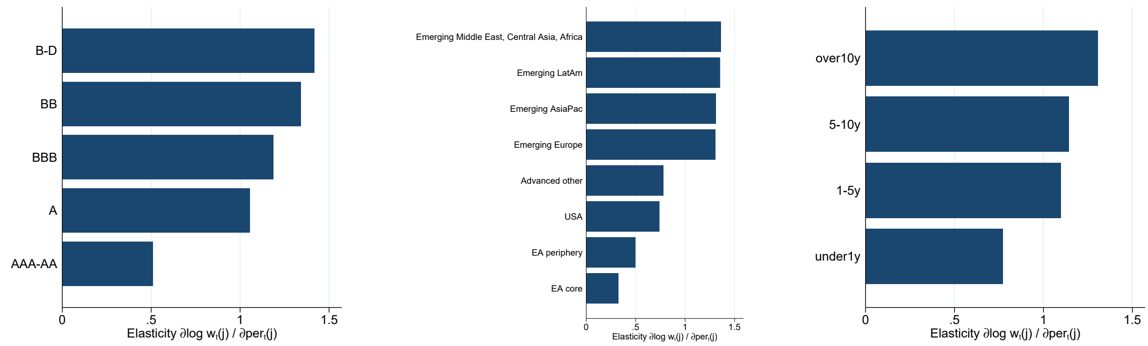
(a) Credit rating **(b)** Issuer region **(c)** Bond maturity



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 E.35 and E.36 perform the same rankings for corporate bonds only as well as for all bonds in the dataset (sovereign, corporate and supranational). For corporate bonds, the especially low elasticity faced by the credit-worthiest bonds (rated "AAA-AA") is not as pronounced as for government bonds, but elasticities do increase moderately with credit risk and are highest for bonds below investment grade (rated "BB" or "B-D"). EA corporate issuers still face low demand elasticities in line with the home bias of less elastic EA funds but US corporate bonds on average face higher demand elasticities from investment funds. The maturity of corporate bonds is not an important aspect of differentiation in terms of funds' demand elasticity.

Finally, demand elasticities also vary a lot by bond currency (Appendix Figure E.37). The euro faces the lowest demand elasticity and not only because of EA funds' home (currency) bias – US funds' elasticities bonds issued in non-US other advanced economy currrencies like JYP, EUR and GBP are also lower. The US dollar, on the other hand, faces a relatively high demand elasticity unless the issuer identity is taken into account, since riskier US corporate bonds and, to a lesser extent, dollar-denominated emerging market bonds account for a large share of the USD-denominated bonds in the dataset.

In summary, the variation in own demand elasticities across bonds offers novel insights of the features of bonds widely considered as safe assets from the perspective of private international investors' demand. Low demand elasticities are especially prevalent for the sovereign bonds of advanced economies with a shorter maturity (presumably, making them a closer substitute for cash). These findings are helpful when thinking about the drivers of the non-pecuniary value that investors derive from holding such safe assets. 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.

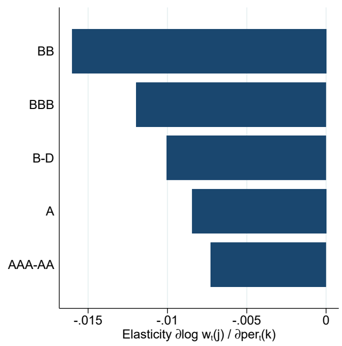
5.2 Global and regional safe assets: a bond substitution view

The next key aspect of safe assets I characterize is how changes in their returns spill over to different segments of international bond markets via portfolio rebalancing. 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?

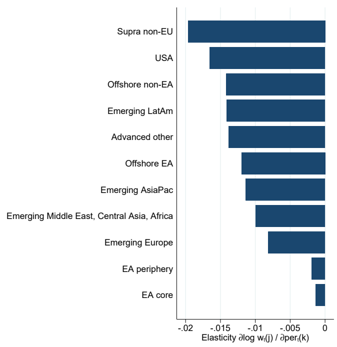
First, Figure 9 summarizes how portfolio spillovers (captured by funds' substitution elasticities) from US T-bills vary by key bond characteristics. A surprising ranking of substitution elasticities by credit rating emerges from the first panel. Bonds that see greatest portfolio reallocations after a 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. Since 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 E.38 and E.39 confirms that riskier bonds see the greatest rebalancing, with EA funds particularly prone to such risk-rebalancing behaviour.

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

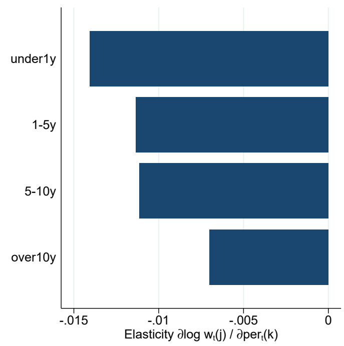
(a) Credit rating



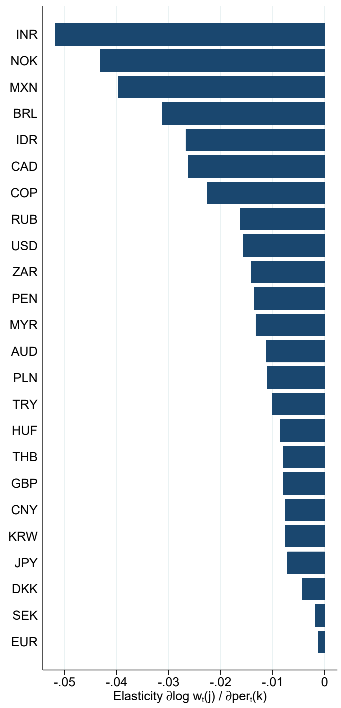
(b) Issuer region



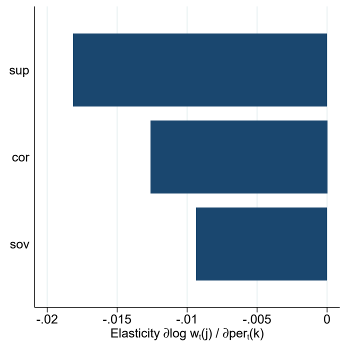
(c) Bond maturity



(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.

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 by the portfolio rebalancing towards US Treasuries. Supranational issuers other than the European Union (mostly development banks issuing bond primarily in US dollars and other hard currency), 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 E.38 and E.39. 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 decrease with bond maturity (third panel of Figure 9) and this finding holds across funds domiciled in the US and euro area alike. In other words, funds seek to rebalance to a similar maturity as that of the US Treasuries experiencing a shock. 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. Indeed, EA asset managers seem to manage funds seeking exposure to global risky bonds, which counterbalance this risk by predominantly holding US Treasuries as the safe asset of choice. 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 E.42-E.44).

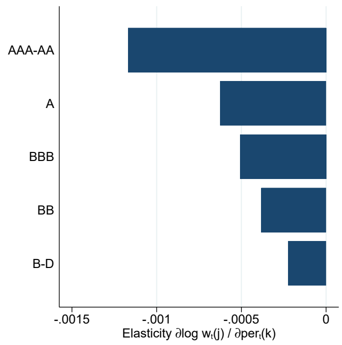
I next turn to the substitution elasticities following a shock to the predicted returns on the safest asset in the euro currency area – German government bonds with residual maturity of less than one year (Figure 10). For the sake of brevity, I continue to abuse the short-hand "T-bills" when describing 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.

Most of these substitution patterns are shared among US (Appendix Figure E.40) and EA funds (Appendix Figure E.41). 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 E.40). 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 E.45-E.47). And the overall substitution patterns for both US

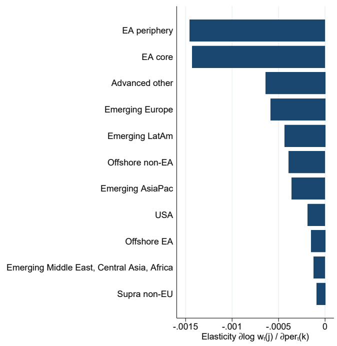
Treasuries and German Bunds reflect more closely the behaviour of active rather than passive funds, as the former are generally more sensitive to changes in expected returns (Appendix Figures E.48-E.49).

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

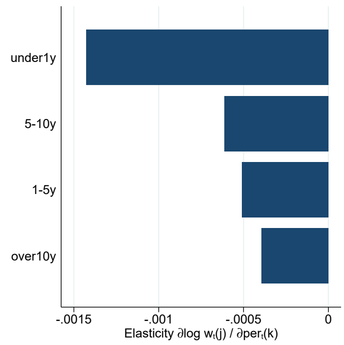
(a) Credit rating



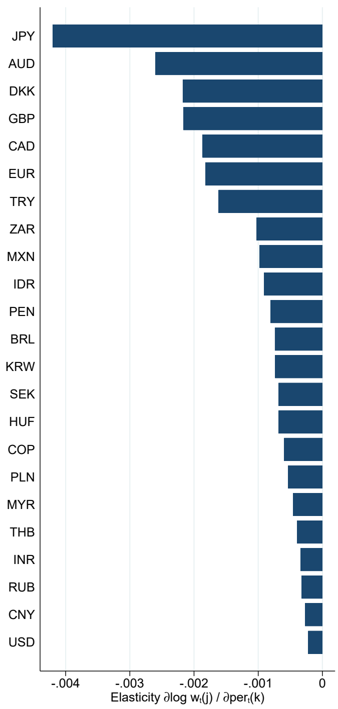
(b) Issuer region



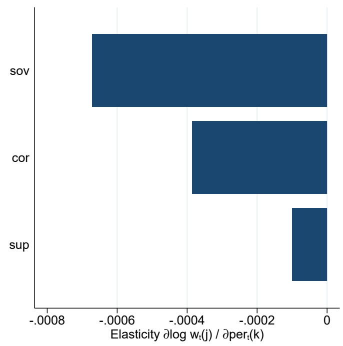
(c) Bond maturity



(d) Bond currency



(e) Issuer type

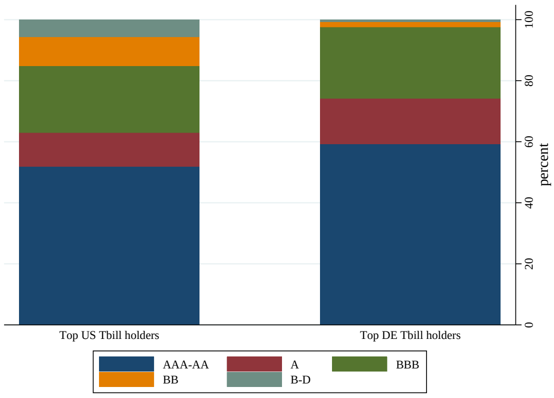


Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

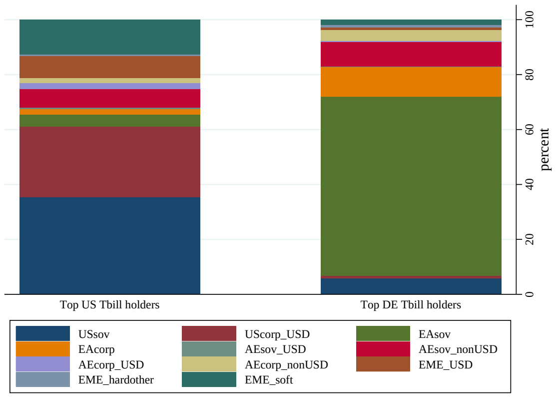
These substitution patterns consistently suggest that the safest bonds of the dollar and euro currency areas trigger very different international portfolio adjustments. Investment funds reduce their portfolio allocation to bonds with high credit risk most to make room for more US Treasuries holdings 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.

Figure 11: Comparison of the bond portfolios of funds that are 'top substituters' from US and German short-term government bonds

(a) Credit rating



(b) Issuer region



Note: 'Top substituters' are funds whose bond portfolios are characterized by a high product of the portfolio weight in the relevant safe asset (US or German T-bills) *and* the weight on the rest of their bond portfolio. Specifically, I rank funds by this product of portfolio weights in each quarter and classify as 'top substituters' those who rank at or above the product's 75th percentile more than half of the time. The portfolio allocation by bond credit rating and issuer region of these funds (average over the full sample period) is described in the plots above.

Figure 11 summarizes these differences in the observed bond portfolios of the funds most likely to substitute away from each safe asset and into other bonds. Top substituters from US T-bills hold nearly 40% of their portfolios in bonds rated BBB or lower, whereas German T-bill substituters allocate around 25% with almost none of those to below-investment-grade bonds (panel a). In terms of geographical allocation, almost 40% of top US T-bill substituters' portfolios are allocated internationally, with substantial investment into soft-currency emerging market debt (panel b, left bar). In contrast, top German T-bill substituters hold almost exclusively advanced-economy bonds, with around three-quarters of the porfolio allocated to local euro area bonds – sovereign and to a much smaller degree, corporate.[74]

Hence, whether looking at the estimated substitution elasticities or at the corresponding data on the portfolio allocation, one safe asset emerges with 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. 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

[74] Appendix Figure E.50 confirms this difference in portfolios remains if all bond portfolio weights are re-calculated at bond face value rather than at market value.

the safe asset component only of bond portfolios more concentrated on euro area safe assets. Shocks to German Bunds thus spill over more locally.

These findings are, of course, specific to the mutual fund sector and one may expect other global investors to step in and arbitrage between some of the world's largest and most liquid sovereign debt markets. Nevertheless, mutual funds' rebalancing is especially important for understanding international portfolio flows more broadly and cross-border monetary policy spillovers through this channel. It is also likely no coincidence that mutual funds portfolios are structured in this way because of demand for specific risk exposures by end-investors (retail and institutional) – an area where our knowledge is more limited due to lack of granular data with global coverage. Further work on the economic drivers or financial constraints behind such portfolio segmentation is essential to fully rationalize the very different spillovers implied by such different roles of safe assets in global bond portfolios.

5.3 Flight to safety

So far, I have averaged each elasticity over the available sample period before summarizing the cross-sectional patterns above. However, demand elasticities recovered with this estimation methodology can vary over time primarily due to shifts in the investor base of different bonds (equation 14). 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.

Focusing on the global safe asset – US Treasuries – I first summarize how funds' own demand elasticities for the four maturity buckets comove with commonly-used measures of market risk (Table 7). Reassuringly, own elasticities of US Treasuries of different maturity are significantly correlated with each other (top panel). They are also negatively correlated with most measures of market stress – when aggregate risk aversion is high, US Treasuries face the lowest *own* demand elasticities. The pattern broadly holds across different Treasury maturities, albeit is most pronounced for the shortest-dated Treasuries which also face on average lower demand elasticities (Figure 6). The first three measures of risk aversion (based on equity markets like VIX, on multiple asset classes – BEX and BHL) are most correlated with the fund elasticity of short-term US Treasuries. The bond-market-based measures of risk (especially the EBP - measuring stress in US corporate bond markets) correlate more with medium- to long-term US Treasury elasticities. Investment funds appear to 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.

Table 7: Correlations between US Treasuries' *own* 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	0.611***	1.000		
US sov 5-10y	0.424***	0.587***	1.000	
US sov >10y	0.433***	0.560***	0.463***	1.000
Risk:				
VIX	-0.393***	-0.256*	-0.163	-0.245*
BEX risk aversion	-0.284**	-0.204	-0.103	-0.213
BHL risk aversion	-0.413***	-0.187	-0.080	-0.187
MOVE	0.093	0.018	-0.114	-0.149
EBP	-0.091	-0.289**	-0.270**	-0.252*
CISSEAbond	-0.141	-0.205	-0.075	-0.220

NOTES: The upper panel reports pairwise correlations between the four maturity buckets of US Treasuries; the lower panel reports the correlations between each bucket's elasticity and six different measures of market stress. *** Significant at 1% level. ** Significant at 5% level. * Significant at 10% level.

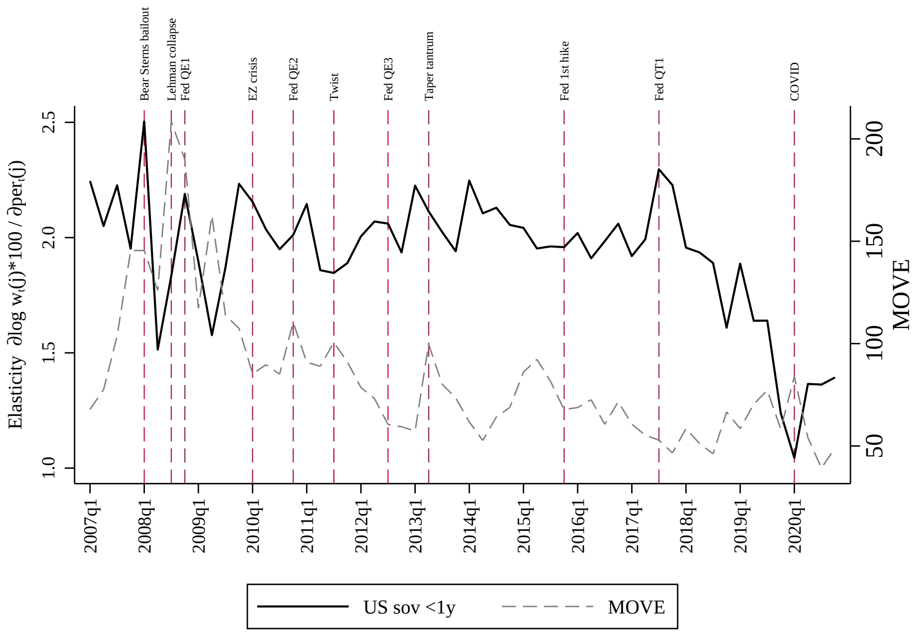
Appendix Tables E.19-E.21 report the same *own* elasticity correlations over time for three other safe asset candidates – German, Swiss and Japanese sovereign bonds – and find they are less of a focal point for flight to safety episodes. German elasticity have little correlation with market stress and at long maturities even increase when risk aversion rises at odds with being the beneficiary of a global flight to safety. Swiss bonds experience lower demand elasticities during market stress but predominantly at maturities of 10 years or longer, while the correlations of Japanese bond demand elasticities with risk aversion suggest a flight to safety predominantly to the shortest-dated bonds.

To shed more light on which funds may drive such flights to the safety of US Treasuries in particular and why, I zoom in on the more extreme episodes of heightened market stress in the sample. Figure 12 compares the fluctuations in the US T-bill elasticity (black line) to the risk aversion measures most closely related to the Tresury market – the option-implied volatility of long-dated US Treasuries (the MOVE index). For better visibility, key market and policy events are marked with vertical red dashed lines. The Lehman Brothers collapse at the pinnacle of market panic during the Global Financial Crisis (2008:Q3) and the lead-up to it saw a marked drop in the elasticity of US T-bills (from 2 to about 1.5). Examining the underlying holdings data suggests this decline in elasticity can be traced back to buying of Treasuries by return-insensitive US balanced funds. Presumably these funds were exposed to the equity market crash and experienced or were anticipating singnificant investor redemptions – that may have prompted them to increase their holdings of liquid assets including short-term US Treasuries. Similarly, 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 restrictions) to the safest assets.[75] To sum up,

[75] Interestingly, the latter 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

return-insensitive / passive funds tend to buy the safe assets when risk aversion increases. This may be due to a response to heightened liquidity risks or simply to passive channeling of net inflows by end-investors to the least risky mutual funds. Both of these episodes are consistent with greater demand for cash and close substitutes like short-term Treasuries – either due to greater institutional liquidity risk or spikes in end-investor precautionary savings.

Figure 12: 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.

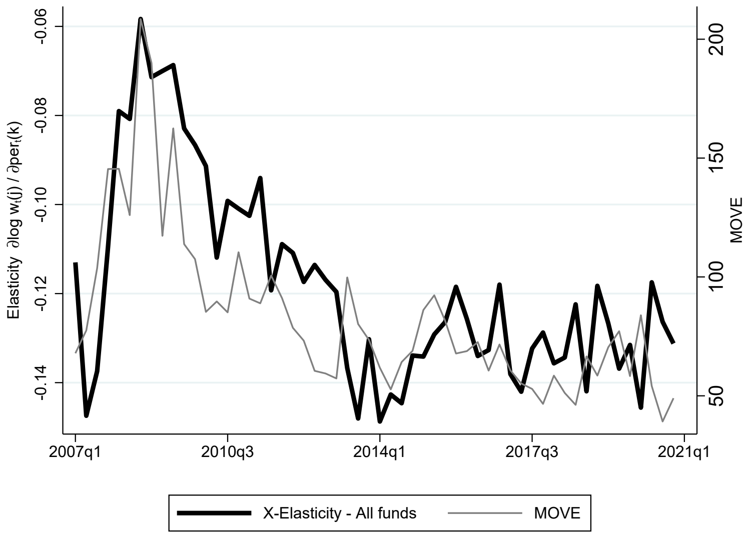
While the above evidence on safe asset own elasticities showcases how the relative safety compared to all bonds in the demand system changes with time, the substitution elasticities of safe assets with risky bonds, in particular, are key for understanding shifts in monetary policy transmission via portfolio rebalancing. Figure 13 tracks the substitutability between long-dated US Treasuries and "BBB"-rated US corporate bonds of comparable maturity.[76] When the black line (substitution elasticity) increases or approaches zero, 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 in an even more pronounced way than the general substitutability of US Treasuries with all international bonds (i.e., the *own* elasticity of US Treasuries in Figure 12). At the height of the global financial crisis in 2008, the substitution elasticity of US corporate bonds in response to US Treasuries halves (from -0.12 to -0.06) and only returns back to pre-crisis levels towards the end of 2013. The COVID market turmoil in March 2020 sees the elasticity tick up towards zero again (i.e. substitutabil-

E.51). 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).

[76]Appendix Figure E.52 compares the US Treasury-BBB US corporate bond substitutability across all four maturity buckets.

ity declines) but only marginally so perhaps thanks to the swift intervention of the Fed in US corporate bond markets (Gilchrist et al., 2020).

Figure 13: 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.

Textbook monetary policy transmission – whether following conventional rate changes, forward guidance or government bond purchases – 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.[77] 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 2.4[78] and would need predicted excess returns to decrease by, on average, 9.7 percentage 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

[77] 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.

[78] This figure corresponds to the average elasticity across the four maturity buckets of US Treasuries. The bucket-specific elasticities are 2.5 for bonds with less than a year until maturity, 2.2 for 1-5 year bonds, 2.5 for 5-10 year bonds, and 2.4 for bonds with maturity over 10 years.

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 4.8%. Fund holdings of US BBB-rated corporate bonds are $556 billion at the end of 2020, so this 5% increase corresponds to $27 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.

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 (1.4 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 predicted excess US Treasury returns – an average fall by 16 percentage points across the four maturity buckets – to induce them to sell to the Fed. Even with the larger shift in US Treasury returns, 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 2.1% or $12 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.

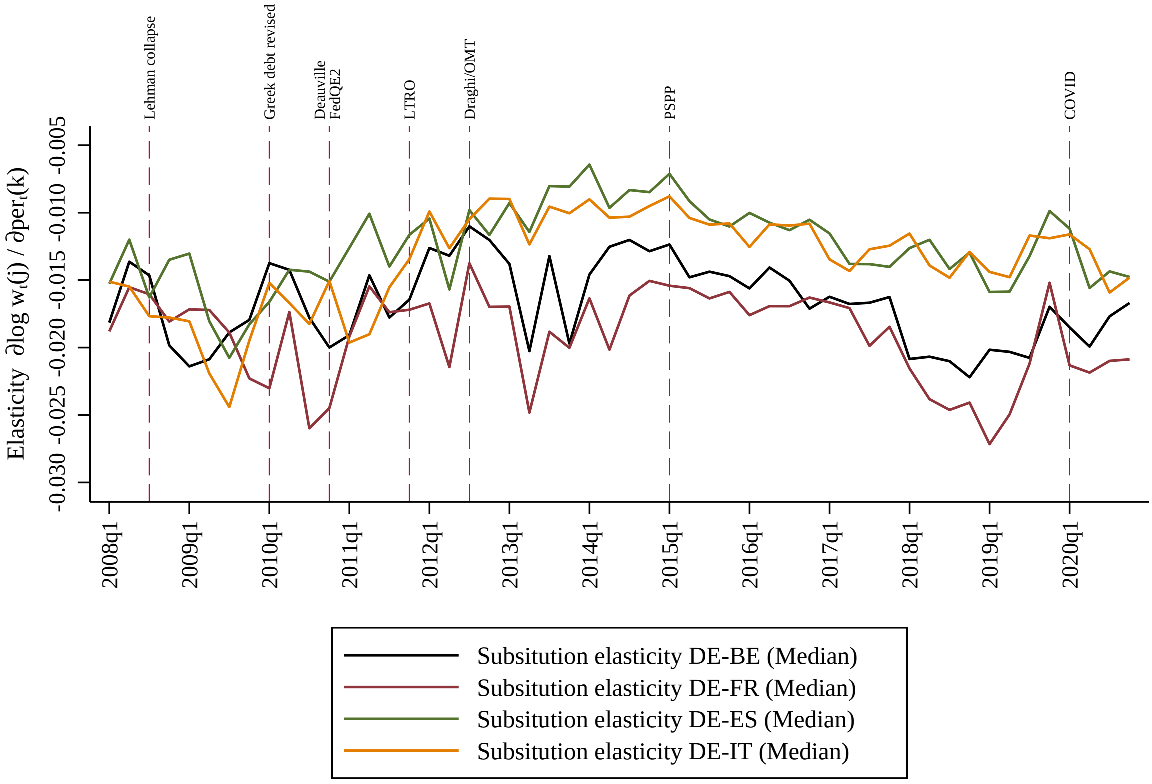
Finally, I show that the decline in substitutability between safe and risky assets in bad times is not limited to the global safe asset. However, for a regional safe asset such as German Bunds flight to safety takes a very different form. Consistent with the concentration of German Bund substitutes within euro area sovereigns and motivated by the euro area crisis that unfolded in the middle of my estimation sample (2010–2012), I focus on the time variation in substitutability of German Bunds with other euro area sovereign bonds – both of so-called 'core' and 'periphery' countries.

Figure 14 compares the substitutability of Germany with two 'core' euro area countries – France and Belgium – and with two 'periphery' issuers – Italy and Spain. Substitutability starts from a low level at the height of the GFC in late-2008 but as market stress eases post-crisis, euro area sovereigns become better substitutes for Germany (substitution elasticities becomes more negative) by the end of 2009. When Greek debt problems become clear in early 2010, euro area 'core' countries such as France are distinguished from the 'periphery' (Italy and Spain). But by the end of 2010, when contagion spreads across the euro area[79], the status of French government

[79] 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

bonds as substitutes for Germany sharply deteriorates (the elasticity jumps towards zero). As the euro area crisis unfolds and as multiple interventions from the ECB targeting precisely this fragmentation in bond markets (e.g. the launch of Long-Term Refinancing Operations and President Mario Draghi's famous 'whatever it takes' pledge to preserve the euro) take effect, this deterioration of substitutability of German Bunds with other euro area bonds halts (Spain and Italy) or even reverses to some degree (Belgium and France). However, from investment funds' perspective a persistent gap remains between the 'core' and 'periphery' even after the ECB commences purchases of all euro area sovereigns[80] as part of the Public Sector Purchase Programme (PSPP).

Figure 14: Substitutability of German Bunds with other Euro Area sovereign bonds



Notes: Substitution elasticity of Belgian (*black line*), French (*maroon line)*, Italian (*yellow line*) and Spanish (*green line*) sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Each line corresponds to the median of four substitution elasticities – within each of the four maturity buckets (under 1y, 1-5y, 5-10y, over 10y) for the four country pairs.

These substitution elasticities paint a grimmer picture of persistent fragmentation in euro area sovereign debt markets than the corresponding spreads between sovereign yields (see Appendix Figures E.53 – E.56). This implies that either the effect of substantial direct holdings of the

broader contagion within the euro area.

[80] Apart from Greece, which did not satisfy the minimum rating requirement for eligibility during the course of asset purchases.

ECB or other bond holders such as euro area banks contributed to greater substitutability overall. From international investors' vantage point, however, the euro area remains a fragmented bond market. Such a 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 more limited effects on borrowing costs of the periphery than of core countries. 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.

In summary, the time variation in bond elasticities reveals three important patterns: (i) safe asset demand increases in times of stress in line with a flight to safety by mutual funds; (ii) 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 via portfolio rebalancing; (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. These findings call for monetary policy to be conducted in a state-contingent and asset-specific manner by focussing less on policies that directly affect primarily the returns on safe assets (e.g. by purchasing only the safest government bonds as part of QE programmes) during times of market turmoil. In these circumstances, private investor rebalancing from these safe assets is more limited and has less power to ease risky borrowing conditions. This time variation in risky asset substitutability is consistent with the literature which compares the effects of different QE programmes on risky asset prices and finds that QE composition is crucial – e.g., the first round of QE in the US, which involved direct purchases of mortgage-backed securities perceived as risky at the time, had more powerful effects on risky asset prices than later programmes (Krishnamurthy and Vissing-Jorgensen, 2011).

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 me to recover bond-specific, time-varying 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 insight into the bond characteristics that make 'safe assets' special in investors' eyes.

In addition, heterogeneous 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. Flights to the safety of these different safe assets in times of market stress manifest themselves as deteriorating substitutability with key risky asset alternatives. The associated decrease in portfolio rebalancing from safe to risky assets could impair the transmission of monetary policies 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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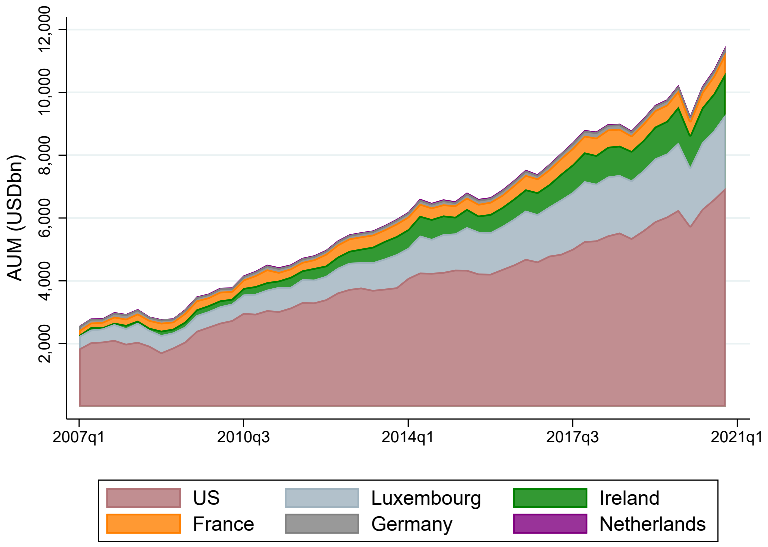
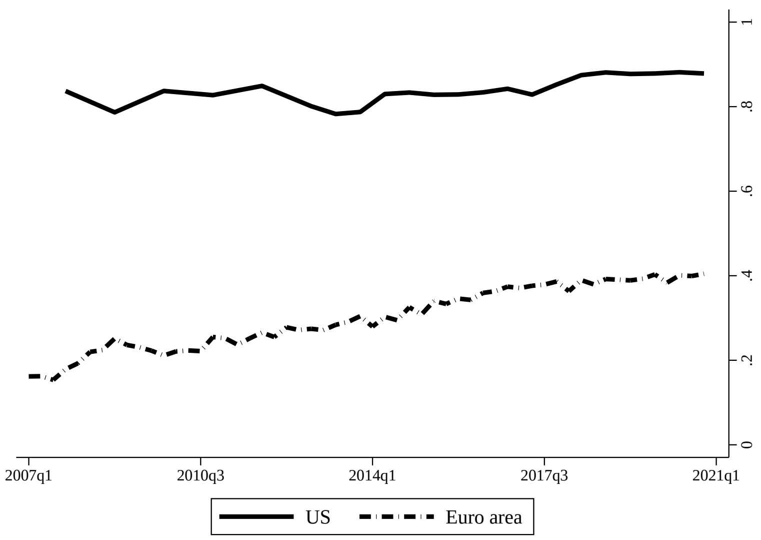
A Dataset

Figure A.15: Morningstar funds' AUM by country of fund domicile



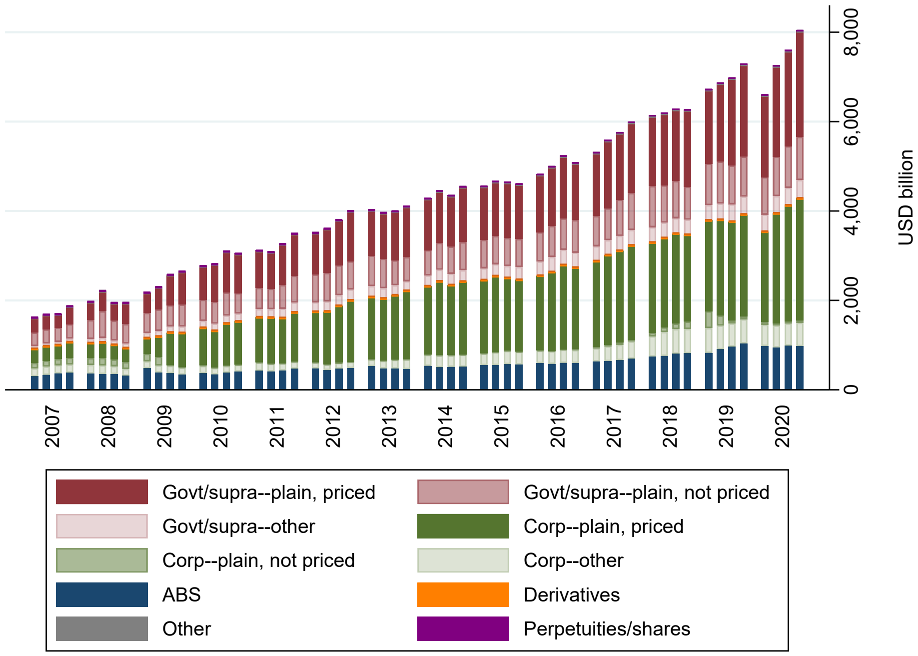
Notes: Total assets under management (AUM) of funds domiciled in one of the top five euro area domiciles or the US, which report portfolio holdings of debt securities to Morningstar.

Figure A.16: Morningstar funds' AUM: representativeness vs financial accounts



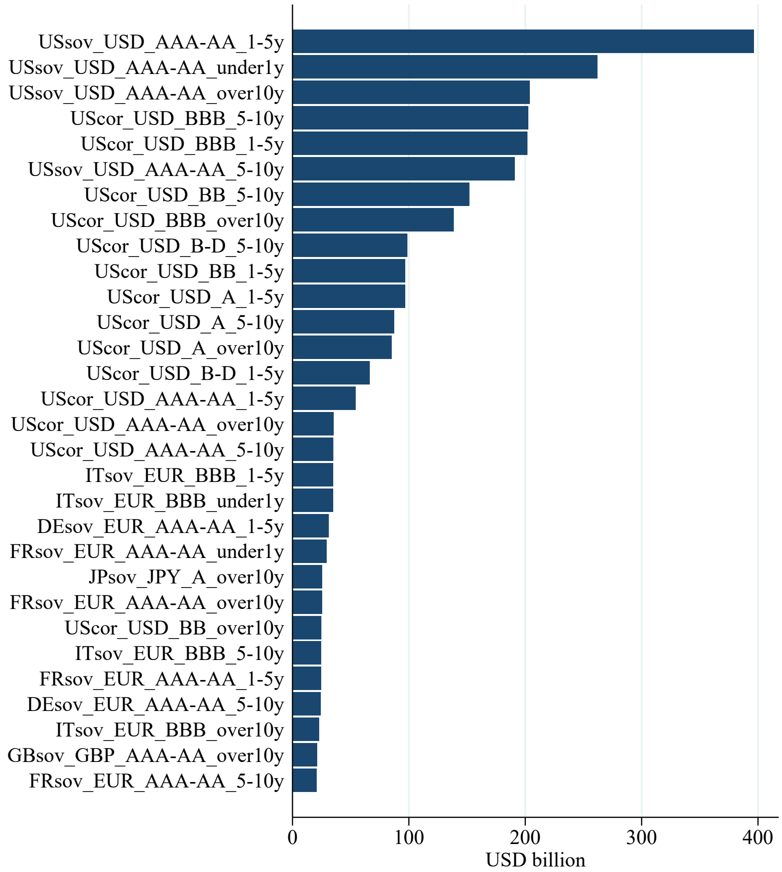
Notes: Each line corresponds to the total assets under management (AUM) of funds with bond holdings in the Morningstar dataset collected for this paper as a share of the respective country of domicile's official statistics on its fund sector's total AUM. To obtain the overall AUM of the bond-holding euro area investment fund industry, I sum the total assets of bond, mixed and other (other than equity, bond, mixed, real estate, hedge funds) investment funds reported in the ECB's Investment Funds Balance Sheet Statistics (IVF). To obtain the overall AUM of the bond-holding US investment fund industry, I sum the total assets of taxable bond, municipal bond and hybrid mutual funds and exchange-traded funds (ETFs) reported by the Federal Reserve as part of the Financial Accounts of the United States – Z.1.

Figure A.17: Breakdown of Morningstar funds' total debt security holdings by security type – with pricing data availability



Notes: Breakdown of Morningstar fund debt security holdings by security type and bond price data availability (from Refinitiv Datastream). The security classification is based on Refinitiv Eikon reference data extracted using individual security identifiers reported in the portfolio holdings of Morningstar funds used in the dataset of this paper. 'Plain' bonds (government, supranational and corporate) exclude 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 and are the focus of the empirical analysis that follows. 'Priced' bonds are those for which data on the bond's clean price is available from Refinitive Datastream at the end of each respective quarter.

Figure A.18: Top bond buckets by market value of fund holdings as of end-2020



Notes: Each bar corresponds to the market value of the respective bond bucket held by the investment funds in the Morningstar dataset collected for this paper. Only the 30 largest buckets by value of their fund holdings as of end-2020 are shown.

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

Notes: List of the largest funds in the Morningstar dataset according to the market value of the reported security-level bond holdings as of December 2020. Euro area Money Market Funds are included here for illustrative purposes but do not feature in the later demand estimation due to a lack of Morningstar data on the legal and regulatory status of euro area money market funds, which are crucial for controlling for their investment universe.

Table A.9: Summary of funds' bond portfolio weights

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US fixed income	0.015	0.037	0.006	0.000	0.157	4,474,696
EA fixed income	0.013	0.041	0.003	0.000	0.169	2,447,997
US balanced	0.010	0.027	0.003	0.000	0.104	1,397,732
EA balanced	0.005	0.017	0.001	0.000	0.067	629,988
Total	0.013	0.036	0.004	0.000	0.148	8,950,413

NOTES: Summary statistics for individual funds' bond portfolio weights calculated over all fund-bond-quarter observations within the fund type indicated in each row.

Table A.10: Selected bonds' overall share in the fund sector portfolio

Fund Type	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
US govt. bonds	0.036	0.006	0.036	0.023	0.053	56
DE govt. bonds	0.004	0.001	0.003	0.002	0.007	56
JP govt. bonds	0.001	0.000	0.001	0.001	0.002	56
CH govt. bonds	0.000	0.000	0.000	0.000	0.000	56
US corp. bonds (BBB)	0.015	0.003	0.016	0.008	0.021	56

NOTES: Summary statistics refer to the weight of each bond bucket within the category of bonds indicated in each row and are pooled across all quarterly observations. The portfolio weight here is no longer that of individual funds but the the aggregated portfolio of all funds covered in the Morningstar dataset collected in this paper.

Table A.11: Summary of continuous variables in bond demand regression

Variable	Mean	S.D.	Median	1st %ile	99th %ile	Obs.
Bond weight w_$i, t(j)$	0.013	0.036	0.004	0.000	0.148	8,950,413
Outside asset weight w_$i, t(0)$	0.465	0.247	0.448	0.003	0.964	6,865,348
Bond yield	0.033	0.025	0.030	-0.004	0.106	8,793,883
Bond excess return rx_i, t	0.045	0.157	0.034	-0.408	0.492	8,793,883
Residual maturity (years)	7.335	6.654	6.403	0.341	27.330	8,793,883
Amt. outstanding (ln of USD value)	23.524	2.001	23.415	19.440	28.470	8,793,883
Bond seniority (1=highest; 9=lowest)	4.760	0.824	5.000	1.000	6.500	8,793,883

NOTES: Summary statistics calculated over all fund-bond bucket-quarter observations used in the estimation of the empirical bond demand model.

Table A.12: Summary of funds' bond portfolio composition

Portfolio of:	All funds	EA bond	US bond	EA allocation	US allocation
Mat. bucket under1y	0.08	0.08	0.07	0.11	0.07
Mat. bucket 1-5y	0.40	0.41	0.39	0.43	0.38
Mat. bucket 5-10y	0.38	0.39	0.39	0.37	0.38
Mat. bucket over10y	0.20	0.21	0.21	0.18	0.20
Weighted maturity	7.40	7.26	7.86	6.48	7.98
Rating bucket AAA-AA	0.42	0.37	0.37	0.50	0.42
Rating bucket A	0.20	0.22	0.18	0.20	0.19
Rating bucket BBB	0.27	0.30	0.28	0.25	0.25
Rating bucket BB	0.11	0.11	0.14	0.08	0.10
Rating bucket B-D	0.08	0.10	0.11	0.06	0.07
Asset type cor	0.55	0.55	0.61	0.46	0.59
Asset type sov	0.47	0.48	0.42	0.54	0.43
Asset type sup	0.03	0.05	0.02	0.06	0.01
USD bonds	0.64	0.51	0.87	0.27	0.89
EUR bonds	0.39	0.62	0.15	0.69	0.10
CHF bonds	0.20	0.30	0.03	0.42	0.04
JPY bonds	0.11	0.14	0.11	0.08	0.11
GBP bonds	0.07	0.12	0.05	0.06	0.04
US bonds	0.46	0.25	0.68	0.18	0.75
DE bonds	0.09	0.12	0.04	0.18	0.03
FR bonds	0.08	0.12	0.02	0.14	0.02
IT bonds	0.06	0.10	0.02	0.11	0.02
ES bonds	0.04	0.07	0.02	0.08	0.01

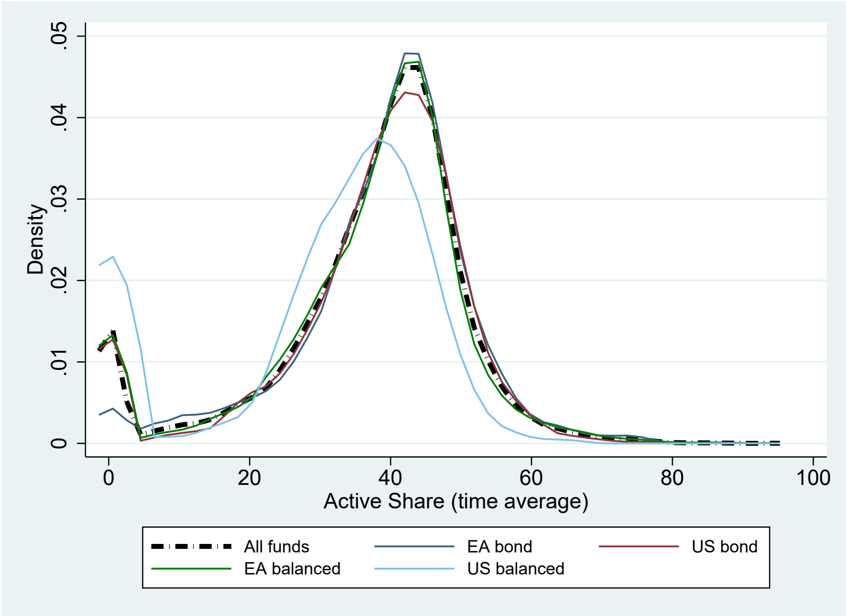
NOTES: Summary statistics describing the bond portfolios of all funds within a given broad fund type (as indicated in the column title). Apart from the row *Weighted maturity*, all rows report the portfolio share of bonds with each characteristic indicated in the row. E.g. row *Mat. bucket under1y* is the portfolio weight of all bonds with a residual maturity of under a year. The row *Weighted maturity* is expressed in years and weighted by each bond's weight in the respective fund type's portfolio. All statistics are averages over all quarters in the sample from 2007 to 2020.

Table A.13: Summary of funds, with Active Weight

Fund Type	Number of Funds	%All-fund AUM	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th %ile)	Act. Weight % (Median)	Act. Weight % (90th %ile)
US bond passive	1,232	20	0.93	294	3,460	33	45
US bond active	1,231	29	1.27	385	4,356	45	56
EA bond passive	2,141	8	0.54	141	1,078	34	43
EA bond active	2,507	14	0.72	185	1,507	45	53
US balanced passive	518	12	0.16	353	3,931	32	44
US balanced active	221	9	0.18	311	3,727	44	53
EA balanced passive	1,560	2	0.05	62	513	35	45
EA balanced active	1,492	5	0.13	90	878	45	51

NOTES: *Number of Funds* counts how many unique funds of each type exist during the entire sample between 2007 and 2020. In total, the analysis uses 10,902 bond and balanced mutual funds and ETFs. *%All-fund AUM* describes the share of the total AUM of funds in the dataset managed by each fund type, on average during the sample period. *%Outstanding* reports the share that each fund type holds of the face value of all corporate and government bonds *ever* held by the funds in the dataset, on average during the sample period. The remaining statistics refer to simple averages within each fund type across the 56 quarterly observations between 2007 and 2020. E.g. *AUM USDmil (Median)* is the quarterly median AUM across the funds of each type, averaged over 2007–2020.
Bond Active Weight : Sum of absolute bond portfolio weight deviations from market-value-weighted fund bond universe weights, divided by 2. Doshi et al. (2015) propose this measure of activeness and relate it to fund performance; Koijen, Richmond and Yogo (2020b) apply it to group funds in an asset demand estimation setting. In this paper, it is used to allocate funds into *Passive / Active types* depending on whether a fund's average Active Weight over time is below or above the median Bond Active Weight.

Figure A.19: Distribution of Bond Active Weight by 4 broad fund types



Notes: Kernel densities of fund *Bond Active Weight*, on average over time, within each of four broad fund types. Bond Active Weight defined as in Appendix Table A.13.

Table A.14: Summary of funds over time

Year	Number of Funds	%Outstanding	AUM USDmil (Median)	AUM USDmil (90th Percentile)	Active Weight % (Median)	Active Weight % (90th Percentile)
2007	2,086	2.17	184	1,686	40	49
2008	2,487	2.37	162	1,463	40	49
2009	2,903	2.70	143	1,237	40	50
2010	3,236	3.45	169	1,530	40	50
2011	3,603	3.37	159	1,558	41	50
2012	3,950	3.58	160	1,690	41	50
2013	4,253	3.76	172	1,854	41	50
2014	4,660	3.98	172	1,987	41	50
2015	5,078	4.62	164	1,918	41	50
2016	5,429	4.75	164	1,937	41	51
2017	5,726	5.14	178	2,042	41	50
2018	6,018	5.26	178	2,130	41	51
2019	6,471	5.40	182	2,097	41	53
2020	6,586	5.31	192	2,188	42	56

Notes: *Number of Funds* tracks the number of unique funds within each year of the sample. *%Outstanding* reports the share that each fund type holds of the face value of all corporate and government bonds *ever* held by the funds in the dataset, on average during each year. The remaining statistics refer to simple averages across all funds for each year. E.g. *AUM USDmil (Median)* is the quarterly median AUM across all funds in a given quarter, averaged over the four quarters of the respective year.

Table A.15: 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

NOTES: This table reports the percentage of bond buckets held in the current quarter that were ever held in the previous one to 11 quarters. Each cell is a pooled median across time and all funds within a given fund type. The sample period is spans all quarters from 2007 to 2020.

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:

$$\max_{\mathbf{w}_{i,t}} \quad \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big]$$

$$\text{s.t.} \quad A_{i,t+1} = A_{i,t}[R_{i,t+1}(0) + \mathbf{w}'_{i,t}(\mathbf{R}_{i,t+1} - R_{i,t+1}(0)\mathbf{1})] \tag{B.1}$$

$$\mathbf{w}_{i,t} \geq \mathbf{0} \tag{B.2}$$

$$\mathbf{1}'\mathbf{w}_{i,t} \leq 1 \tag{B.3}$$

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

$$\max_{\mathbf{w}_{i,t}} \quad \mathbb{E}_{i,t}\Big[\frac{A_{i,t+1}^{1-\rho_{i,t}}}{1-\rho_{i,t}}\Big] = \max_{\mathbf{w}_{i,t}} \quad \ln \mathbb{E}_{i,t}\big[A_{i,t+1}^{1-\rho_{i,t}}\big] = \max_{\mathbf{w}_{i,t}} \quad (1-\rho_{i,t})\mathbb{E}_{i,t}a_{i,t+1} + \frac{1}{2}(1-\rho_{i,t})^2\sigma^2_{a_i,t}$$

$$\text{s.t.} \quad a_{i,t+1} = a_{i,t} + r_{p,i,t+1} \qquad \text{where} \quad r_{p,i,t+1} = \ln(R_{p,i,t+1})$$

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 $a_{i,t+1}$:

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

where $\sigma^2_{r_p,i,t}$ 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):

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

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:

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

The investor then chooses portfolio weights to maximize the objective:

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

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

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

with first-order condition:

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

implying optimal portfolio weight:

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

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

$$\mathbf{\Omega}^{(1)}_{i,t} = \Big(\mathbf{\Sigma}^{(1,1)}_{i,t} - \mathbf{\Sigma}^{(1,2)}_{i,t}\mathbf{\Sigma}^{(2,2)-1}_{i,t}\mathbf{\Sigma}^{(2,1)}_{i,t}\Big)^{-1}$$
$$\mathbf{\Omega}^{(2)}_{i,t} = \Big(\mathbf{\Sigma}^{(2,2)}_{i,t} - \mathbf{\Sigma}^{(2,1)}_{i,t}\mathbf{\Sigma}^{(1,1)-1}_{i,t}\mathbf{\Sigma}^{(1,2)}_{i,t}\Big)^{-1}$$

Then re-write the optimal portfolio allocation:

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

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

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

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

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

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:

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

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 $\hat{\mathbf{x}}_{\mathbf{i},\mathbf{t}}(n)$, 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:

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

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)\prime} + \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)\prime}}{\gamma_{i,t}}\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{I} + \underbrace{\frac{\mathbf{\Gamma}_{i,t}^{(1)\prime}\mathbf{\Gamma}_{i,t}^{(1)}}{\gamma_{i,t}}}_{\text{scalar}})^{-1}\mathbf{\Gamma}_{i,t}^{(1)\prime}}{\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)\prime}}{\gamma_{i,t} + \mathbf{\Gamma}_{i,t}^{(1)\prime}\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)\prime}}{\gamma_{i,t} + \mathbf{\Gamma}_{i,t}^{(1)\prime}\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:

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

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 3.2 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.[81] 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 maximize one-period-ahead wealth. The approximated portfolio return is the same function of individual portfolio returns and their variance and covariances:

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

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

but now greater care is required as this only holds if the return covariance matrix $\boldsymbol{\Sigma}_{i,t}$ 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):

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

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

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:

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

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.[82]

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:

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

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 outside asset:

$$w_{i,t}(0) = 1 - \mathbf{1}'\Big(\rho_{i,t}\boldsymbol{\Sigma}^{(1,1)}_{i,t}\Big)^{-1}(\mu^{(1)}_{i,t} - \lambda_{i,t}\mathbf{1} + (1 - \rho_i)\sigma^{(1)}_{i,t}(\mathbf{rx}, 0)) \tag{B.21}$$

This trade-off is also reflected in the value of the Lagrange multiplier on the constraint on the

[82] 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 $\mathbb{E}_{i,t}\big[\mathbf{r}_{t+1} - r_{t+1}(0)\mathbf{1}\big], \boldsymbol{\Sigma}_{i,t}, \sigma^2_{i,t}$. See discussion in Campbell & Viceira, ch.2.1.3, pp.24-25.

sum of portfolio weights on bonds and the outside asset (3):

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

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:

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

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

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

$$\kappa_{i,t} \equiv \frac{\boldsymbol{\Gamma}_{i,t}^{(1)\prime}}{\gamma_{i,t} + \boldsymbol{\Gamma}_{i,t}^{(1)\prime}\boldsymbol{\Gamma}_{i,t}^{(1)}}(\mu_{i,t}^{(1)} - \lambda_{i,t}\mathbf{1} + (1-\rho_{i,t})\sigma_{i,t}^{(1)}(\mathbf{rx},0))$$

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 ($\boldsymbol{\Xi}_i > 0$), 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 (**??**):

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

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:

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

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

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

where the second line reflects the definition of $\log(Q_{i,t}(j)) = \log[AUM_{i,t}w_{i,t}(j)] - p_{\chi(i),t}(j)$ as the face value of bond j held by investor i and expressed in the investor's own currency. The third equality omitting the investor's AUM reflects the partial equilibrium empirical set-up in this paper, where the overall wealth of each investor is taken as exogenous and the end-investors' decision to allocate wealth across funds is not modelled due to a lack of data on household portfolios. Next, note that the bond price in investor i's home currency is the ratio of the bond price in local currency j and the spot nominal exchange rate of currency i per unit of currency j: $P_{\chi(i),t}(j) = P_{\chi(j),t}(j)/S_{\chi(i)/\chi(j),t}$. Equivalently, in log terms: $p_{\chi(i),t}(j) = p_{\chi(j),t}(j) - s_{\chi(i)/\chi(j),t}$. The relationship between the excess return and the local currency bond price can be approximated by the estimated relation between bond returns and the bond yield in (9), using the simple relation between the log price and continuously-compounded yield of a zero-coupon bond: $p_{\chi(j),t}(j) = -mat_t(j) \times y_{\chi(j),t}(j)$, where $mat_t(j)$ is the residual maturity of bond j at time t.[83] The implied partial derivative of predicted excess returns *w.r.t.* prices can

[83] Here, I abstract from the joint dynamics between local currency yields and exchange rates. This has no direct counterpart in the empirical specification that can be utilized.

thus be approximated as follows:

$$\begin{aligned}\frac{\partial per_{\chi(i),t}(j)}{\partial(p_{\chi(j),t}(j)-s_{\chi(i)/\chi(j),t})} &\approx \frac{\partial per_{\chi(i),t}(j)}{\partial p_{\chi(j),t}(j)} \\ &\approx \frac{\partial per_{\chi(i),t}(j)}{\partial(-mat_t(j)\times y_{\chi(j),t}(j))} \\ &\approx -\frac{1}{mat_t(j)}\frac{\partial per_{\chi(i),t}(j)}{\partial y_{\chi(j),t}(j)} \\ &\approx -\frac{\widehat{A}_i^h}{mat_t(j)}\end{aligned}$$

where $\widehat{A}_i^h$ is the estimated coefficient from the predictive bond regression (9). Under these assumptions, the alternative demand elasticity definition is related to the semi-elasticity discussed in this paper as follows:

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

Finally, in some applications one 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:

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

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 other definitions in Section 4 only to facilitate comparison 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:

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

where the forth equality makes the assumption that the fund sector's AUM is entirely exogenous to the individual fund's portfolio choice problem studied here. This expression for the fund-sector demand elasticity 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 Identification through high-frequency monetary policy shocks

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 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.[84] 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)[85]. 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.[86]

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).[87] Therefore, to avoid including multiple observations with identical endogenous

[84] 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 for bond with residual maturity of more than a year.

[85] 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.

[86] 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.

[87] 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 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 $per^h_{i,t}(n)$.

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:

$$\begin{aligned} per^h_{\chi(i),t}(n) = \mathbb{a}^{Fed}_{\chi(i),cx}\, FEDiv_t(n) \;+\; \mathbb{a}^{ECB}_{\chi(i),cx}\, ECBiv_t(n) \\ +\; \mathbb{b}_{\chi(i),cx}\, \mathbf{x}_t(n) \;+\; \mathbb{c}_{\chi(i),cx}\, Risk_t \;+\; \mathbb{d}_{\chi(i),t}(n) \end{aligned} \tag{C.26}$$

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 (C.26) is estimated twice – once with predicted returns in terms of US dollars and once with returns in euros. 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.[88]

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.[89] The baseline first-stage specification in (C.26) 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).

The strength of instruments used in (C.26) is formally tested using effective F-statistics and 30% critical values by Olea and Pflueger (2013) (Figure C.20).[90] There is a trade-off between

[88] 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.

[89] A direct application of control variables from the second stage would imply including a time fixed effect in the first stage regression (C.26). This approach, however, absorbs all time variation in the monetary policy instruments.

[90] Estimates from the country-currency panel regressions are labelled by the respective ISO 2-letter country code and 3-letter currency code, such that for instance "JP_JPY" stands for results based on the panel formed from bonds issued by Japanese entities and denominated in yen.

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 (C.26).[91] 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 (C.26).[92] 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 first panel of Appendix Figure C.20 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.20 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.

[91] Estimates from these residual country panel regressions are labelled by the respective ISO 2-letter country code followed by "othfx" in the results presented below.

[92] Estimates from these residual currency panel regressions are labelled by the respective ISO 3-letter currency code followed by "rest" in the results presented below.

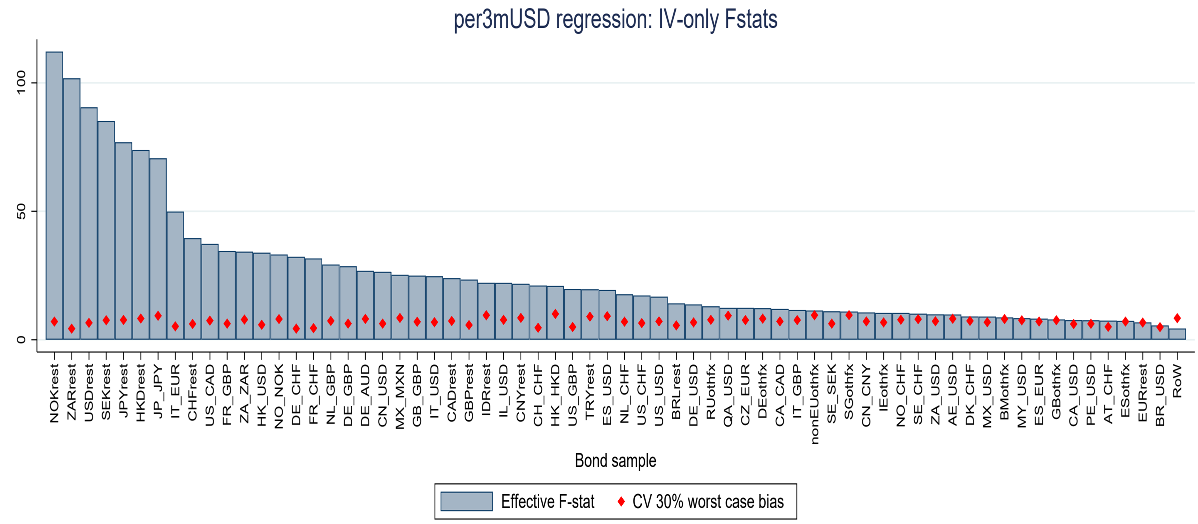
Table C.16: Correlation matrix between Fed and ECB monetary policy shocks

	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									

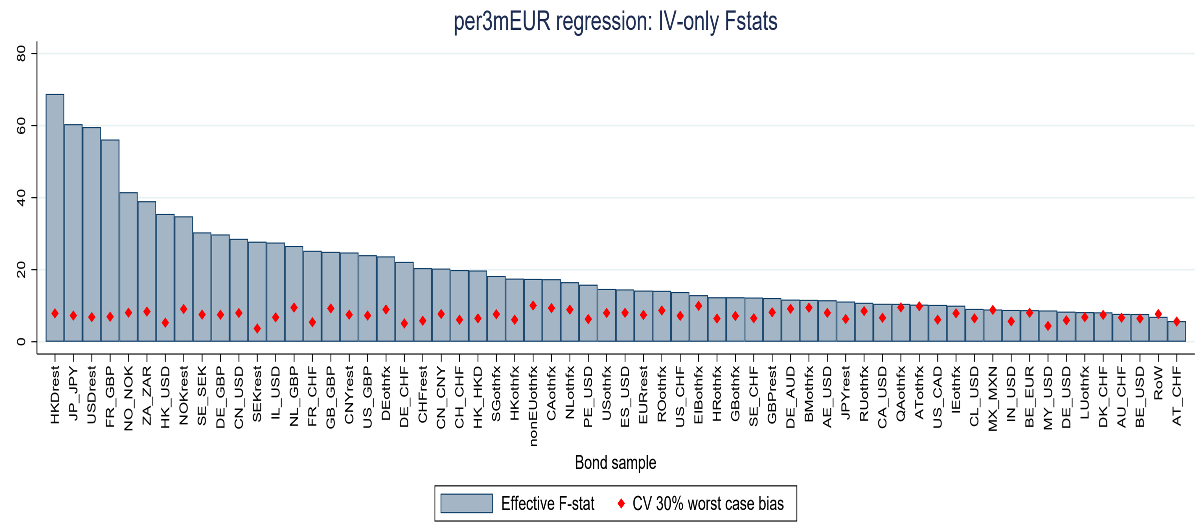
Note: Monthly shocks constructed as the sum of announcement days shocks if multiple announcements are made by each central bank within a month. Sample period: 1999M1:2021M12 (unbalanced with only ECB shocks data post-2019M6). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure C.20: First stage F-statistics

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



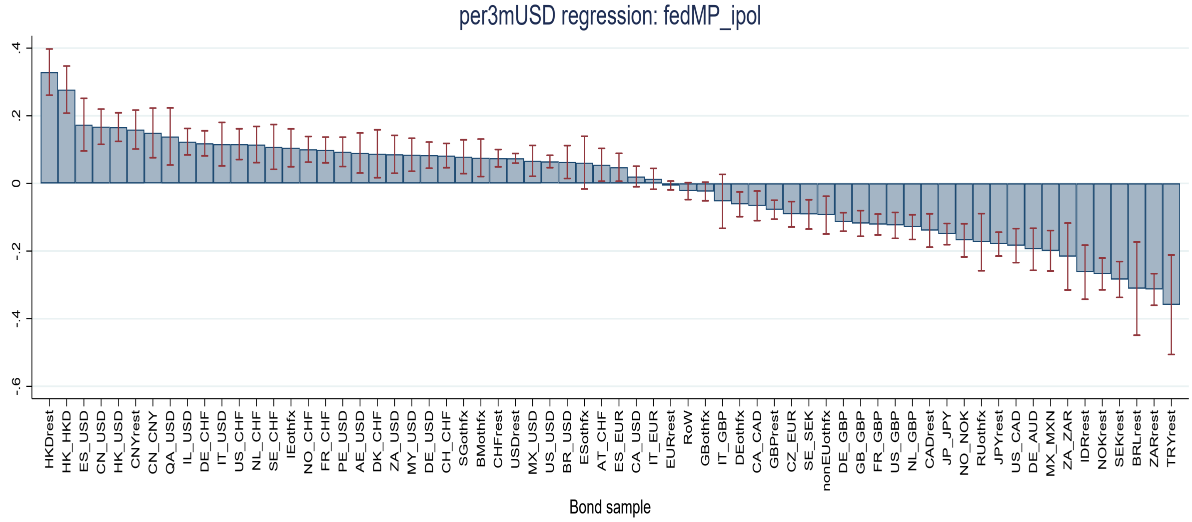
(b) Euro returns: $per^3_{€,t}(n)$



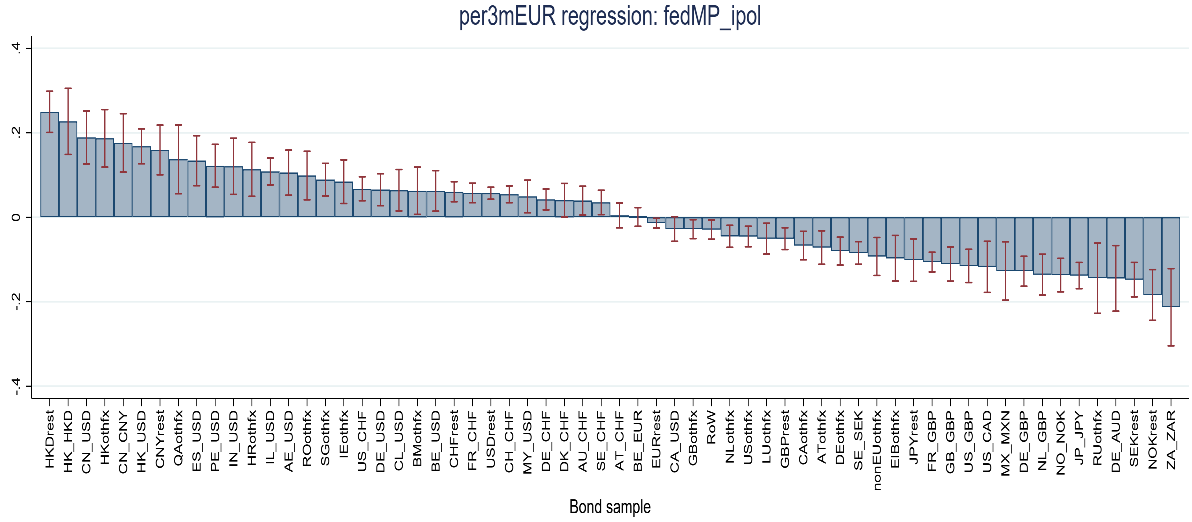
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective 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.21: Estimated coefficients on Fed monetary policy shock

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



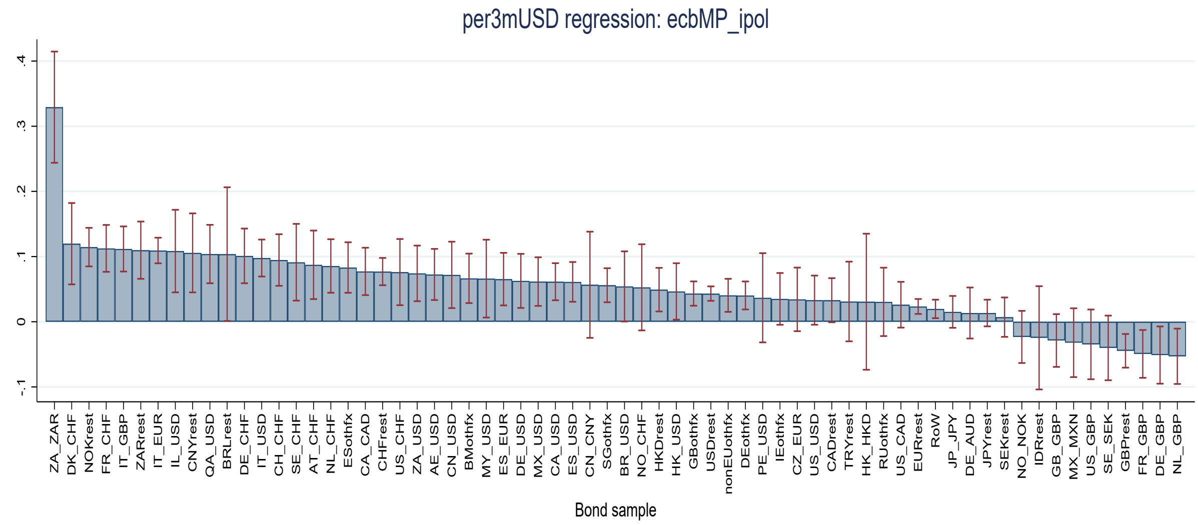
(b) Euro returns: $per^3_{€,t}(n)$



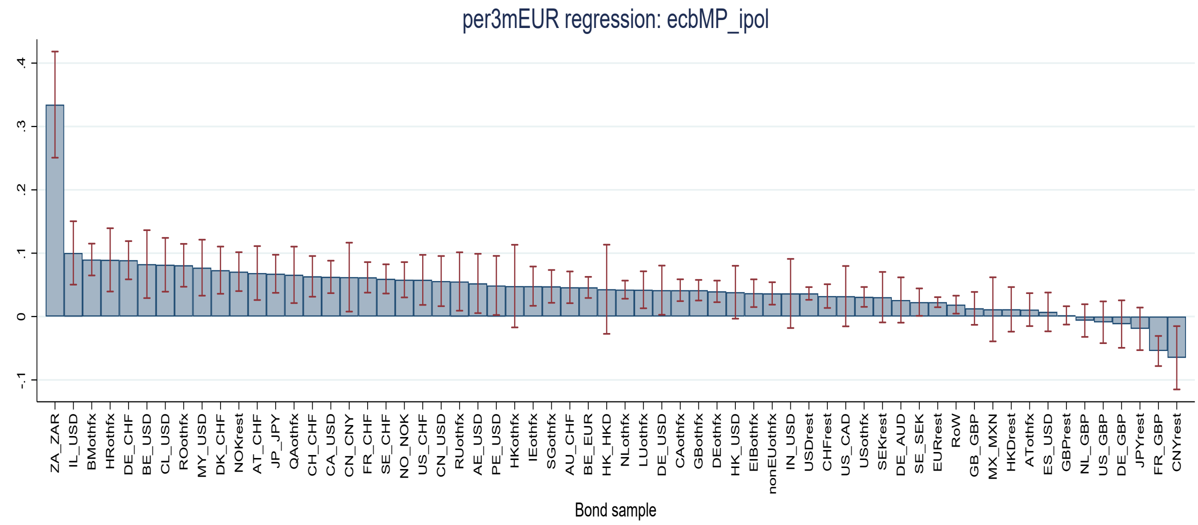
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure C.22: 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.

Table C.17: Comparison of OLS and IV demand system estimates of $\alpha_{T(i)}$ (coefficient on endogenous predicted excess returns)

	US fixed inc. Passive	US fixed inc. Active	EA fixed inc. Passive	EA fixed inc. Active	US balanced Passive	US balanced Active	EA balanced Passive	EA balanced Active
OLS	0.0549	0.6041$*$	-1.2674$***$	-0.0006	-0.7196	0.3459	-1.0749$***$	-1.1932$***$
	(0.4772)	(0.3085)	(0.1990)	(0.1690)	(0.5533)	(0.4272)	(0.3498)	(0.2507)
2SLS	2.0661$*$	3.8106$***$	0.5537	1.6549$***$	1.2114	2.5316$**$	1.4376	0.6656
	(1.2166)	(0.8799)	(0.6108)	(0.4829)	(1.5947)	(1.1180)	(1.0042)	(0.5906)

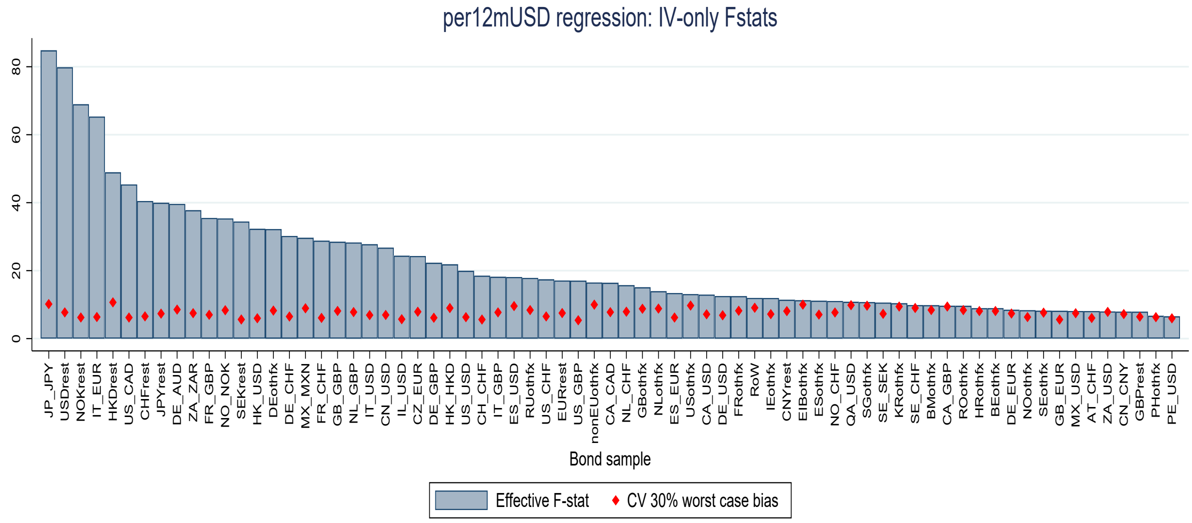
Note: The table reports the coefficient on predicted excess bond returns $per^3_{\chi(i),t}(n)$ estimated using OLS in the first row and those estimated using two-stage least squares with Fed and ECB monetary policy instruments as described in Section 3.4. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D Additional estimation results

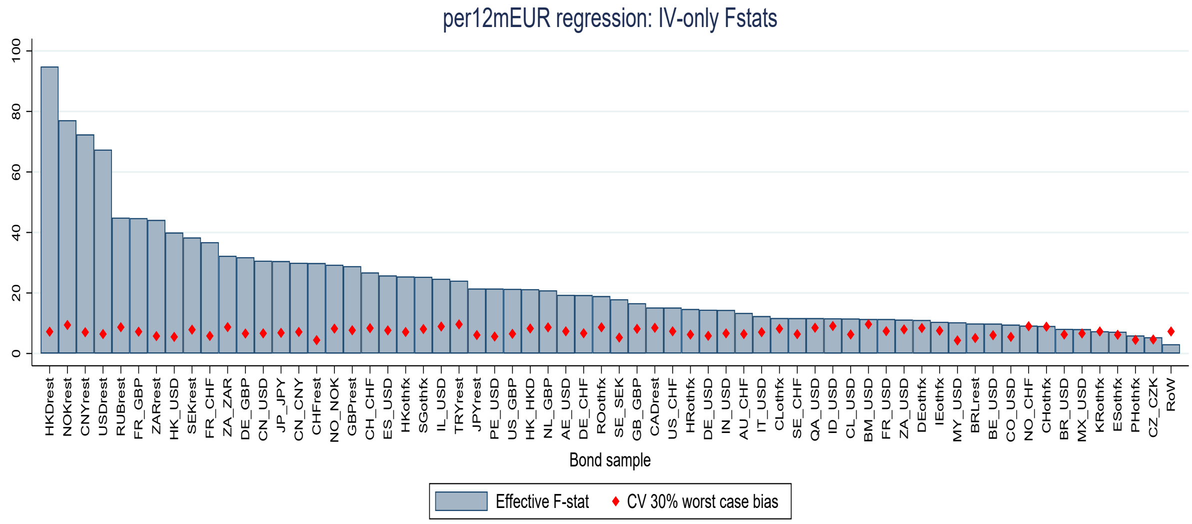
D.1 First stage robustness: monetary policy instruments

Figure D.23: First stage F-statistics: 12-month returns

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



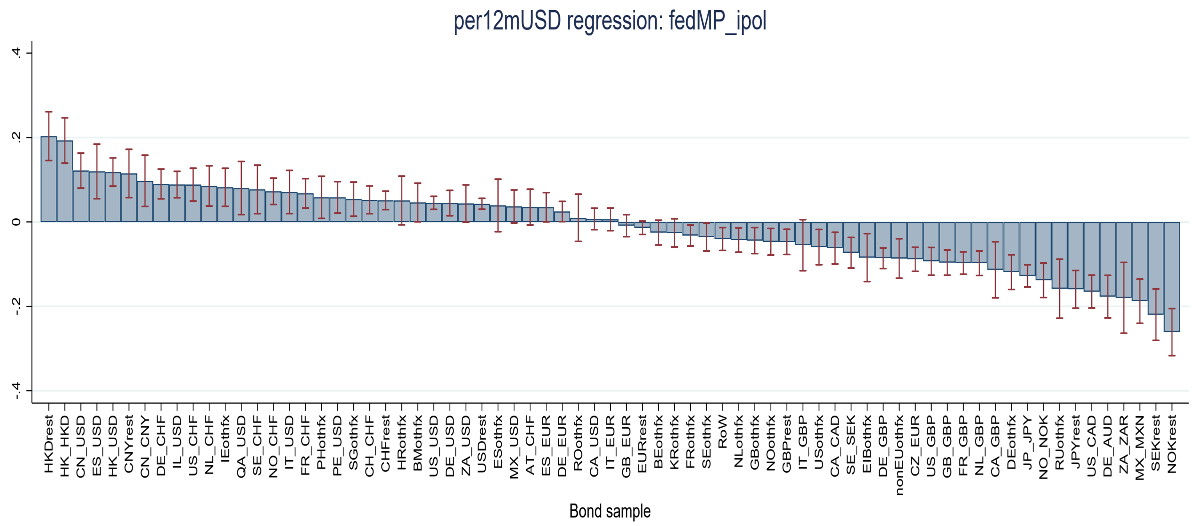
(b) Euro returns: $per^{12}_{€,t}(n)$



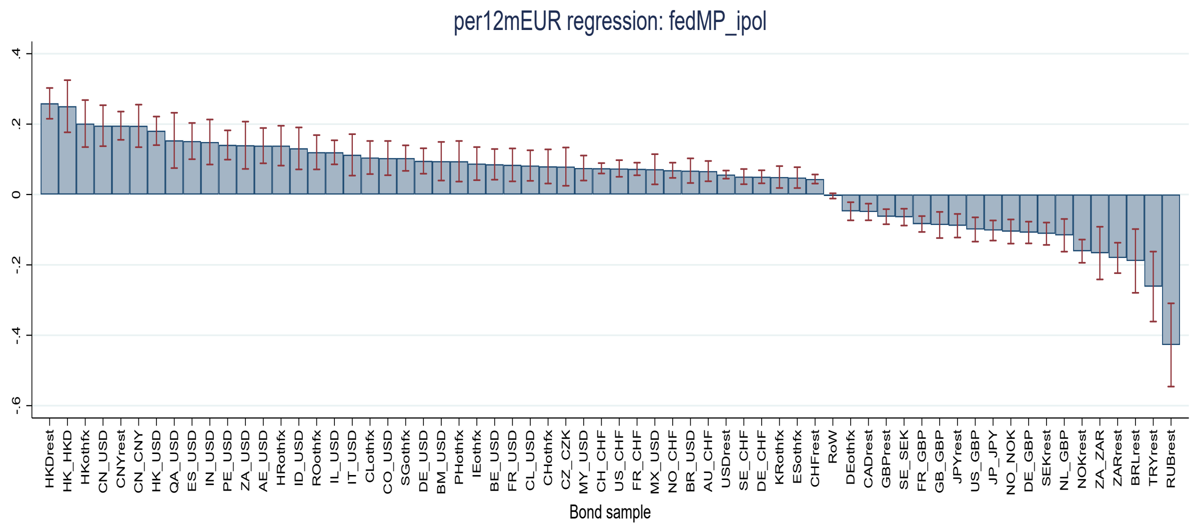
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective 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 D.24: Estimated coefficients on Fed monetary policy shock: 12-month returns

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



(b) Euro returns: $per^{12}_{€,t}(n)$

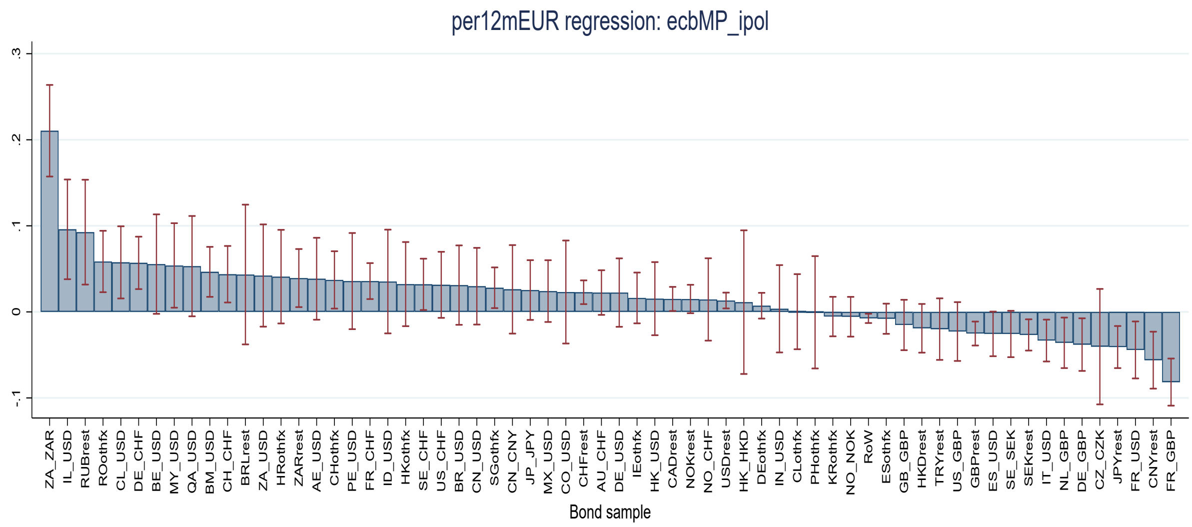


Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.25: Estimated coefficients on ECB monetary policy shock: 12-month returns

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

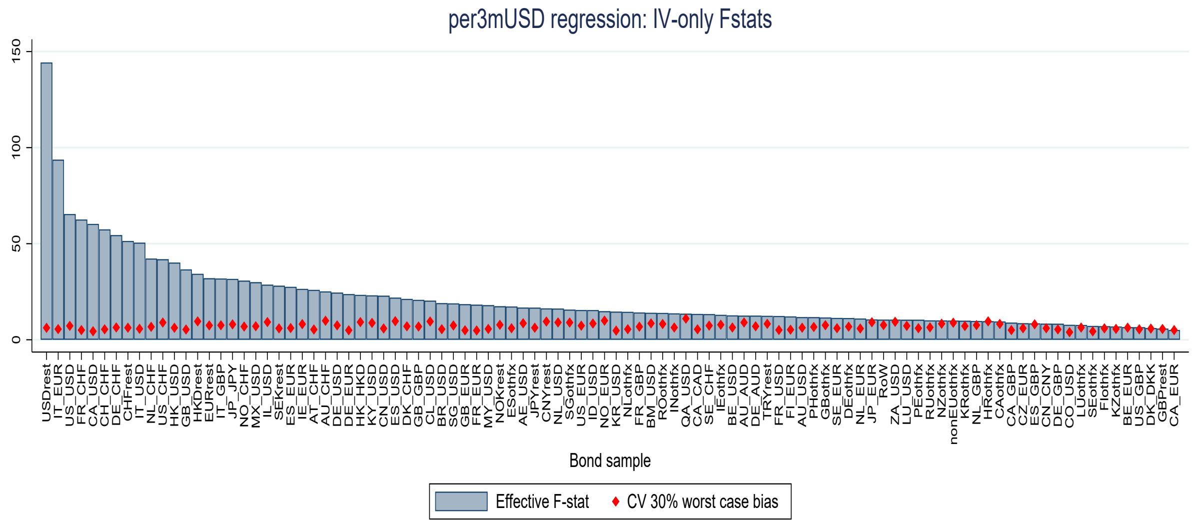
(b) Euro returns: $per^{12}_{€,t}(n)$



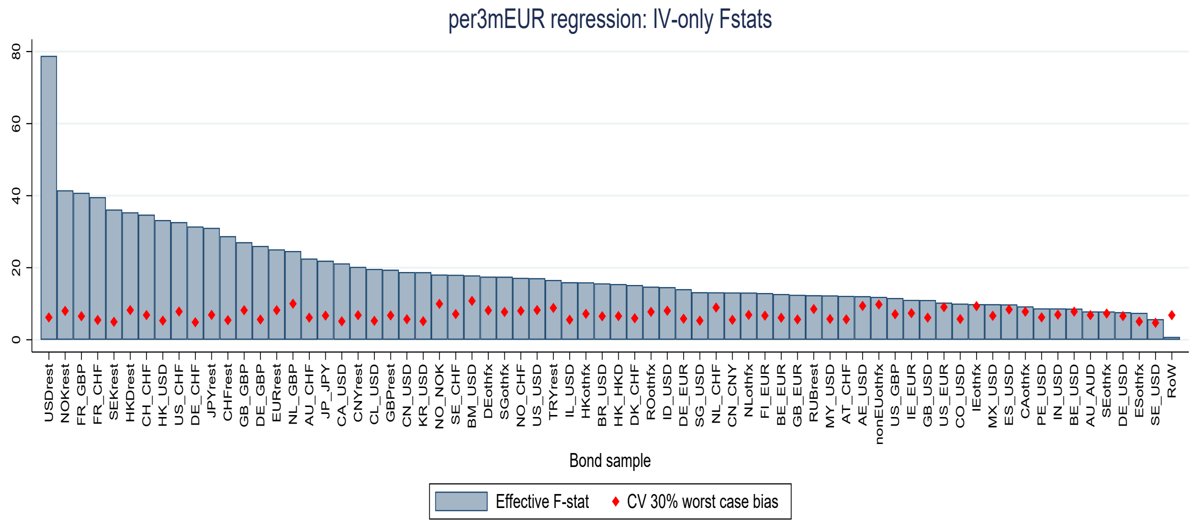
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.26: First stage F-statistics, controlling for EBP

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



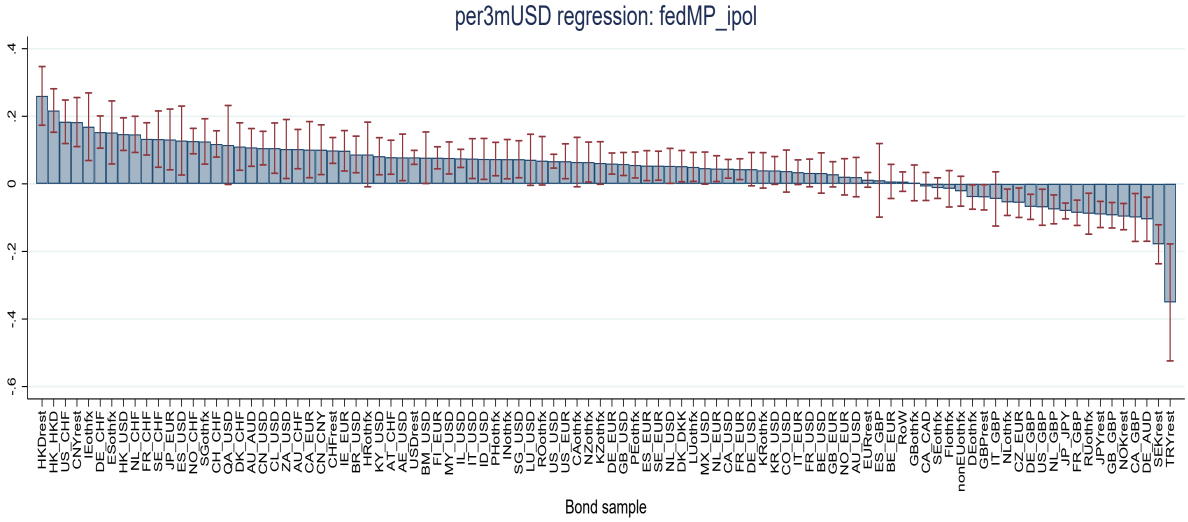
(b) Euro returns: $per^{3}_{€,t}(n)$



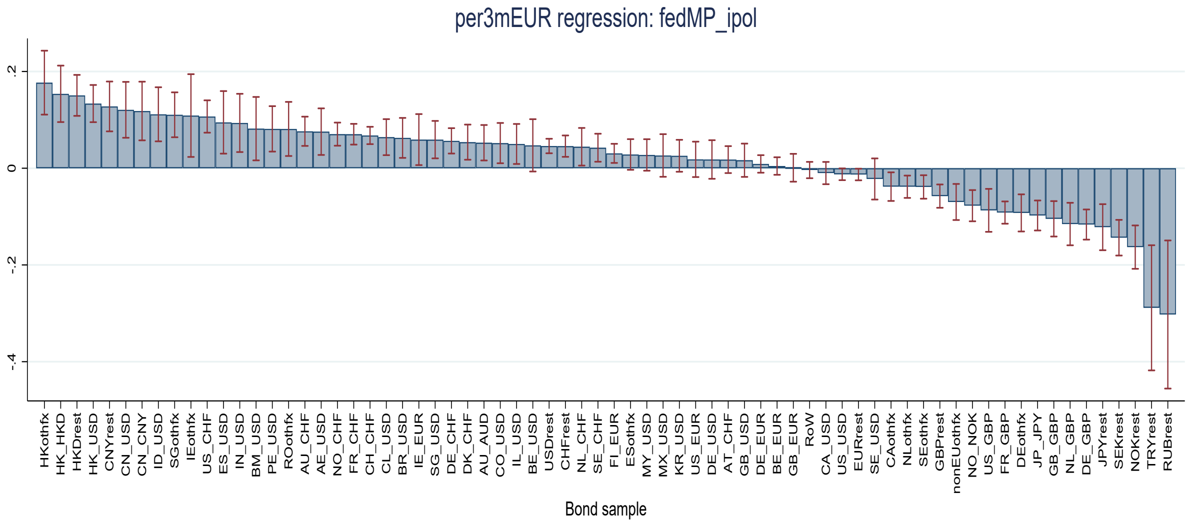
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective 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 D.27: Estimated coefficients on Fed monetary policy shock, controlling for EBP

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



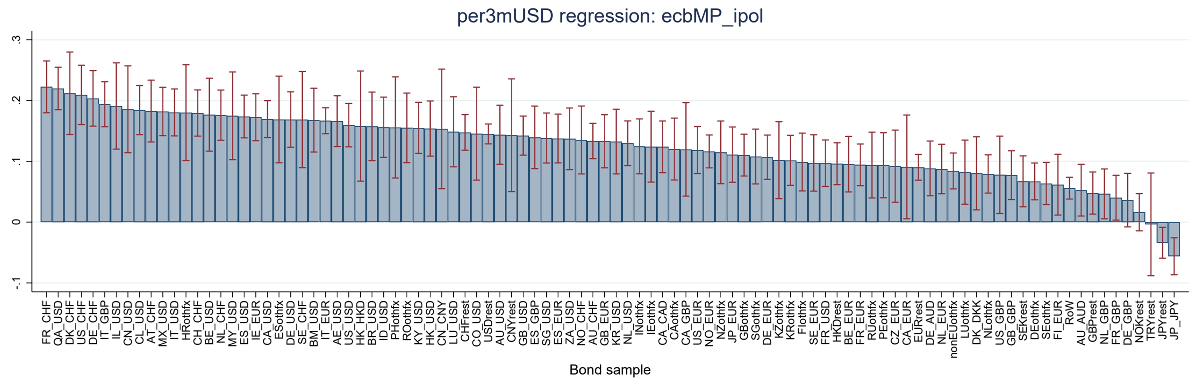
(b) Euro returns: $per^{3}_{€,t}(n)$



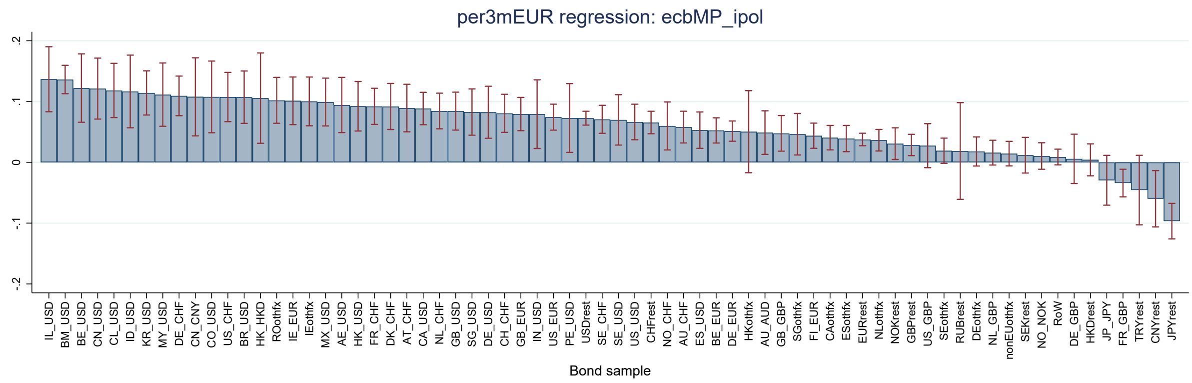
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.28: Estimated coefficients on ECB monetary policy shock, controlling for EBP

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



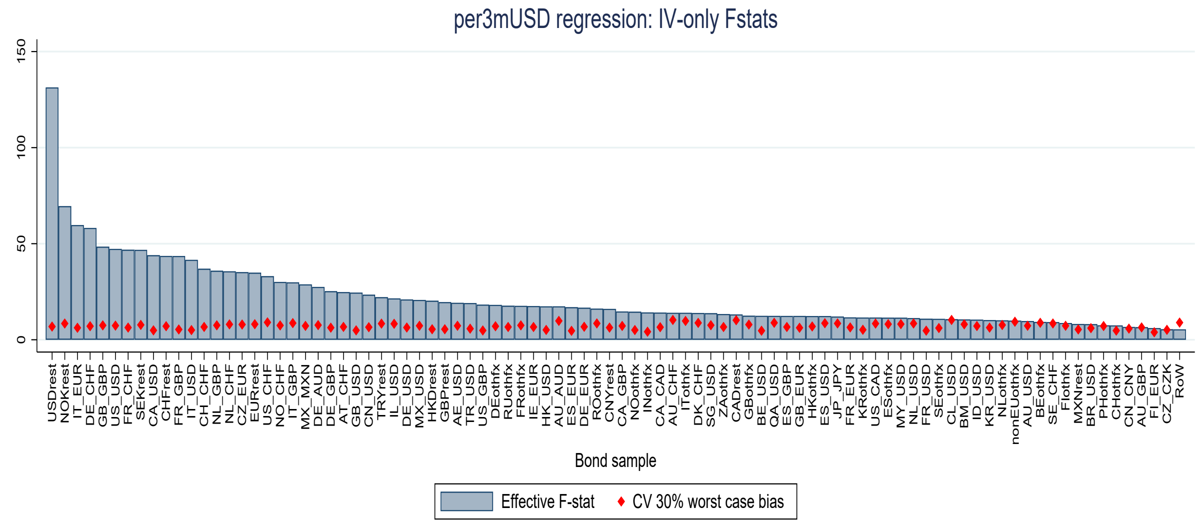
(b) Euro returns: $per^3_{€,t}(n)$



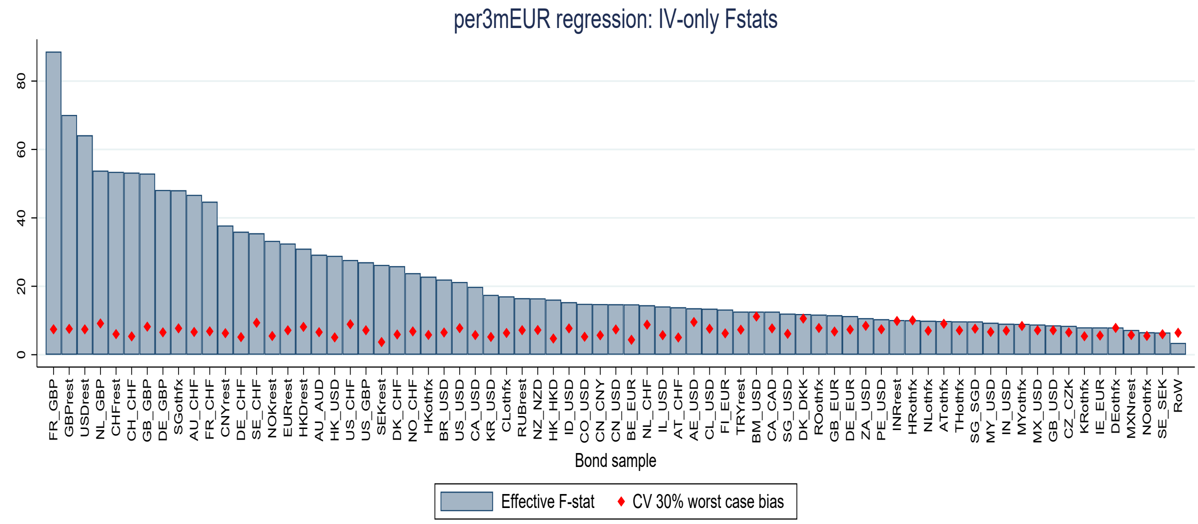
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.29: First stage F-statistics, controlling for EBP & CISSEAbond

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



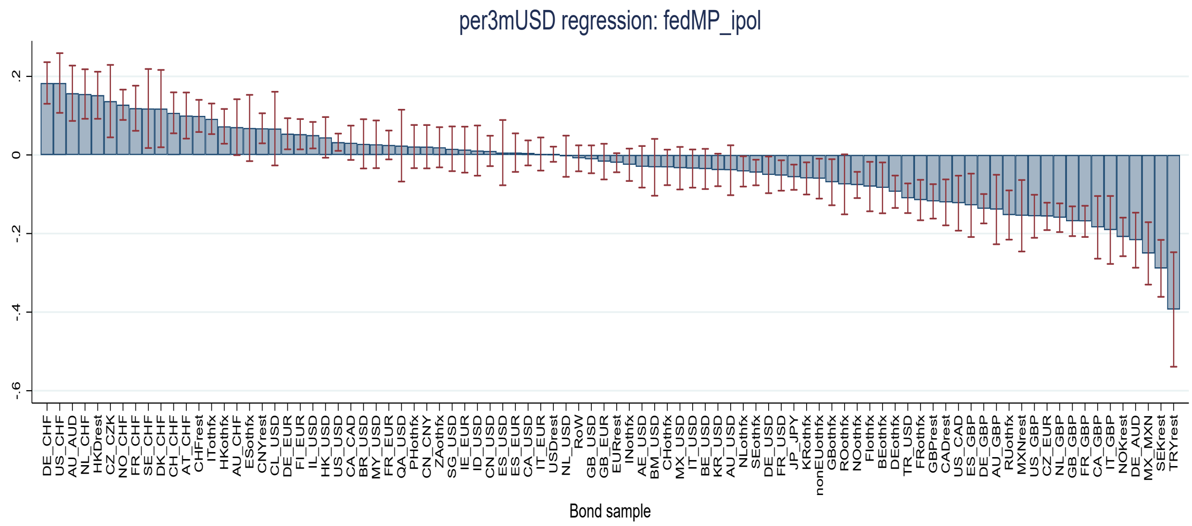
(b) Euro returns: $per^{3}_{€,t}(n)$



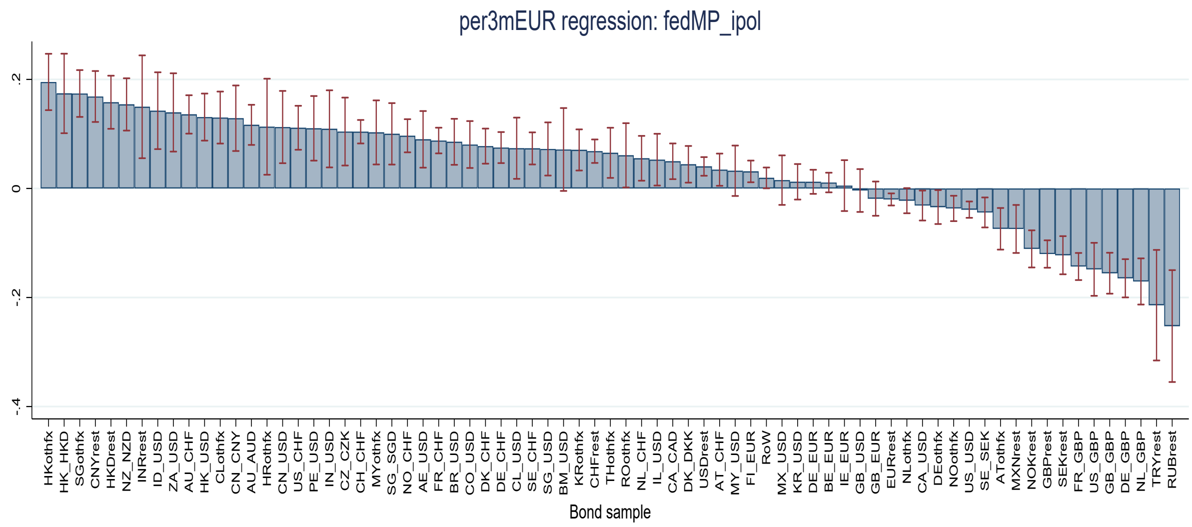
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the effective 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 D.30: Estimated coefficients on Fed monetary policy shock, controlling for EBP & CISSEAbond

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



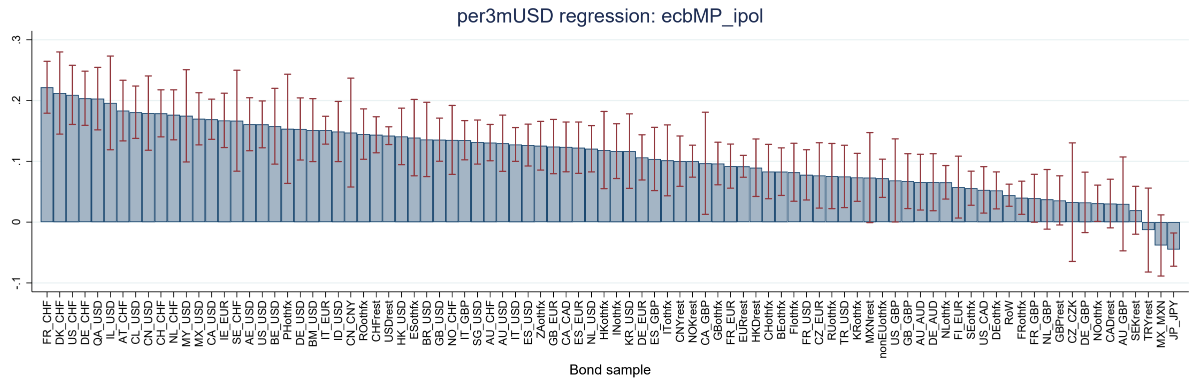
(b) Euro returns: $per^{3}_{€,t}(n)$



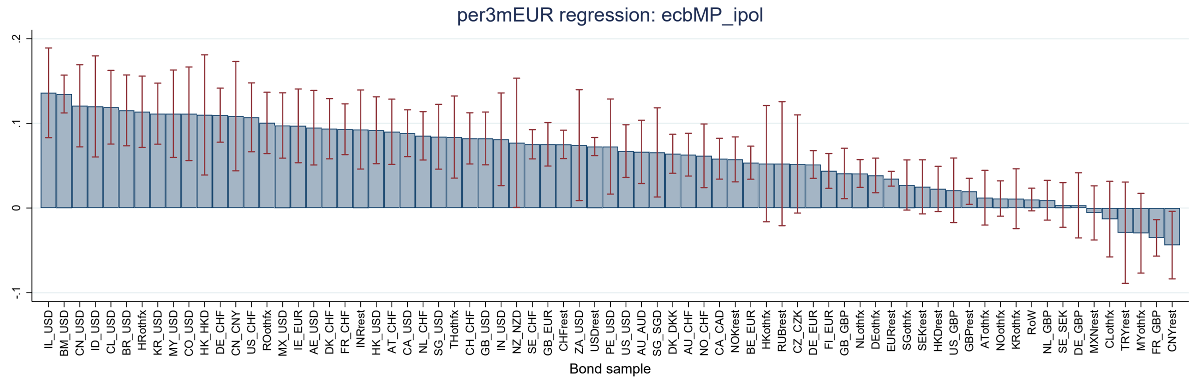
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.31: Estimated coefficients on ECB monetary policy shock, controlling for EBP & CISSEAbond

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



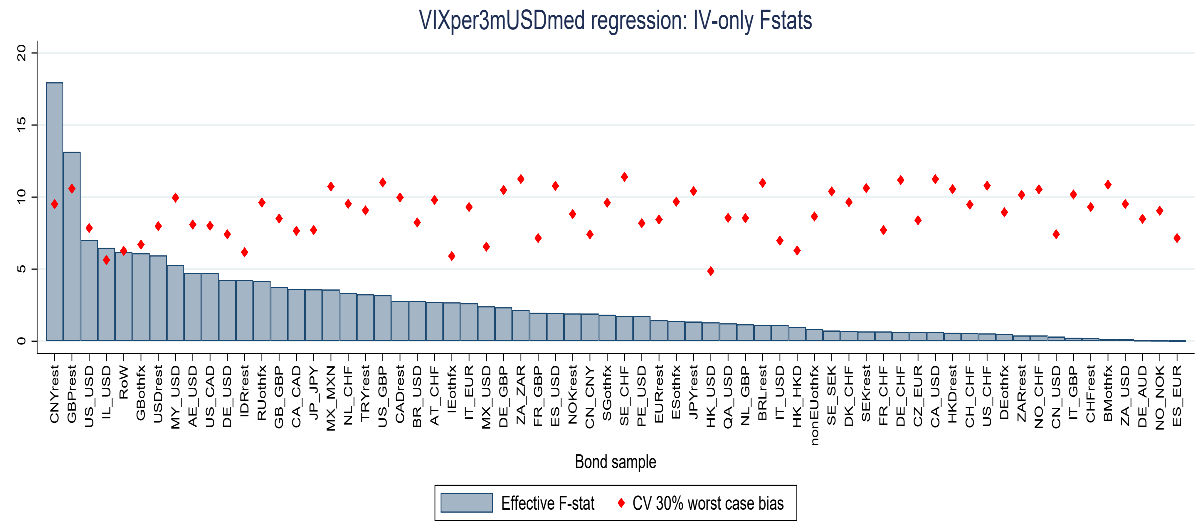
(b) Euro returns: $per^{3}_{€,t}(n)$



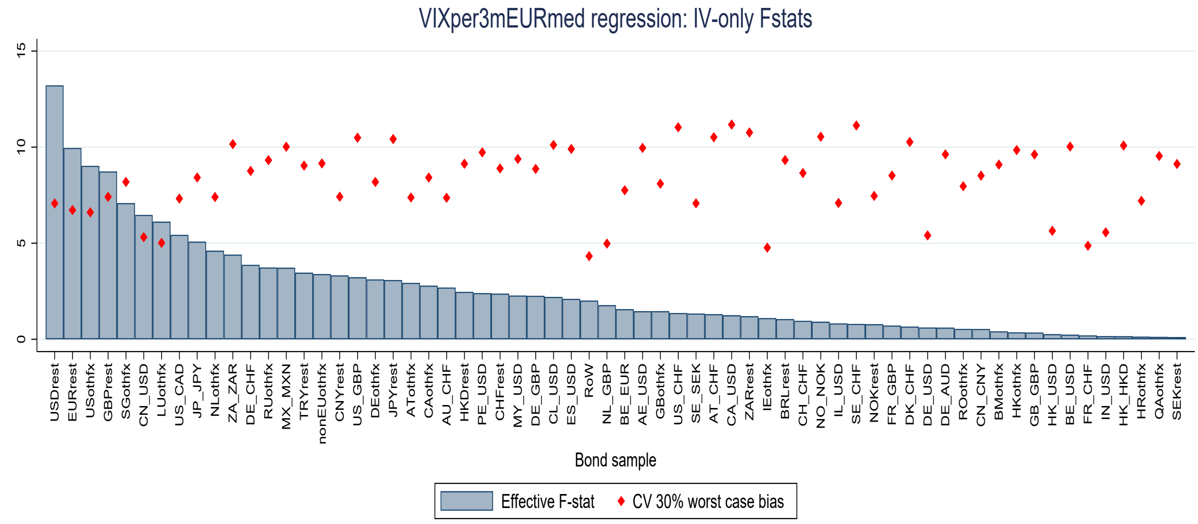
Note: Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government and corporate). The blue bars show the estimated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

Figure D.32: First stage F-statistics from a demand function with 2 endogenous variables: $per^3_{\chi(i),t}(n)$ and VIX interacted with median (over time) realized excess bond return

(a) VIX interacted with median full sample realized \$ bond excess returns



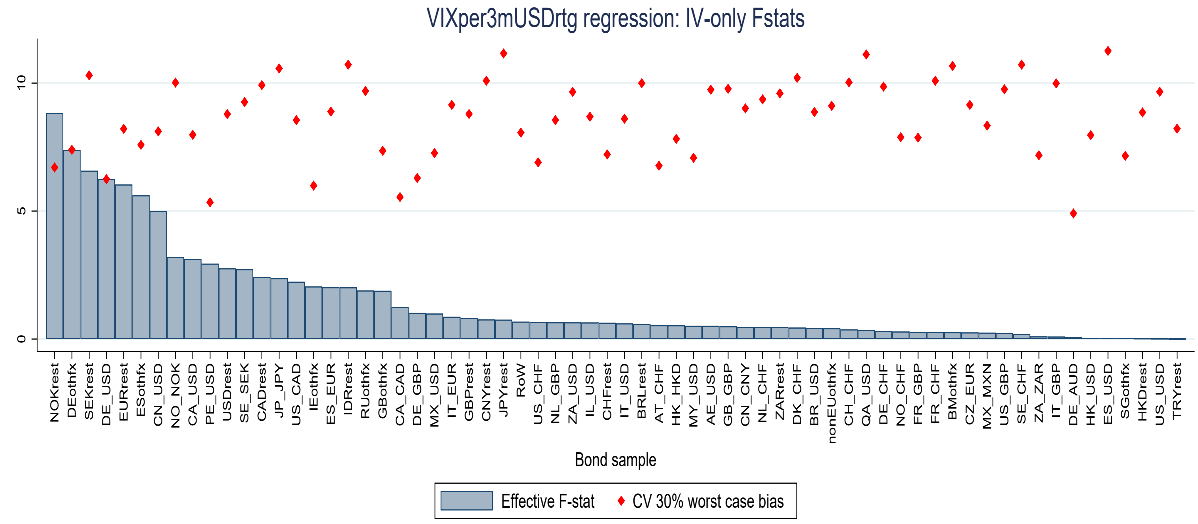
(b) VIX interacted with median full sample realized € bond excess returns



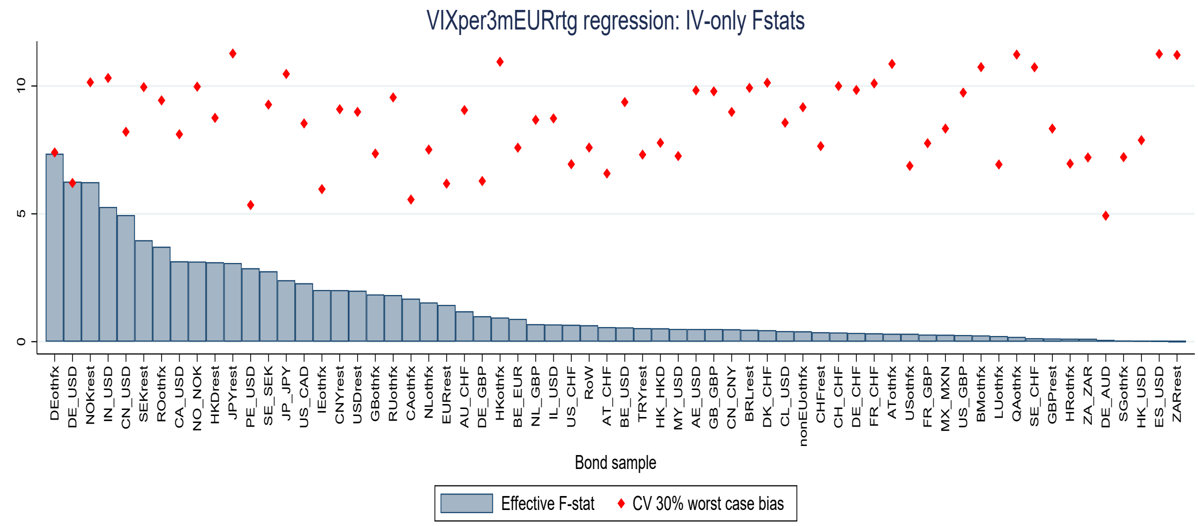
Note: The upper plot reports F-stats for monetary policy shocks Each bar corresponds to a single first-stage regression and the label in the x-axis indicates the sample of bonds included in each panel regression. For instance, "JP_JPY" includes all yen-denominated bonds issued by Japanese entities (government 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 D.33: First stage F-statistics from a demand function with 2 endogenous variables: $per^3_{\chi(i),t}(n)$ and VIX interacted with bond rating score

(a) VIX interacted with bond rating score as second endogenous variable in demand function with $per^3_{\$,t}(n)$



(b) VIX interacted with bond rating score as second endogenous variable in demand function with $per^3_{€,t}(n)$



Note: The upper plot reports F-stats for monetary policy shocks 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).

D.2 Second stage: bond demand panel Logits

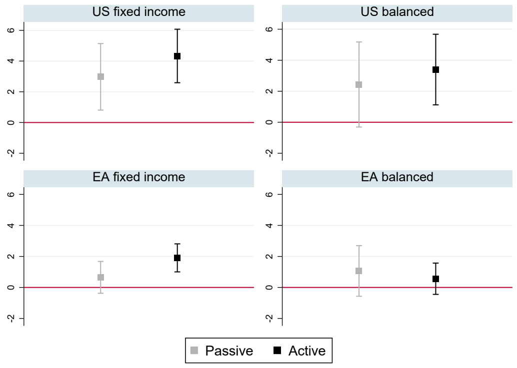
Table D.18: Panel Logit models by fund type

	(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
$\text{per}^3_{i,t}$	3.8032***	2.3453*	4.2543***	1.6446***	0.0919	1.7251***	2.6718*	1.5737	3.4274**	0.7678	0.7338	0.3644
	(1.0408)	(1.3504)	(1.0508)	(0.4539)	(0.6384)	(0.5254)	(1.4106)	(1.6994)	(1.3284)	(0.6180)	(1.0027)	(0.6198)
Maturity	-0.0097*	-0.0075	-0.0086	-0.0017	0.0007	-0.0016	-0.0077	-0.0041	-0.0108**	-0.0074***	-0.0087**	-0.0054**
	(0.0050)	(0.0056)	(0.0056)	(0.0017)	(0.0022)	(0.0020)	(0.0054)	(0.0063)	(0.0053)	(0.0027)	(0.0037)	(0.0027)
AAA-AA=1	0.2711**	0.6365***	0.0137	0.0940	0.2296***	0.0243	0.2439	0.3776**	0.0602	0.2681***	0.4277***	0.2138**
	(0.1204)	(0.1672)	(0.1424)	(0.0636)	(0.0889)	(0.0828)	(0.1490)	(0.1742)	(0.1583)	(0.0868)	(0.1380)	(0.0871)
A=1	0.2500**	0.6387***	0.0559	0.0156	0.1377*	-0.0050	0.3561**	0.5586***	0.1176	0.0918	0.2767**	0.0341
	(0.1071)	(0.1688)	(0.1267)	(0.0579)	(0.0817)	(0.0787)	(0.1391)	(0.1606)	(0.1469)	(0.0789)	(0.1258)	(0.0813)
BBB=1	0.2295*	0.5941***	0.0994	0.0350	0.1534*	0.0265	0.2934**	0.5035***	0.1077	0.1016	0.2719**	0.0562
	(0.1187)	(0.1730)	(0.1347)	(0.0556)	(0.0789)	(0.0751)	(0.1473)	(0.1675)	(0.1560)	(0.0731)	(0.1200)	(0.0740)
BB=1	0.1176	0.2834**	0.0912	0.0091	-0.0217	0.0351	0.1524	0.2523***	0.0990	0.0553	0.1721*	0.0272
	(0.0902)	(0.1316)	(0.1342)	(0.0561)	(0.0698)	(0.0800)	(0.0972)	(0.0958)	(0.1402)	(0.0659)	(0.1021)	(0.0629)
Amt. Outstanding	0.3777***	0.4642***	0.3304***	0.3036***	0.3764***	0.2591***	0.4395***	0.4867***	0.3499***	0.2476***	0.3134***	0.2158***
	(0.0236)	(0.0301)	(0.0260)	(0.0090)	(0.0141)	(0.0104)	(0.0293)	(0.0308)	(0.0327)	(0.0116)	(0.0175)	(0.0128)
Bond Seniority	-0.0214	-0.0089	-0.0111	-0.0058	-0.0067	-0.0017	0.0098	0.0443	-0.0045	-0.0131	-0.0242	-0.0099
	(0.0143)	(0.0173)	(0.0150)	(0.0065)	(0.0100)	(0.0063)	(0.0216)	(0.0310)	(0.0173)	(0.0094)	(0.0148)	(0.0094)
Home Bond	0.0000	0.0000	0.0000	0.0691***	0.0736**	0.0779***	0.0000	0.0000	0.0000	-0.0023	-0.0194	0.0615
	(.)	(.)	(.)	(0.0233)	(0.0301)	(0.0268)	(.)	(.)	(.)	(0.0403)	(0.0464)	(0.0490)
Bond in Fund Investment Area	0.3250***	0.1734**	0.3245***	0.2389***	0.1541***	0.2692***	0.1622	0.0383	0.3200**	0.1289**	0.0932*	0.1532
	(0.0613)	(0.0822)	(0.0598)	(0.0345)	(0.0370)	(0.0402)	(0.1207)	(0.1480)	(0.1390)	(0.0633)	(0.0507)	(0.1020)
Govt Bond=1 X Govt Fund=1	0.6465***	0.5009***	0.6878***	0.7014***	0.6275***	0.7097***	1.3234***	1.3006***	1.0302***	0.9269***	0.8598***	0.9630***
	(0.0857)	(0.1140)	(0.1126)	(0.0413)	(0.0565)	(0.0514)	(0.1499)	(0.1666)	(0.3268)	(0.0842)	(0.1051)	(0.1120)
Govt Bond=1 X Mixed Fund=1	0.2227***	0.2296***	0.1927***	0.2952***	0.3481***	0.2058***	0.3610***	0.3890***	0.2400***	0.3458***	0.3905***	0.3198***
	(0.0658)	(0.0741)	(0.0643)	(0.0296)	(0.0364)	(0.0307)	(0.0703)	(0.0844)	(0.0695)	(0.0322)	(0.0448)	(0.0328)
Corp Bond=1 X Corp Fund=1	0.2993***	-0.1679	0.3569***	0.2202***	0.0436	0.2604***	-0.1202	-0.4616***	0.1398	0.0825	-0.2445***	0.1484*
	(0.1140)	(0.1071)	(0.0939)	(0.0394)	(0.0460)	(0.0374)	(0.1386)	(0.1197)	(0.1289)	(0.0684)	(0.0553)	(0.0790)
Obs	1,925,552	805,104	1,087,860	3,199,509	1,224,388	1,919,441	531,894	333,552	194,708	1,019,188	323,461	671,090
DoF	1,925,377	804,941	1,087,688	3,199,315	1,224,208	1,919,247	531,737	333,405	194,553	1,019,013	323,304	670,915
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	0.73	0.89	0.93	0.85	0.82	0.85	0.73	0.79	0.82	0.77
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

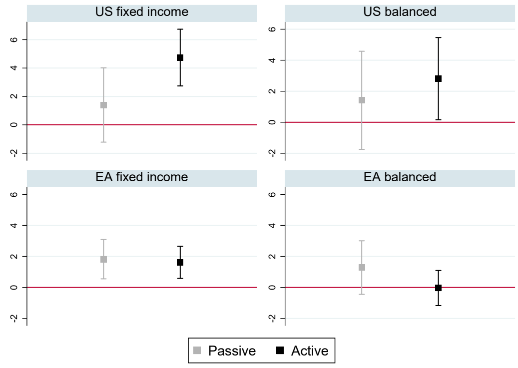
Note: Each column corresponds to a separate panel regression for a subset of funds: (1) all US fixed income funds, (2) passive US fixed income funds, (3) active US fixed income funds, etc. The dependent variable is the log ratio of bond bucket portfolio weight over the outside asset weight $\log\left(w_{i,t}(n)/w_{i,t}(0)\right)$. $per^{12}_{i,t}$ 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 D.34: Estimates of $\alpha_{T(i)}$: compare fund splits

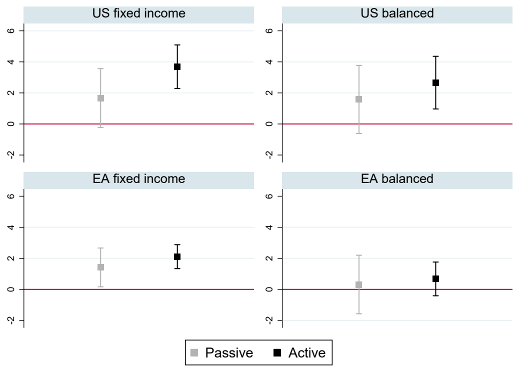
(a) Baseline: Above / Below Median Active Share, $per^3_{\chi(i),t}(n)$



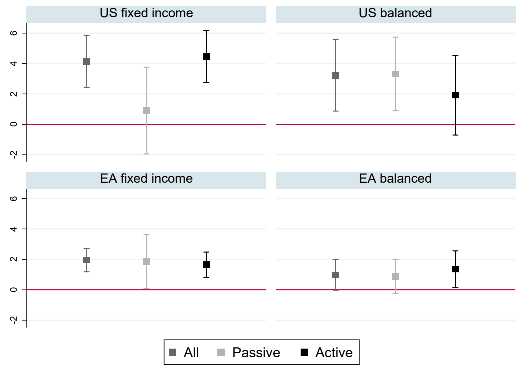
(b) Above / Below Median Active Share, $per^{12}_{\chi(i),t}(n)$



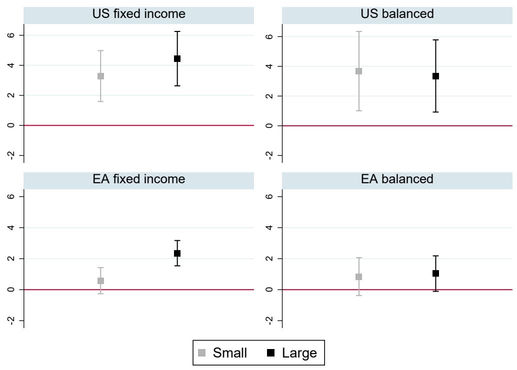
(c) Controlling for EBP in first stage, $per^3_{\chi(i),t}(n)$



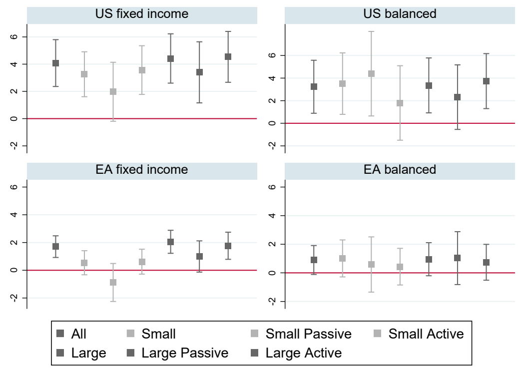
(d) Index funds vs other, $per^3_{\chi(i),t}(n)$



(e) Small vs Large, $per^3_{\chi(i),t}(n)$



(f) Small/Large $\times$ Active/Passive, $per^3_{\chi(i),t}(n)$



E Additional elasticities

E.1 Safety and low demand elasticity

Figure E.35: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond characteristics – Corporate bonds

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

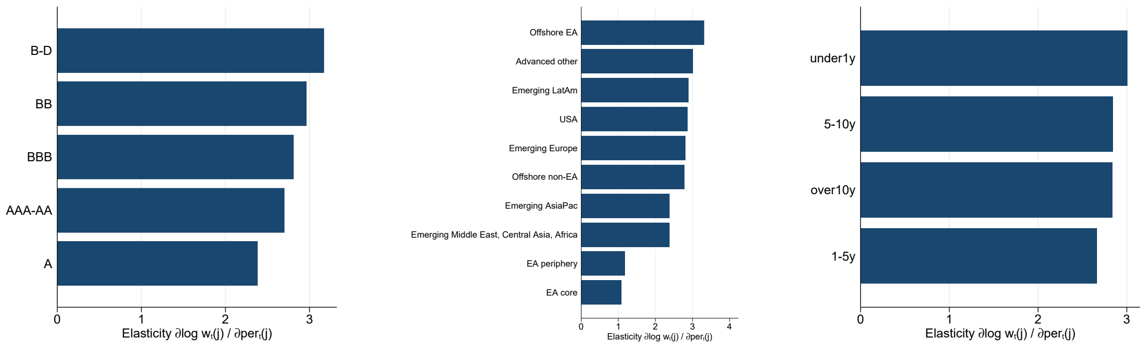


Figure E.36: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond characteristics – All bonds

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

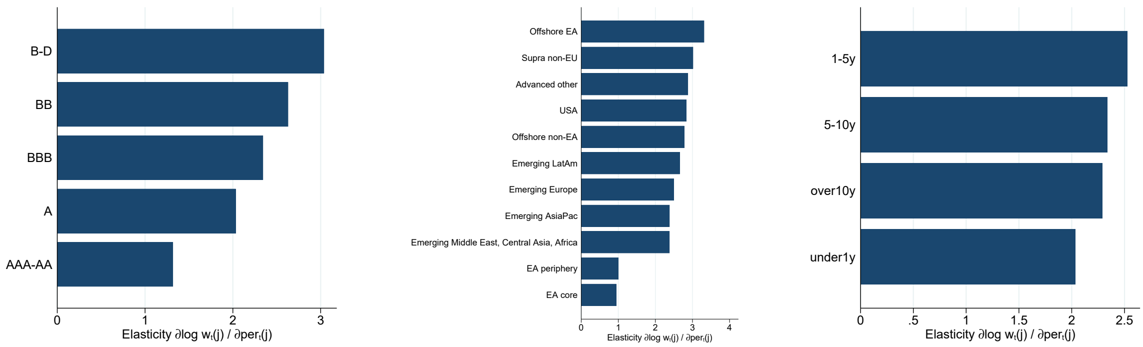
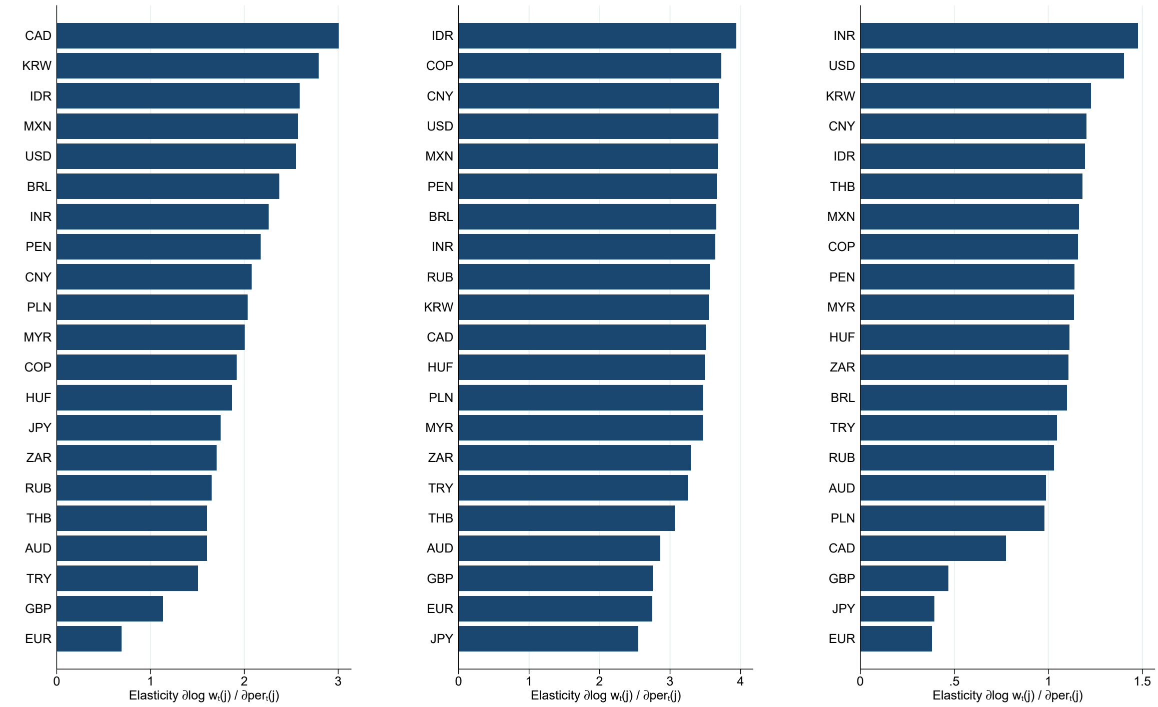


Figure E.37: Average (over time) own elasticities $\bar{\eta}(jj)$ by bond currency – Sovereign bonds

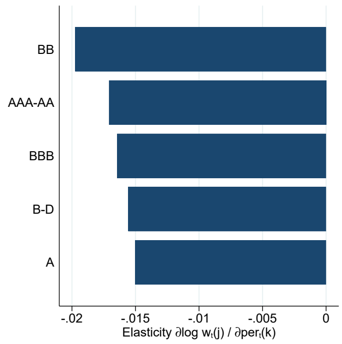
(a) All funds **(b)** US funds **(c)** EA funds



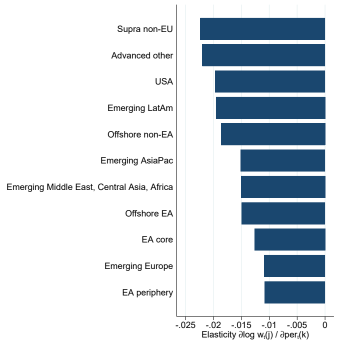
E.2 Global and regional safe assets: a bond substitution view

Figure E.38: Substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds with maturity of less than 1 year by bond characteristics – US funds

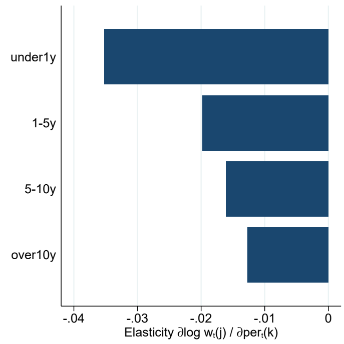
(a) Credit rating



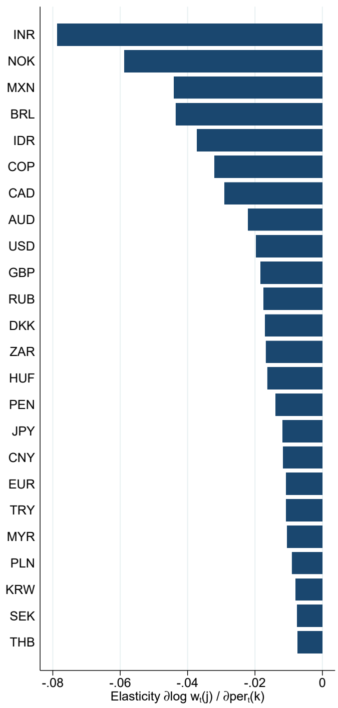
(b) Issuer region



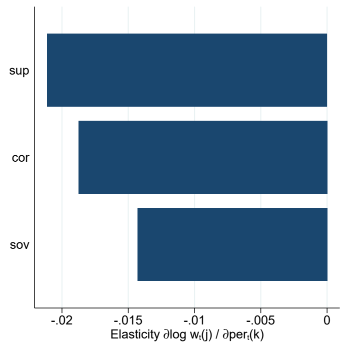
(c) Bond maturity



(d) Bond currency

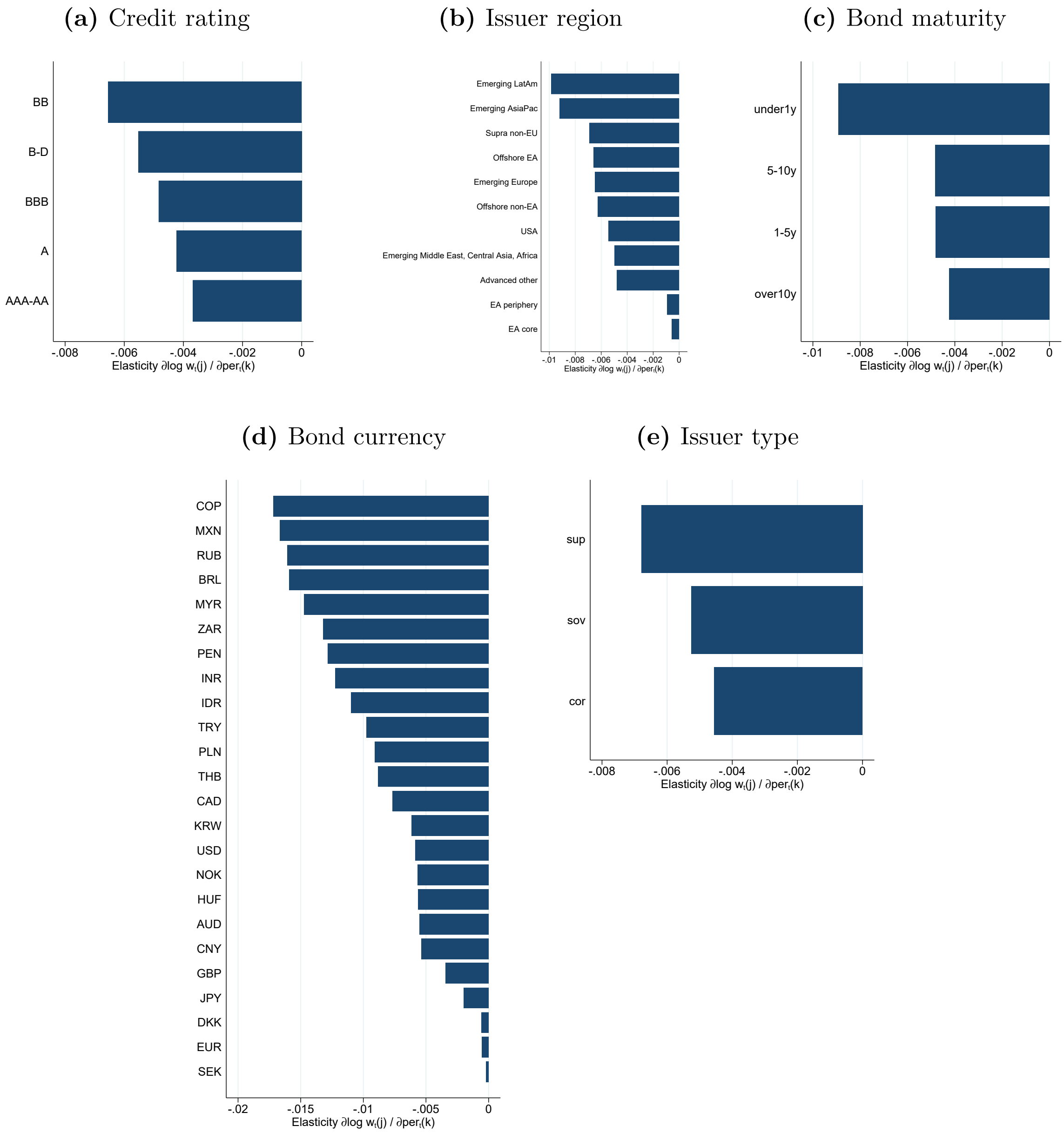


(e) Issuer type



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.

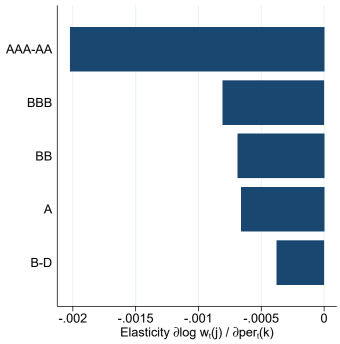
Figure E.39: Substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds with maturity of less than 1 year by bond characteristics – EA funds



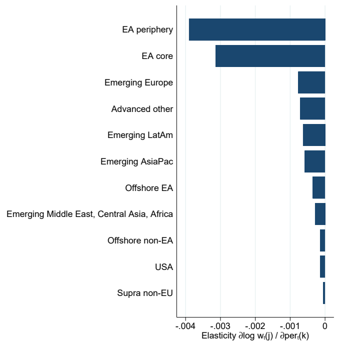
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure E.40: Substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds with maturity of less than 1 year by bond characteristics – US funds

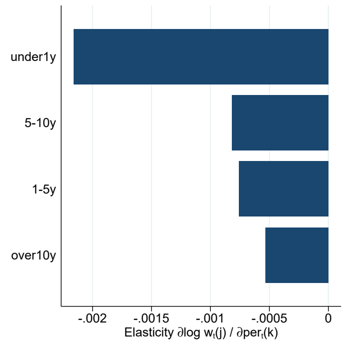
(a) Credit rating



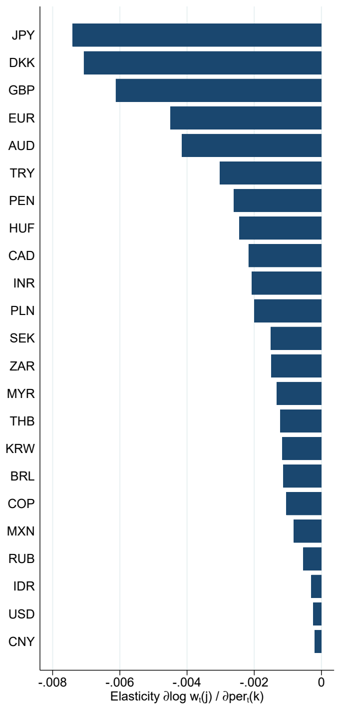
(b) Issuer region



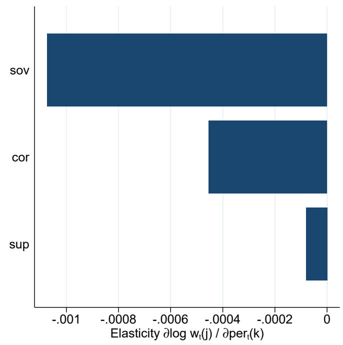
(c) Bond maturity



(d) Bond currency



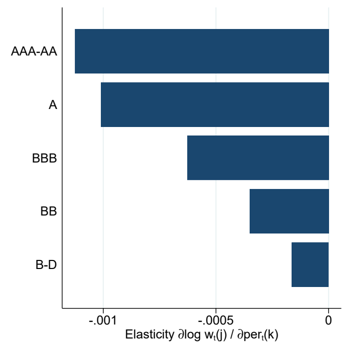
(e) Issuer type



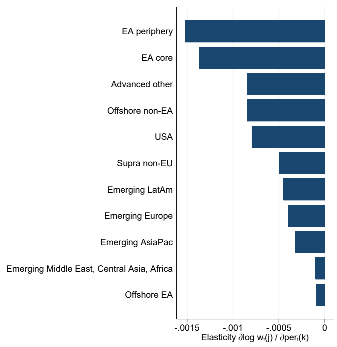
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure E.41: Substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds with maturity of less than 1 year by bond characteristics – EA funds

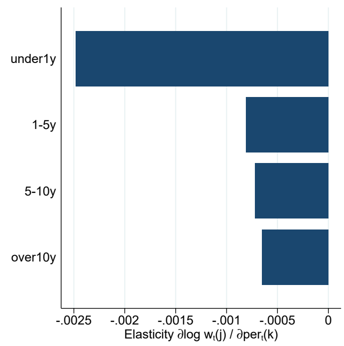
(a) Credit rating



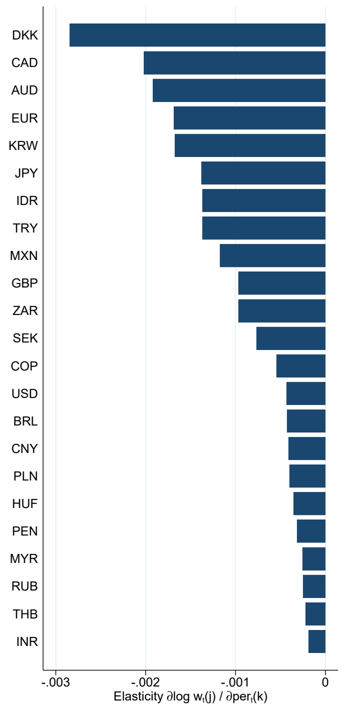
(b) Issuer region



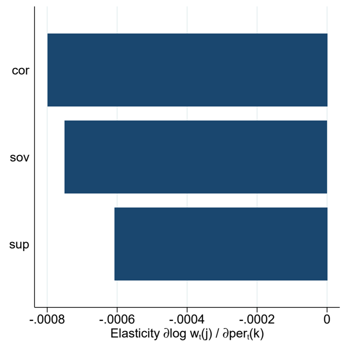
(c) Bond maturity



(d) Bond currency



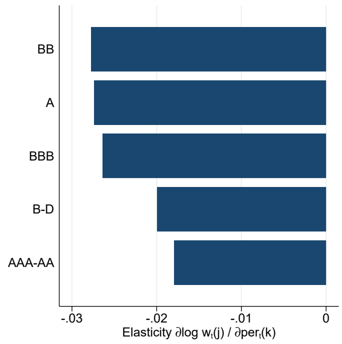
(e) Issuer type



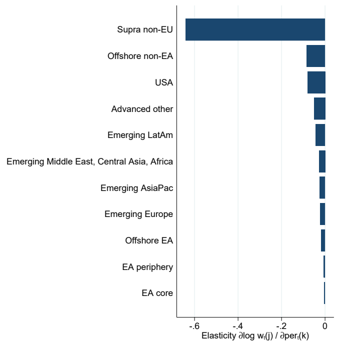
Note: Aggregate demand elasticities, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure E.42: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of 1-5 year maturity by bond characteristics

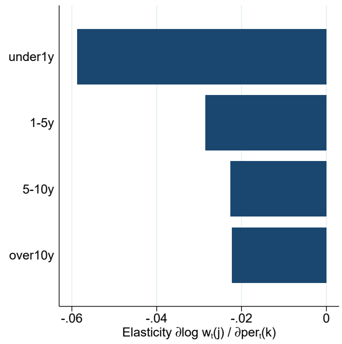
(a) Credit rating



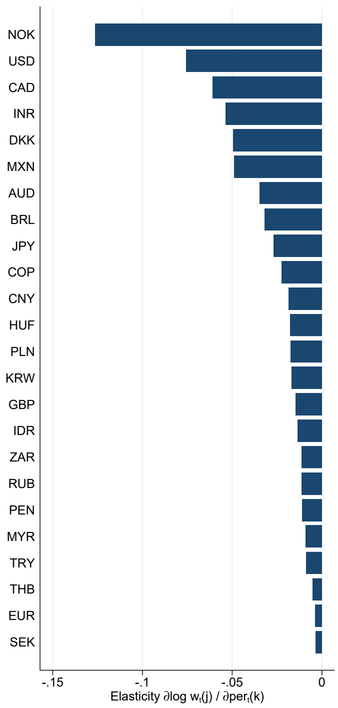
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

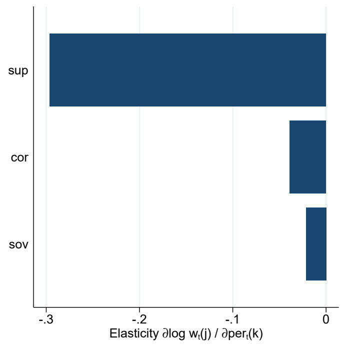
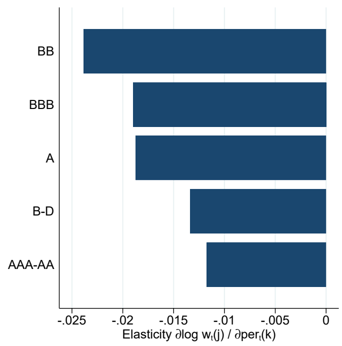
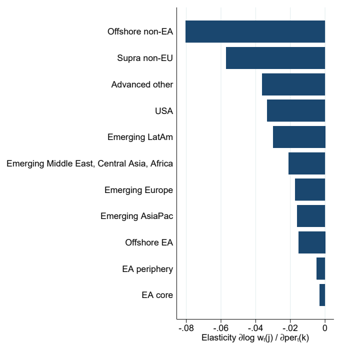


Figure E.43: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of 5-10 year maturity by bond characteristics

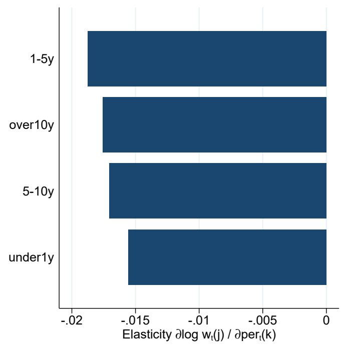
(a) Credit rating



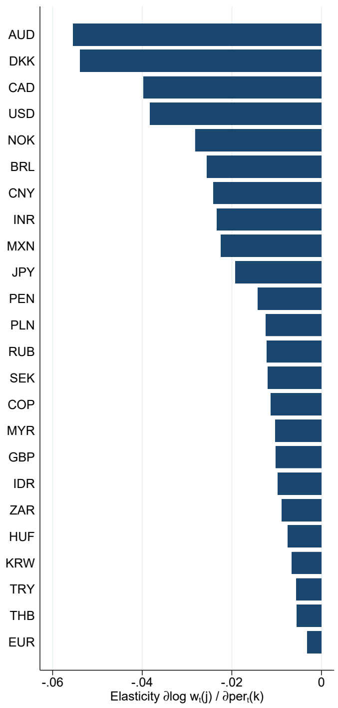
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

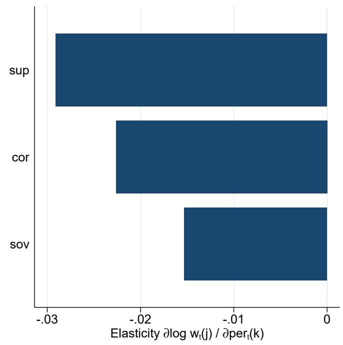
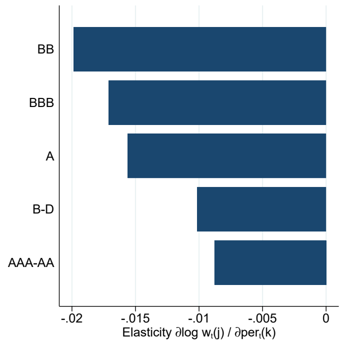
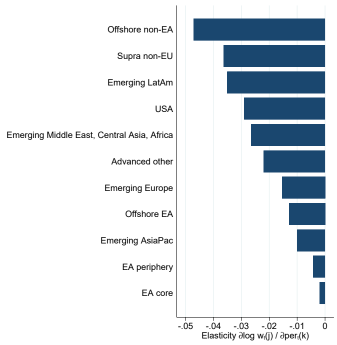


Figure E.44: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from US sovereign bonds of over 10-year maturity by bond characteristics

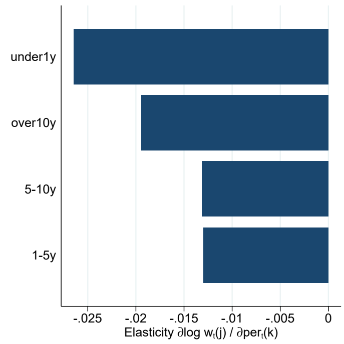
(a) Credit rating



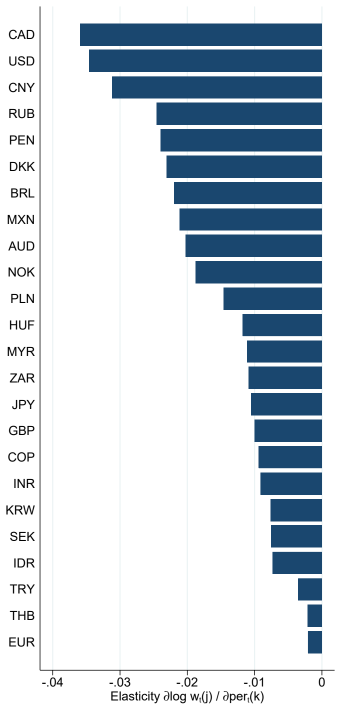
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

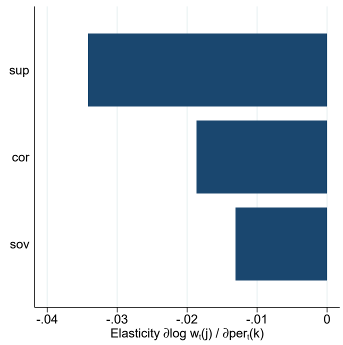
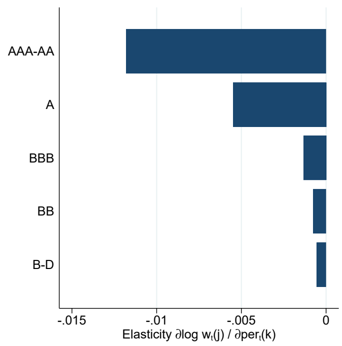
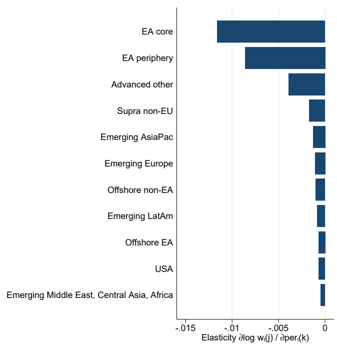


Figure E.45: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of 1-5 year maturity by bond characteristics

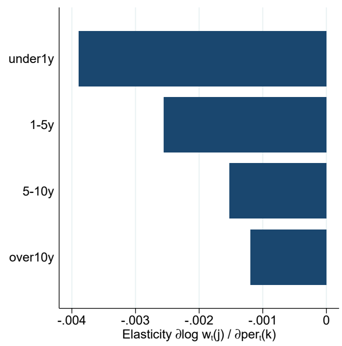
(a) Credit rating



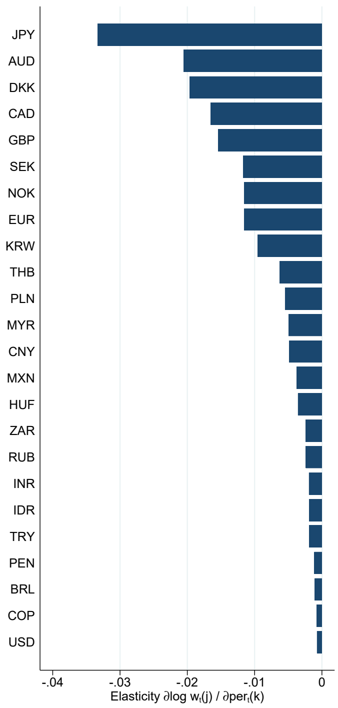
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

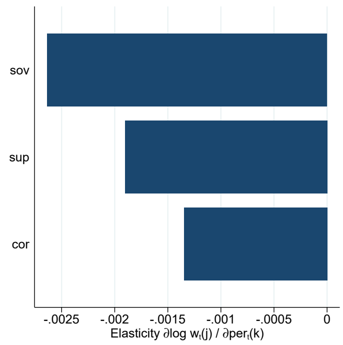
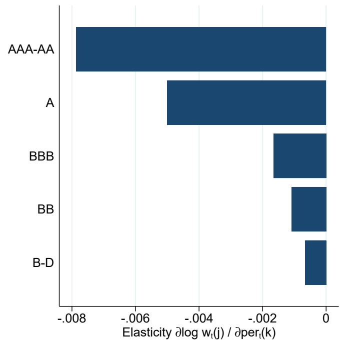
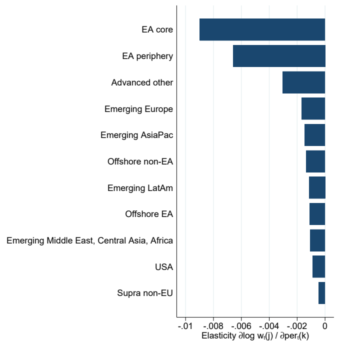


Figure E.46: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of 5-10 year maturity by bond characteristics

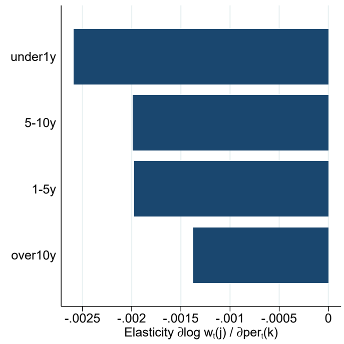
(a) Credit rating



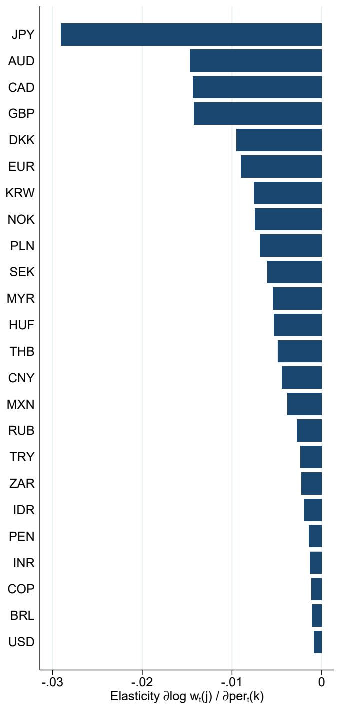
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

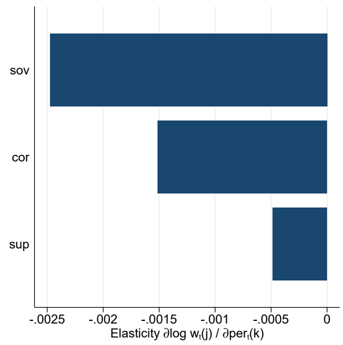
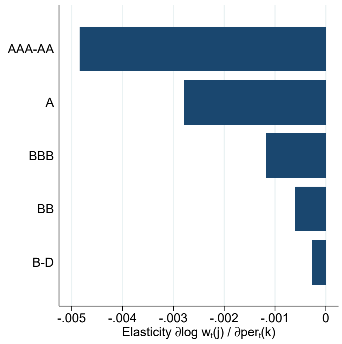
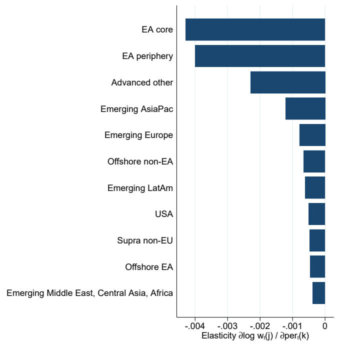


Figure E.47: Average (over time) substitution elasticities $\bar{\eta}(jk)$ from German sovereign bonds of over 10-year maturity by bond characteristics

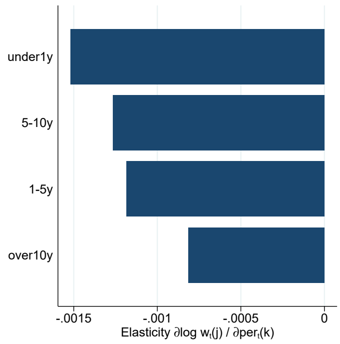
(a) Credit rating



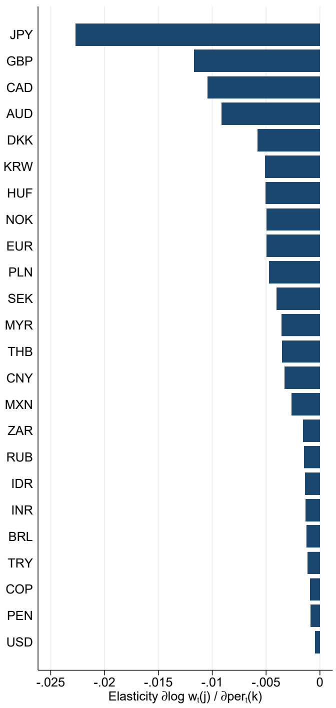
(b) Issuer region



(c) Bond maturity



(d) Bond currency



(e) Issuer type

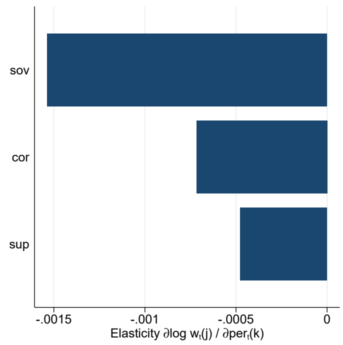
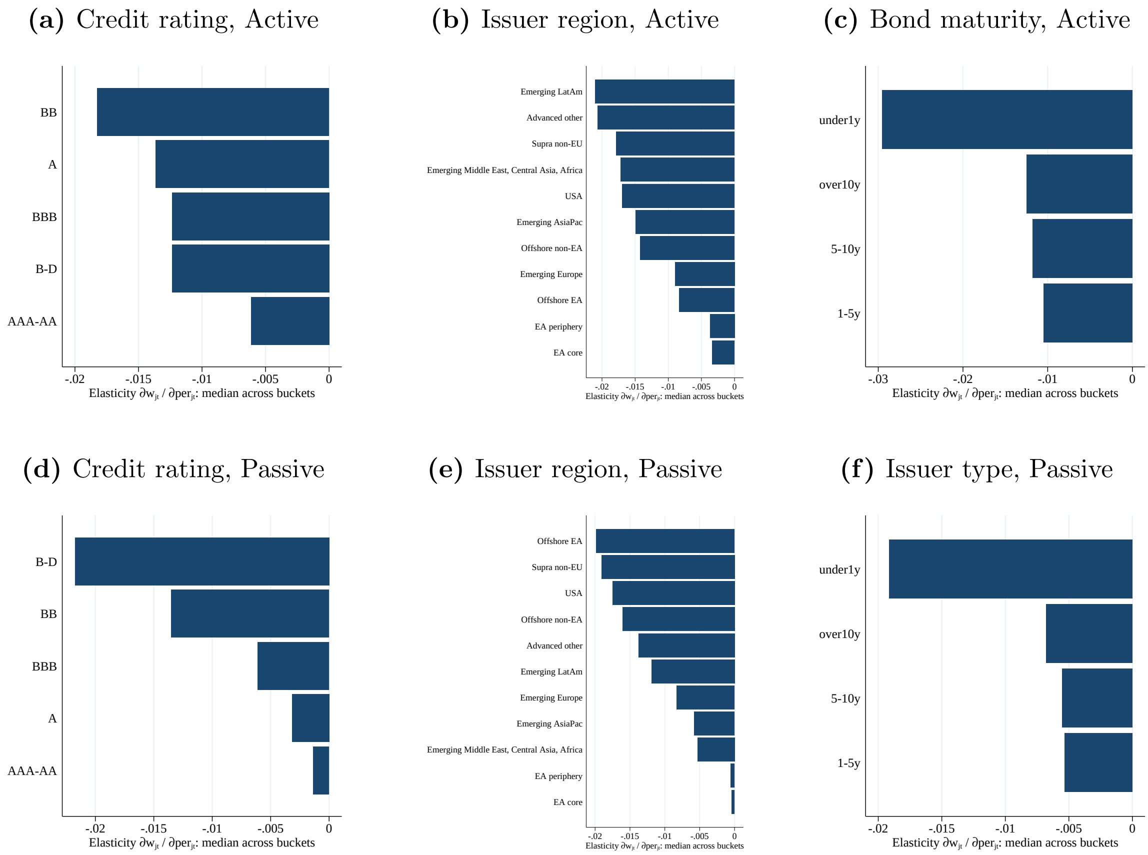


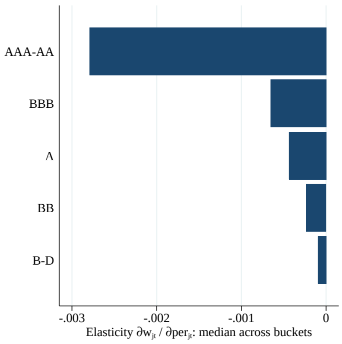
Figure E.48: Substitution elasticities $\bar{\eta}(jk)$ of Active *vs* Passive funds from US sovereign bonds with maturity of less than 1 year by bond characteristics



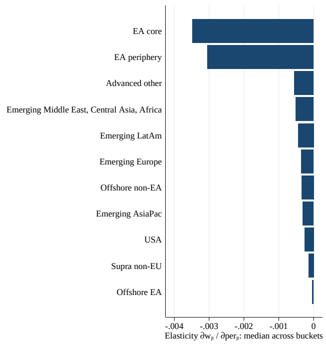
Note: Demand elasticities of active vs passive funds *w.r.t.* changes in German government bond returns, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure E.49: Substitution elasticities $\bar{\eta}(jk)$ of Active *vs* Passive funds from German sovereign bonds with maturity of less than 1 year by bond characteristics

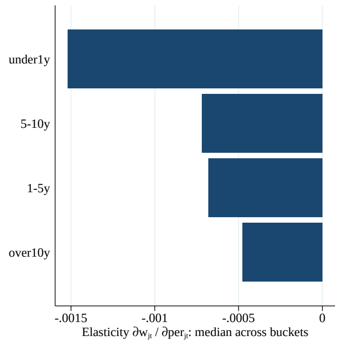
(a) Credit rating, Active



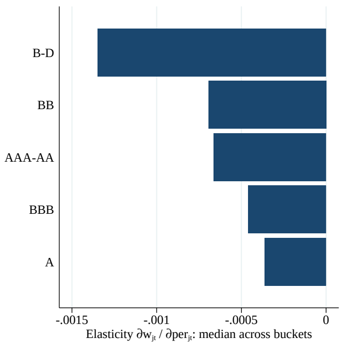
(b) Issuer region, Active



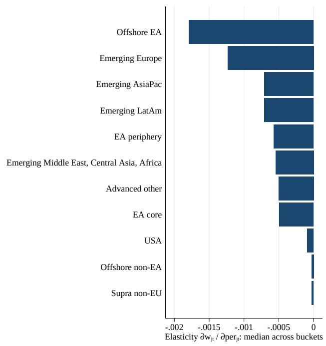
(c) Bond maturity, Active



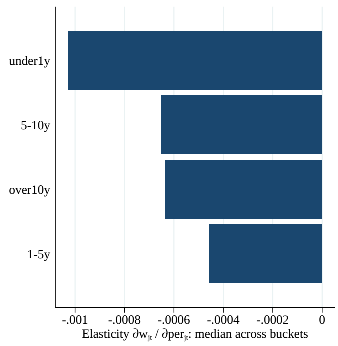
(d) Credit rating, Passive



(e) Issuer region, Passive



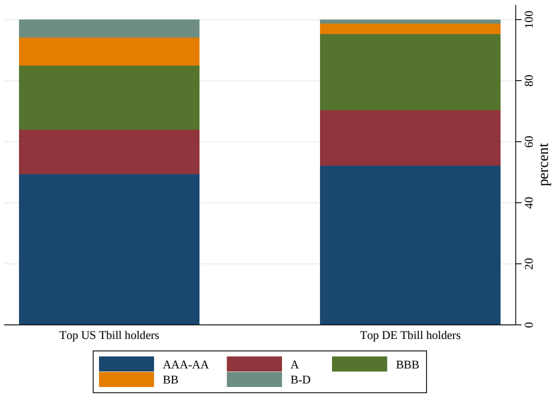
(f) Issuer type, Passive



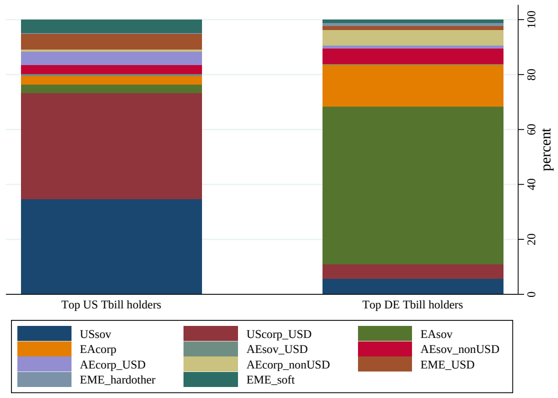
Note: Demand elasticities of active vs passive funds *w.r.t.* changes in German government bond returns, averaged over time for each bucket. Bars report the median of these bucket-specific time-average elasticities by each bond characteristic.

Figure E.50: Comparison of the bond portfolios *at face value* of funds that are 'top substituters' from US and German short-term government bonds

(a) Credit rating



(b) Issuer region



Note: 'Top substituters' with respect to changes in US and German T-bills are defined in the same way as in Figure 11. The only difference to the graph in the main text is that the bond portfolio weights summarized here are calculated at face value of the bond (in the currency of denomination, converted into USD at current exchange rates.

E.3 Flight to safety

Table E.19: 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	0.121	1.000		
DE sov 5-10y	0.084	0.489***	1.000	
DE sov >10y	0.227*	0.293**	0.421***	1.000
Risk				
VIX	0.229*	0.132	0.179	0.226*
BEX risk aversion	0.202	0.068	0.155	0.163
BHL risk aversion	0.229*	0.128	0.165	0.217
MOVE	0.455***	-0.061	0.202	0.330**
EBP	0.140	0.052	0.223*	0.282**
CISSEAbond	0.261*	0.110	0.278**	0.158

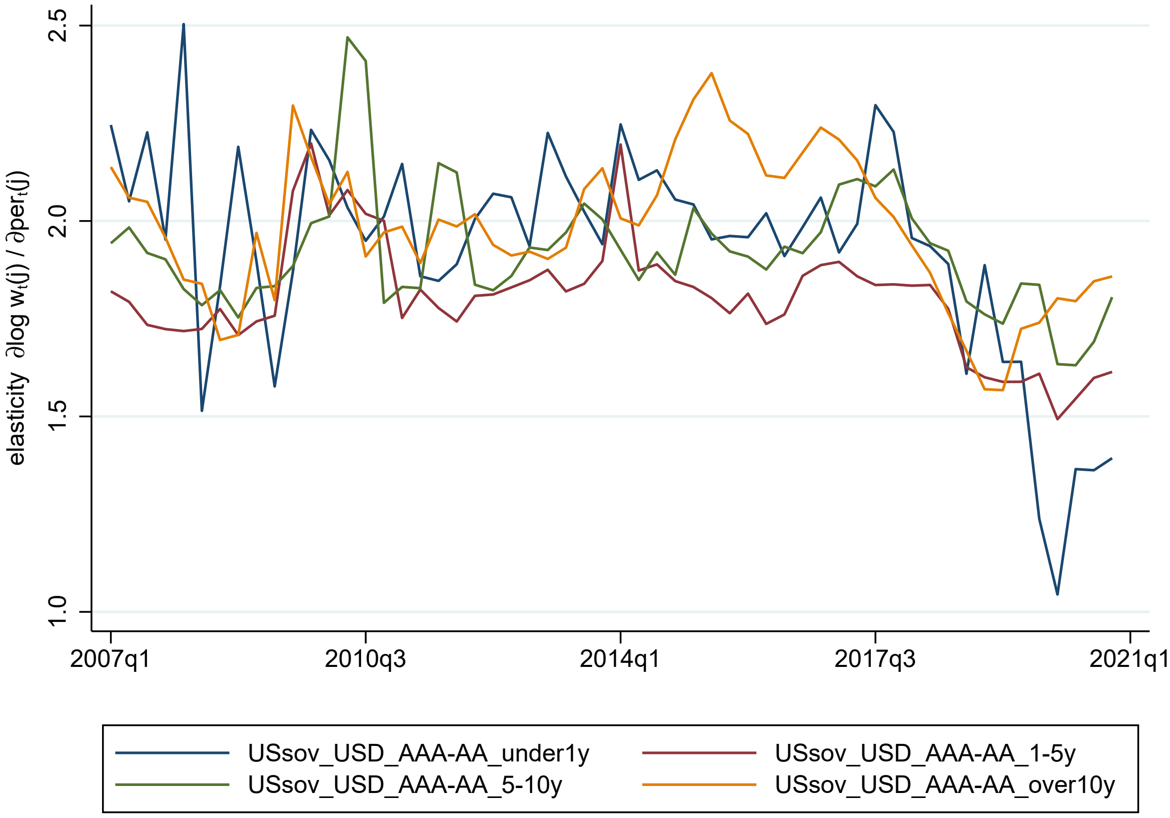
Table E.20: Correlations between Swiss sovereign bond elasticities and risk measures

	CH sov <1y	CH sov 1-5y	CH sov 5-10y	CH sov >10y
Elasticities				
CH sov <1y	1.000			
CH sov 1-5y	0.161	1.000		
CH sov 5-10y	0.405**	0.472***	1.000	
CH sov >10y	-0.505***	0.369***	0.043	1.000
Risk				
VIX	-0.190	-0.048	-0.104	-0.376***
BEX risk aversion	-0.029	0.016	-0.004	-0.388***
BHL risk aversion	-0.160	-0.033	-0.089	-0.363***
MOVE	0.270	-0.211	0.097	-0.716***
EBP	-0.139	-0.041	0.073	-0.441***
CISSEAbond	0.143	-0.077	0.087	-0.416***

Table E.21: 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	-0.364***	1.000		
JP sov 5-10y	-0.085	0.354***	1.000	
JP sov >10y	0.192	0.380***	0.268**	1.000
Risk				
VIX	-0.280**	0.161	-0.039	-0.178
BEX risk aversion	-0.326**	0.139	-0.024	-0.264**
BHL risk aversion	-0.304**	0.136	-0.035	-0.196
MOVE	-0.446***	0.530***	-0.084	-0.187
EBP	-0.257*	0.270**	-0.102	-0.089
CISSEAbond	-0.205	0.176	0.019	-0.305**

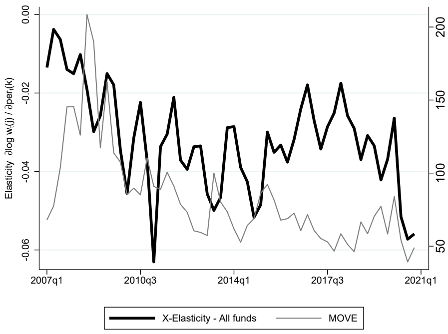
Figure E.51: Own demand elasticities $\eta_t(jj)$ of US sovereign bonds



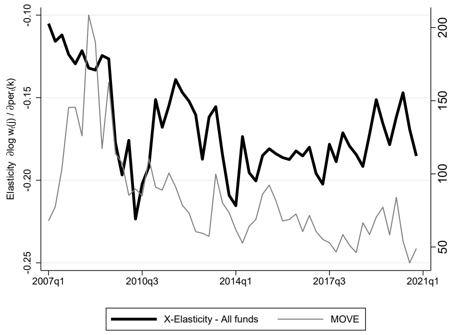
Black line: Funds' demand elasticity for US Treasuries with maturity under 1 year to changes *w.r.t.* 1ppt change in its predicted excess returns.

Figure E.52: Substitutability of US corporate bonds (BBB-BB) with US Treasuries of the same maturity

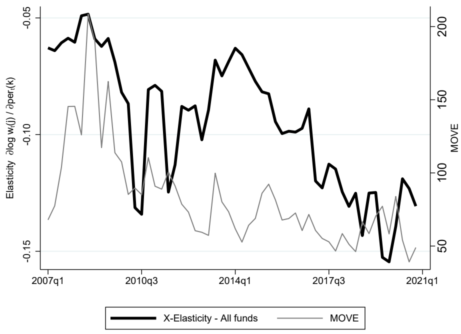
(a) US corporate BBB <1y bonds



(b) US corporate BBB 1-5y bonds



(c) US corporate BBB 5-10y bonds



(d) US corporate BBB >10y bonds

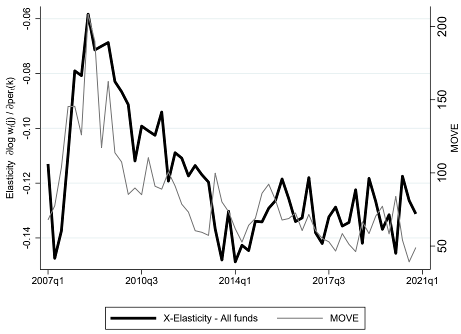
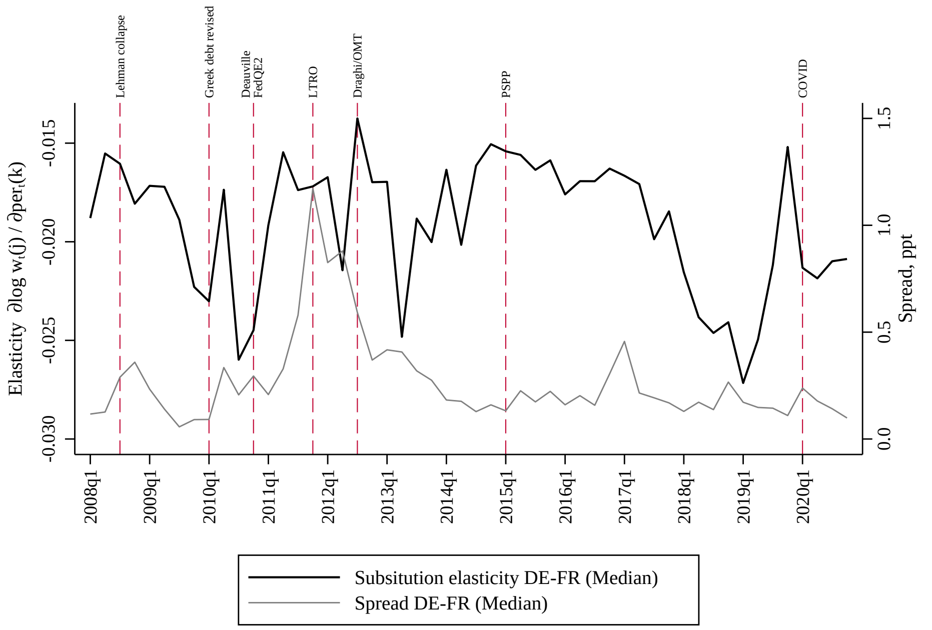
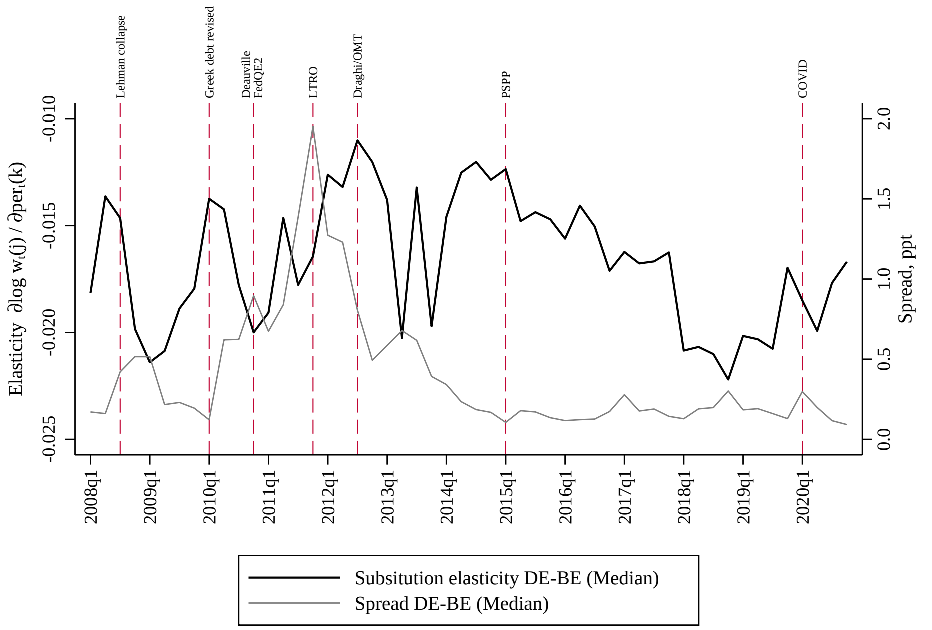


Figure E.53: Substitutability of German and French sovereign bonds



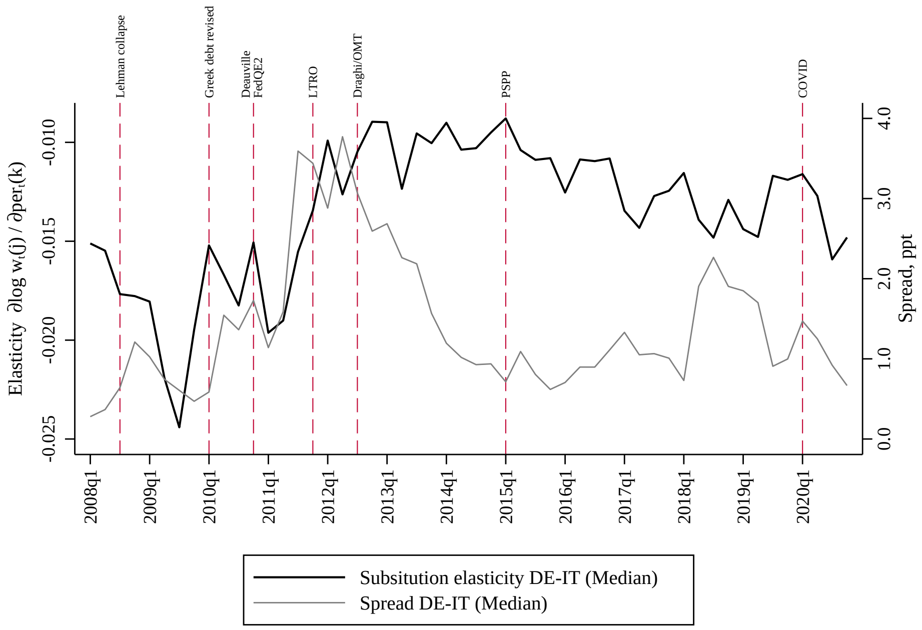
Black line: Substitution elasticity of French sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

Figure E.54: Substitutability of German and Belgian sovereign bonds



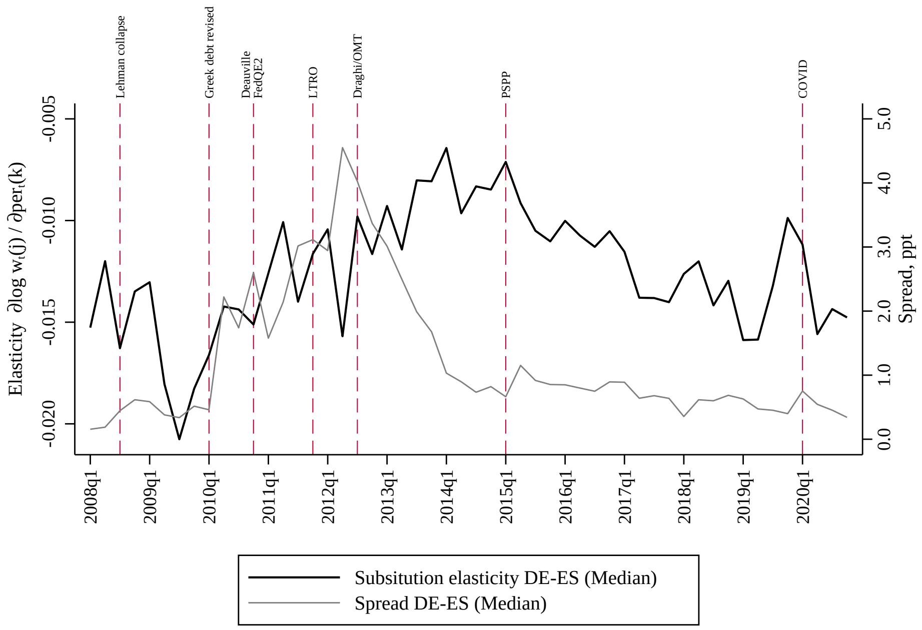
Black line: Substitution elasticity of Belgian sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

Figure E.55: 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).

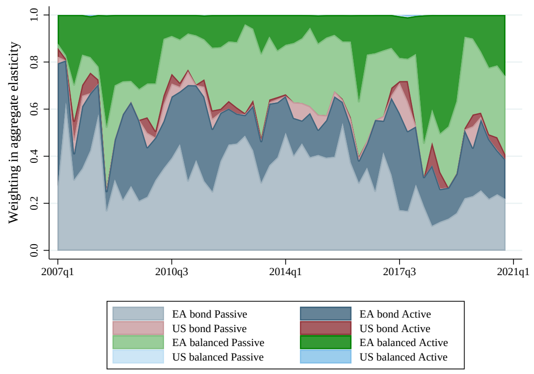
Figure E.56: Substitutability of German and Spanish sovereign bonds



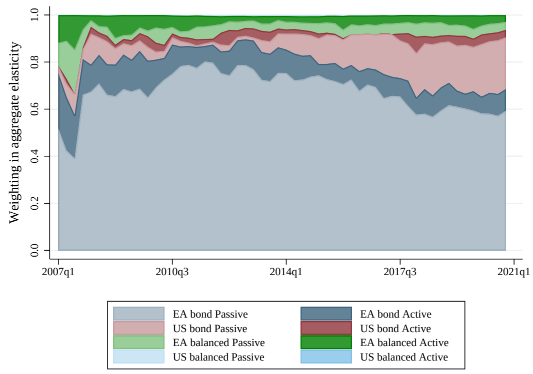
Black line: Substitution elasticity of Spanish sovereign bonds *w.r.t.* 1ppt change in predicted excess returns on German sovereign bonds. Median of substitutions within all four maturity buckets (under 1y, 1-5y, 5-10y, over 10y).

Figure E.57: French government bond ownership by fund type

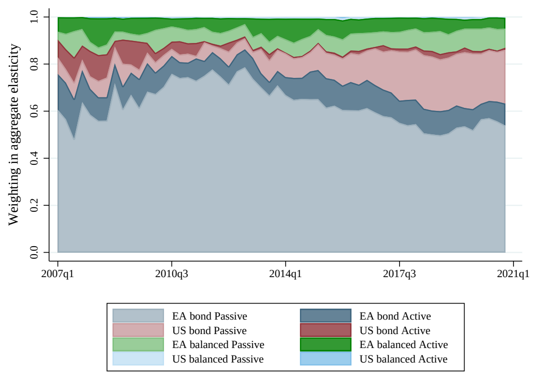
(a) Maturity under 1 year



(b) Maturity of 1-5 years



(c) Maturity of 5-10 years



(d) Maturity over 10 year

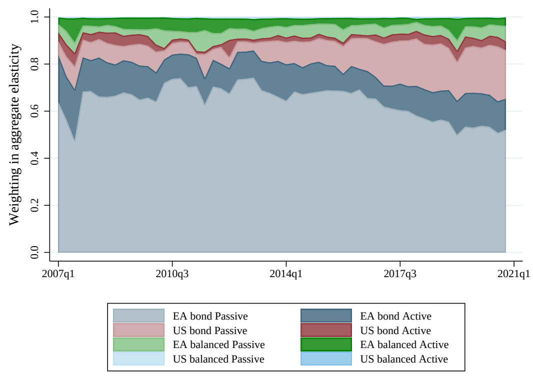
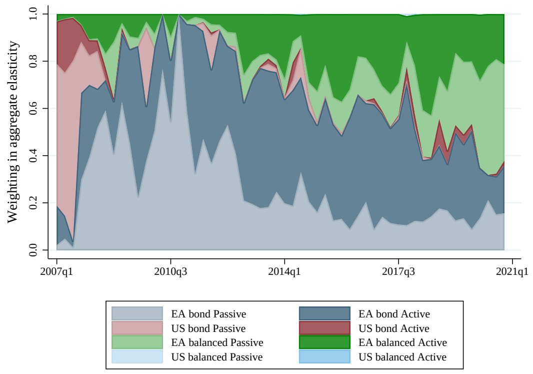
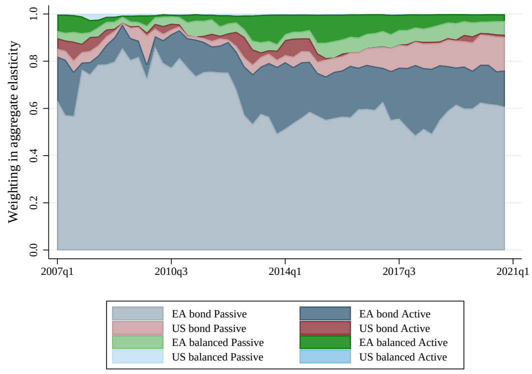


Figure E.58: Spanish government bond ownership by fund type

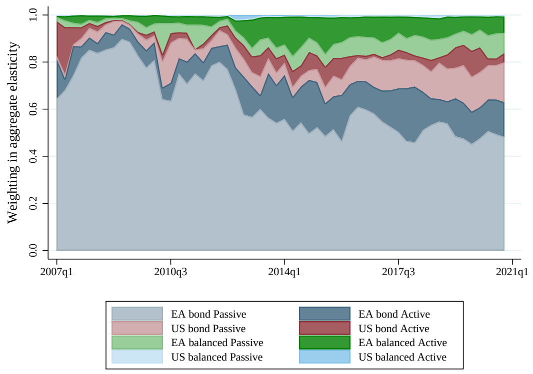
(a) Maturity under 1 year



(b) Maturity of 1-5 years



(c) Maturity of 5-10 years



(d) Maturity over 10 year

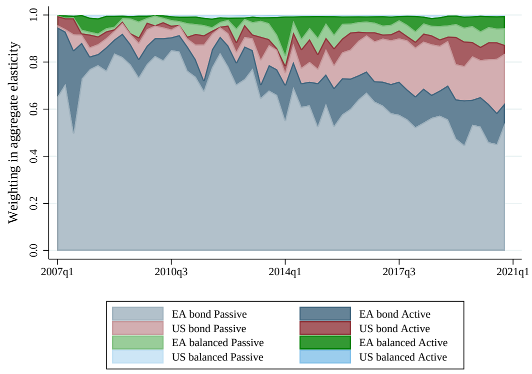
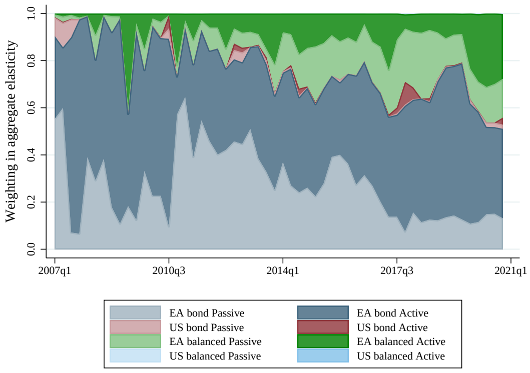
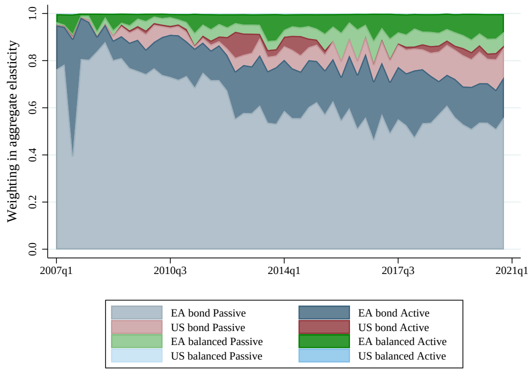


Figure E.59: Italian government bond ownership by fund type

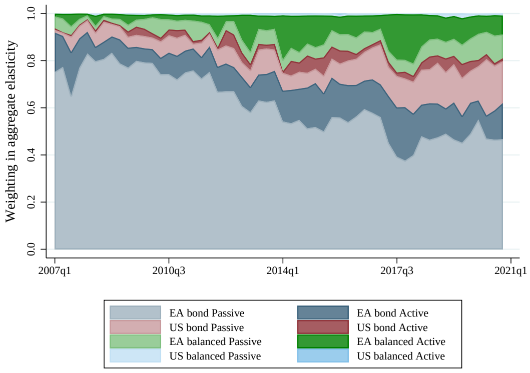
(a) Maturity under 1 year



(b) Maturity of 1-5 years



(c) Maturity of 5-10 years



(d) Maturity over 10 year

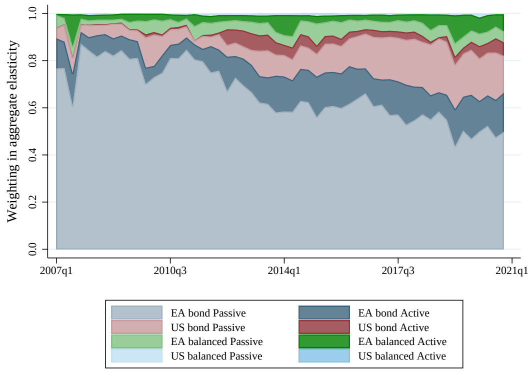
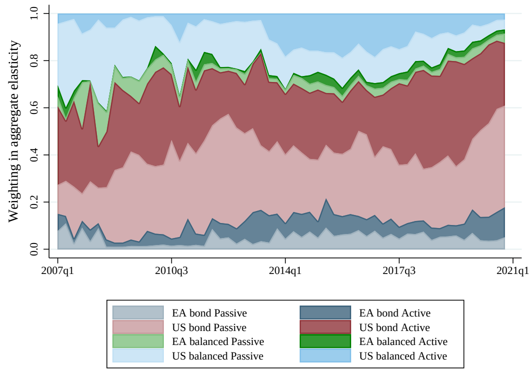
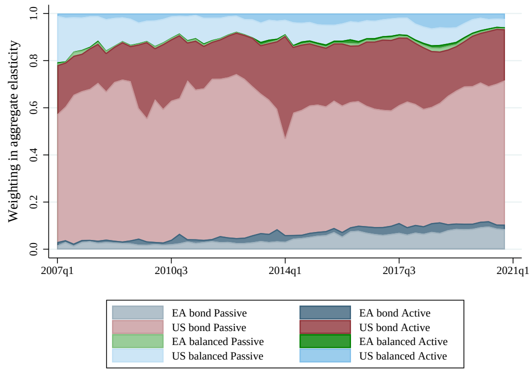


Figure E.60: US government bond ownership by fund type

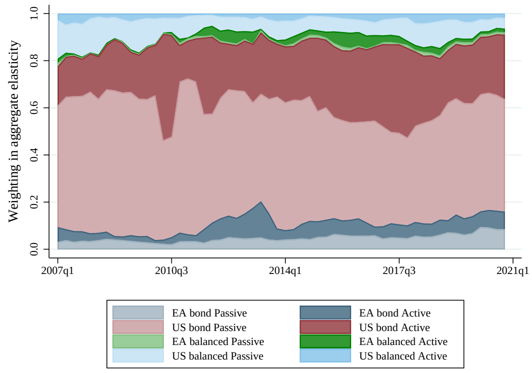
(a) Maturity under 1 year



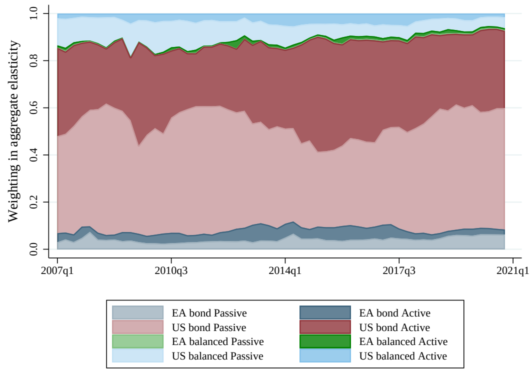
(b) Maturity of 1-5 years



(c) Maturity of 5-10 years



(d) Maturity over 10 year



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