Dissecting Bond Market Transmission of Monetary Policy*

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Abstract

This paper develops a random-coefficient demand system to study how monetary policy is transmitted through the bond market, utilizing granular portfolio holdings data on multiple interconnected classes of bonds, including Treasury, corporate, municipal, and mortgage-backed securities. The analysis ranks mutual fund and bank flows, changes in demand for credit rating and duration, and changes in callable bond duration as top amplifiers of bond yield sensitivity to monetary policy, whereas bond issuances and redemptions significantly dampen it. The framework reveals important heterogeneities and state dependencies. The contribution of a channel varies across the term structure and credit spectrum and depends on the composition and elasticity of investors. These findings highlight the role of financial markets in shaping the transmission of monetary policy.

Keywords: monetary policy, demand system, state dependency

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1 Introduction

The standard monetary theory in macroeconomics emphasizes the interactions among interest rates, output, and inflation, often sidelining the role of financial markets. In recent years, however, a growing body of literature has questioned the adequacy of this perspective. For instance, high-frequency event studies indicate that changes in short-term policy rates have a much greater effect on long-term yields than what the standard New Keynesian models predict, implying that the impact of monetary policy on the borrowing costs for households and firms may be far larger than traditionally understood.[1] This leads to the growing consensus that monetary policy not only affects risk-free rates, it can also influence risk premia. Since the pricing of risk is determined within financial markets, these markets may play a greater role in the transmission mechanism of monetary policy than previously acknowledged.

This study seeks to deepen our understanding of financial markets as a central component of monetary policy transmission. It draws on a growing body of theoretical research that illustrates how monetary policy interacts with institutional frictions among financial intermediaries and behavioral tendencies of individual investors, thereby influencing the pricing of risk. One class of theories suggests that monetary policy can impact how households allocate their wealth across different financial intermediaries, each of which invests in distinct types of assets. This reallocation by households leads to equilibrium repricing of risk in the economy. A second class of theories posits that monetary policy may also alter the asset allocation strategies of financial intermediaries. For instance, intermediaries with fixed return targets may respond to lower risk-free rates by taking on greater risk to maintain returns,

[1] Gürkaynak, Sack, and Swanson (2005), Hanson and Stein (2015) and Nakamura and Steinsson (2018) show that monetary policy shocks have large impacts on long-term Treasury yields, employing different definitions of policy shocks and different windows around FOMC announcements. Gertler and Karadi (2015) and Brooks, Katz, and Lustig (2018) find additional delayed responses by examining the impulse responses of long-term Treasury and corporate yields to monetary policy shocks. Hanson, Lucca, and Wright (2021) notes the decay in long-term yield sensitivity at lower frequency. Nagel and Xu (2024) shows consistent evidence on the long-term yield sensitivity to monetary policy and suggests that it can explain the stock sensitivity to monetary policy.

thereby compressing risk premia. A third class of theories highlights the effect of monetary policy on the characteristics of available assets in the economy. For example, declining rates make mortgage prepayments more likely, resulting in a shortage of duration in the market, which subsequently affects the term premia.

We contribute to the literature by developing a unified framework to quantify the different channels of bond market transmission of monetary policy, utilizing the demand system approach to asset pricing from Koijen and Yogo (2019). We jointly model the asset demand of major investors — including mutual funds, insurance companies, and banks — across multiple interconnected asset classes, including Treasuries, corporate bonds, municipal bonds, and mortgage-backed securities (MBS). We demonstrate that existing theories can be mapped to a vector of investor demand parameters, including preferences for bond characteristics like credit rating and duration, as well as bond supply parameters such as issuances and redemptions. Policymakers influence short-term yields through conventional monetary policy and affect the supply of long-term bonds via quantitative easing or tightening. Notably, these monetary policy actions simultaneously impact both investor demand and bond supply. The various transmission channels proposed in the literature are evaluated by counterfactually altering the relevant demand and supply parameters.

We have three main findings. First, the household reallocation channel, as evidenced by investor flows into financial intermediaries, is the most significant amplifier of monetary transmission. Intermediary asset reallocation and changes in asset characteristics have notable, though comparatively smaller, effects on both term and credit spreads. Second, issuances and redemptions significantly dampen yield sensitivity by absorbing investor demand fluctuations, emphasizing the need to account for both investor demand and issuer supply to understand asset prices. Last but not the least, our framework demonstrates important heterogeneities and state dependencies. The strength of a channel varies across investors, operates on different segments of term structure and credit spectrum, and depends on time-varying state variables such as investor composition and investor elasticity.

We begin by building a random-coefficient asset demand system, which departs from the existing asset demand systems that typically rely on logit or nested logit demand structures. We demonstrate that random coefficients are necessary for capturing complex portfolio changes induced by monetary policy. For example, the logit demand model assumes that, in response to changes in asset prices or characteristics, such as monetary policy-induced MBS duration shortening, investors substitute proportionally to all other assets within their portfolios. To address this limitation, we use insights from the industrial organization literature (Berry, Levinsohn, and Pakes, 1995) and introduce random coefficients into the asset demand framework. This modeling technique relaxes the proportionality assumption and enables us to capture the fact that there is more substitutability across assets with more similar characteristics, which is essential for transmission channels such as MBS convexity (Hanson, 2014).

To estimate the model, we assemble a large, granular dataset of Treasury bonds, corporate bonds, municipal bonds, and MBS, which together cover virtually the entire U.S. bond market. As these bonds share similar characteristics and investor base, their yields must be jointly determined in equilibrium. The joint analysis of multiple interconnected bond classes enables us to capture transmission channels that rely on substitution across bond classes (e.g., between Treasury bonds and MBS), which might otherwise be overlooked. Assembling the dataset using individual bond securities further allows us to examine heterogeneity across different maturities of bonds along the term structure and different ratings of bonds across the credit spectrum.

We use the estimated model to assess how different channels contribute to the impact of short-term interest rates on bond market risk premia. In the data, a 100 basis point (bps) increase in the one-year Treasury rate is associated with a 20 bps rise in the term spread at the ten-year maturity. If we eliminate household reallocation across financial intermediaries, the term spread would instead decrease by 7 bps. This implies that household reallocation contributes 27 bps to the change in the ten-year term premium, making it the most significant amplifier of term spread sensitivity to monetary policy. We also find that institutional demand for duration and changes in callable bond duration are important, though to a lesser extent compared to the household reallocation channel, contributing 11 bps and 12 bps, respectively. Government and corporate bond issuances dampen the term spread sensitivity to monetary policy by 32 bps, absorbing a substantial portion of the investor demand effect on the term spread, while the rebalancing between bonds and equities plays a much smaller role in the transmission mechanism.

The results for credit spreads are largely consistent with those for term spreads, with household reallocation being the most important channel, but there are some notable differences. The demand for credit risk plays a significant role, while the supply of credit risk has a more muted effect. Additionally, unlike term spreads, government bond issuances amplify the impact on credit spreads rather than dampen it. These differences highlight competition between public and private bond issuances, as government borrowing can crowd out private corporate bond issuances.

Our framework captures important heterogeneity across investors and characteristics. For term spread sensitivity to monetary policy, bond mutual funds and banks drive most of the investor flow effect, and insurance companies drive most of the effect from demand for duration. Among characteristics, changes in callable bond duration have a large amplifying effect on term spread sensitivity to monetary policy, whereas changes in rating and bid-ask spread have little effect. For credit spread sensitivity to monetary policy, different investors can actually have the opposite effects — during monetary easing, credit demand by insurers increases credit spread, whereas credit demand by other investors decreases it. This highlights the need for a structural framework, as reduced-form analysis would not be able to cleanly separate out these heterogeneous and sometimes opposing effects.

We identify additional heterogeneity across different segments of the term structure and the credit spectrum. Flows to mutual funds and banks have a greater impact on the short end of the term structure, as these investors exhibit a preference for shorter durations compared to other bond investors. Insurance companies tilt towards long-duration bonds, so changes in their demand for credit rating and duration primarily affect long-term yields and have the opposite effect on short-term yields. The effects of issuances and redemptions are concentrated in the maturities where they occur.

In addition to the average effect, our framework can be used to dissect transmission for *individual* monetary policy episodes, tracing out the evolution of monetary transmission over time. For example, the recent 2022-2023 rate hike is associated with a larger increase in term premium and credit spread than the rate hike in 2004-2006. Our framework shows that this is primarily because of larger investor outflows and larger mortgage convexity during the recent episode. On the other hand, corporate and mortgage issuances have become more sensitive to monetary policy over time, which prevents bond yield increases to be even higher in the recent rate hike episode.

Our framework identifies important state-dependent effects of monetary policy. For instance, a key state variable is the wealth distribution of the different investors, and the implied aggregate demand elasticity in the bond market. Based on our estimates, if each investor's sensitivity to yield (measured by its yield coefficient) shifts from its median value to the 10th percentile over time due to changes in investor composition, the responsiveness of the term spread of monetary policy can more than double. This result highlights the state-dependent nature of monetary transmission and demonstrates how our framework can be utilized to forecast market reactions to future monetary policy.

Finally, we use our framework to analyze the transmission of unconventional monetary policies such as quantitative easing (QE). A longstanding puzzle is that the impact of QE far exceeds what would be expected based on the amount of bonds purchased by the central bank, which often seems small relative to the overall market size (Krishnamurthy and Vissing-Jorgensen, 2011).[2] We find that responses of the financial markets amplify the direct effects from the Fed's reduction in bond amount outstanding by a factor of two. Specifically, QE is associated with significant investor inflows, increases in demand for duration and shortening of callable bond duration, which all further push down bond yields. These results highlight the impact of central bank actions on investor behavior (Haddad, Moreira, and Muir, 2024).

Our paper contributes to the extensive literature on the bond market transmission of monetary policy. Section 2 provides a detailed overview of the individual channels proposed in the existing literature. Our contribution lies in offering a unified empirical framework to quantify the *relative* importance of these channels. Moreover, our analysis uncovers heterogeneity across investor types, term structure, and credit spectrum. Our framework can quantify the dependency of each channel on the underlying state variables, allowing us to dissect monetary transmission for individual episodes over time. In addition, our study highlights the role of bond supply through issuances and redemptions, suggesting that the evaluation of monetary transmission requires more than just analyzing yield impacts.

This paper also relates to the growing body of research that uses the asset demand system and granular portfolio holdings to understand asset pricing (Koijen and Yogo, 2019, 2020; Koijen, Koulischer, Nguyen, and Yogo, 2021; Bretscher, Schmid, Sen, and Sharma, 2021; Fang, Hardy, and Lewis, 2024; Darmouni, Siani, and Xiao, 2024; Azarmsa and Davis, 2024; Jansen, Li, and Schmid, 2024). Our contribution is twofold. First, we extend the existing logit and nested logit frameworks by introducing a random-coefficient demand model, which enable us to capture characteristics-based portfolio substitution patterns and heterogeneous cross-price elasticities (Chaudhary, Fu, and Li, 2022). Second, prior studies have typically focused on broad asset classes (Koijen and Yogo, 2020; Jiang, Richmond, and Zhang, 2022) or one specific segment of the fixed income market such as Treasury bonds (Jansen et al.,

[2]Ben Bernanke famously said that QE "works in practice but doesn't work in theory."

2024) or corporate bonds (Bretscher et al., 2021; Darmouni et al., 2024). In comparison, we construct a comprehensive security-level dataset that covers Treasury, corporate, municipal and MBS securities, which together virtually span the entire U.S. bond market. This dataset allows us to reveal transmission dynamics not only within but also across individual market segments, such as the substitution between Treasury bonds and MBS with varying duration. We believe our framework and our data coverage establish a new data benchmark for future studies.

2 Channels of Monetary Transmission to Bond Yields

This section describes the channels that have been proposed to explain bond market transmission of monetary policy. According to the expectations hypothesis, long-term interest rates are naturally sensitive to changes in short-term interest rates as long as short rates are persistent. However, many papers show that the sensitivity is too high relative to what the expectations hypothesis implies (Shiller, 1979; Hanson and Stein, 2015; Brooks et al., 2018; Hanson et al., 2021). This suggests that monetary policy affects the risk premium component of bond yields, with several channels proposed to explain this phenomenon.

We organize the literature on monetary policy's transmission to bond yields into three broad categories: (1) the allocation of wealth by households, (2) the asset allocation strategies of financial intermediaries, and (3) the characteristics of available assets in the economy. Each category reflects a distinct mechanism by which monetary policy influences long-term bond yields.

2.1 Household Wealth Allocation

A growing body of research highlights how monetary policy affects the allocation of wealth across different financial intermediaries, thereby altering the equilibrium pricing of risk in the economy. For instance, investors often exhibit extrapolative expectations. When monetary easing leads to positive bond returns, households with such expectations tend to allocate more capital to bond mutual funds, assuming that positive returns will persist. This behavior further depresses bond yields (Brooks et al., 2018; Hanson et al., 2021; Fang, 2023; Darmouni et al., 2024). Similarly, low interest rates can increase households' risk appetite (Lian, Ma, and Wang, 2019) or demand for income-generating assets (Daniel, Garlappi, and Xiao, 2021), prompting a shift toward long-term bond mutual funds in search of higher yields or income.

Monetary policy may also influence household allocation indirectly by altering the pricing of financial products. For example, low interest rates compress bank deposit spreads — the difference between deposit rates and market interest rates (Drechsler, Savov, and Schnabl, 2017). Consequently, households may shift funds from short-term bond funds to bank deposits (Xiao, 2020), which in turn depresses the yields of long-term assets held by banks.

2.2 Intermediary Asset Allocation

Monetary policy also impacts the asset allocation strategies of financial intermediaries by interacting with their regulatory constraints and risk management practices.

Financial institutions often adjust their portfolios in response to lower interest rates by taking on more risk to meet return targets (Rajan, 2006). This behavior leads to a compression of risk premia, as investors move from cash to riskier bonds, particularly those with longer durations, lower credit ratings, and poorer liquidity (e.g., Choi and Kronlund, 2018; Anadu, Bohn, Lu, Pritsker, and Zlate, 2019). However, not all intermediaries respond uniformly.

For instance, Li (2024) finds that insurers may reduce credit risk-taking during periods of monetary easing due to regulatory capital constraints, highlighting the heterogeneity in responses among intermediaries.

Duration hedging represents another critical channel through which monetary policy affects bond yields. On the asset side, the duration of mortgage-backed securities (MBS) declines when interest rates fall, prompting MBS investors to increase their holdings of longer-term bonds to maintain portfolio duration (Hanson, 2014; Hanson et al., 2021). This "asset duration hedging" behavior contributes to lower bond yields.

On the liability side, annuities and pension funds face increasing liability durations when interest rates decline, driving these institutions to tilt their portfolios toward longer-term bonds to balance asset duration (Domanski, Shin, and Sushko, 2017; Ozdagli and Wang, 2019). Studies such as Greenwood and Vissing-Jorgensen (2018) and Jansen (2023) provide compelling evidence of the significant impact of pension funds and life insurers on long-term bond yields, underscoring the importance of liability-side hedging in this context.

2.3 Characteristics of Available Assets

Finally, monetary policy influences bond yields through its effects on the characteristics of available assets. For instance, monetary policy can influence the supply of duration in the economy through call options on callable bonds and the maturity choices of new issuances. Unconventional monetary policies, such as quantitative easing (QE), also play a crucial role in altering asset characteristics. Through mechanisms like the portfolio rebalancing channel, QE reduces yields across asset markets by inducing investors to shift funds from Treasuries to corporate bonds with similar maturities (Krishnamurthy and Vissing-Jorgensen, 2011; Greenwood, Hanson, Rudolph, and Summers, 2015; Christensen and Rudebusch, 2012).

3 Data

We assemble a large granular dataset of the U.S. bond market. We cover four classes of bonds, which together span virtually the entire U.S. bond market: Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities (MBS).[3] As they share similar characteristics and similar investor base, the yields of these four bond classes are tightly linked, and they should be jointly determined in equilibrium. Having a diverse set of bonds is essential for us to capture some of the transmission channels that would have been silent otherwise (e.g. MBS convexity). One key consideration is the availability of data on amount outstanding, which is required to derive equilibrium through market clearing — this why we exclude, for example, foreign bonds and private (non-144A) bonds.

Data on Treasury bonds come from CRSP. We focus on Treasury notes and Treasury bonds and treat Treasury bills as cash. We exclude flower bonds. Data on corporate bonds (including agency direct obligations) come from Mergent FISD (for characteristics) and TRACE (for pricing). We include private placement bonds under Rule 144A. We exclude convertible bonds, equity-linked bonds, preferred securities and puttable bonds. Data on municipal bonds come from Mergent Municipal Bond Database (for characteristics) and MSRB (for pricing). Data on agency MBS come from Refinitiv. We focus on agency pools and TBAs and exclude CMOs. We exclude foreign bonds and private (non-144A) bonds because they lack data on amount outstanding, trading, or other characteristics that are essential for our demand system analysis.

We take the median credit rating from S&P, Moody's, and Fitch. All Treasury bonds are AAA-rated, all agency securities are rated AA or higher, most of corporate bonds are rated, and the majority of municipal bonds are rated and have A or above. For municipal bonds, we use the average rating at the issuer level (captured by six-digit CUSIP) across its bonds.

[3] We treat agency direct obligations as corporate bonds with high credit ratings. Our main results are similar if we treat agency direct obligations as a stand-alone bond class.

We convert letter rating to a numeric scale from 0 (AAA) to 6 (CCC or lower). Bonds without credit rating are dropped. Our main results are robust to treating unrated bonds as having the lowest rating.

We measure duration by weighted-average life, that is, the weighted average of years to each coupon or principal payment. The calculation is straightforward for non-callable bonds. For callable bonds such as MBS, we estimate duration by simulation. Specifically, for given values of macroeconomic variables such as monetary policy rate, we simulate a large set of future scenarios. For each scenario, we predict prepayments based on their historical conditional means. We take the average of realized duration across scenarios.

Bid and ask quotes are directly available for Treasury bonds through CRSP. For agency MBS, we randomly sample 10,000 CUSIPs, hand collect their historical bid and ask quotes from Refinitiv, and assume that they represent their respective cohorts (i.e. those with the same origination year, coupon and term). For corporate and municipal bonds, the convention is to calculate bid-ask spreads using trades. Specifically, for each bond on each date, we calculate bid price as the average price of dealer purchases from customers and ask price as the average price of dealer sales to customers.

The timings of early redemptions can be inaccurate for corporate bonds, so we cross-check with firm-level total bond outstanding from Capital IQ and make manual corrections. For agency MBS, we randomly sample 10,000 CUSIPs, hand collect their historical amount outstanding (factor history) from Refinitiv, and assume that they represent their respective cohorts (i.e. those with the same origination year, coupon and term). For resecuritizations, such as Treasury strips and agency megas, we make sure not to double count them when calculating total amount outstanding.

The core of our analysis relies on a comprehensive dataset of portfolio holdings. We focus on four types of bond investors for which we have granular holdings data: mutual funds and

ETFs, insurance companies, banks, and the Federal Reserve. Data on mutual fund holdings come from Morningstar Direct. We include both U.S.-domiciled funds and foreign funds that focus on U.S. assets (indicated by base currency). We restrict to funds whose broad investment category is fixed income or allocation and therefore make meaningful investment in bonds. Data on insurance company general account holdings come from NAIC statutory filings (Schedule D). We focus on those that sell life insurance or P&C insurance.[4] Data on bank holdings come from call reports. Based on reported holdings across asset classes (e.g. Treasury, municipal, and etc.) and maturity buckets (e.g. 1-3Y, 3-5Y, and etc.), we map bank holdings to more granular levels according to amount outstanding. Data on the Fed holdings come from SOMA (for Treasury and agency securities) and SMCCF (for corporate bonds).

Figure 1 shows aggregate holdings for each investor type. It confirms that the four bond classes we consider capture the majority of these bond investors' holdings. Figure 2 shows aggregate ownership of each bond class. It confirms that the four investors we consider capture the majority of the ownership of these bonds.

4 Demand System with Random Coefficients

We build a demand system of bonds in the spirit of Koijen and Yogo (2019). The demand system framework is particularly suited to analyze bonds for several reasons. First, many bond investors have direct demand for bond characteristics — for example, life insurance companies prefer long-duration bonds that match the long duration of their insurance liabilities. Moreover, demand can be heterogeneous — a short-term bond mutual fund can have drastically different preference for duration than a life insurer does. Lastly, many bond investors buy-and-hold and can be quite price inelastic due to regulatory reasons (e.g. Fang,

[4]Health insurance companies, the other type of insurers, have small bond holdings.

2024), so quantity changes (e.g. fund flows) can have large price impacts.

One innovation we make relative to Koijen and Yogo (2019) is to incorporate random demand coefficients that accommodate flexible portfolio substitution patterns. This is important to capture some transmission channels that would otherwise be silent mechanically. As a simplifying example, consider an investor who invests 50% in short-term bonds and 50% in long-term bonds. The original fixed coefficient model would infer that this investor does not care about duration, so changes in a bond's duration do not affect its portfolio weight or those of other bonds. With random coefficients, the investor's demand for duration is allowed to vary during the portfolio construction process. For example, a life insurer's sales may be evenly split between one-year group life insurance policies and 30-year annuities, so it prefers short-term (long-term) bonds 50% of the time to hedge its short-term (long-term) liabilities. In other words, the 50-50 allocation is a result of variation in inelastic demand for duration, not indifference to duration. In this scenario, supply shocks such as MBS duration changes should have large price impacts, which would be captured by our random coefficient framework but mechanically absent under the fixed coefficient one.

4.1 Assets

Bonds are indexed by $n = 1, ..., N$. Each bond has par amount outstanding $S_t(n)$, yield to maturity $y_t(n)$, and a vector of characteristics $\boldsymbol{x}_t(n)$, which include rating, duration, coupon rate, and bid-ask spread. We focus on yield instead of price because bonds with different coupon or maturity can mechanically have different prices while having the same expected returns. For callable bonds and other bonds without definitive cash flows, we calculate yield by simulation, where conditional prepayment behavior is inferred through historical data. We do not use credit spread because that assumes an exogenous Treasury yield curve, which we aim to endogenize. Our counterfactual analyses will focus on the risk premium component of yield, namely term spread and credit spread.

Instead of individual bonds, we work with portfolios of bonds. This is because we are primarily interested in aggregate bond yields (e.g. the yields on 5-year BBB-rated bonds), and others have shown that investor elasticities vary at different aggregation levels (Li and Lin, 2024; Chaudhary et al., 2022). In our baseline framework, bonds are grouped by 4 classes (Treasury, corporate, municipal and MBS), 6 rating groups (AA or higher, A, BBB, BB, B, CCC or lower), 30 maturity groups (1 year or less, ..., 30 years or longer), 11 coupon groups (0%, 1%, ..., 10% or higher), and callability (yes vs no). For MBS, instead of grouping by remaining maturity, we group by issuance year and original term (15, 20 or 30 years), which is the standard practice. We focus on this level of portfolio aggregation to strike a balance between having a big-enough cross section to identify demand coefficients and capturing investor elasticities at the aggregate level. Working with bond portfolios also greatly simplifies computation.[5]

We treat cash and cash equivalents (including deposits, money market instruments, Treasury bills, and Treasury bonds with less than one year to maturity) as the base bond ($n = 0$). Cash carries the one-year Treasury yield that is directly controlled by the Fed, so there is no market clearing. Cash has AAA rating, 0 year to maturity, 0% coupon, and 0% bid-ask spread.

Other bonds (e.g. foreign bonds) and other assets (e.g. equities) are outside of our model. Instead, we will treat investors' allocation between U.S. bonds and other assets as a parameter and study the effect of changing this parameter for equilibrium bond yields — for example, how would bond yields change if investors increase or decrease the rebalancing between bonds and other assets. We make the deliberate decision not to treat these outside assets as cash, which is conventionally done, because they can have large returns due to

[5]At a given point in time, there are on average 300+ Treasury CUSIPs, 25,000+ corporate CUSIPs, 1,000,000+ municipal CUSIPs, and 500,000+ MBS CUSIPs outstanding.

monetary policy, and treating them as yield-less cash may severely bias the results.

4.2 Investors

Investors are indexed by $i = 1, ..., I$. We focus on four types of institutional bond investors for which we have detailed data on portfolio holdings: mutual funds (including offshore ones), insurance companies, banks and the Federal Reserve. Banks report coarser holdings (by bond classes and maturity buckets) and we assume that their portfolio weights within each reporting category is proportional to amount outstanding. Many investors hold a small set of bonds, which is problematic for estimation. To address this, we group individual investors into groups and end up with 79 mutual fund groups (by Morningstar Category and by active vs passive), 20 insurance company groups (by life vs P&C and by size decile) and 10 bank groups (by size decile). The residual investors are grouped together, and their holdings are given by the difference between the combined holdings of our four types of investors above and the total amount outstanding for each bond.

Following Koijen and Yogo (2019), investor i's time t portfolio weight in bond n is modeled as:

$$w_{i,t}(n) = \frac{\exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t}\boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\}}{\sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t}\boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\}} \tag{1}$$

Intuitively, the portfolio weight of a bond depends on its "utility" — determined by its yield $y_t(n)$, characteristics $\boldsymbol{x}_t(n)$ and latent demand $\epsilon_{i,t}(n)$ — relative to other bonds. Notice how bond n's portfolio weight $w(n)$ depends on not only its own yield $y(n)$ but also yields of all other bonds $\{y(m)\}$. Latent demand for cash $n = 0$ is normalized such that $\exp\{\alpha_{i,t} y_t(0) + \boldsymbol{\beta}'_{i,t}\boldsymbol{x}_t(0) + \epsilon_{i,t}(0)\} = 1$.

This original form of demand specification implies a restrictive form of portfolio substitution pattern. Specifically, we can derive the semi-elasticity of portfolio weight with respect to yield as:

$$\frac{\partial w(m)/w(m)}{\partial y(n)} = \begin{cases} \alpha(1 - w(n)) & m = n \\ -\alpha w(n) & m \neq n \end{cases} \tag{2}$$

The cross-elasticity on the second line shows that, when yield on bond n changes, all other bonds' portfolio weights change by the exact same proportion, as m does not enter the expression at all. In other words, the investor simply scales up or down the rest of her portfolio. However, in reality, we should expect that the investor primarily substitutes bond n with the bonds that have similar characteristics, and portfolio weights of bonds with disparate characteristics should not be affected as much (Chaudhary et al., 2022).

To capture flexible portfolio substitution pattern, we use the insights from the industrial organization literature (Berry et al., 1995) and introduce random coefficients: $\boldsymbol{\beta}_{i,t} \sim N(\mu_{i,t}, \Sigma_{i,t})$. Portfolio weights in Equation 1 then become an integral over the distribution of $\boldsymbol{\beta}$:

$$w_{i,t}(n) = \int \frac{\exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\}}{\sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\}} dP(\boldsymbol{\beta}_{i,t}) \tag{3}$$

This allows demand across bonds to be correlated based on characteristics, with the correlation controlled by Σ. The semi-elasticity of portfolio weight to yield can be derived as:

$$\frac{\partial w(m)/w(m)}{\partial y(n)} = \begin{cases} \frac{\alpha}{w(n)} \int \tilde{w}(n)(1 - \tilde{w}(n)) dP(\boldsymbol{\beta}) & m = n \\ -\frac{\alpha}{w(m)} \int \tilde{w}(m)\tilde{w}(n) dP(\boldsymbol{\beta}) & m \neq n \end{cases} \tag{4}$$

where portfolio weight conditional on demand $\boldsymbol{\beta}$ is given by $\tilde{w}(n) = \frac{\exp\{\alpha x_t(n) + \boldsymbol{\beta}' \boldsymbol{x}(n) + \epsilon(n)\}}{\sum_m \exp\{\alpha y_t(m) + \boldsymbol{\beta}' \boldsymbol{x}_t(m) + \epsilon(m)\}}$. We can see that the cross-elasticity between two bonds now depends on the *covariance* of the portfolio weights of the two bonds, where the probability space is over $\boldsymbol{\beta}$. As a result, if two bonds have similar characteristics, their portfolio weights will have higher covariance, and their cross-substitution will be stronger.

This portfolio flexibility is essential for us to capture portfolio substitution channels such as mortgage convexity (Hanson, 2014). Suppose there are three bonds, one short-term and two long-term that are otherwise identical. Under the fixed coefficient framework, decreasing the price of one of the long-term bonds will increase portfolio weights of both the short-term bond and the other long-term bond, and the increase will be proportional to their existing portfolio weights. In contrast, it is possible that the demand for duration β varies. When β is high, an increase in the price of one long-term bond will significantly increase the portfolio weight of the other long-term bond, leaving the portfolio weight of the short-term bond relatively unchanged. Our random coefficient framework is designed to capture this type of dynamics.

4.3 Identification

Latent demand ϵ are likely correlated with yield, so we need instruments for identification. We construct two sets of instruments, . The first set of instruments are bond characteristics, where we make the standard assumption that the supply of bonds and their characteristics are exogenous to investors. We include both the bond's own characteristics and its peers' characteristics, where peer is defined as bonds whose rating, duration, coupon are within one standard deviation of the target bond's.

Our second set of instruments are flow-induced trading by other investors Lou (2012); Gabaix and Koijen (2021). The idea is that inflows into (outflows out of) an investor create disproportionate buying (selling) pressure on the bonds that the investor already owns ex ante, e.g. due to investment mandate. Flows to other investors, after residualized against common factors, are therefore plausibly exogenous shocks to yields for the investor of interest. Formally, mutual fund i's idiosyncratic flows at time t are given by residuals from a principal component regression:

$$InvestorFlow_{i,t} = a + \sum_k b_k PC_{k,t} + Invest\tilde{o}rFlow_{i,t}$$

where $PC_{k,t}$ denotes the kth principal component of flows across mutual funds. These investor-level idiosyncratic flows are then aggregated for each bond, excluding flows to the investor of interest:

$$FIT_{-i,t}(n) = \sum_i \frac{AmountHeld_{i,t-1}(n)}{AmountOutstanding_{t-1}(n)} Invest\tilde{o}rFlow_{i,t} \tag{5}$$

The verify the relevance of flow-induced trading as instrument for bond yields, we follow Koijen and Yogo (2019); Bretscher et al. (2021) and run the following OLS regression for each investor at each time:

$$y_{i,t}(n) = \tilde{\beta} FIT_{-i,t}(n) + \tilde{\gamma} Controls + \tilde{\epsilon}_{i,t}(n)$$

Table 2 shows the average t-statistic of $\tilde{\beta}$ for different investor periods and for different time segment. The t-statistics are on average much higher higher than the 5% critical value in Stock and Yogo (2005). Similar to characteristics, we include both the bond's own flow-induced trading and its peers' flow-induced trading, where peers are similarly defined as above. These instruments, including characteristics and flow-induced trading on the bond and its peers, are denoted by $\boldsymbol{z}(n)$.

4.4 Estimation

We want to estimate demand for yield $\alpha_{i,t}$ and characteristics $(\boldsymbol{\mu}_{i,t}, \Sigma_{i,t})$ for each investor at each time. We make a number of assumptions to simplify computation. We restrict Σ to be a diagonal matrix. That is, we assume that there is no correlation in demand for different characteristics within each portfolio formation. To simplify computation additionally, we only allow random coefficients on rating and duration. Because identification primarily comes from changes in demand over time Nevo (2000), we include not only the investor's current holdings, but also its holdings in the quarter before and the quarter after

We follow the estimation procedure in Berry et al. (1995). Specifically, we define mean utility of a bond as $\delta := \alpha y + \boldsymbol{\mu}'\boldsymbol{x} + \epsilon$ and re-write Equation 3 as:

$$w_{i,t}(n) = \int \frac{\exp\{\delta_{i,t}(n) + \boldsymbol{\eta}'_{i,t}\boldsymbol{x}_t(n)\}}{\sum_m \exp\{\delta_{i,t}(m) + \boldsymbol{\eta}'_{i,t}\boldsymbol{x}_t(m)\}} dP(\boldsymbol{\eta}_{i,t})$$

where $\boldsymbol{\eta} = \boldsymbol{\beta} - \boldsymbol{\mu}$. In other words, $\boldsymbol{\eta}$ is the random part of $\boldsymbol{\beta}$. We can invert the equation above to express mean utility as a function of portfolio weights. This inversion does not have an analytical solution but can be solved via contraction mapping:

$$\delta^{h+1} = \delta^h + \log(w) - \log(w(\delta^h))$$

where w is observed portfolio weight and $w(\delta^h)$ is portfolio weight under the current guess of mean utility δ^h. After obtaining mean utility δ, we can then perform a linear IV GMM regression of the form:

$$\delta(n) = \alpha y(n) + \boldsymbol{\mu}'\boldsymbol{x}(n) + \epsilon(n)$$

Denote $\theta = (\alpha, \boldsymbol{\mu}, \Sigma)$. Moments are then constructed by interacting the estimated latent demand $\epsilon(n)$ with the instruments $\boldsymbol{z}(n)$ to form:

$$g(\theta) = \frac{1}{N} \sum \boldsymbol{z}(n)'\epsilon(n)$$

The GMM problem is:

$$\min_\theta g(\theta)' W g(\theta)$$

where W is the weighting matrix.

Table 3 and Figure 3 show our estimated demand coefficients. The mean coefficients $\boldsymbol{\mu}$ can be roughly interpreted as semi-elasticities. For example, if a bond's duration increases by 1 year, its portfolio weight in a long-term bond fund's portfolio is expected to increase by 10-30%. However, we note that the precise semi-elasticities vary from bond to bond depending on its substitutability, as can be seen from the integral in Equation 4.

These mean coefficients $\boldsymbol{\mu}$ exhibit expected regularities. High-yield funds have higher coefficients on credit rating (i.e. more credit risk) than investment-grade funds. Long-term funds have higher coefficients on duration than short-term funds. Insurance companies have low credit rating coefficients similar to investment-grade funds, reflecting the fact that they are subject to rating-based capital regulation. Life insurance companies have high duration coefficients and high coupon coefficients, reflecting the characteristics of life insurance and annuity liabilities. Banks have low coefficients on bid-ask spread especially after the 2008 financial crisis, reflecting the increased stringency of bank liquidity regulations.

There is noticeable variation in mean coefficients $\boldsymbol{\mu}$ over time. For example, demand for duration by life insurers is quite volatile, increasing steadily during monetary easing after the 2008 financial crisis, decreasing following QE tapering in 2013, and rising again during monetary easing following the 2020 COVID crisis. This dependency of duration demand on interest rates is consistent with the "reaching-for-duration" behavior documented Ozdagli and Wang (2019).

Our estimation shows that within-portfolio demand variation Σ is economically meaningful. For almost all investors and for both rating and duration, σ is well above zero and similar in magnitude to the mean coefficient. This means that, for example, life insurance companies not only prefer long-duration bonds *on average*, the preference *varies within each portfolio construction*, as they sometimes tilt towards bonds with short duration (e.g. to match short-duration products sold, such as group term life insurance) and sometimes tilt toward bonds with long duration (e.g. to match with long-term annuities and other products sold with distant payoff).

Yield coefficients α are small and sometimes negative. This is because of the valuation effect. Consider an investor that is completely inelastic to yield — when a bond's yield goes up, its price goes down, and its portfolio weight go down, so the yield coefficient would show up as negative. This value effect is particularly large for long-duration bonds, so α is mechanically lower for long-term investors than for short-term investors.

To better understand the economic magnitude of yield coefficients α, we calculate price elasticities. We express price elasticities as a simple transformation of yield semi-elasticities from Equation 4:

$$\frac{\partial q(m)/q(m)}{\partial p(n)/p(n)} = \begin{cases} -1 - \frac{100\alpha}{w(n)d(n)} \int \tilde{w}(n)(1 - \tilde{w}(n))dP(\boldsymbol{\beta}) & m = n \\ \frac{100\alpha}{w(m)d(n)} \int \tilde{w}(m)\tilde{w}(n)dP(\boldsymbol{\beta}) & m \neq n \end{cases} \tag{6}$$

where portfolio weight $w(m)$ and amount of par value held $q(m)$ is connected through:

$$w(m) = p(m)q(m)/A$$

and bond n's duration $d(n)$ approximates the relationship between yield and price:

$$\frac{d(n)}{100} = -\frac{\partial p(n)/p(n)}{\partial y(n)}$$

The equation shows that price elasticity varies for each pair of bond. Indeed, a key feature of our framework is that cross-elasticities can vary depending on the two bonds' similarity in characteristics. Bonds with similar characteristics would have higher covariance in conditional portfolio weight $\tilde{w}$, which leads to higher cross-substitution. Instead of showing cross-elasticities for all millions of pairs of bonds, we group bonds along rating letters (AAA, AA, ..., CCC) and duration buckets (1-3Y, 3-5Y, ..., 15-30Y) and calculate the averages.

Table 4 shows estimated own-price (cross-price) elasticities, averaged across bonds (bond prices) with the given rating letters or duration buckets and averaged across mutual funds, insurance companies or banks over time. The diagonal numbers show own-price elasticities according to Equation 6, with $m = n$. Own-price elasticities are almost always negative and generally less than 5 in magnitude. Mutual funds and banks have the largest own-price elasticities, whereas insurers have the smallest price elasticities. The average own-price elasticity across funds, insurers and banks, weighted by their AUM, is -2.17. The average elasticity without funds is -1.22, meaning that +1% mutual fund flow-induced demand shock implies -0.82% return, or +8.2 bps in 10-year bond yield. Our estimated price elasticity is very similar to that of Chaudhary et al. (2022), who finds that the market multiplier (the average price elasticity) is 1.25 (0.8) at the level of coarse rating $\times$ short/medium/long-term maturity portfolios and 0.33 (3) at the level of detailed rating *times* quarters to maturity portfolios, so our portfolios at the coarse rating $\times$ years to maturity $\times$ rounded coupon rate level is in the middle and our estimated price elasticity is also in the middle.

The off-diagonal numbers show cross-price elasticities according to Equation 6, with $m \neq n$. More specifically, the cell in row m and column n shows percent change in the holding of a bond in row m to one-percent change in the price of a bond in column m, averaged across all bond pairs with the given combinations of rating letters or duration buckets. As a key feature of our innovation to incorporate random coefficients, cross-elasticities vary across bond pairs. Notably, the largest cross-elasticities occur close to the diagonal. This means that cross-elasticities are largest among bonds that are most similar in rating or duration. This localized substitution pattern has been demonstrated to be a key feature of the bond market (Chaudhary et al., 2022) and we are able to achieve this through the incorporation of random coefficients.

To illustrate the difference with the original fixed coefficient framework, we calculate the same elasticity tables when demand coefficients β are fixed at their means μ. In other words, coefficient variation σ is set to zero. Table A1 shows that, consistent with the prediction in Equation 2, fixed coefficients produce rigid homogeneous cross-substitution, as the cross-elasticity numbers are basically invariant for each column.[6]

4.5 Equilibrium

In equilibrium, market clears, meaning that the demand by investors equals market supply for each bond. Given bond outstanding (S), bond characteristics ($\boldsymbol{x}$), investor AUM in bonds (A), investor demand coefficients ($\theta = (\alpha, \boldsymbol{\mu}, \Sigma)$), investor latent demand ϵ and equilibrium bond yields y, the market clearing condition is:

$$S_t(n)P_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n) \tag{7}$$

where the left-hand side is market value of bond outstanding, and right-hand side is total demand across all investors. Price of a bond is the sum of its periodic coupon payments and its final principal payment, discounted by yield: $P = \sum_{\tau=1}^{T} Ce^{-y\tau} + e^{-yT}$. Market clearing applies to all bonds except for cash ($n = 0$), where the supply is controlled by the Fed.

Similar to Koijen, Richmond, and Yogo (2023), we endogenize investor AUM with respect to asset prices. Bond AUM obeys the following law of motion:

$$A_{i,t} = A_{i,t-1}R_{i,t} + T_{i,t} \tag{8}$$

[6] Cross-elasticity is not exactly the same within each column because of variation in group composition and duration adjustment (Equation 6).

where T denotes net purchases of bonds, measured by changes in par values Q and prices P:

$$T_{i,t} = \sum_n (Q_{i,t}(n) - Q_{i,t-1}(n))P_{t-1}(n)$$

and R denotes return on the bond portfolio, given by:

$$R_{i,t} = \sum_n w_{i,t}(n)R_t(n)$$

where bond return includes both price change and coupon payments. Note that we use portfolio weights as of the current equilibrium, because we want endogenize the effects of current portfolio weights on prices. We separate out net purchases that are driven by flows $T^F_{i,t} = A_{i,t-1}F^{\%}_{i,t}$ and other net purchases $T^O_{i,t} := T_{i,t} - T^F_{i,t}$. $F^{\%}_{i,t}$ denotes flows as fraction of investor's total AUM that includes both bonds and non-bonds $F^{\%}_{i,t} = F^{\$}_{i,t}/A^{total}_{i,t-1}$.

Notice that yields enter the market clearing condition through R, A and w. If we treat bond yields y as the only endogenous variable, we can solve for equilibrium bond yields as a implicit function:

$$y(S, \boldsymbol{x}, A, \boldsymbol{\theta}, \epsilon) \tag{9}$$

In other words, the demand system framework allows us to derive counterfactual bond yields for any given values of environment variables. However, since we treat parameter values (e.g. investor AUM) as given, the resulting market-clearing bond yields are only partial equilibrium. In reality, these parameter values are endogenous — indeed, as discussed in 2, we think all these parameter values are affected by monetary policy. Nonetheless, these partial-equilibrium bond yields provide a way to isolate the effect coming from each specific channel, as we discuss further below.

We use the following procedures to derive counterfactual bond yields numerically. First, we take an initial guess at yields $\{y(n)\}$ (e.g. the actual yields from last period). Then, given bond characteristics $\{\boldsymbol{x}(n)\}$, investor demand $\{\boldsymbol{\theta}(n)\}$, and latent demand $\{\epsilon(n)\}$, we obtain portfolio weights $\{w(n)\}$. Given bond AUM $\{A\}$ and portfolio weights $\{w(n)\}$, investors' total dollar demand for bond n is $\sum A_{i,t} w_{i,t}(n)$, the right hand side of Equation 7. If total investor demand is higher (lower) than market value of bond supply, the yield needs to be adjusted downward (upward) to close the gap. We follow the method in Koijen and Yogo (2019) to control the speed of adjustment.

4.6 Decomposition

Using the method above to calculate counterfactual bond yields, we can perform an empirical decomposition of bond yield changes into different channels (Koijen and Yogo, 2019). For each channel c, we derive the market-clearing bond yields before and after its change, while holding all other channels fixed:

$$\Delta y_t(c) := y(c_t, -c_{t-1}) - y(c_{t-1}, -c_{t-1}) \tag{10}$$

where c refers to the channel of interest and $-c$ refers the collection of all other channels. For example, to quantify changes in yields from $t-1$ to t that are due to changes in amount outstanding S, we separately feed the model S_{t-1} and S_t while holding all other channels fixed at their values as of $t-1$, and we calculate the market-clearing bonds yields $y(S_{t-1}, x_{t-1}, A_{t-1}, \theta_{t-1}, \epsilon_{t-1})$ and $y(S_t, x_{t-1}, A_{t-1}, \theta_{t-1}, \epsilon_{t-1})$ from Equation 9. We do this for supply-side channels, including amount outstanding S, bond characteristics $\boldsymbol{x}$, and the demand-side channels, including investor AUM A, demand for characteristics $\theta = (\alpha, \mu, \Sigma)$, and latent demand ϵ.

Changes in bond AUM can come from bond returns — which we have endogenized in Equation 8 — or purchases or sales of bonds. As described in the previous sub-section, we further separate out flow-induced net purchases T^F and other net purchases T^O. Intuitively, T^F

shows changes in bond AUM if the investor proportionally scale up or down its bond portfolio in response to flows. Any remaining changes in bond AUM T^O represents allocation between bonds and other non-bond assets (e.g. equities).

We can further refine the decomposition to capture heterogeneity across investors and across bonds. For example, we calculate yield changes separately for mutual fund flows, insurance company flows, and bank flows. As another example, rather than lumping together yield changes due to all demand changes, we partition yield changes into changes in demand coefficients on 1) credit rating, 2) duration, 3) coupon rate, and 4) bid-ask spread.

Changes in credit ratings show up as reconstruction of bond portfolios based on new ratings while holding all other bond characteristics unchanged. For example, suppose that there is a widespread credit migration from AA to BB, then amount outstanding of the AA portfolios would shrink while that of the BB portfolios would expand. Bonds that are redeemed during the process are assumed to have unchanged rating and bid-ask spreads.

Bonds mature over time, so duration naturally shortens and amount outstanding naturally disappears at maturity. We focus on "active" changes in duration, defined as duration changes for callable bonds (e.g. MBS) due to changes in conditional prepayment rates. We pool together the natural maturing process with changes in amount outstanding (e.g. new issuances and early redemptions). To see why, suppose that there is a representative firm that borrows equally across the maturity spectrum, from 1 year to 30 years, which means that every year an equal amount of bonds will mature, an equal amount of new 30-year bonds will be issued, and duration shortens by 1 for all other bonds. In this case, it is clear that amount outstanding is constant and we should not separate natural redemptions from new issuances.

5 Dissecting Monetary Transmission to Bond Yields

With our demand system framework laid out in the previous section, we set out to measure how much each channel (e.g. changes in investor demand for duration) contributes to the sensitivity of bond yields to monetary policy rates (i.e. one-year Treasury rates). The contribution of channel c to yield sensitivity to monetary policy is measured through the following regression:

$$\Delta y_t(c) = \alpha + \beta \Delta r_t + \gamma X_t + \epsilon_t \tag{11}$$

where $\Delta y_t(c)$ denotes year-over-year yield changes attributable to channel c according to Equation 10, Δr_t year-over-year changes in one-year Treasury rate, and X_t macroeconomic variables including contemporaneous GDP growth, inflation rate, unemployment rate changes, and changes in VIX. We focus on year-over-year changes (e.g. from 2010Q2 to 2011Q2) because some channels such as fund flows operate at relatively low frequency. Standard errors are adjusted for serial correlation with four lags (Newey and West, 1994).

Since our framework is static and cannot speak to changes in expected future short rates, we focus on the risk premium component of bond yields, namely term spreads and credit spreads. Credit spread is measured for corporate bonds and municipal bonds as the excess yield over duration-matched Treasury bonds. To measure term spread changes, we follow Nagel and Xu (2024) and use survey forecasts from Survey of Professional Forecasters (SPF). Specifically, changes in T-year Treasury yields that come from changes in current and expected short rates are given by:

$$\Delta SR = \frac{1}{T} \sum_{k=0}^{T-1} (E_+ i_k - E_- i_k)$$

where i_k denotes k-year forward rate. Since forecasts are only available for up to five quarters ahead, we assume that forecasters model the short rate process as AR(1) and calculate changes in longer-term forecasts ($k > 1$) as:

$$E_+ i_k - E_- i_k = \gamma^{k-1}(E_+ i_1 - E_- i_1)$$

Term spread changes are then calculated as the remaining part of Treasury yield changes:

$$\Delta TS = \Delta y - \Delta SR$$

5.1 Term spread

Figure 4 shows results for the monetary sensitivity of 10-year term spread. In Panel A, the black bar on the right shows the observed term spread sensitivity to monetary policy. In line with existing literature, monetary policy has a large impact on term premia. 100 bps increase in one-year Treasury yield is associated with 20 bps increase in 10-year term spread.

The rest of red and blue bars in Panel A show our estimated contributions from different channels, where red (blue) indicates positive (negative) contribution. Note that the channels do not add up to the total monetary sensitivity, because latent demand ϵ drives a large part of the variation in bond yields, similar to the findings in Koijen and Yogo (2019).

Investor flows are a leading factor in enhancing the monetary sensitivity of bond yields, increasing the 10-year term spread sensitivity to monetary policy by 27 bps Panel B further decomposes the effect into different investor groups and shows that the contribution primarily comes from bonds mutual funds and ETFs (16 bps) and banks (6 bps). During monetary easing (tightening), bond mutual funds and banks experience large inflows (outflows) of retail capital, which creates large buying (selling) pressure on bonds (Drechsler et al., 2017; Fang, 2023; Darmouni et al., 2024). At the same time, other investors do not offset flow-induced demand from bond funds and banks, due to investment mandate and other forms of yield inelasticity.[7]

Allocation between bonds and other assets (e.g. equities) slightly dampens the monetary sensitivity of 10-year term spread by 5 bps Panel C shows that this is primarily due to balanced funds, i.e. funds flexible mandates to invest in a broad set of assets. During monetary easing (tightening), long-duration bonds experience large valuation increase (decrease), which prompts investors such as balanced funds and pension funds with fixed investment ratio to sell (buy) bonds and rebalance into (away from) other assets (Lu and Wu, 2023).

Demand for characteristics amplifies the monetary sensitivity of 10-year term spread by 16 bps Panel D shows that the effect mainly comes from demand for duration (8 bps). During monetary easing (tightening), the duration of insurance and pension liabilities increase (decrease), which require these investors to increase (decrease) their asset duration in order to stay hedged against future interest rate shocks (Domanski et al., 2017; Ozdagli and Wang, 2019). There is also meaningful effect from demand for coupon rate (4 bps). Daniel et al. (2021) shows that monetary easing increases investor demand for high-income assets such as high-coupon bonds in order to maintain income yield.

Supply of characteristics amplifies the monetary sensitivity of 10-year term spread by 10 bps. Panel E shows that the supply of bond duration alone amplifies monetary sensitivity by 9 bps. As detailed in Section 4.6, natural maturity shortening is excluded here, so all changes in duration come from callable bonds such as MBS. Hanson (2014) shows that, during monetary easing (tightening), the duration of callable bonds decreases (increases), which leads investors to tilt the rest of their portfolios towards (away from) long-term bonds in order to maintain duration neutral. Note that the random-coefficient framework allows for localized substitution with respect to characteristics, which is crucial for us to capture

[7]We can derive similar estimates through a back of envelop calculation. Fang (2023) shows that 100 bps increase in monetary policy rate is associated with 10% bond fund outflow, which translates to about -2% market wide demand. Given the average price elasticity of about 1.5 for non-bond investors (Section 4.4), this implies a return of -1.33%, which translates to an yield increase of 25 bps for the average bond duration of 5.6.

this channel.

Changes in the outstanding amount of bonds is a key force in dampening the bond term spread sensitivity to monetary policy. During monetary easing (tightening), governments, corporations and households (mortgage borrowers) issue more (less) new bonds, increasing (decreasing) the total amount of bonds outstanding, which raises (lowers) equilibrium bond yields. Our estimates show that issuances and redemptions together dampen the monetary sensitivity by 32 bps Panel F shows that the effect is across the board for all bond classes, with the supply of municipal bonds having the smallest effect, possibly due to its small size in relative terms.

To further understand this issuance sensitivity to monetary policy, we estimate the price elasticity of net issuance through the following OLS regression, run separately for each class of bonds:

$$\Delta \log S_t(n) = \tilde{\alpha}\Delta \widehat{\log} P_t(n) + \tilde{\beta}' x_t(n) + \tilde{\epsilon}_t(n)$$

where, for each bond portfolio n, $\Delta log S_t(n)$ denotes log change in amount outstanding, $\Delta \widehat{\log} P_t(n)$ log change in price instrumented with contemporaneous flow-induced trading (Equation 5), and $x_t(n)$ bond characteristics such as credit rating and duration. Table A2 shows the results and confirm that bond issuances are highly sensitive to bond prices, particularly for Treasury and corporate bonds. The magnitude is smaller but still on the same order as investor elasticity in Table 4. These findings are consistent with the large evidence that governments, corporations and households are sensitive to credit market conditions (e.g. GREENWOOD, HANSON, and STEIN, 2010; Ma, 2019).

Our results also highlight the importance of taking into consideration issuances and redemptions by the real sector, rather than focusing on bond yields alone, when evaluating monetary policy transmission. In particular, our results provide an explanation for the small magnitude of yield sensitivity to monetary policy at low frequency (Hanson et al., 2021) — the lack of yield sensitivity partially reflects the strength of issuance sensitivity, not necessarily indicating a failure of transmission. Moreover, the results reveal a potential substitutability between public issuances by governments and private issuance by corporations and households. For example, during monetary easing, corporate issuances and mortgage borrowings would likely have been greater without government issuances. In other words, public issuances can crowd out private issuances.

Panel A of Figure 6 shows the sensitivity of term spread to monetary policy across the term structure. Consistent with existing literature (e.g. Hanson and Stein, 2015), the black line shows that monetary policy has large effect on term spreads many years into the future. The effect is hump-shaped, slightly higher in 5-10 year range, but is above zero for duration beyond 15 years.

The colored bars show contributions from the top channels and suggest that the importance of a channel is heterogeneous across duration. Investor flows are more important for short-duration term spreads than for long-duration term spreads, reflecting the fact that mutual funds and banks invest more in short-duration bonds than other bond investors such as insurance companies.

Demand for duration is more important for long-duration term spreads and can even have negative contribution to short-duration term spreads. This is likely because, when insurers and pension funds reach for duration, they simultaneously sell short-term bonds and buy long-term bonds, which twists the term structure instead of lifting it upwards everywhere.

Supply of duration mainly amplifies monetary sensitivity in the 5-10 year range. This is because callable bonds such as MBS have a median duration of 7.53 (Table 1), so changes in their duration mainly affect bonds in the nearby duration. During monetary easing (tightening), the duration of callable bonds goes down (up), which leads to portfolio substitution towards (away from) other bonds with 5-10 duration and pushing down (up) their yields.

The effect of amount outstanding is concentrated in the 5-15 year range, which coincides with the most common duration of new issuances of corporate bonds, municipal bonds and MBS. The effect of amount outstanding is lowest in the shortest-duration range. This is partially because, during monetary easing, firms and municipalities issue new long-term bonds to preemptively refinance bonds that are about to mature, which lowers amount outstanding of short-duration bonds and lowers their yields.

5.2 Credit spread

Figure 5 shows contributions from different channels for 10-year BBB spread, that is, the difference between 10-year BBB-rate corporate bond yield and 10-year Treasury yield. In Panel A, the black bar on the right shows the total observed monetary sensitivity, which says that BBB spread narrows by 4 bps per 100 bps increase in one-year Treasury rate.

The red (blue) bars indicate positive (negative) contributions from different channels. One salient result is that, without changes in bond amount outstanding, the sensitivity of credit spread to monetary policy would have been significantly higher, as shown by the big blue bar on amount outstanding. Panel F shows that this is primarily due to opposing effects from corporate bond supply and the supply of Treasury bonds and MBS. During monetary easing (tightening), firms issue more (less) bonds, which increase (decrease) credit spread and therefore decrease the total sensitivity of credit spread. At the same time, governments and government-sponsored mortgage borrowers, which have minimal credit risk, also borrow more (less), which increase the gap between risk-free yields and corporate yields.

Demand for characteristics increase credit spread sensitivity to monetary policy by 5 bps Panel D shows that demand for rating has heterogeneous effects across investors. During monetary easing, life insurers tend to decrease credit risk-taking due to tighter regulatory constraint (Li, 2024). In contrast, investors such as mutual funds tend to tilt towards bonds with higher credit risk in order to obtain higher yields (Choi and Kronlund, 2018). As a result, insurers' demand for rating decreases monetary sensitivity, whereas mutual funds have the opposite effect. Reaching-for-income can lead to lower credit spreads since lower-rated corporations are a main source of high-coupon bonds (Daniel et al., 2021).

Panel B of Figure 6 shows monetary sensitivity across the credit spectrum, from AA (or higher) to CCC (or lower). Here we focus on bonds with 5-year duration, as there are few speculative-grade bonds outstanding longer duration.[8] The observed monetary sensitivity, given by the black line, is mostly negative and downward sloping in credit risk. This is consistent with the stylized facts on the negative correlation between credit spreads and risk-free rates (e.g. Duffee, 1998).

The colored bars show that the impact of a channel can have large heterogeneity across the credit spectrum. The effect of investor flows concentrate on A-rated and BBB-rated bonds. This reflects the fact that during monetary easing (tightening), there are large inflows to (outflows from) investment-grade bond funds, but not as much to high-yield bond funds (Fang, 2023).

Insurer demand for credit rating increases monetary sensitivity for A-rated bonds and decreases monetary sensitivity for other lower-rated bonds. This is consistent with the fact that, during monetary easing, insurers become more constrained with regulatory capital and tilt towards higher-rated bonds with lower regulatory charges, and A-rated bonds have the highest yields while having the lowest regulatory charges (Becker and Ivashina, 2015). The other investors' demand credit rating has the opposite effect, increasing (decreasing) their risk-taking during monetary easing (tightening), amplifying the monetary sensitivity of bonds rated BBB or lower.

Changes in amount outstanding has large negative effect on the credit spread sensitivity

[8] A typical speculative-grade bond is issued with 10 years to maturity and 7.8 of duration.

to monetary policy across the credit spectrum. The effect is largest for BB-rated firms, reflecting the combined forces of: 1) the issuances and redemptions of these firms are highly sensitive to monetary policy, 2) the substitution between BB-rated bonds and other bonds is weak, so quantity shocks can have particularly large price effects.

5.3 State dependency

Our analyses so far focus on the average effect — for example, what is the average contribution of investor flows to bond yield sensitivity to monetary policy over the entire sample period. It is natural to expect that the strength of these transmission channels can vary over time, contingent on different levels of the underlying state variables. Figure 7 showcases this state dependency by zooming in on two rate hike episodes — an earlier one from June 2004 to July 2006 and a recent one from February 2022 to August 2023 — where monetary sensitivity is simply measured as the ratio of total bond yield changes to total policy rate changes for each episode ($\Delta y(c)/\Delta r$). For example, the amplificatory effect of investor flows on term spread is almost twice as big in the recent rate hike as the earlier one, likely due to the growth of bond mutual funds and ETFs over time (Ma, Xiao, and Zeng, 2022). The dampening effect of amount outstanding (due to issuances and redemptions) has also significantly increased, likely due to bond issuers becoming more sophisticated market timers.

To formally quantify this state dependency, we ask what would be the changes in bond yields in response to a unit increase in monetary policy rate, when some state variables are set at different percentiles of their distributions. Counterfactual bond yields are derived in the same manner as before (Section 4.6), and all other parameters are held fixed. For example, we will quantify the contribution of bond fund flows for different degrees of bond fund flow sensitivity to monetary policy, while investors' AUM, their demand for characteristics, and characteristics and amount of bonds outstanding are held fixed at their values as of year-end

2022.

The results are shown in Table 5. We focus on 10-year term spread and the four channels that ranked the highest in our previous decomposition exercise, further narrowed down to a specific dimension: bond fund flows, insurer demand for duration, the level of MBS duration, and the amount of corporate bond outstanding. Starting with Panel A, the middle cell shows the average contribution of bond fund flows to 10-year term spread in response to 100 bps increase in monetary policy rate, when all bond funds experience 8% outflow (which is the average monetary sensitivity across funds over time) and each investor's elasticity is set to its median level over time. The contribution (20 bps) is higher than that from our decomposition exercise (16 bps), reflecting the fact that bond funds account for a larger share of the bond market in 2022 than in earlier periods. The other cells show bond fund flow contributions when the two state variables are set to different values. The northeast cell shows that, when bond fund flows are twice as sensitive to monetary policy as the observed average, and when the elasticity of other investors is at the lowest decile of the distribution, the contribution from bond fund flow rises to almost four times as large. On the other hand, when bond fund flows are half as sensitive to monetary policy and other investors are much more elastic to any price impacts created by bond fund flows, the amplificatory effect of bond fund flows is significantly weakened.

Panel B focuses on changes in insurer demand for duration. On average, when monetary policy rate increases by 100 bps, the mean coefficient (μ) of insurer demand for duration falls by 0.12, shown by the middle cell. The associated decline in demand for long-term bonds lead to 8 bps increase 10-year term spread, when other investors' yield coefficients are at historical means. This effect is greatly amplified (dampened), when the sensitivity of insurer demand for duration increases (decreases) and when investor elasticity decreases (increases), shown by the northeast (southwest) corner of the table.

Panel C focuses on the level of MBS duration. When monetary policy rate increases, the duration of MBS increases by 20 bps on average, as refinancing activities are expected to fall. This relationship, known as mortgage convexity, depends on the past path of mortgage rates (Eichenbaum, Rebelo, and Wong, 2022). If past mortgage rates were high and most outstanding mortgages carry high coupon rates, then additional increases in mortgage rates would not significantly discourage refinancing activities. Indeed, the sensitivity of MBS duration to 1-year Treasury rate can be as high as 0.49 during the recent 2022-23 rate hike and nearly zero during the 2003-07 rate hike, when a lot of outstanding mortgages still carried high coupons from the previous rate cycles. The estimates show the amplificatory effect of the MBS duration channel depends critically on MBS convexity, as well as investor elasticity, i.e. how much yield effects are required to offset the supply gap created by MBS duration changes.

Lastly, Panel D shows the distribution of effects from changes in corporate bond outstanding due to issuances and redemptions. On average, 100 bps increase in monetary policy rate is associated with 4% reduction in corporate bond outstanding. This sensitivity has increased over time, reflected in Figure 7. On average, corporate bond issuances and redemptions dampen bond yield sensitivity to monetary policy by 18 bps, shown by the middle cell. This effect is significantly magnified (reduced) when bond issuers are more (less) sensitive to rate changes and when investors are less (more) elastic, as more (less) yield changes are required for investors to adjust the quantity of their demand.

Investor composition has been shown as important state variable for the bond market (Coppola, 2022; Li and Yu, 2022; Fang, 2023). There has been a secular rise of bond mutual funds and ETFs relative to other bond investors, and this trend is poised to continue. Our next exercise asks: what would be the bond yield sensitivity to monetary policy, if bond funds become larger or smaller relative to other investors? To make the analysis tractable, we examine the counterfactual outcomes of re-allocating bond AUM between bond funds and life insurers, keeping their total bond AUM constant at its value as of year-end 2022. All other state variables, such as other investors' AUM and their demand coefficients, are also set to their year-end 2022 values. The responses of state variables to monetary policy, such as bond fund flow sensitivity to monetary policy, are set to their means estimated using the whole sample period.

The results are shown in Table 6. Panel A focuses on term spread sensitivity to monetary policy. In the middle column, we re-allocate bond fund AUM and life insurer AUM such that they are 1:1, which is very close to reality at year-end 2022. In response to 100 bps policy rate hike, our framework predicts a 18 bps increase in 10-year term spread, combined across all the channels. If more bond AUM is re-allocated to bond funds so that the ratio between bond fund AUM and life insurer AUM is 2 (the rightmost column), then term spread sensitivity to monetary policy will be significant amplified, and vice versa if bond AUM is re-allocated away from bond funds.

More importantly, the shift in investor composition has heterogeneous effects across the term structure, shown by the vertical direction. The re-allocation of AUM towards bond funds — which corresponds to moving from left to right — amplifies term spread sensitivity for short-term bonds (the top rows) but dampens it for long-term bonds (the bottom rows). This is because bond funds and life insurers tilt towards different ends of the term structure, so shift in AUM towards bond funds will amplify the yield sensitivity of short-term bonds more, through the bond fund flow channel, whereas shift in AUM towards life insurers will primarily amplify the yield sensitivity of long-term bonds, through the insurer duration hedging channel.

Panel B of Table 6 focuses on 5-year BBB spread sensitivity. Similarly, changes in the relative AUM of bond funds and life insurers will change the relative weights of the underlying transmission channels. In response to monetary tightening, bond funds tend to decrease credit risk-taking, decrease the portfolio weights of low-rating bonds relative to high-rating bonds (Choi and Kronlund, 2018). Life insurers tend to do the opposite due to the relaxation of capital constraints (Li, 2024). Therefore, an increase in the AUM of bond funds relative to life insurers (from left columns to right columns) will increase credit spreads during monetary tightening, especially for bonds with lower credit ratings (the bottom rows).

In summary, this section shows that the contribution of a channel can vary significantly over time, depending on the relevant state variables. Investor elasticity is a particularly important state variable across all channels, as it determines the magnitude of price impacts required to absorb imbalances between demand and supply. We illustrate how our demand system framework can be used to anatomize why a specific monetary policy episode has had weak or strong transmission. It can also be easily parametrized to make predictions for future monetary policy actions.

5.4 Unconventional monetary policies

In this sub-section, we use our framework to dissect the transmission of quantitative easing (QE). There are four QE episodes:

- QE1: from November 2008 to June 2010, \$300 billion Treasury bonds, \$1,250 billion agency MBS, and \$175 billion agency direct obligations
- QE2: from November 2010 to June 2011, \$600 billion Treasury bonds
- QE3: from September 2012 to October 2014, \$790 billion Treasury bonds and \$823 billion agency MBS
- QE4: from March 2020 to March 2022, \$3,000 Treasury bonds and \$1,200 agency MBS

In order to make the different episodes comparable to each other, we rescale everything to correspond to bond purchases that equal to 1% of the total bond market outstanding. For the four episodes, 1% of market outstanding is \$149 billion, \$204 billion, \$234 billion, and $336 billion, which is 9%, 34%, 15% and 8% of the actual purchases, respectively. We apply these scaling factors to the estimated total contributions from different channels. For example, for QE1, we will derive bond yield changes due to total investor flows during the episode, apply the scaling factor of 9%, and define the product as the contribution from investor flows to bond yield changes in response to QE1.

We focus on the first half each QE episode to exclude changes in expectations of future policies. For example, during a congressional hearing in May 2013, which was in the middle of QE3, the Fed chair disclosed the intention of tapering future asset purchases, which led to large bond fund outflows and large bond yield increases, known as the "Taper Tantrum".

Figure 8 shows the results. The gray bars on the right shows term spread changes attributable to decreases in amount outstanding solely due to Fed purchases, while all other channels (e.g. investor AUM) are held constant at their values at the beginning of each episode. They show that, when amounts of bond outstanding decrease by 1% due to Fed purchases, term spread decrease by 26-32 bps. The magnitude depends on two factors: what specific assets are purchased and what is aggregate investor elasticity. Investor elasticity is lower during crisis periods, leading to large yield changes per unit of Fed purchase.

The other colored bars show contemporaneous yield changes attributable to, respectively, investor flows, demand for duration, changes in callable bond duration, and changes in amount outstanding due to issuances and redemptions. It is clear the total effect of QE depends not only on the Fed purchases themselves but significantly on the other channels we consider. When the Fed's purchases push down long-term yields, they can lead to return-chasing retail inflows to mutual funds and banks, increase in the duration of insurance or pension liabilities, shortening of duration of callable bonds, and more bond issuances, similar to the effects of decreases in short-term monetary policy rates. These changes in demand and supply, in turn, exert further pressure on bond yields.

The strengths of these channels vary considerably over the four episodes. For example, investor flows amplify rate declines by another 16 bps during QE1, this number drops to 7 and 8 for QE2 and QE3, and it soars to 32 for QE4. This is because: 1) investor elasticity is considerably smaller during crisis periods, and 2) inflows to bond mutual funds and banks were particularly large in 2009 and 2020. The results here echo our earlier results with conventional monetary policy and emphasize the state dependency of how demand and supply channels respond to monetary policy.

In summary, we quantify yield changes attributable to different channels in response to direct bond purchases by the Federal Reserve. The direct effect from changes in amount outstanding is small compared to the total effects coming from changes investor demand or issuer supply.

6 Conclusion

In this paper, we utilize a demand system framework to dissect the bond market transmission of monetary policy. We find that flows to mutual funds and banks, changes in demand for credit rating and duration, and changes in callable bond duration play significant roles in amplifying bond yield sensitivity to monetary policy. A large portion of these amplifications are absorbed by bond issuances, where government issuances can partially crowd out issuances by corporations and mortgage borrowers. The contribution of a channel is heterogeneous across term structure and credit spectrum and contingent on time-varying state variables such as investor composition and investor elasticity.

To achieve this, we develop a random-coefficient asset demand system, which relaxes the proportionality assumption and captures localized substitution based on asset characteristics. We apply this framework to granular holdings of the U.S. bond market, encompassing four interconnected classes of U.S. dollar-denominated bonds: Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities (MBS). The flexibility of investor demands and the diversity of asset classes together enable us to quantify a wide set of transmission channels, such as MBS convexity, which can be silent under alternative frameworks.

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Tables

Table 1: **Bond Portfolio Summary Statistics.** This table shows summary statistics of our bond portfolios. Bond portfolios are formed by grouping together bonds that have similar credit rating, coupon rate, time to maturity and callability, separately for Treasury bonds, corporate bonds, municipal bonds and agency MBS. The reported statistics include credit rating (ranging from 0 for AAA to 6 for CCC), duration (years), coupon rate (%), callability (0 or 1), bid-ask spread (%), and amount outstanding (billion USD). All statistics are calculated using amount outstanding as frequency weight.

	Mean	SD	P10	P50	P90
	538 Treasury Bond Portfolios				
Credit Rating	0.00	0.00	0.00	0.00	0.00
Duration	5.04	5.77	1.00	2.93	6.00
Coupon Rate	2.13	1.96	0.50	2.00	3.00
Callability	0.00	0.05	0.00	0.00	0.00
Bid-Ask Spread	0.04	0.03	0.02	0.04	0.05
Amount Outstanding	737	1217	90	236	772
	2132 Corporate Bond Portfolios				
Credit Rating	2.18	1.61	1.00	2.00	3.00
Duration	6.53	5.73	2.77	4.67	7.94
Coupon Rate	4.90	2.38	4.00	4.00	6.00
Callability	0.13	0.33	0.00	0.00	0.00
Bid-Ask Spread	0.49	0.56	0.20	0.34	0.55
Amount Outstanding	58	58	14	39	83
	1753 Municipal Bond Portfolios				
Credit Rating	1.22	0.86	1.00	1.00	2.00
Duration	9.39	5.83	4.54	8.71	13.59
Coupon Rate	5.19	1.71	4.00	6.00	6.00
Callability	0.72	0.45	0.00	1.00	1.00
Bid-Ask Spread	1.15	0.73	0.61	1.01	1.56
Amount Outstanding	14	12	4	11	19
	537 Agency MBS Portfolios				
Credit Rating	0.00	0.00	0.00	0.00	0.00
Duration	7.53	2.47	5.51	7.95	9.49
Coupon Rate	4.21	1.40	3.00	4.00	5.50
Callability	1.00	0.00	1.00	1.00	1.00
Bid-Ask Spread	0.06	0.03	0.04	0.06	0.07
Amount Outstanding	260	322	57	165	322

Table 2: **Flow-Induced Trading as Yield Instrument.** The tables examine the relevance of flow-induced trading (FIT, Equation 5) as instrument for bond yields. Specifically, they show the median t-statistic for $\tilde{\beta}$ for each investor type (Panel A) or each time segment (Panel B) from the following regression, run separately for each investor i at each time t:

$$y_{i,t}(n) = \tilde{\beta} FIT_{-i,t}(n) + \tilde{\gamma} Controls + \tilde{\epsilon}_{i,t}(n)$$

Panel A: By Investor Type

Bond mutual funds	-6.43
Other mutual funds	-5.54
Life insurance companies	-7.07
P&C insurance companies	-6.58
Banks	-4.03

Panel B: By Time Segment

2003-2005	-4.72
2006-2008	-4.38
2009-2011	-7.23
2012-2014	-6.49
2015-2017	-6.01
2018-2020	-9.98
2021-2022	-6.36

Table 3: **Estimated Demand Coefficients.** This table shows estimated demand coefficients for our investor groups. There are 79 mutual fund groups (by Morningstar Category and by active vs passive), 20 insurance company groups (by life vs P&C and by size decile) and 10 bank groups (by size decile). The reported statistics include AUM (billion USD), mean coefficients (μ) for yield (%), credit rating (from 0 for AAA to 6 for CCC), duration (year), coupon rate (%) and bid-ask spread (%), and variation in coefficient (σ) for credit rating and duration.

Mutual Funds

	Mean	SD	P10	P50	P90
Bond AUM	45	84	0.1	12	123
Mean Coefficients (Mu)					
Yield	0.14	0.33	-0.48	0.24	0.73
Credit Rating	-0.04	1.13	-1.92	-0.01	1.36
Duration	0.03	0.21	-0.32	0.08	0.31
Coupon Rate	0.27	0.31	-0.29	0.04	0.41
Bid-Ask Spread	0.29	0.30	-0.29	0.27	0.41
Coefficient Variation (Sigma)					
Credit Rating	0.23	0.05	0.21	0.26	0.37
Duration	0.22	0.08	0.17	0.26	0.42

Insurance Companies

	Mean	SD	P10	P50	P90
Bond AUM	106	296	0.07	5	230
Mean Coefficients (Mu)					
Yield	-0.08	0.27	-0.19	0.01	0.41
Credit Rating	-0.39	0.73	-1.26	-0.51	0.65
Duration	0.04	0.19	-0.05	0.07	0.30
Coupon Rate	0.24	0.37	0.03	0.16	0.49
Bid-Ask Spread	0.21	0.44	-0.05	0.14	0.45
Coefficient Variation (Sigma)					
Credit Rating	0.26	0.03	0.23	0.26	0.32
Duration	0.49	0.09	0.33	0.49	0.63

Banks

	Mean	SD	P10	P50	P90
Bond AUM	351	1139	5	24	2971
Mean Coefficients (Mu)					
Yield	0.12	0.18	-0.03	0.11	0.29
Credit Rating	0.01	0.53	-0.70	0.01	0.73
Duration	-0.02	0.08	-0.11	-0.01	0.08
Coupon Rate	-0.15	0.10	-0.27	-0.14	-0.05
Bid-Ask Spread	-0.77	0.48	-1.34	-0.71	-0.24
Coefficient Variation (Sigma)					
Credit Rating	0.21	0.03	0.17	0.21	0.25
Duration	0.43	0.06	0.35	0.42	0.50

Table 4: **Estimated Own- and Cross-Price Elasticities.** These tables display estimated own- and cross- price elasticities according to Equation 6. The diagonal cells show average own-price elasticities for all bonds with the given rating or duration, across all periods and across all mutual funds (Panel A), insurance companies (Panel B), or banks (Panel C). The off-diagonal cell in row m and column n shows percent change in the holding of bond m with one-percent change price of bond n, averaged across all bond pairs with the given rating or duration combination, across all periods and across all mutual funds (Panel A), insurance companies (Panel B), or banks (Panel C).

Panel A: Mutual Funds

	AA	A	BBB	BB	B	CCC
AA	-2.42	2.59	1.28	0.11	0.31	0.01
A	1.21	-2.78	2.93	0.87	0.08	0.07
BBB	0.93	1.35	-4.03	2.04	1.49	0.03
BB	0.14	0.18	1.25	-1.96	1.22	1.02
B	0.28	1.27	0.02	2.98	-2.06	1.00
CCC	0.03	0.34	0.94	0.08	1.12	-1.58

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-3.12	2.01	1.98	0.34	0.53	0.54
3-5Y	3.23	-3.54	2.44	1.72	0.11	0.31
5-7Y	1.88	2.44	-4.72	2.90	1.03	0.82
7-10Y	1.32	0.29	1.92	-2.52	1.45	0.06
10-15Y	0.02	0.43	0.44	1.53	-1.27	1.03
15-30Y	0.11	0.03	0.44	0.36	1.34	-0.84

Panel B: Insurance Companies

	AA	A	BBB	BB	B	CCC
AA	-0.54	1.66	0.77	0.19	0.03	0.01
A	1.21	-1.01	1.42	0.42	0.26	0.07
BBB	0.93	0.89	-1.54	1.04	0.85	0.04
BB	0.14	0.14	1.76	-0.77	0.93	0.37
B	0.28	0.06	1.03	1.28	-0.29	0.43
CCC	0.03	0.01	0.02	0.08	1.12	-0.03

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-0.47	1.02	0.78	0.55	0.53	0.23
3-5Y	0.54	-1.04	1.54	1.03	0.11	0.01
5-7Y	0.88	0.59	-0.98	1.88	1.03	0.27
7-10Y	0.23	0.91	1.25	-1.24	1.46	1.23
10-15Y	0.05	0.20	1.03	1.96	-1.93	1.22
15-30Y	0.01	0.14	0.58	0.31	1.34	-0.92

Panel C: Banks

	AA	A	BBB	BB	B	CCC
AA	-2.14	1.52	1.46	0.26	0.72	0.03
A	0.67	-2.01	1.23	0.28	0.83	0.13
BBB	0.19	1.02	-1.02	0.39	0.97	0.48
BB	0.28	0.20	0.49	-1.34	1.43	0.08
B	0.06	0.40	1.02	0.41	-1.23	0.15
CCC	0.01	0.07	0.09	0.08	0.97	-0.77

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-3.22	2.05	0.93	1.05	0.28	0.02
3-5Y	2.32	-2.44	1.99	1.72	0.11	0.09
5-7Y	1.79	2.46	-1.49	2.24	1.03	0.43
7-10Y	1.03	1.25	2.03	-2.03	1.46	1.45
10-15Y	0.57	0.56	1.54	1.58	-3.17	1.03
15-30Y	0.11	0.18	0.43	0.45	1.34	-2.79

Table 5: **State Dependency of Monetary Transmission Channels.** The tables illustrate state dependency for each of the top channels through which monetary policy transmits to bond yields. For each channel, we quantify its contribution to 10-year term spread sensitivity to monetary policy given a range of 1) investor yield coefficients ($\{\alpha\}$, which govern price elasticities) on the vertical axis, and 2) the sensitivity of the underlying state variable to monetary policy. All other state variables are held constant at year-end 2022.

Panel A: Bond Fund Flow

Yield Coeff	∂Bond Fund Flow / ∂1Y Treasury Rate				
	-4.0%	-6.0%	-8.0%	-12.0%	-16.0%
10th Pct	0.18	0.28	0.37	0.57	0.72
25th Pct	0.14	0.20	0.26	0.33	0.50
Median	0.11	0.15	0.20	0.30	0.42
75th Pct	0.09	0.13	0.18	0.25	0.26
90th Pct	0.05	0.09	0.13	0.19	0.25

Panel B: Insurer Demand for Duration

Yield Coeff	∂Insurer Demand for Duration / ∂1Y Treasury Rate				
	-0.06	-0.09	-0.12	-0.16	-0.24
10th Pct	0.11	0.13	0.18	0.25	0.33
25th Pct	0.07	0.12	0.15	0.21	0.28
Median	0.05	0.06	0.08	0.11	0.15
75th Pct	0.02	0.05	0.07	0.09	0.14
90th Pct	0.01	0.03	0.04	0.09	0.10

Panel C: MBS Duration

Yield Coeff	∂MBS Duration / ∂1Y Treasury Rate				
	0.10	0.15	0.20	0.30	0.40
10th Pct	0.11	0.17	0.20	0.30	0.39
25th Pct	0.08	0.12	0.16	0.24	0.33
Median	0.08	0.10	0.14	0.18	0.19
75th Pct	0.08	0.09	0.11	0.15	0.21
90th Pct	0.03	0.06	0.10	0.15	0.17

Panel D: Corporate Bond Outstanding

Yield Coeff	∂Corporate Bond Outstanding / ∂1Y Treasury Rate				
	-2%	-3%	-4%	-6%	-8%
10th Pct	-0.16	-0.24	-0.33	-0.50	-0.66
25th Pct	-0.11	-0.17	-0.23	-0.35	-0.46
Median	-0.08	-0.13	-0.18	-0.26	-0.36
75th Pct	-0.07	-0.11	-0.15	-0.22	-0.31
90th Pct	-0.05	-0.08	-0.11	-0.16	-0.21

Table 6: **The Dependency of Monetary Transmission on Investor Composition.** The tables show our estimated monetary sensitivity of term spread (Panel A) and 5-year credit spread (Panel B) for different relative sizes of bond funds versus life insurers. All state variables are set to their year-end 2022 values and their responses to monetary policy are set to their means estimated using the whole sample period.

Panel A: Term Structure

	Relative Bond Ownership between Bond Funds vs Life Insurers				
	0.50	0.75	1.00	1.50	2.00
2Y	-0.06	0.03	0.11	0.20	0.28
5Y	0.03	0.11	0.20	0.33	0.41
10Y	0.13	0.16	0.18	0.22	0.25
15Y	0.07	0.08	0.08	0.09	0.10
20Y	0.05	0.02	-0.01	-0.03	-0.04
30Y	0.06	0.03	0.02	0.00	-0.02

Panel B: Credit Spectrum

	Relative Bond Ownership between Bond Funds vs Life Insurers				
	0.50	0.75	1.00	1.50	2.00
AA	0.00	-0.01	-0.03	-0.04	-0.04
A	0.02	-0.01	-0.03	-0.04	-0.06
BBB	-0.10	-0.08	-0.05	-0.01	0.03
BB	-0.18	-0.15	-0.12	-0.07	-0.03
B	-0.11	-0.09	-0.09	-0.05	-0.02
CCC	-0.05	-0.04	-0.04	-0.02	0.00

Figures

Figure 1: **Investor Holdings.** The figures show holdings by the investors for which we have granular portfolio data: mutual funds and ETFs (bond funds vs other funds), insurance companies (life vs P&C), banks, and Federal Reserve.

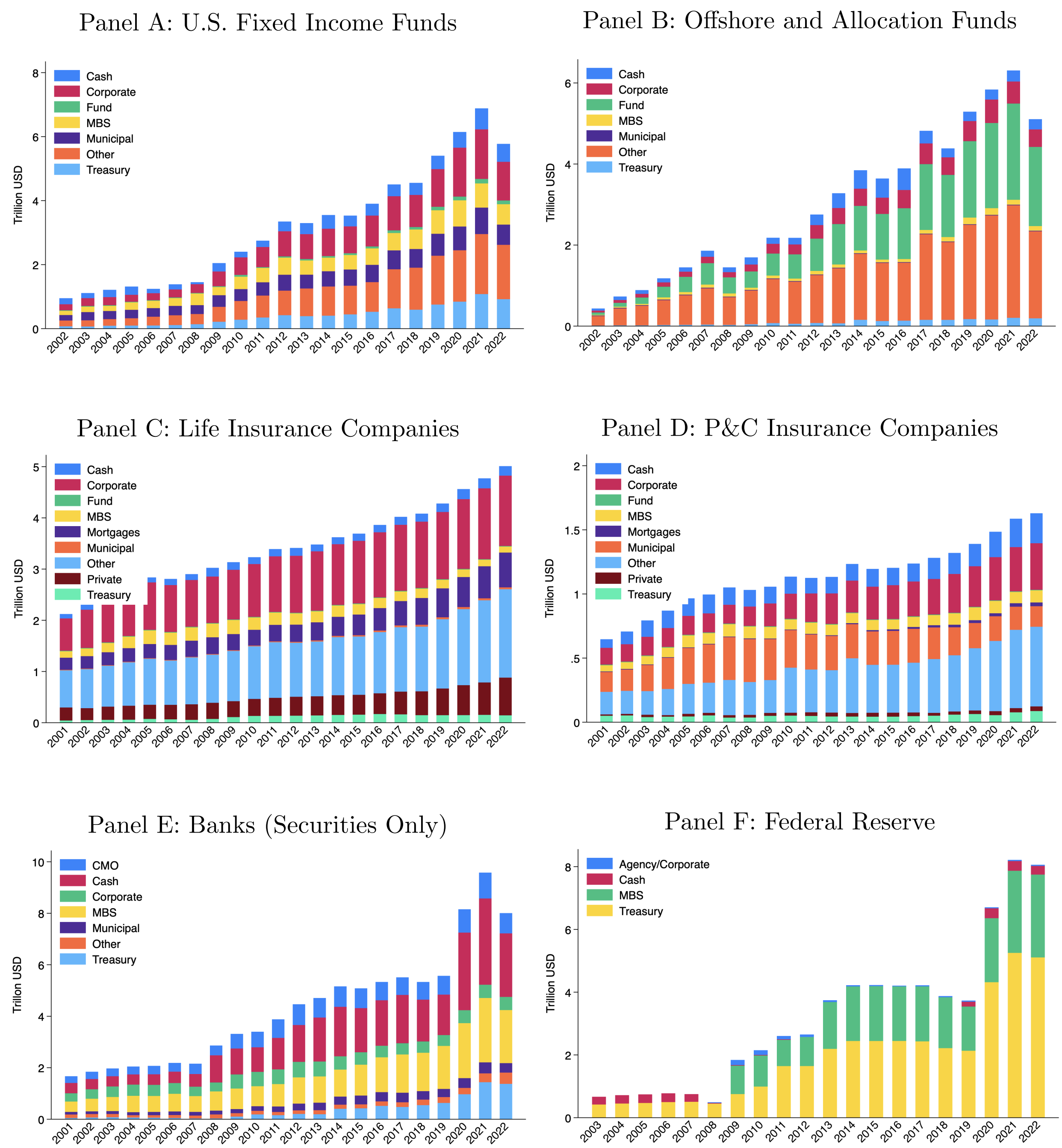


Figure 2: **Bond Ownership.** The figures show investor composition for the four classes of bonds that we focus on: Treasury bonds, corporate bonds, municipal bonds and agency MBS. We restrict to straight USD-denominated bonds with more than one year to maturity.

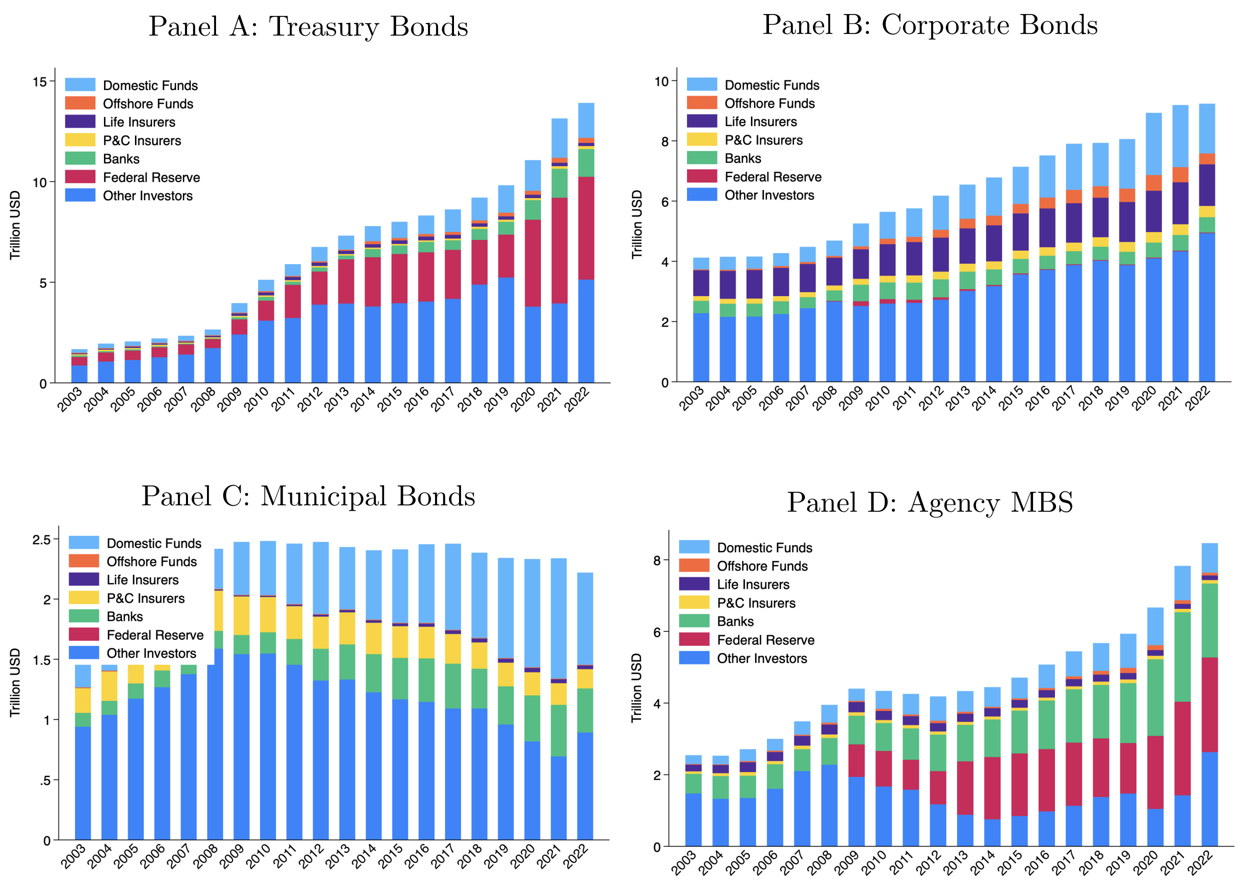
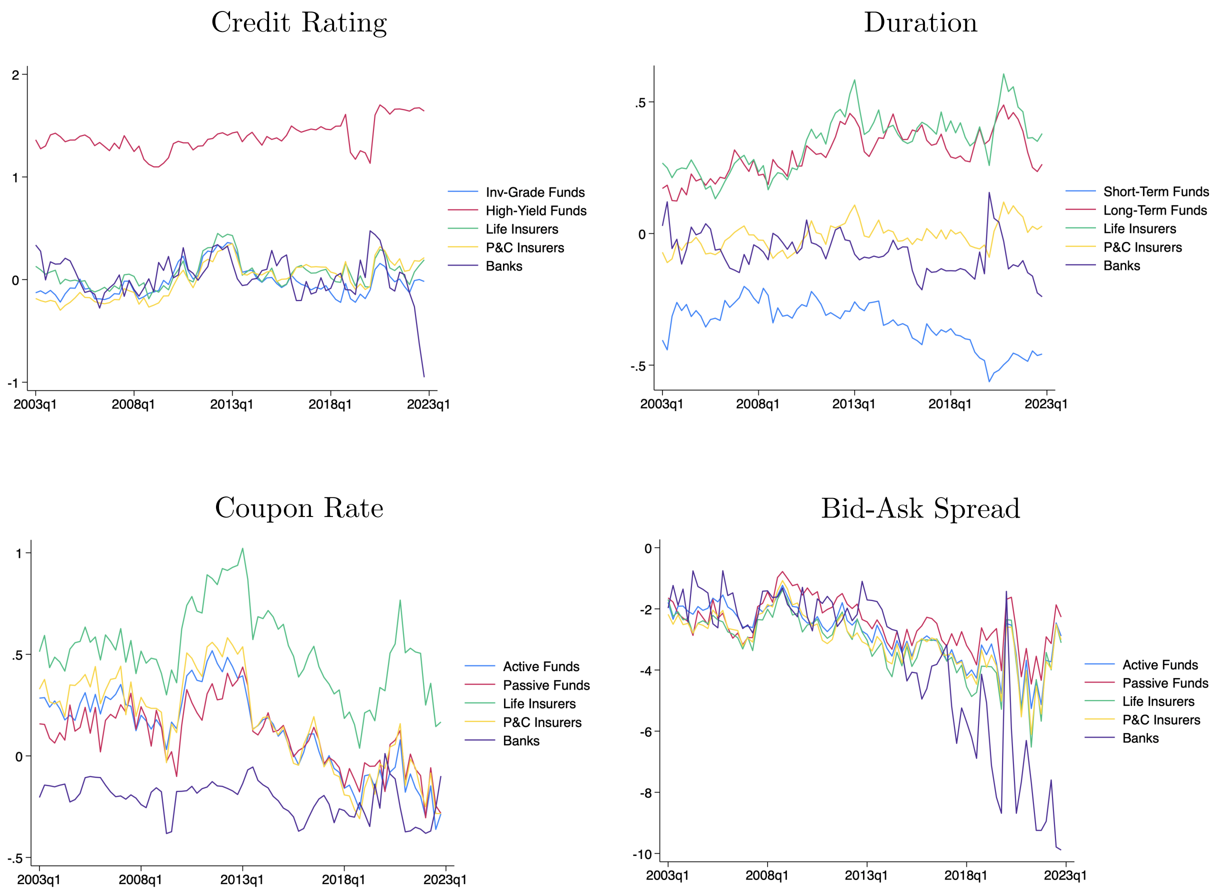


Figure 3: **Estimated Demand Coefficients.** These figures display estimated demand coefficients (μ, Σ) on credit rating (from 0 AAA to 6 CCC), duration (year), coupon rate (%), and bid-ask spread (%), using the procedures described in Section 4.4.

Panel A: Mean Coefficient μ



Panel B: Variation in Coefficient Σ

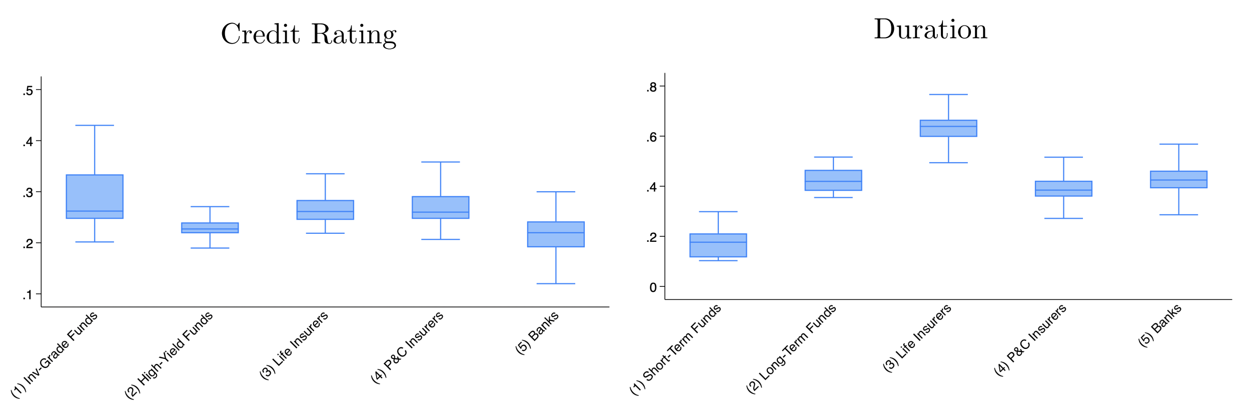


Figure 4: **10-Year Term Spread Sensitivity to Monetary Policy.** These figures show contributions from different channels to the monetary sensitivity of 10-year term spread according to our method described in Section 5.

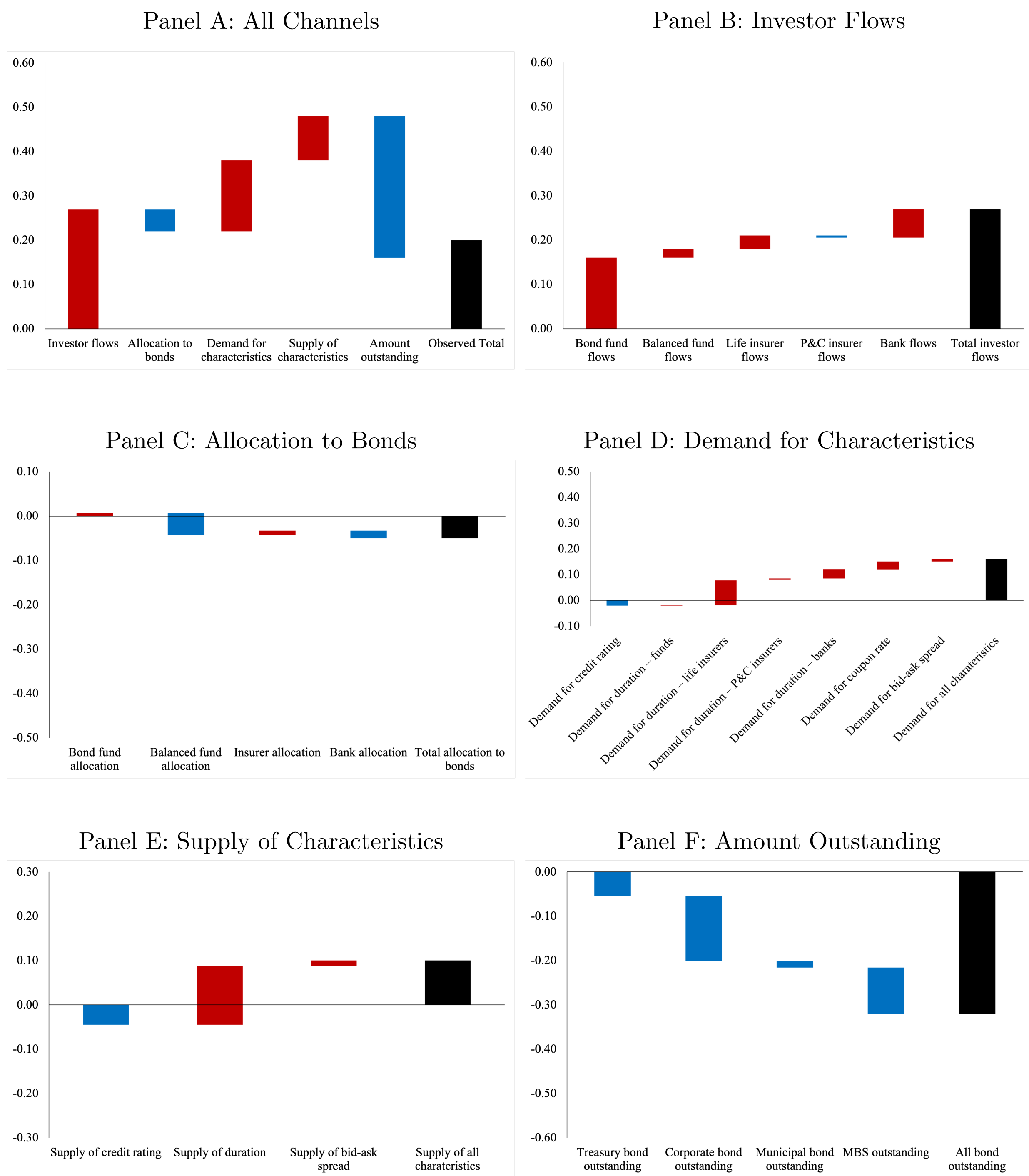


Figure 5: **10-Year BBB Spread Sensitivity to Monetary Policy.** These figures show contributions from different channels to the monetary sensitivity of 10-year BBB spread (over 10-year Treasury yield) according to our method described in Section 5.

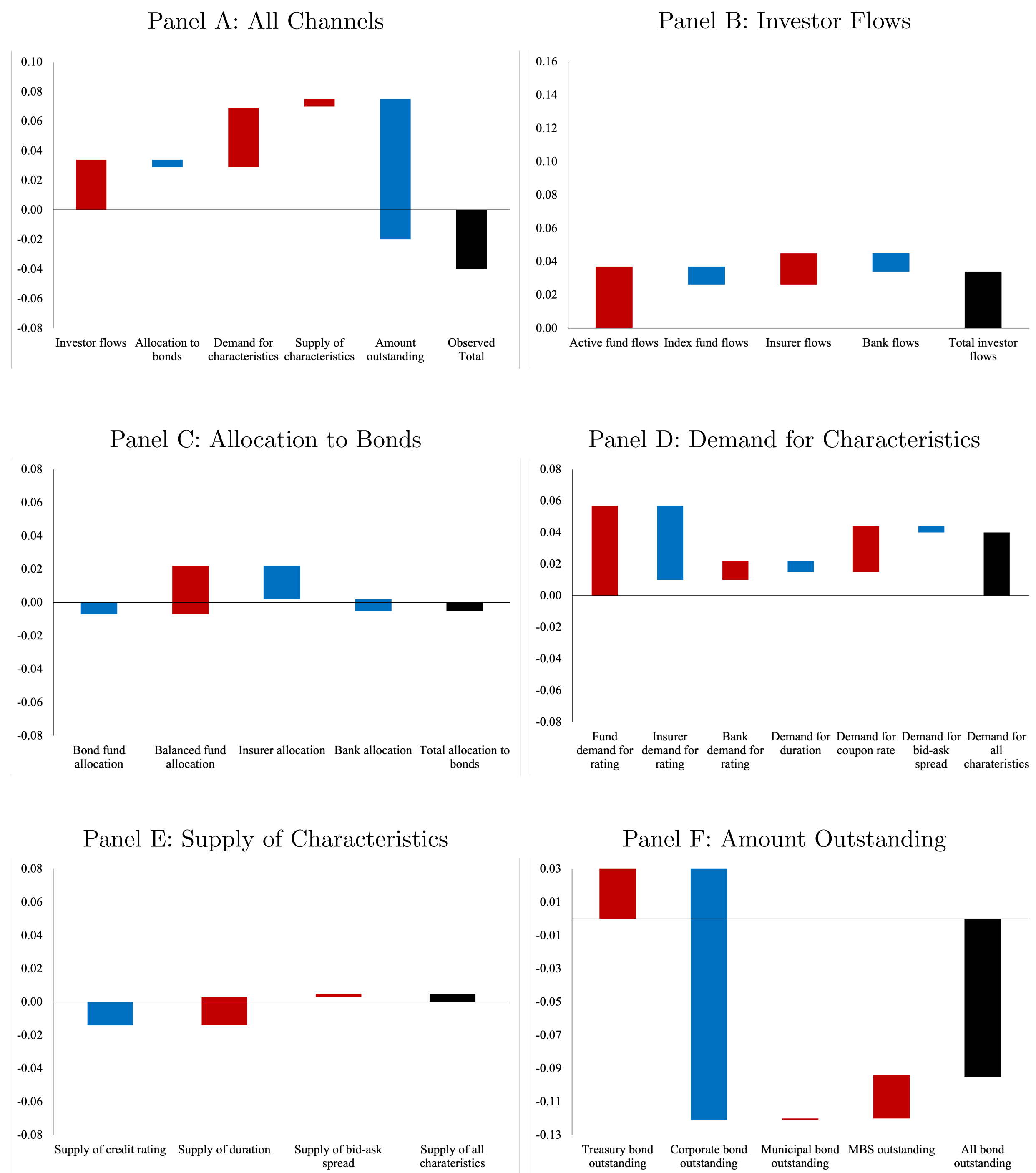
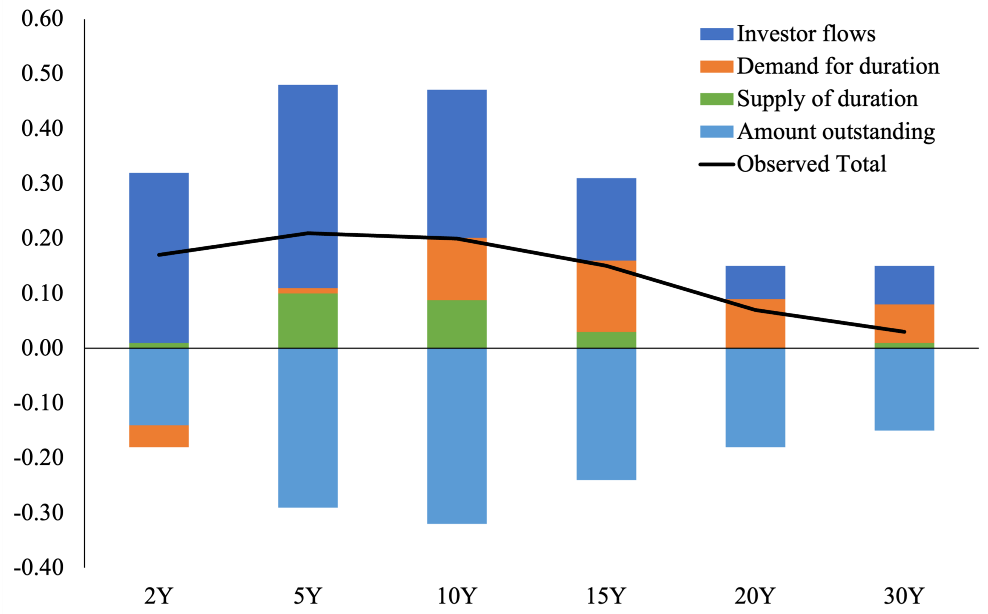


Figure 6: **Monetary Transmission across Term Structure and Credit Spectrum.** Panel A (Panel B) shows contributions from the top channels to the monetary sensitivity of 10-year term spread across different duration (5-year credit spread across different credit ratings), based on our method described in Section 5.

Panel A: Term Structure



Panel B: Credit Spectrum

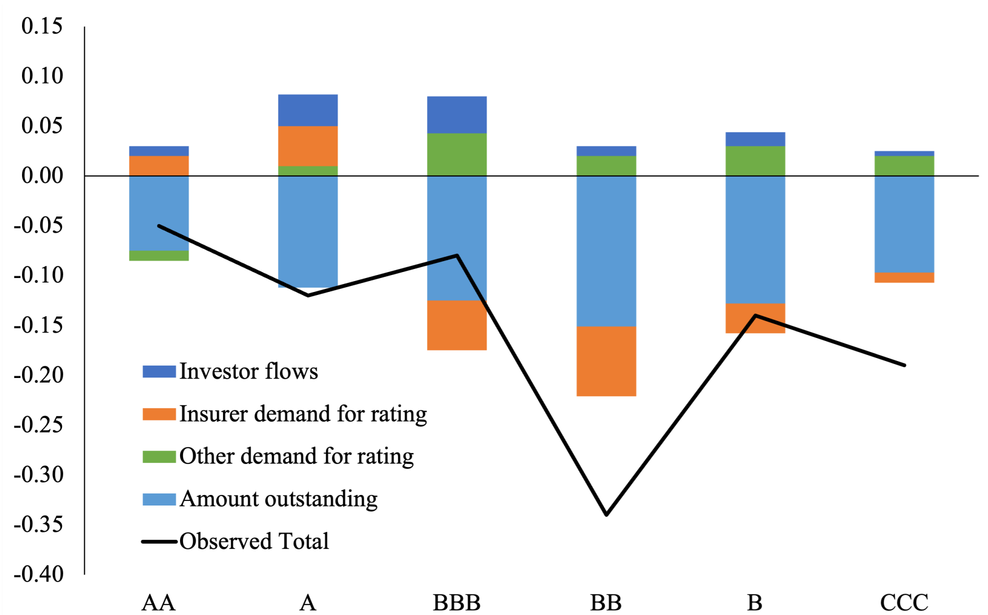
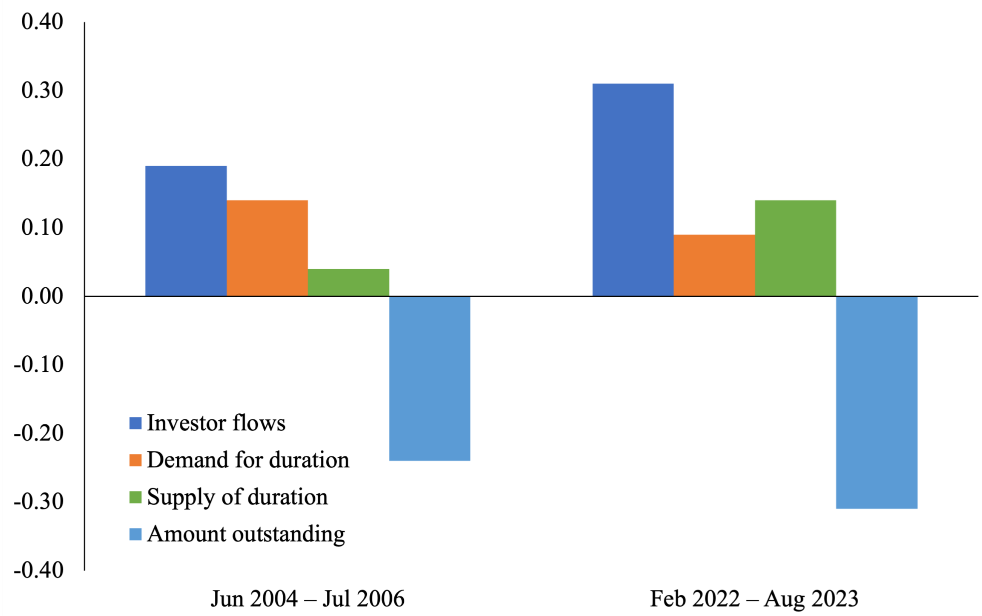


Figure 7: **Monetary Transmission by Episodes, 2004-2006 vs 2022-2023.** The figures show our estimated contributions from the top channels to the sensitivity of 10-year term spread (Panel A) and 10-year BBB credit spread (Panel B) to monetary policy rate hikes in 2004-2006 vs in 2022-2023. Monetary sensitivity is measured as the ratio between bond yield changes attributable to channel c divided by 1-year Treasury rate changes over the entire episode ($\Delta y(c)/\Delta r$).

Panel A: 10-Year Term Spread



Panel B: 10-Year BBB Spread

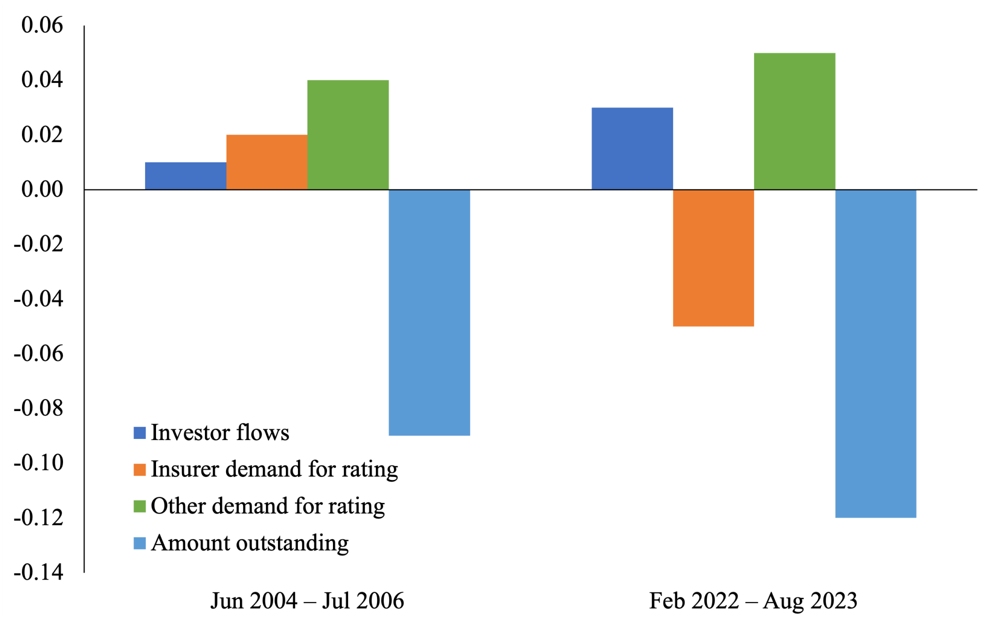
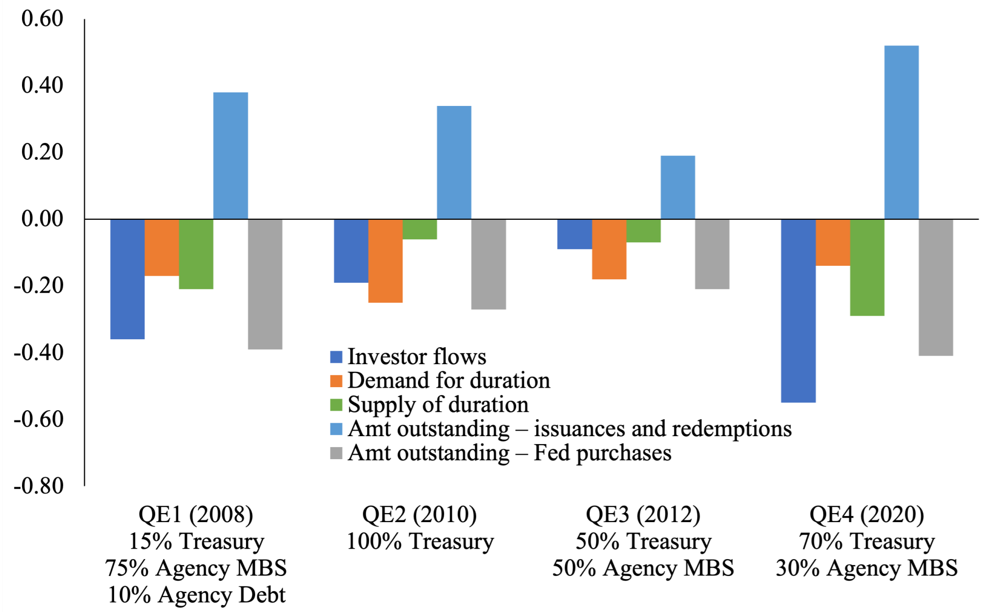
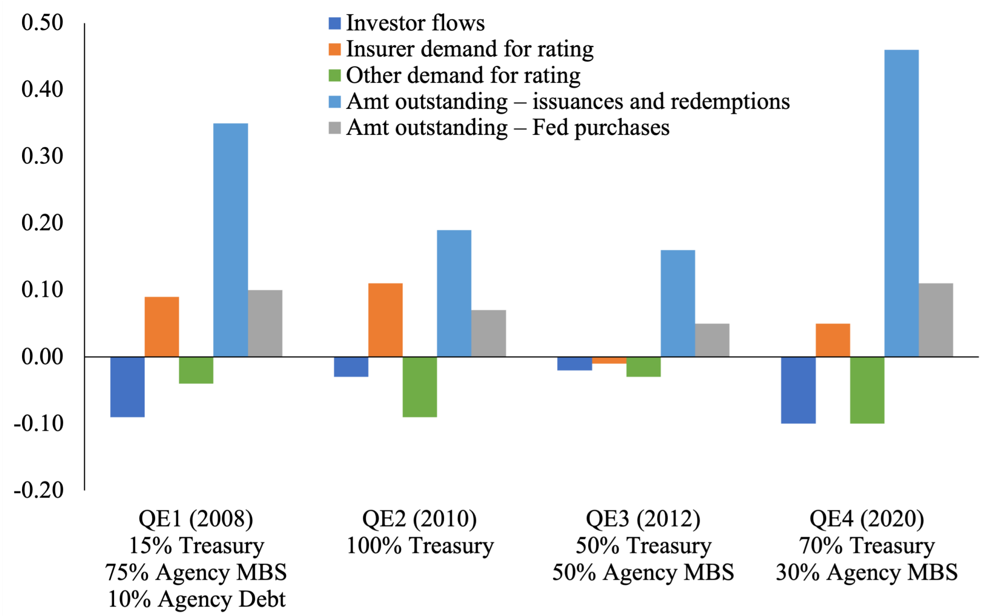


Figure 8: **Transmission of Quantitative Easing.** The figures show our estimated contributions of the top channels to 10-year term spread (Panel A) and 10-year BBB credit spread (Panel B) during each of the four quantitative easing episodes. All estimates are scaled so that the purchases are equal to 1% of total bond market outstanding.

Panel A: 10-Year Term Spread



Panel A: 10-Year BBB Spread



Appendix A Additional Tables

Table A1: **Estimated Own- and Cross-Price Elasticities, Fixed Coefficients.** These tables are the counterparts of Table 4 but coefficient variation σ is set to zero. The diagonal cells show average own-price elasticities for all bonds with the given rating or duration, across all periods and across all mutual funds (Panel A), insurance companies (Panel B), or banks (Panel C). The off-diagonal cell in row m and column n shows percent change in the holding of bond m with one-percent change price of bond n, averaged across all bond pairs with the given rating or duration combination, across all periods and across all mutual funds (Panel A), insurance companies (Panel B), or banks (Panel C).

Panel A: Mutual Funds

	AA	A	BBB	BB	B	CCC
AA	-2.40	1.29	1.32	1.36	1.00	0.46
A	0.58	-2.72	1.41	1.34	1.02	0.51
BBB	0.70	1.24	-3.95	1.27	0.87	0.49
BB	0.62	1.24	1.31	-1.92	0.96	0.53
B	0.70	1.18	1.42	1.28	-1.99	0.60
CCC	0.58	1.27	1.46	1.22	0.93	-1.56

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-3.04	1.12	1.46	1.48	1.05	0.60
3-5Y	1.43	-3.51	1.53	1.57	1.02	0.59
5-7Y	1.42	1.19	-4.64	1.45	0.95	0.65
7-10Y	1.47	1.13	1.62	-2.45	0.96	0.72
10-15Y	1.41	1.04	1.58	1.48	-1.25	0.62
15-30Y	1.45	1.05	1.64	1.56	1.03	-0.79

Panel B: Insurance Companies

	AA	A	BBB	BB	B	CCC
AA	-0.51	0.73	1.19	0.71	0.72	0.22
A	0.59	-0.95	1.18	0.74	0.73	0.30
BBB	0.66	0.56	-1.54	0.68	0.68	0.32
BB	0.61	0.69	1.03	-0.71	0.73	0.35
B	0.64	0.74	1.03	0.70	-0.27	0.36
CCC	0.70	0.72	1.16	0.73	0.70	-0.04

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-0.44	0.59	1.15	1.22	0.96	0.78
3-5Y	0.37	-0.98	1.14	1.18	1.06	0.64
5-7Y	0.37	0.60	-0.91	1.32	0.97	0.77
7-10Y	0.37	0.75	1.09	-1.19	0.90	0.73
10-15Y	0.51	0.65	1.12	1.16	-1.83	0.65
15-30Y	0.41	0.58	1.16	1.24	0.96	-0.85

Panel C: Banks

	AA	A	BBB	BB	B	CCC
AA	-2.12	0.67	1.05	0.35	1.07	0.24
A	0.28	-1.93	0.93	0.42	1.15	0.33
BBB	0.43	0.80	-1.00	0.38	1.08	0.23
BB	0.33	0.69	1.02	-1.24	1.07	0.21
B	0.32	0.75	1.00	0.38	-1.14	0.27
CCC	0.40	0.71	0.96	0.47	0.99	-0.73

	1-3Y	3-5Y	5-7Y	7-10Y	10-15Y	15-30Y
1-3Y	-3.14	1.31	1.57	1.47	0.91	0.70
3-5Y	1.25	-2.41	1.52	1.57	0.88	0.64
5-7Y	1.25	1.48	-1.41	1.47	1.03	0.72
7-10Y	1.34	1.41	1.53	-2.02	0.98	0.77
10-15Y	1.34	1.35	1.57	1.52	-3.08	0.76
15-30Y	1.16	1.34	1.42	1.46	0.94	-2.75

Table A2: **Estimated Price Elasticity of Net Issuances.** The table shows price elasticities of the net issuances of Treasury bonds, corporate bonds, municipal bonds and MBS. We run the following regression, separately for each class of bonds:

$$\Delta \log S_t(n) = \tilde{\alpha} \Delta \widehat{\log} P_t(n) + \tilde{\beta}' x_t(n) + \tilde{\epsilon}_t(n)$$

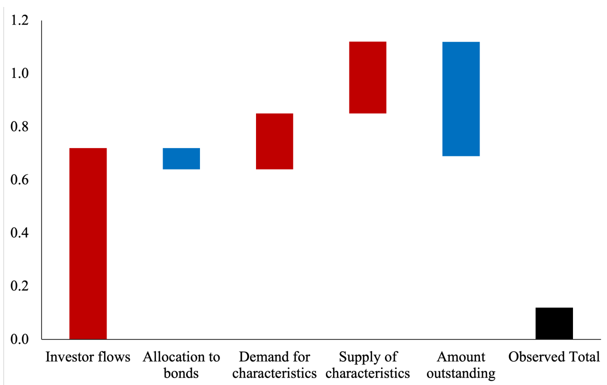
where, for each bond portfolio n, $\Delta \log S_t(n)$ denotes log change in amount outstanding, $\Delta \widehat{\log} P_t(n)$ change in price instrumented with contemporaneous flow-induced trading (Equation 5), and $x_t(n)$ bond characteristics including credit rating, duration, coupon rate, callability and bid-ask spread. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Δlog(S)			
	Treasury	Corporate	Municipal	MBS
	(1)	(2)	(3)	(4)
Instrumented Δlog(P)	0.613***	0.437***	0.117	0.226***
	(3.336)	(3.793)	(1.257)	(4.447)
Credit Rating (log)		0.011***	-0.007*	
		(7.308)	(-1.746)	
Duration (log)	0.008	0.013***	0.053***	0.063***
	(1.353)	(11.094)	(9.477)	(19.835)
Coupon Rate (%)	-0.014***	-0.002***	-0.017**	-0.007
	(-16.401)	(-3.825)	(-2.341)	(-1.365)
Callability	0.012	-0.053***	-0.049***	
	(1.119)	(-12.709)	(-6.779)	
Bid-Ask Spread (%)	-0.359	0.003***	0.861**	0.000
	(-1.311)	(4.241)	(3.011)	(0.419)
Quarter Fixed Effects	Y	Y	Y	Y
Standard Errors	clustered by quarter			
Observations	6866	37697	78673	19108
R2	0.094	0.107	0.062	0.098

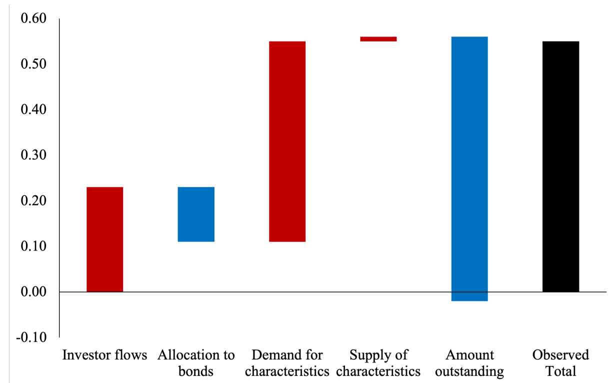
Appendix B Additional Figures

Figure A1: **Robustness with Monetary Policy Shocks.** The figures show decomposition of yield sensitivity with respect to monetary policy shocks constructed by Bu et al. (2021). Panel A (Panel B) shows the decomposition of the monetary sensitivity 10-year term spread (10-year BBB spread). Panel C (Panel D) shows the decomposition of the monetary sensitivity of term spread across duration (credit spread across ratings).

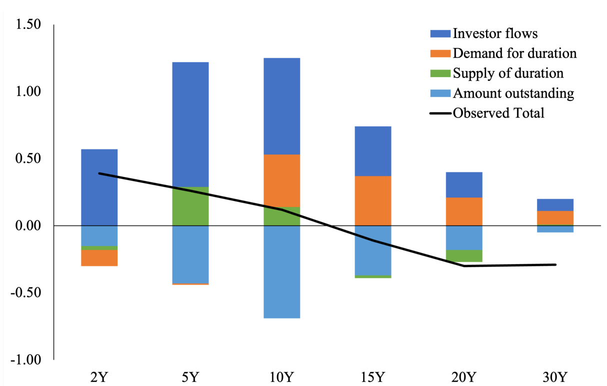
Panel A: 10-Year Term Spread



Panel B: 10-Year BBB Spread



Panel C: Term Structure



Panel D: Credit Spectrum