What Do $40 Trillion of Portfolio Holdings Say about Monetary Policy Transmission? *

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Abstract

We use granular portfolio holdings data covering nearly the entire universe of U.S. bond investors to study the transmission of monetary policy. When the Fed conducts expansionary monetary policy, mutual funds purchase more bonds due to capital inflows; insurance companies extend portfolio duration to hedge liabilities; and banks perform both actions to accommodate deposit inflows and offset the shortening duration of mortgages. The additional investor demand serves as a "helping hand," amplifying the Fed's impact on long-term yields. The excess demand is primarily absorbed through new issuances by the Department of the Treasury, corporations, and mortgage borrowers, with primary dealers playing a more limited role. We use an asset-demand system to quantify the contributions of different investors. Over the past 20 years, the flow-induced demand channel has strengthened, but net issuance has become even more elastic. As a result, bond yield sensitivity to monetary policy has undergone a secular decline, particularly at low frequencies.

Keywords: monetary policy, market clearing, demand system, state dependency

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1 Introduction

The Federal Reserve exerts a surprisingly large influence on long-term interest rates. When the Fed changes short-term interest rates, long-term rates respond much more strongly than implied by the expected trajectory of future short rates alone.[1] Similarly, unconventional monetary policies like quantitative easing (QE) affect long-term interest rates beyond what can be explained solely by the volume of bonds purchased by the Fed, suggesting the presence of additional transmission channels.[2]

A growing consensus is that the Fed, through setting the short-term interest rates or purchasing long-term assets, influences the risk premium component of long-term interest rates. Yet an important open question is how the Fed affects risk pricing in the first place. How does monetary policy influence investors' portfolio holdings? Who absorbs these shifts in investor demand and ensures market clearing? To what extent do these demand and supply dynamics shape equilibrium bond yields, particularly their sensitivity to monetary policy?

To answer these questions, we assemble a comprehensive dataset of granular portfolio holdings by the largest bond investors: mutual funds, insurance companies, banks, primary dealers, and the Federal Reserve. The data capture quarterly snapshots of investor positions across major bond classes—Treasury notes and bonds, corporate bonds, and agency mortgage-backed securities (MBS)—resulting in 546 million portfolio-level observations from 20,595 investors between 2003 and 2022, representing nearly $40 trillion in bond holdings by the end of our sample period.

[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) suggests that yield movement explain the stock sensitivity to monetary policy.

[2] For evidence of QE impacts on long-term interest rates, see Krishnamurthy and Vissing-Jorgensen (2011); D'Amico, English, López-Salido, and Nelson (2012); Swanson (2021); Selgrad (2023); Haddad, Moreira, and Muir (2024).

We begin by documenting a set of stylized facts regarding investor portfolio adjustments following conventional and unconventional monetary policy actions. After a 100 bps rate cut, mutual funds and banks expand their bond holdings by 0.58% and 0.63% of the total market size, acting as a "helping hand" that amplifies the Fed's intervention. This effect arises because both institutions experience significant capital inflows from households, expanding their balance sheets by 8–10%.

When mutual funds and banks purchase more bonds following rate cut, how does the market clear? The existing literature emphasizes primary dealers' role as liquidity providers,[3] but their capacity is insufficient to accommodate all additional demand. Specifically, following a 100 bps rate cut, mutual funds, banks, and the Fed collectively purchase 1.62% of the total bond market.[4] Only 0.16% is absorbed by primary dealers' inventories. Instead, most of the demand is met through new issuances by the Treasury Department, corporations, and mortgage borrowers. The Treasury Department, corporations, and mortgage borrowers respond by issuing more or repurchasing fewer bonds, totaling 1.77%, nearly exactly matching the purchases from mutual funds, banks and the Fed.[5] Insurance companies, facing stable capital flows that are orthogonal to monetary policy, also slightly decrease Treasury and corporate holdings following a rate cut.

Investors adjust not only the size of their portfolio holdings but also their composition. Following a rate cut, banks increase the duration of their Treasury bond holdings, as heightened prepayment probabilities shorten the duration of MBS. Insurance companies extend their portfolio duration to hedge against increased liability duration driven by convexity effects. Regarding credit risk, mutual funds shift toward holding more lower—rated bonds, a pattern also observed—though to a lesser degree—among insurers. These portfolio patterns have important implications on the pricing of duration and credit risks in the cross section

[3]See for instance, the class of preferred habitat models following Vayanos and Vila (2021).

[4]Specifically, 0.56% Treasury bonds, 0.26% corporate bonds, and 0.80% MBS.

[5]Specifically, 0.57% Treasury bonds, 0.57% corporate bonds, and 0.63% MBS.

of bonds.

A similar set of portfolio adjustments occurs under unconventional monetary policy, where the Fed directly purchases Treasury bonds and MBS. Mutual funds and banks, once again experiencing capital inflows, increase their purchases of Treasuries. However, unlike in conventional policy easing, where banks increase purchase of bonds across the board, they mainly buy Treasury bonds following QE but become a net seller of MBS when the Fed conducts quantitative easing.

Just as with conventional monetary easing, the increase in bond demand is primarily met by new issuances rather than by investors selling existing assets. When the Fed purchases Treasury bonds and MBS under QE, mutual funds and banks purchase an additional 0.26% of Treasury bonds, while Treasury issuance rises by 0.98%. Corporate bonds and MBS follow a similar pattern, with issuance playing a dominant role in absorbing investor demand, and primary dealers having only a limited impact, particularly at annual frequencies.

The effects on portfolio characteristics also parallel those observed under conventional monetary policy. When the Fed purchases bonds, mutual funds increase their exposure to credit risk, whereas insurance companies take the opposite approach. The duration of Treasury and corporate bonds lengthens across investor types, while the effective duration of MBS declines. This duration shift is particularly pronounced for insurance companies, similar to their behavior in response to rate cuts.

Informed by these stylized facts, we develop an asset demand framework to quantify the contributions from various investors as well as net issuances to equilibrium bond yields. In the model, investors exhibit heterogeneous preferences for bond characteristics like credit rating and duration, reflecting their investment mandates and regulatory constraints. Policymakers set short-term yields through conventional monetary policy and affect the supply of long-term bonds via quantitative easing or tightening. The various transmission channels proposed in the literature are evaluated by counterfactually altering the relevant demand and supply parameters.

In order to capture the complex portfolio substitution behaviors induced by monetary policy, we depart from the existing logit or nested logit demand structures that face important limitations. 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. 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 heterogeneous cross-elasticities. As a result, investors in our framework exhibit stronger substitutability between bonds with more similar credit rating and duration, which is essential for transmission channels such as MBS convexity (Hanson, 2014).

We use our estimated demand system to quantify the contribution of different investors in the transmission of monetary policy to long-term yields. To do so, we turn on one transmission channel at a time and calculate the market-clearing bond yields, attributing the yield changes to that channel. Our quantification shows that mutual fund flows, bank deposit flows, change in insurer demand for duration are the top amplifiers of bond yield sensitivity to monetary policy. The estimated model also reveals significant spillover effects across bond classes. For instance, monetary easing shortens the duration of MBS and other callable bonds, increasing demand for long-term Treasury and corporate bonds among investors seeking to maintain duration targets. This channel further amplifies the sensitivity of long-term yields to monetary policy. These findings underscore the importance of analyzing different bond classes within a unified demand framework.

There is significant heterogeneity across investors. For example, while mutual funds and banks increase their demand for high-credit-risk bonds during monetary easing, insurance companies do the opposite. Such heterogeneity is difficult to extract from prices, but can be better analyzed through a framework like ours that utilizes granular portfolio holdings data. To understand the importance of investor heterogeneity, we simulate how would monetary transmission change under different scenarios of investor composition, such as the rise of mutual funds relative to banks and insurance companies.

The estimated model also shows that the supply side is quite elastic. Net issuances by the Treasury Department, corporations, and mortgage borrowers largely dampen the effects of investor demand. Our results provide an explanation to the puzzling difference in yield sensitivity at high frequency versus low frequency. According to our framework, when we turn on changes in investor demand and turn off changes in amount outstanding, low-frequency bond yield sensitivities would have been as large as high-frequency ones observed in the literature.

Our structural framework further unveils important dynamics over time. There is a secular rise in the size of bond mutual funds against other investors (Ma, Xiao, and Zeng, 2025). Consistent with this, we find that the amplification effect of mutual fund flows on yield sensitivity to monetary policy has increased over time. Changes in insurer demand for duration is stronger when interest rates are low. The convexity of callable bonds such as MBS, which depends on past monetary policies, determines these bonds' duration sensitivity to new monetary policy. Net issuances, in particular those by corporations and mortgage borrowers, have become more elastic over time. In the most recent monetary tightening episode from 2021 to 2023, net issuances fell by almost twice as large as during tightening episode from 2003 to 2006, conditional per unit change in monetary policy rate. Our results contribute to understanding the decline of bond yield sensitivity to monetary policy, particularly at low frequency. Rather than a sign of weakened monetary transmission, we show that the declining yield sensitivity reflects the heightened responses from the real sector, which should be a key part of policymakers' objective function.

Finally, we use our framework to analyze the transmission of unconventional monetary policies such as quantitative easing (QE). We find that investor demand channels amplify the direct effects from the Fed's purchases by a factor of two. Similar to conventional policies, QE is associated with significant inflows to mutual funds and banks, increases in demand for duration particularly for insurance companies, both of which further push down bond yields. Net issuances increase bond yields and almost entirely neutralize the combined effects of the Fed and other investors. The dampening effects of net issuances help explain why QE effects are concentrated on announcement dates but revert substantially over time.

The transmission of monetary policy to bond markets has been widely studied, with existing literature identifying several key mechanisms. Some studies find that lower interest rates encourage institutional reaching for yield, leading investors to shift toward riskier or longer-duration bonds (Choi and Kronlund, 2018; Anadu, Bohn, Lu, Pritsker, and Zlate, 2019), while others show that regulatory constraints may limit such behavior (Li, 2024). Another major channel is duration hedging: as falling rates reduce the effective duration of mortgages, investors rebalance into long-term non-callable bonds, compressing yields (Hanson, 2014; Hanson et al., 2021). Liability-driven investors, such as insurance companies and pension funds, also adjust their portfolios to maintain asset-liability duration matching, further affecting bond yields (Domanski, Shin, and Sushko, 2017; Ozdagli and Wang, 2019; Greenwood and Vissing-Jorgensen, 2018; Jansen, 2023). Additionally, extrapolative mutual fund flows amplify bond yield sensitivity by reinforcing investor demand following rate cuts (Brooks et al., 2018; Hanson et al., 2021; Fang, 2023; Darmouni, Siani, and Xiao, 2024).

Our paper advances this literature by compiling a comprehensive dataset of portfolio holdings across the near-universe of bond investors, allowing us to use a quantity-based approach to empirically quantify the relative importance of these channels. Using market clearing as the guiding principle, we assess how monetary policy reshapes portfolio allocation across different investor types, the term structure, and the credit spectrum. Our findings highlight the role of bond issuance and redemption dynamics in absorbing monetary shocks, underscoring that understanding monetary transmission requires going beyond yield changes and examining shifts in bond supply by the real sector.

This paper contributes to the growing literature that employs asset demand systems and granular portfolio holdings to study 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 et al., 2024; Azarmsa and Davis, 2024; Jansen, Li, and Schmid, 2024; Chaudhary, Fu, and Zhou, 2024). Our primary contribution is extending existing logit and nested logit frameworks by introducing a random-coefficient demand model, drawing from the industrial organization literature (Berry et al., 1995). This flexibility is essential for accurately modeling key transmission channels, such as MBS convexity effects (Hanson, 2014), and provides a more nuanced view of how monetary policy reshapes bond market allocations.

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., 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 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.

2 Data

2.1 Portfolio holdings

The core of our analysis relies on a comprehensive dataset of portfolio holdings. We focus on five types of bond investors for which we have granular holdings data: mutual funds and ETFs, insurance companies, banks, primary dealers, 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. Quarterly holdings are calculated using annual holdings (Part 1) and daily transactions (Part 3 and 4). We focus on those that sell life insurance or P&C insurance and exclude health insurers, which have small bond holdings.

Data on bank holdings come from call reports. Each bank reports holdings across bond classes – Treasury, agency obligations, municipal, MBS, ABS, and others – and by maturity buckets – less than 1Y, 1-3Y, 3-5Y, 5-15Y, 15Y or above. We map bank holdings to the more granular security level according to amount outstanding.

Data on primary dealer holdings come from New York Fed's Primary Dealer Statistics. The data are aggregated across all primary dealers. Similar to banks, holdings are reported by bond classes and by maturity buckets – less than 2Y, 2-3Y, 3-6Y, 6-7Y, 7-11Y, 11-21Y, 21Y or above.

Data on the Fed holdings come from System Open Market Account (SOMA) and Secondary Market Corporate Credit Facility (SMCCF). SOMA contains weekly holdings of Treasury and agency securities at the CUSIP level, from 2003 to present. SMCCF contains corporate bond holdings and transactions since 2020. Primary Market Corporate Credit Facility (PMCCF) was never actually used.

2.2 Bond securities

We collect data on three classes of bonds, which together span virtually the entire U.S. taxable bond market: Treasury bonds, corporate bonds, and mortgage-backed securities (MBS).[6] As they share similar characteristics and similar investor base, the yields of these three 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 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, and most of corporate bonds are

[6] 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.

rated. 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 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.

Figure 1 shows aggregate holdings for each investor type. It confirms that the three 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.

3 Stylized Portfolio Changes with Monetary Policy

In this section, we use simple regression analyses to understand how different investors' portfolios change in response to conventional and unconventional monetary policy. We categorize investors into the following groups: mutual funds, insurance companies, banks, dealers and the Federal Reserve. Within-group heterogeneity is ignored here but will be captured by our demand system analysis in Section 5. Apart from investors, we also analyze net issuances of Treasury bonds, corporate bonds, and MBS. For consistency, we denote issuances as selling and repurchases as buying. By market clearing, the sum of purchases (including repurchases by bond issuers) must equal to the sum of sales (including new bond issuances). Any differences would come from investors not captured by our data, such as pension funds.

3.1 Changes in holding amounts

We start with changes in holding amounts and analyze how they correlate with conventional monetary policy. Specifically, we run the following quarterly time series regression for each investor group and separately for Treasury bonds, corporate bonds and MBS:

$$\Delta q_t = \alpha + \beta \Delta r_t^{1Y} + \epsilon_t \tag{1}$$

Δq denotes quarterly change in par amount held, scaled by total amount outstanding. Δr^{1Y} denotes quarterly change in one-year Treasury rate. We focus on active purchases and sales of bonds and exclude natural redemption at maturity. We also exclude redemptions through the exercising of call or prepayment options. In these cases, investors are forced to sell to bond issuers.

Results are shown in Panel A of Figure 3. We plot $-\beta$, which can be interpreted as portfolio changes to a 100bps decline in 1Y Treasury rate. Starting at the top of the graph, mutual funds increase holdings across all classes of bonds. Specifically, their Treasury, corporate and MBS holdings increase by 0.13%, 0.26% and 0.19% of total amount outstanding, in the same quarter. This is consistent with the fact that bond mutual funds tend to experience large inflows of return-chasing capital when interest rates decline (Brooks et al., 2018; Fang, 2023). Figure A1 shows that this relationship between rate declines and mutual fund purchases is even stronger at annual frequency, consistent with the fact mutual fund flows chase returns at a low frequency (Barber, Huang, and Odean, 2016).

Similar to mutual funds, banks experience large inflows of checking and savings deposits, which they primarily invest in Treasury bonds and MBS (Drechsler, Savov, and Schnabl, 2017; Drechsler, Savov, Schnabl, and Supera, 2024). Specifically, in response to 100bps decline in 1Y Treasury rate, banks purchase 0.21% of Treasury bond outstanding and 0.42% of MBS outstanding. Banks also increase corporate bond holdings, but the size is minimal compared to total corporate bonds outstanding. Figure A1 shows that the relationship between rate declines and bank purchases is even stronger at annual frequency, reflecting the low-frequency nature of deposit flows.

In contrast to mutual funds and banks, insurance companies decrease Treasury and corporate bond holdings. As shown in Figure 6, insurers have stable flows that do not correlate with monetary policy. In response to rate declines, they actually decrease Treasury and corporate holdings, suggesting that they act as liquidity providers for mutual funds and banks. As we will see later, insurers do adjust the *characteristics* of their bond holdings.

Over the last 20 years, Fed tends to simultaneously conduct conventional monetary policy (i.e. changes in short-term interest rates) and unconventional monetary policy through direct asset purchases. Declines in 1Y Treasury rate tend to coincide with quantitative easing (QE) policies, where the Fed purchases large amount of Treasury bonds and MBS.

Mutual funds, banks and the Fed together purchase 0.59% of Treasury bonds, 0.21% of corporate bonds, and 0.94% of MBS, in response to 100bps decline in 1Y Treasury rate. Who are the sellers, so that the market clears? Perhaps surprisingly, the answer is bond issuers. When 1Y Treasury rate declines, the Treasury Department, corporations and mortgage borrowers issue more or repurchase less bonds, at 0.57%, 0.57% and 0.63% of amount outstanding, which have the magnitude as total purchases by mutual funds, banks and the Fed. It is worth emphasizing that the results here are not mechanically driven by bond issuers redeeming bonds from investors at maturity or through call or prepayment options, which we carefully exclude. The fact that Treasury issuances are very responsive might be particularly surprising, since the conventional wisdom is that government borrowings are inelastic and independent of monetary policy. We delve more into the large sensitivity of Treasury and other bond issuances in Section 3.4.

Perhaps also surprisingly, primary dealers do not play an important role in absorbing the bond purchases by mutual funds and banks. In response to 100bps decline in 1Y Treasury rate, primary dealers' Treasury, corporate and MBS purchases change by 0.05%, -0.07% and -0.19% of market outstanding, respectively, over the same quarter. Figure A1 shows that primary dealers' portfolio changes are even smaller at annual frequency. Although primary dealers are pivotal in intermediating bond transactions, they do not seem to absorb demand and supply imbalances at quarterly or annual frequency.

3.2 Changes in portfolio characteristics

After examining portfolio holding amounts, we turn to changes in portfolio characteristics. We run a similar quarterly time series regression for each investor group and separately for

Treasury bonds, corporate bonds and MBS:

$$\Delta x_t = \alpha + \beta \Delta r_t^{1Y} + \epsilon_t \tag{2}$$

Δx denotes quarterly change in the weighted average of either credit rating (AAA = 1, CCC- = 19) or option-adjusted duration across all bonds in the portfolio. Δr^{1Y} denotes quarterly change in 1Y Treasury rate. In additional to investor holdings, we also analyze changes in the characteristics of all bonds outstanding, i.e. the market. Note that market changes represent the weighted average of portfolio changes across all investors.

Results on changes in credit rating are shown in Panel B of Figure 3. In response to 1Y Treasury rate decline, the average credit rating of all corporate bonds outstanding in the market deteriorates. Relative to this market average, mutual funds' credit rating deteriorates more, consistent with the reaching-for-yield behavior documented in Choi and Kronlund (2018). In contrast, the average credit rating of insurers' bond holdings improves, consistent with the motive to preserve regulatory capital due to the increase of unhedged insurance liabilities when interest rate declines (Li, 2024).

Results on changes in duration are shown in Panel C of Figure 3. The most salient result is that MBS duration declines substantially when 1Y Treasury rate declines. This is known as mortgage convexity (Hanson, 2014) and can be explained by the increased propensity of households to refinance their mortgages at lower interest rates. In contrast, most corporate bonds are not callable or only callable with make-whole provision, and almost all Treasury bonds are non-callable.

While the duration of their MBS holdings declines, most investors increase the duration of their Treasury and corporate bond holdings. For example, the duration of banks' Treasury and corporate bonds increase by 0.06. This is consistent with the evidence that investors have duration targets and active adjust their bond holdings in response to duration shocks in order to stay on those targets. In Section 4, we discuss in detail how our demand system framework captures this channel.

Of all the investors we consider, insurance companies are the most aggressive in increasing the duration of their bond holdings. This is because, in addition to hedging the duration decline of MBS holdings, insurers also need to hedge the duration increase of their pension-like liabilities, which also feature convexity (Domanski et al., 2017). As a result, in response to 100bps 1Y Treasury rate decline, the duration of insurers' Treasury bonds (corporate bonds) increases by 0.09 (0.11), or 4 (5) times the market average increase.

Due to the simultaneity of conventional and unconventional monetary policy, the Fed purchases more Treasury bonds and MBS that are typically newly issued. As a result, the Fed's portfolio duration increases significantly more – or decreases significantly less – relative to the market.

3.3 Unconventional monetary policy

In additional to conventional short-term interest rate changes, we also analyze how unconventional Fed policies – specifically, directly purchases or sales of Treasury bonds and MBS – affect investors' portfolio holdings. We run the following quarterly time series regression for each investor group and separately for Treasury bonds, corporate bonds, and MBS:

$$\Delta q_t = \alpha + \beta \Delta q_t^{FED} + \epsilon_t \tag{3}$$

Δq denotes quarterly net purchases by the investor group, scaled by total amount outstanding. Δq^{FED} denotes quarterly net purchases of Treasury bonds and MBS by the Federal Reserve, scaled by total Treasury bonds and MBS outstanding. By net purchases, we mean changes in par amounts held, excluding redemptions at maturity or through call or prepayment.

Results are shown in Panel A of Figure 4. The patterns are very similar to those with conventional monetary policy. When the Fed conducts expansionary monetary policy by directly purchasing Treasury bonds and MBS, mutual funds and banks also purchase more bonds due to inflows of capital. In other words, these additional purchases by the private sector investors act as a "helping hand" that amplifies the Fed's purchase programs.

From whom do the Fed and other investors buy the bonds? Banks appear to be a major seller of MBS. However, the bars at the bottom of the graph show that the purchases are almost entirely from bond issuers: the Treasury Department, corporations, and mortgage borrowers. When the Fed purchases 1% of Treasury bonds outstanding, mutual funds and banks buy another 0.26%, and Treasury issuances increase by 0.98%. The patterns are similar for corporate bonds and MBS and more salient for annual frequency, shown in Figure A2. Primary dealers play a limited role, especially at annual frequency.

Changes in portfolio characteristics are also similar to those with conventional monetary policy. When the Fed purchases bonds, mutual funds increase credit risk, and insurance companies do the opposite. MBS effective duration declines, and the duration of Treasury and corporate bonds increase for all investors, but particularly large for insurance companies.

3.4 Understanding net issuances

In the stylized facts above, net issuances appear to be the main counterparty to net purchases by the Fed and other investors. One concern is that this is due to some omitted variables that drive both net issuances and investor purchases. For example, times with bad economic shocks often require both expansionary monetary policy and expansionary fiscal policy, and as a result there would be a mechanical correlation between Fed purchases and Treasury issuances. As another example, during financial crises, corporations may be forced to borrow from the bond market due to reduced bank lending, at the same time bond investors may experience inflows due to expansionary monetary policy, and so the correlation between corporate bond issuances and investor purchases could also be spurious.

To rule out these potential omitted variables in the time series, we examine the *cross-sectional* relationship between investor purchases and net issuances. Specifically, we run the following panel regression using maturity bucket-quarter observations, for each group of investors:

$$\Delta q_{m,t} = \alpha + \beta \Delta q_{m,t}^{FED} + \gamma_m + \gamma_t + \epsilon_{m,t} \tag{4}$$

$\Delta q_{m,t}$ denotes quarterly net issuances of a certain maturity bucket of bonds. $\Delta q_{m,t}^{FED}$ denotes quarterly Fed net purchases of bonds in the same maturity bucket. γ_m and γ_t are maturity bucket fixed effects and time fixed effects. We follow the same maturity bucket designation as New York Fed's Primary Dealer Statistics: less than 2 years, 2-3 years, 3-6 years, 6-7 years, 7-11 years, 11-21 years, 21 years or longer.

The inclusion of time fixed effects purges out time series variations in macroeconomic variables that could drive the simultaneous implementations of monetary policies and fiscal policies. In effect, the regression identifies correlation between net issuances and Fed purchases in the *cross section* of bond buckets.

Results are shown in Panel A of Figure 5. In a given quarter, when the Fed purchases 1% of certain maturity bucket of Treasury bonds, the Treasury Department issues 0.894% of bonds in that particular maturity bucket. Banks accommodate 0.071% of the Fed's purchases. Net purchases by primary dealers and other investors are negligible. By market clearing, the remaining investors for which we do not have holdings data also provide liquidity in a negligible way. Figure A3 shows that the pattern is similar at annual frequency.

These fixed-effect regression results provide additional evidence that: when the Fed conducts QE and purchases Treasury bonds, it effectively purchases new issuances from the Treasury Department, and other investors' holdings remain essentially unchanged. This fact poses a challenge for models that explain the effect of QE through the quantity of risk born by financial intermediaries. Instead, the results suggest that the Treasury Department supplies most of the elasticity in the Treasury market, at least in terms of accommodating the Fed's purchases and sales.

To further evaluate the elasticity of Treasury issuances and also issuances by corporations, we run the same fixed-effect regression but replacing the Fed' purchases with passive mutual funds' net purchases, following Sammon and Shim (2024):

$$\Delta q_{m,t} = \alpha + \beta \Delta q_{m,t}^{PASSIVE} + \gamma_m + \gamma_t + \epsilon_{m,t} \tag{5}$$

The idea is that, net purchases by passive mutual funds are supposed to be particularly inelastic, as these funds are mandated to mechanically translate inflows or outflows into purchases or sales of the index constituents. Passive bond mutual funds are identified by the "Index Fund" flag provided in Morningstar Direct. Most passive bond funds track the aggregate bond market, but a significant portion also have specific credit or duration focus.

Results are shown in Panel B of Figure 5. In a given quarter, when passive funds purchases 1% of certain maturity bucket of Treasury bonds, active funds and, to a less extent, banks tend to similarly purchase Treasury bonds in the same maturity bucket, amplifying the inelastic purchases to a total of 1.51% of amount outstanding. This is possible if active funds and banks track similar indexes or if retail flows are attracted to funds and banks with similar characteristics (e.g. past returns).

Who clears the market when passive funds and other investors purchase Treasury bonds? The answer is the Treasury Department, consistent with the findings for the equity market in Sammon and Shim (2024). The Treasury Department actually issues 2.29% more bonds in the same maturity bucket where passive bond mutual funds buy. This could be because of the presence of other foreign funds with correlated purchases due to similar indexation, but these foreign funds are not covered by our data. Interestingly, the Fed also supplies a significant amount of liquidity. Primary dealers play a negligible role in clearing the market. The results are broadly the same if we instead look at year-over-year net purchases and net issuances, as shown in Figure A3.

The red bars show market clearing for passive funds' corporate bond purchases. In defining buckets for corporate bonds, we again follow the New York Fed's Primary Dealer Statistics: less than 1 year, 1-5 years, 5-15 years, more than 15 years, interacted with investment-grade vs below-investment-grade. Similar to the Treasury results, active funds tend to buy the same buckets of corporate bonds as passive funds, and issuances by corporations accommodate most of these purchases. Again, primary dealers play a negligible role.

4 Demand System Framework

The reduced-form evidence above focuses exclusively on quantities, i.e. who buys and who sells in response to monetary policy. This section develops a Koijen and Yogo (2019) style demand system to jointly analyzes both prices and quantities, similarly under the principle of market clearing. 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, 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. 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, Fu, and Li, 2022). In our baseline framework, bonds are grouped by 4 classes (Treasury, corporate 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.[7]

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

[7] At a given point in time, there are on average 300+ Treasury CUSIPs, 25,000+ corporate 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:

$$w_{i,t}(n) = \frac{\exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t}\boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\}}{\sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t}\boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\}} \tag{6}$$

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:

$$\frac{\partial w(m)/w(m)}{\partial y(n)} = \begin{cases} \alpha(1 - w(n)) & m = n \\ -\alpha w(n) & m \neq n \end{cases} \tag{7}$$

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 6 then become an integral over the distribution of $\boldsymbol{\beta}$:

$$w_{i,t}(n) = \int \frac{\exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\}}{\sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\}} dP(\boldsymbol{\beta}_{i,t}) \tag{8}$$

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:

$$\frac{\partial w(m)/w(m)}{\partial y(n)} = \begin{cases} \frac{\alpha}{w(n)} \int \tilde{w}(n)(1 - \tilde{w}(n)) dP(\boldsymbol{\beta}) & m = n \\ -\frac{\alpha}{w(m)} \int \tilde{w}(m)\tilde{w}(n) dP(\boldsymbol{\beta}) & m \neq n \end{cases} \tag{9}$$

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:

$$InvestorFlow_{i,t} = a + \sum_k b_k PC_{k,t} + Investo\tilde{r}Flow_{i,t}$$

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:

$$FIT_{-i,t}(n) = \sum_i \frac{AmountHeld_{i,t-1}(n)}{AmountOutstanding_{t-1}(n)} Investo\tilde{r}Flow_{i,t} \tag{10}$$

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 A1 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 8 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 A2 and Figure A4 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 9.

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 9:

$$\frac{\partial q(m)/q(m)}{\partial p(n)/p(n)} = \begin{cases} -1 - \frac{100\alpha}{w(n)d(n)} \int \tilde{w}(n)(1-\tilde{w}(n))dP(\boldsymbol{\beta}) & m = n \\ \frac{100\alpha}{w(m)d(n)} \int \tilde{w}(m)\tilde{w}(n)dP(\boldsymbol{\beta}) & m \neq n \end{cases} \tag{11}$$

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 2 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 11, 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 11, 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 A3 shows that, consistent with the prediction in Equation 7, fixed coefficients produce rigid homogeneous cross-substitution, as the cross-elasticity numbers are basically invariant for each column.[8]

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:

$$S_t(n)P_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n) \tag{12}$$

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:

$$A_{i,t} = A_{i,t-1}R_{i,t} + T_{i,t} \tag{13}$$

[8] Cross-elasticity is not exactly the same within each column because of variation in group composition and duration adjustment (Equation 11).

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:

$$y(S, \boldsymbol{x}, A, \boldsymbol{\theta}, \epsilon) \tag{14}$$

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 3, 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 12. 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:

$$\Delta y_t(c) := y(c_t, -c_{t-1}) - y(c_{t-1}, -c_{t-1}) \tag{15}$$

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 14. 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 13 — 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:

$$\Delta y_t(c) = \alpha + \beta \Delta r_t + \gamma X_t + \epsilon_t \tag{16}$$

where $\Delta y_t(c)$ denotes year-over-year yield changes attributable to channel c according to Equation 15, 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 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 7 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.[9]

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, Garlappi, and Xiao (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

[9]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 10), and $x_t(n)$ bond characteristics such as credit rating and duration. Table A4 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 2. 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 A5 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. The effect of amount outstanding is lowest in the shortest-duration range. This is partially because, during monetary easing, firms and households 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 8 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 A5 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.[10] 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

[10] 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 Evolution over time

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. To analyze *changes* in different transmission channels over time, we split the sample in half, one from beginning of 2003 to end of 2012 and the other from beginning of 2013 to end of 2022. We perform our decomposition exercise separately for these two periods.

Figure 9 shows the results. The amplificatory effects of investor flows has increased significantly in the later half of our sample, from 0.16 to 0.25 percentage points. This reflects the secular rise of bond mutual funds relative to insurance companies and banks (Ma et al., 2025) and also the increased flightiness of bank deposits in the low-rate environment, so that changes in monetary policy rates are associated with larger quantities of flow-induced bond demand relative to bond outstanding.[11] The amplificatory effect of changes in duration has declined, reflecting the fact that insurance companies' convexity exposure has reduced over time (Ozdagli and Wang, 2019).

The dampening effect of amount outstanding (due to issuances and redemptions) has almost doubled, from -0.21 to -0.39 percentage points. Bond issuances, in particular those by

[11] One reason for the growth of mutual funds is the secular shift from defined-benefit to defined-contribution pension plans, where retirees directly select mutual funds in their 401k accounts, instead of delegating to a pension manager.

corporations and mortgage borrowers, have become more sensitive to market condition, which counteract the amplificatory effects from investors. Because of this, the net effect of investor demand and net issuances has declined over time, from 0.20 in the first half of our sample to 0.03 in the second half of our sample. Our results provide an explanation for the puzzling findings in Hanson et al. (2021) regarding the decline of bond yield sensitivity to monetary policy at annual frequency. Rather than a sign of weakened monetary transmission, we show that the decline in yield sensitivity is partly attributable to the increase of issuance sensitivity, a sign of strengthened transmission to the real sector.

These time series dynamics suggest that the strength of a monetary transmission channel depends on the relevant state variables. To further understand 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 3. 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 amplification 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 amplification 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 9. 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 4. 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 4 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 have been 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 10 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 use portfolio holdings data 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 three interconnected classes of U.S. dollar-denominated bonds: Treasury bonds, corporate 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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Figure 1: **Investor Holdings.** The figures show holdings by the investors for which we have granular portfolio data: mutual funds and ETFs, insurance companies, banks, and the Federal Reserve.

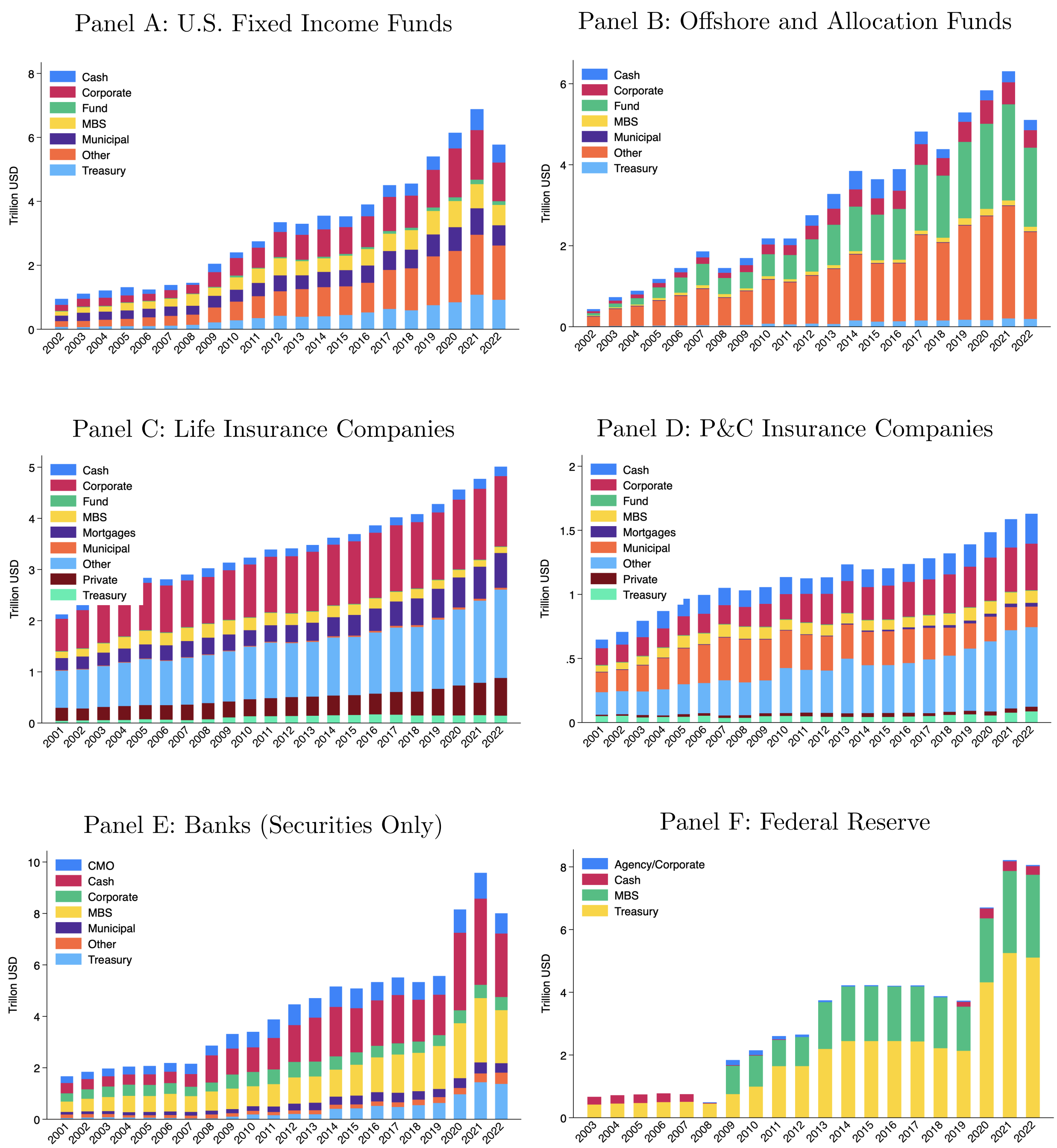
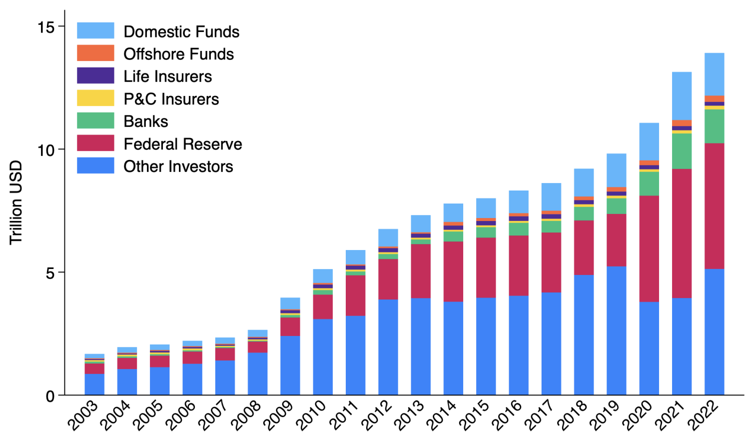
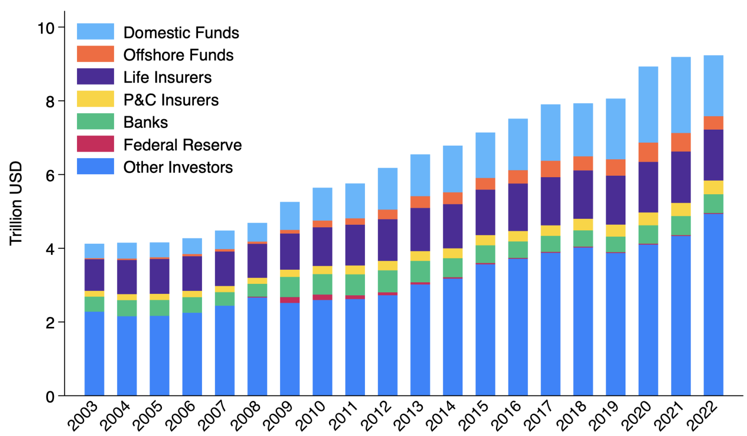


Figure 2: **Bond Ownership.** The figures show investor composition for Treasury bonds, corporate bonds, and agency MBS. We restrict to straight USD-denominated bonds (including callable bonds) with more than one year to maturity.

Panel A: Treasury Bonds



Panel B: Corporate Bonds



Panel C: Agency MBS

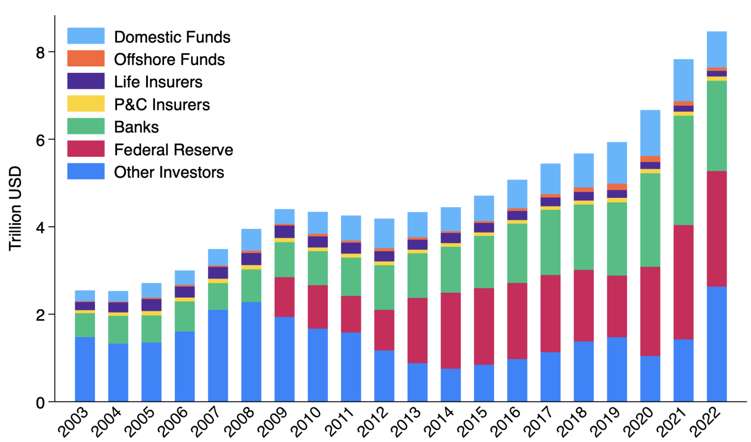
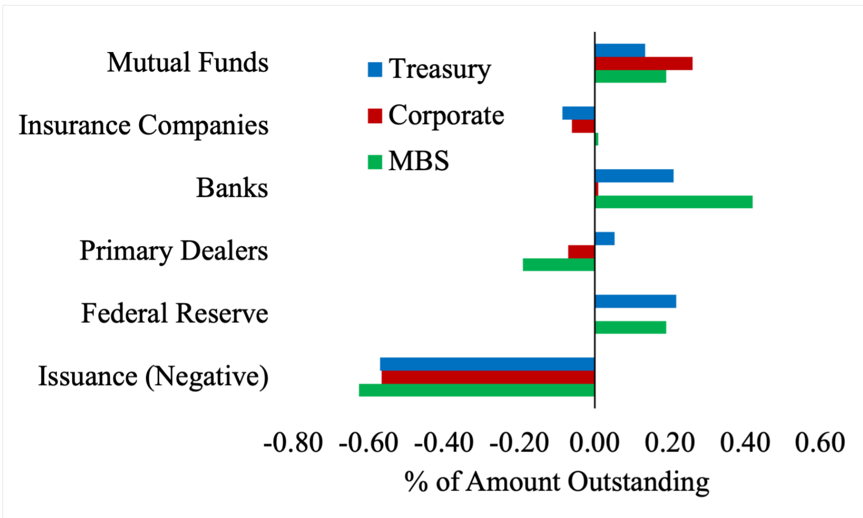


Figure 3: **Portfolio Changes to -100bps 1Y Treasury Rate.** These figures report $-\beta$ from the quarterly time series regression (1):

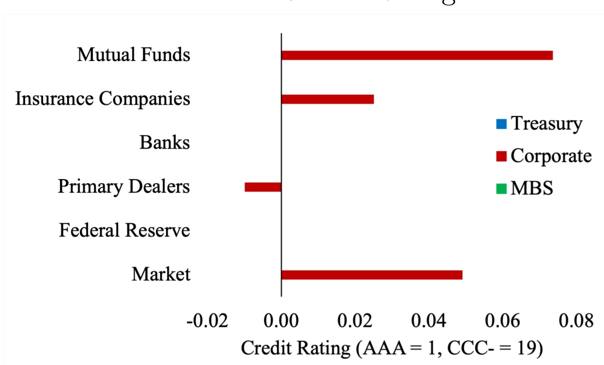
$$\Delta q_t = \alpha + \beta \Delta r_t^{1Y} + \epsilon_t$$

where Δq denotes change in holding amount (relative to amount outstanding), change in portfolio credit rating (AAA = 1, CCC- = 19), or change in portfolio duration (year), and r^{1Y} denotes 1Y Treasury rate (%). The regression is run separately for each investor group and for each bond class.

Panel A: Amount



Panel B: Credit Rating



Panel C: Duration

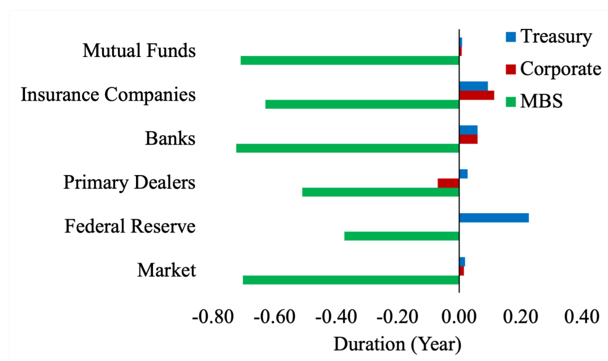
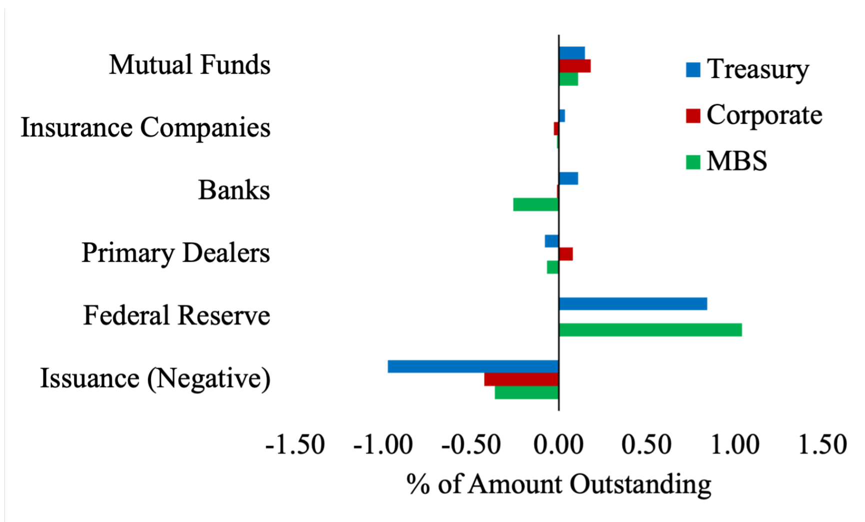


Figure 4: **Portfolio Changes to 1% Net Purchases by the Federal Reserve.** These figures report β from the quarterly time series regression (3):

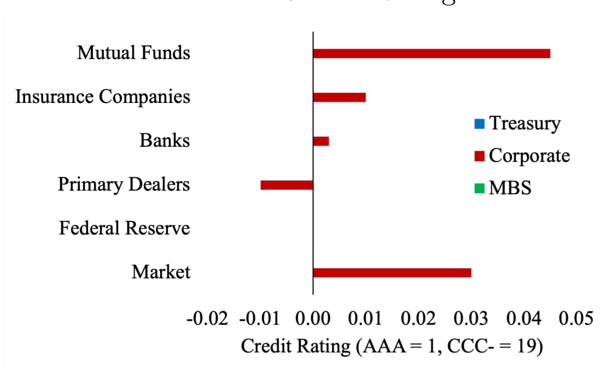
$$\Delta q_t = \alpha + \beta \Delta q_t^{FED} + \epsilon_t$$

where Δq denotes change in holding amount (relative to total amount outstanding), change in portfolio credit rating (AAA = 1, CCC- = 19), or change in portfolio duration (year), and q^{FED} denotes net purchases of Treasury bonds and MBS by the Federal Reserve (relative to total Treasury and MBS outstanding). The regression is run separately for each investor group and for each bond class.

Panel A: Amount



Panel B: Credit Rating



Panel C: Duration

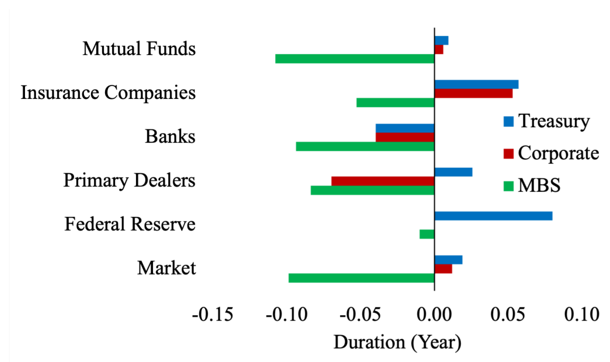
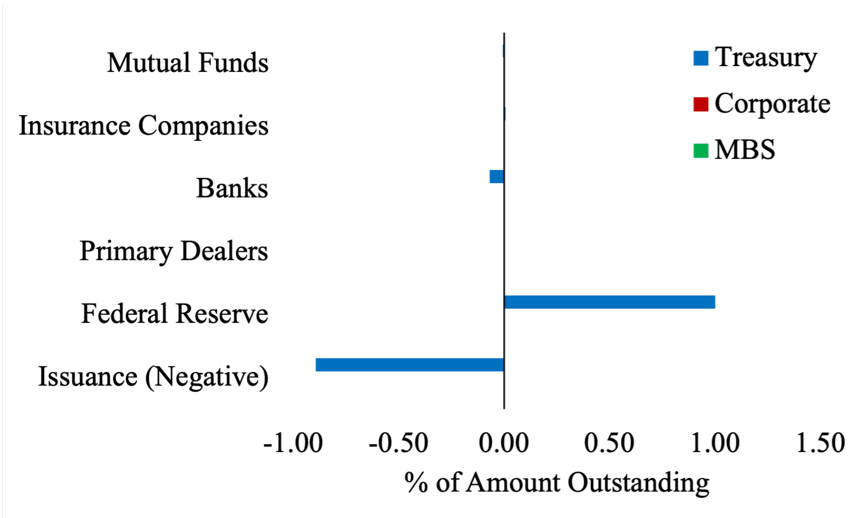


Figure 5: **Portfolio Changes across Bond Buckets.** These figures report β from the panel regressions (4) and (5) with maturity bucket-quarter observations:

$$\Delta q_{m,t} = \alpha + \beta \Delta q_{m,t}^{FED/PASSIVE} + \gamma_m + \gamma_t + \epsilon_{m,t}$$

where Δq denotes net purchases by the investor (relative to amount outstanding), $q^{FED/PASSIVE}$ denotes net purchases by the Federal Reserve or by passive mutual funds (relative to amount outstanding), and γ_m and γ_t denote maturity bucket and time fixed effects. The regression is run separately for each investor group and for each bond class.

Panel A: Fed Purchase



Panel B: Passive Purchase

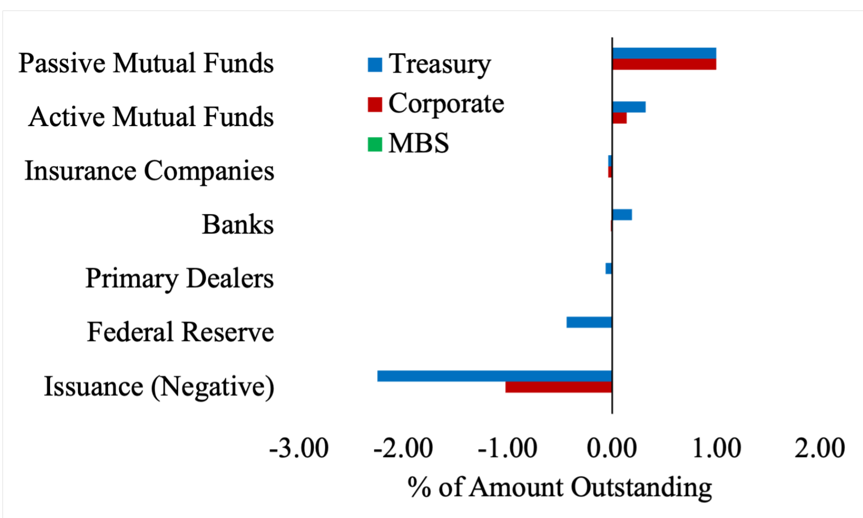
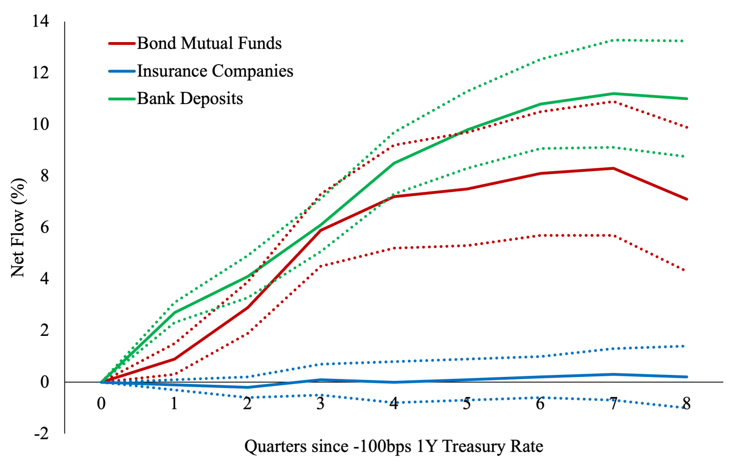


Figure 6: **Net Flow Response to Monetary Policy.** The figures show impulse responses of net flows of bond mutual funds, bank deposits and insurance companies to monetary policy, estimated as β_h from the following quarterly regression for different horizon h:

$$NetFlow_{t,t+h} = \alpha_h + \beta_h \Delta r_{t,t+1} + \epsilon_{t,t+h}$$

Panel A shows net flow responses to -100bps change in 1Y Treasury rate. Panel B shows net flow responses to 1% Fed purchases of Treasury bonds and MBS.

Panel A: Conventional Monetary Policy



Panel B: Unconventional Monetary Policy

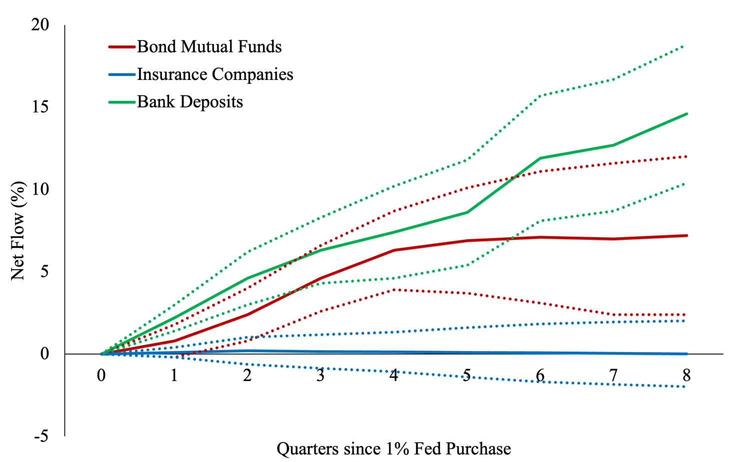
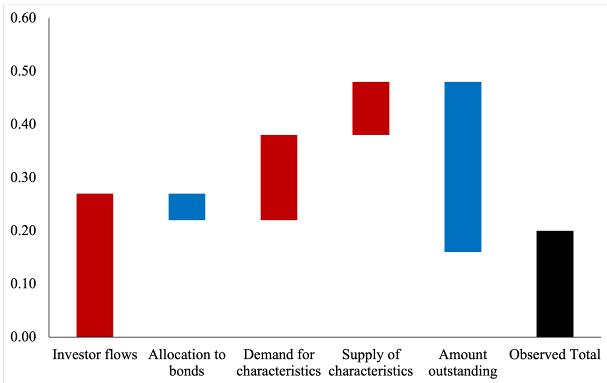
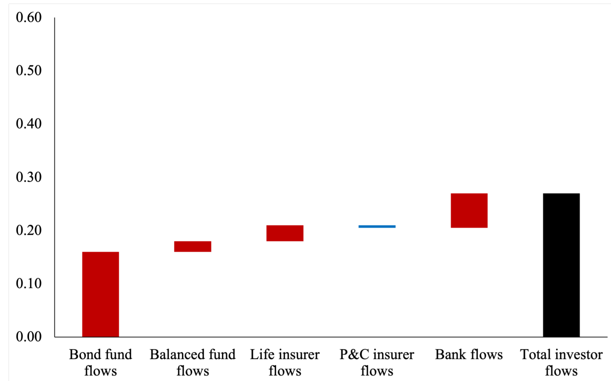


Figure 7: **10-Year Term Spread Sensitivity to Monetary Policy.** These figures show contributions from different channels to the monetary sensitivity of 10-year term spread according to our method described in Section 5.

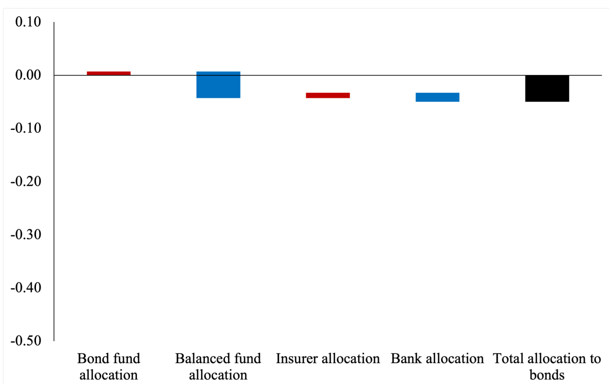
Panel A: All Channels



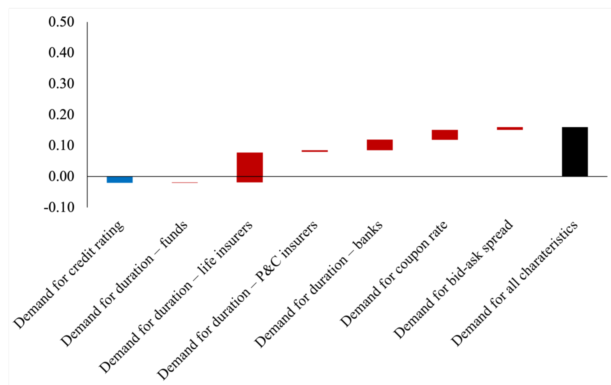
Panel B: Investor Flows



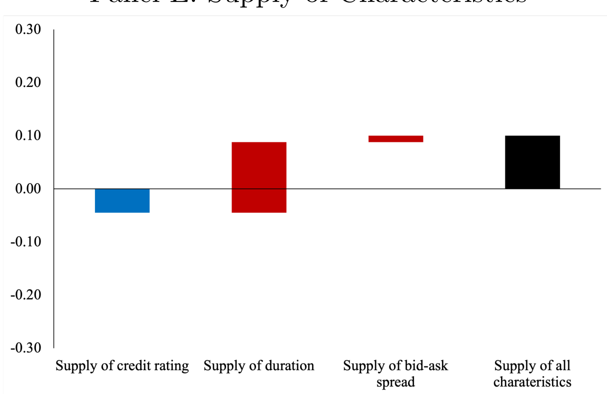
Panel C: Allocation to Bonds



Panel D: Demand for Characteristics



Panel E: Supply of Characteristics



Panel F: Amount Outstanding

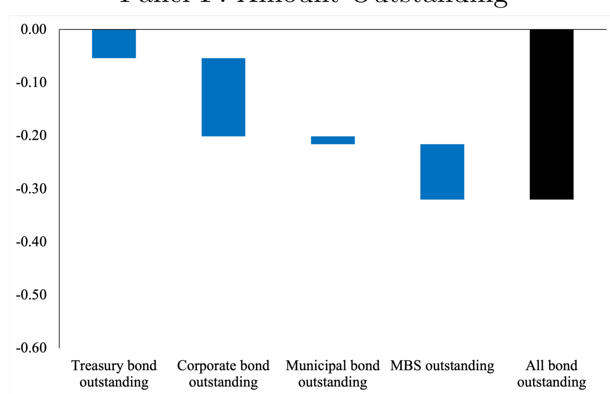


Figure 8: **10-Year BBB Spread Sensitivity to Monetary Policy.** These figures show contributions from different channels to the monetary sensitivity of 10-year BBB spread (over 10-year Treasury yield) according to our method described in Section 5.

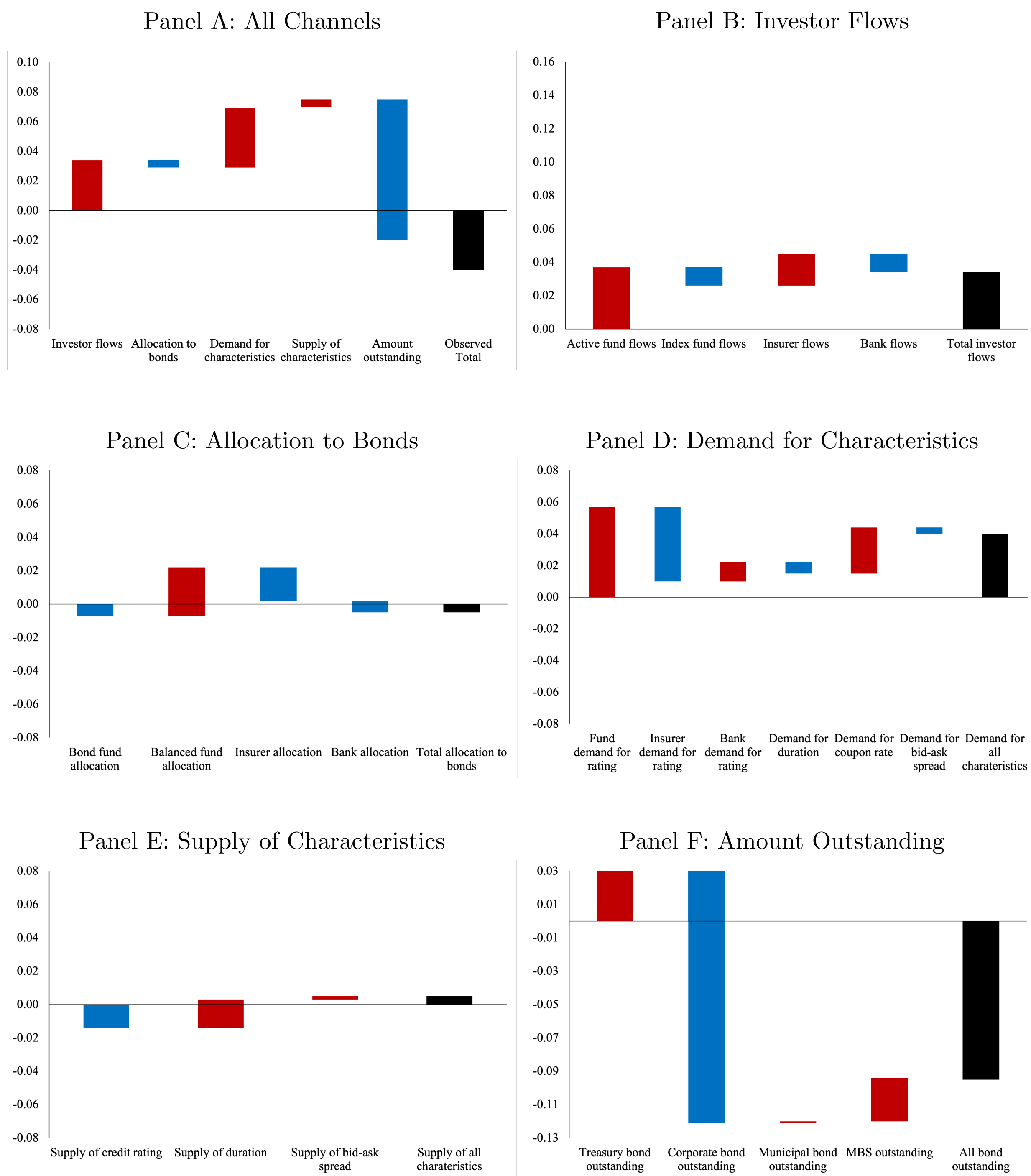
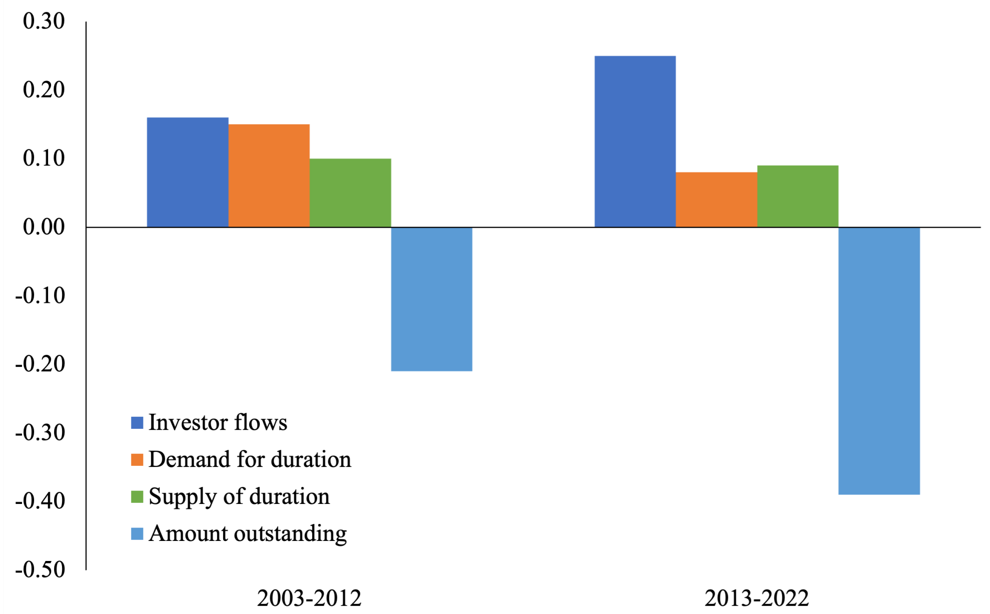


Figure 9: **The Evolution of Monetary Transmission over Time.** The figures show our estimated contributions from the top channels to monetary sensitivity of 10-year term spread (Panel A) and 10-year BBB credit spread (Panel B) in 2003-2012 versus in 2013-2022 according to our method described in Section 5.

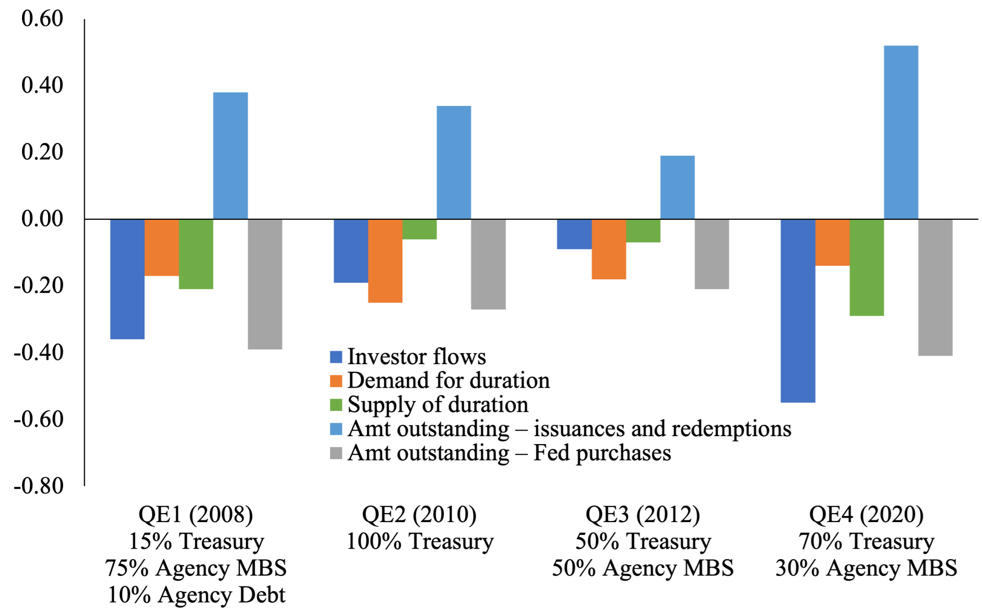
Panel A: 10-Year Term Spread



Panel B: 10-Year BBB Spread

Figure 10: **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

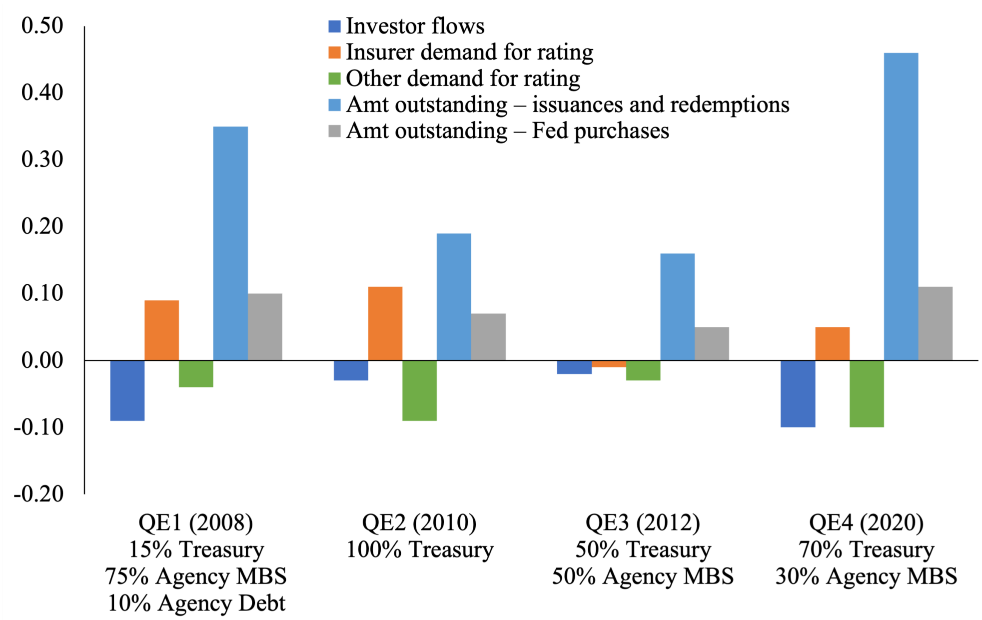


Table 1: **Bond Portfolio Summary Statistics.** This table shows summary statistics of our bond portfolios. Bond portfolios are formed by grouping together bonds that have similar credit rating, coupon rate, time to maturity and callability, separately for Treasury bonds, corporate bonds, municipal bonds, 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: **Estimated Own- and Cross-Price Elasticities.** These tables display estimated own- and cross- price elasticities according to Equation 11. 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 3: **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 4: **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

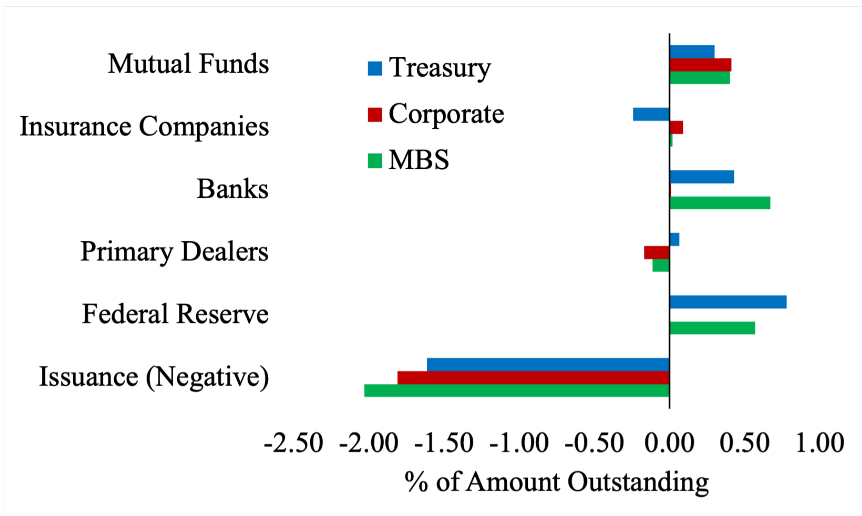
Appendix A Additional Figures

Figure A1: **Portfolio Changes to -100bps 1Y Treasury Rate, Year over Year.** These figures report $-\beta$ from the following quarterly time series regression:

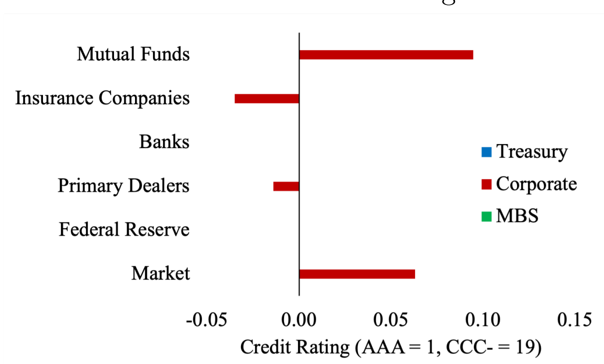
$$\Delta q_{t-4,t} = \alpha + \beta \Delta r^{1Y}_{t-4,t} + \epsilon_{t-4,t}$$

where Δq denotes change in holding amount (relative to amount outstanding), change in portfolio credit rating (AAA = 1, CCC- = 19), or change in portfolio duration (year), and r^{1Y} denotes 1Y Treasury rate (%). The regression is run separately for each investor group and for each bond class.

Panel A: Amount



Panel B: Credit Rating



Panel C: Duration

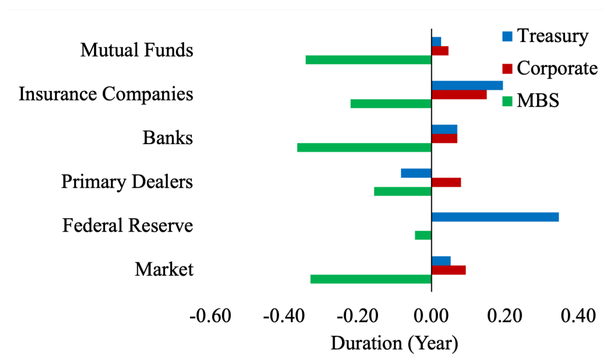
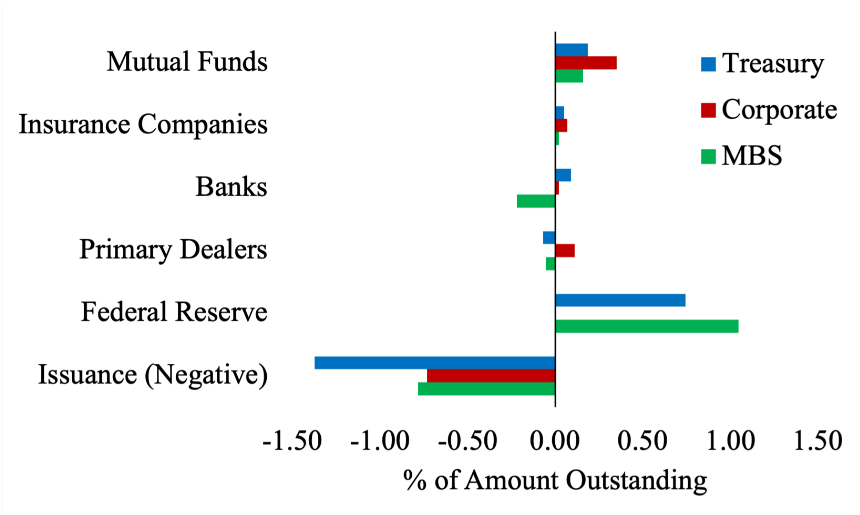


Figure A2: **Portfolio Changes to 1% Net Purchases by the Fed, Year over Year.** These figures report β from the following quarterly time series regression:

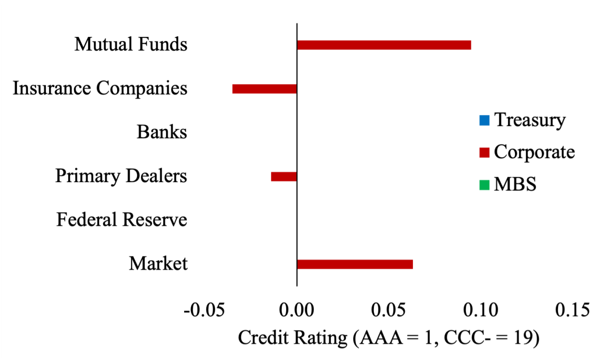
$$\Delta q_{t-4,t} = \alpha + \beta \Delta q^{FED}_{t-4,t} + \epsilon_{t-4,t}$$

where Δq denotes change in holding amount (relative to total amount outstanding), change in portfolio credit rating (AAA = 1, CCC- = 19), or change in portfolio duration (year), and q^{FED} denotes net purchases of Treasury bonds and MBS by the Federal Reserve (relative to total Treasury and MBS outstanding). The regression is run separately for each investor group and for each bond class.

Panel A: Amount



Panel B: Credit Rating



Panel C: Duration

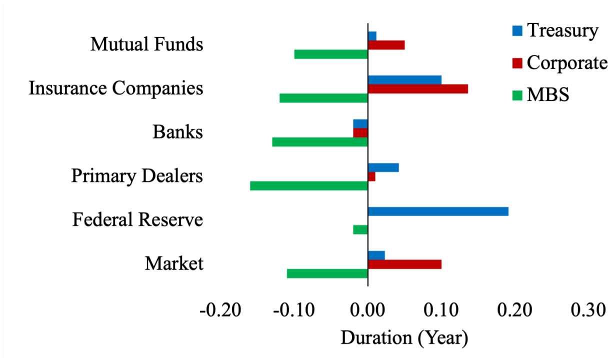
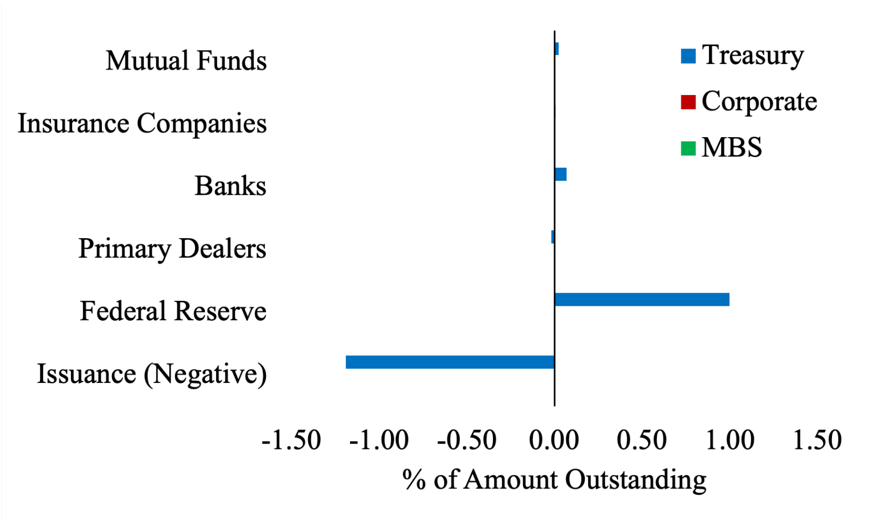


Figure A3: **Portfolio Changes with Time Fixed Effects, Year over Year.** These figures report β from the following panel regression with maturity bucket-quarter observations:

$$\Delta q_{m,t-4,t} = \alpha + \beta \Delta q_{m,t-4,t}^{FED/PASSIVE} + \gamma_m + \gamma_t + \epsilon_{m,t-4,t}$$

where Δq denotes net purchases (relative to amount outstanding), q^{FED} denotes net purchases by the Federal Reserve or by passive mutual funds (relative to amount outstanding), and γ_m and γ_t denote maturity bucket and time fixed effects. The regression is run separately for each investor group and for each bond class.

Panel A: Fed Purchase



Panel B: Passive Purchase

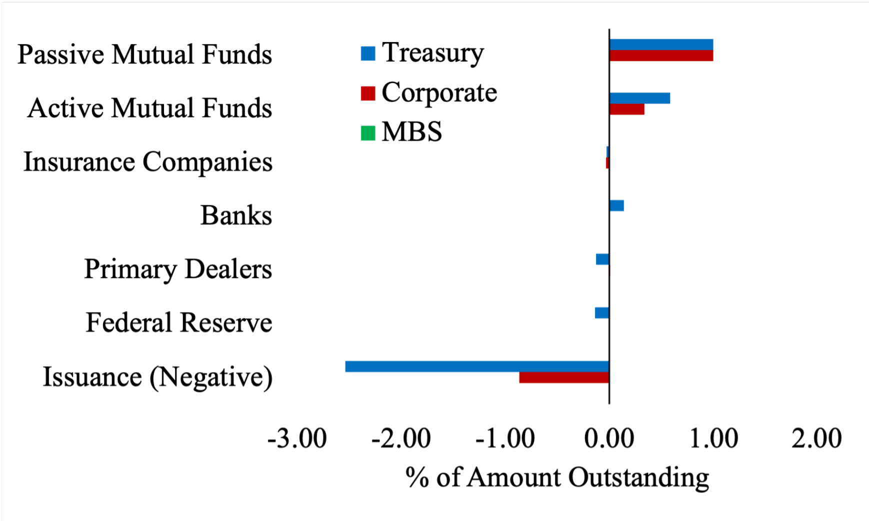


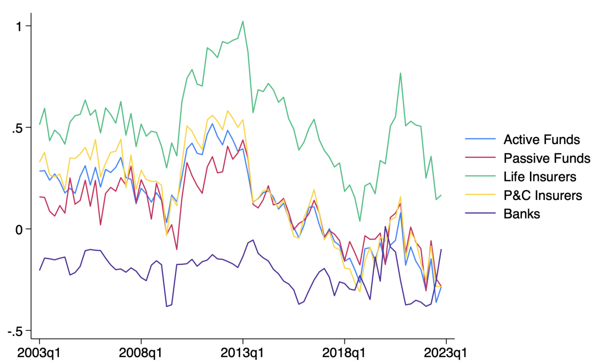
Figure A4: **Estimated Demand Coefficients.** These figures display estimated demand coefficients (μ, Σ) on credit rating (from 0 AAA to 6 CCC), duration (year), coupon rate (%), and bid-ask spread (%), using the procedures described in Section 4.4.

Panel A: Mean Coefficient μ

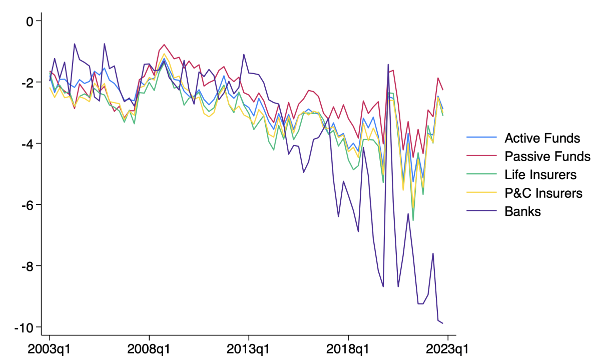
Credit Rating

Duration

Coupon Rate

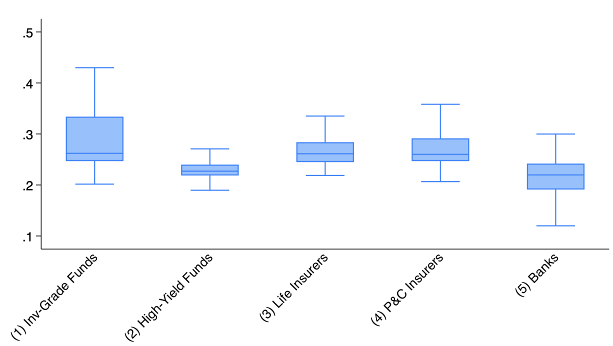


Bid-Ask Spread



Panel B: Variation in Coefficient Σ

Credit Rating



Duration

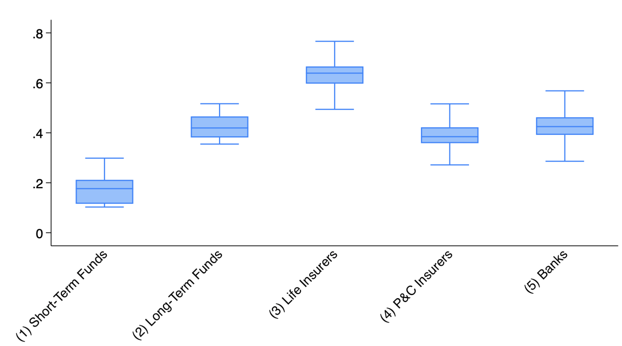
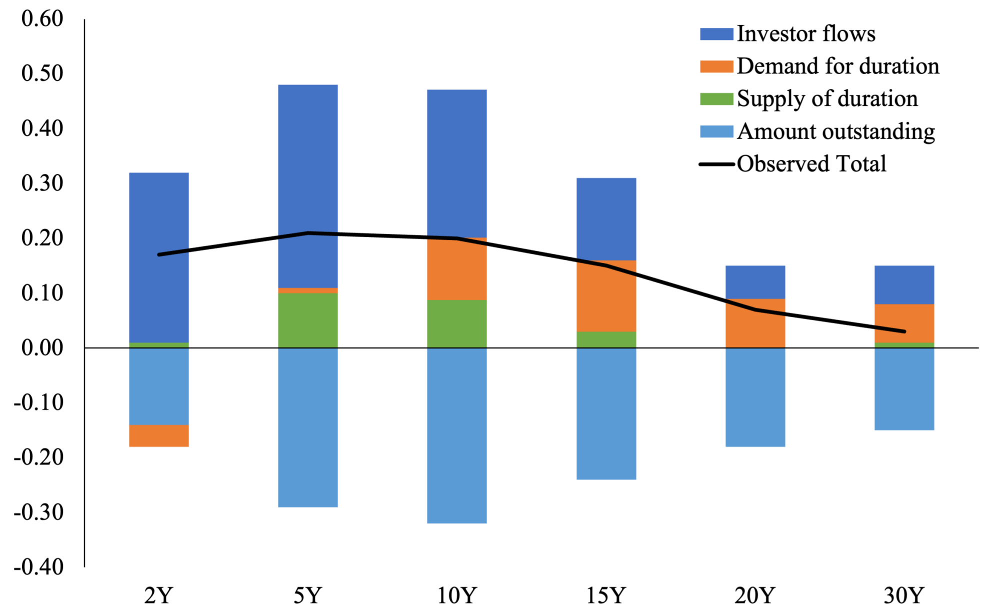


Figure A5: **Monetary Transmission across Term Structure and Credit Spectrum.** Panel A (Panel B) shows contributions from the top channels to the monetary sensitivity of 10-year term spread across different duration (5-year credit spread across different credit ratings), based on our method described in Section 5.

Panel A: Term Structure



Panel B: Credit Spectrum

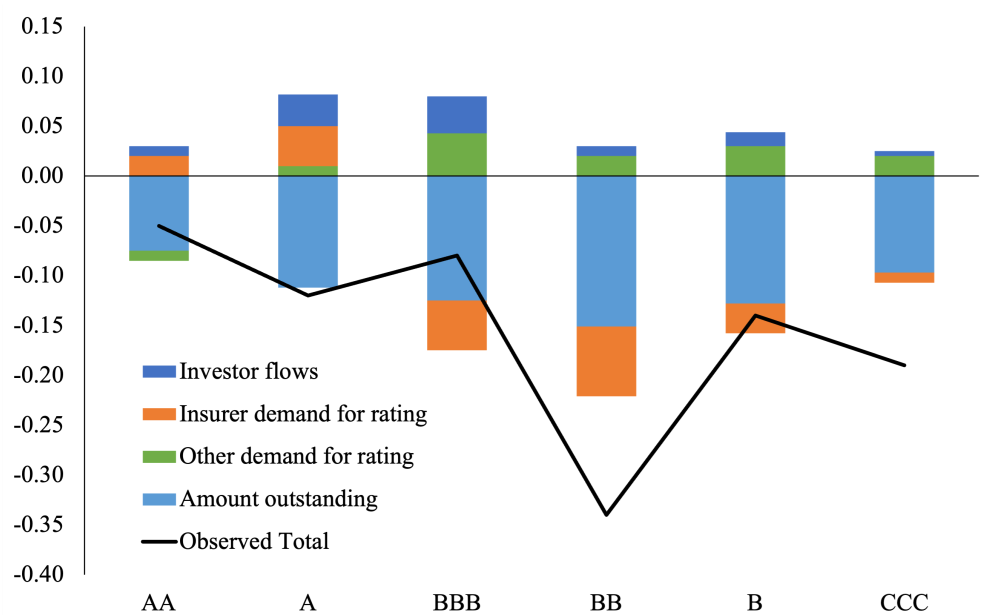
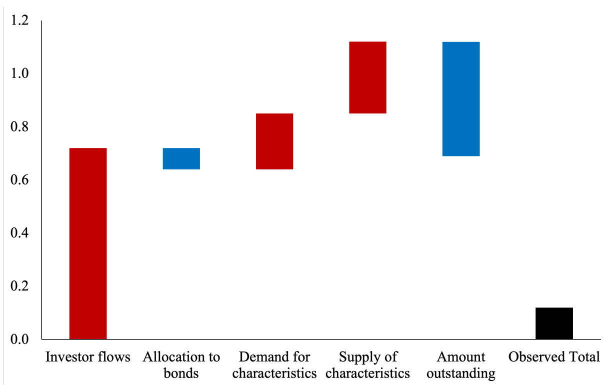
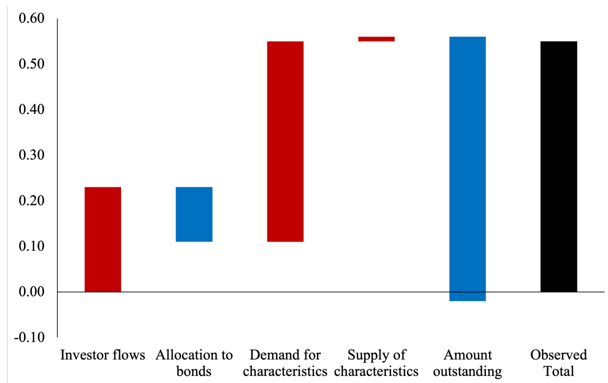


Figure A6: **Robustness with Monetary Policy Shocks.** The figures show decomposition of yield sensitivity with respect to monetary policy shocks constructed by Bu et al. (2021). Panel A (Panel B) shows the decomposition of the monetary sensitivity 10-year term spread (10-year BBB spread). Panel C (Panel D) shows the decomposition of the monetary sensitivity of term spread across duration (credit spread across ratings).

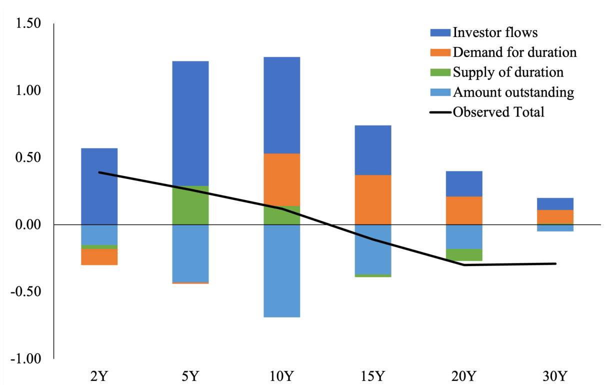
Panel A: 10-Year Term Spread



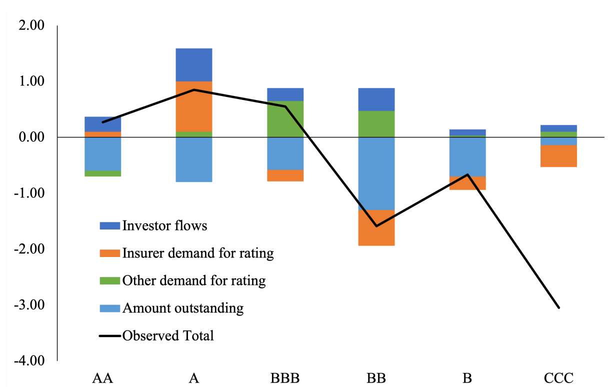
Panel B: 10-Year BBB Spread



Panel C: Term Structure



Panel D: Credit Spectrum



Appendix B Additional Tables

Table A1: **Flow-Induced Trading as Yield Instrument.** The tables examine the relevance of flow-induced trading (FIT, Equation 10) 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 A2: **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 A3: **Estimated Own- and Cross-Price Elasticities, Fixed Coefficient Logit Model.** These tables are the counterparts of Table 2 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 A4: **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 10), 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