Dissecting Bond Market Transmission of Monetary Policy*

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Abstract

This paper evaluates the bond market transmission of monetary policy using a demand system framework and granular data on portfolio holdings. We identify key transmission channels, including mutual fund flows, bank deposit flows, and duration demand changes, which significantly impact bond yield sensitivity to monetary policy. Our comprehensive dataset, covering Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities, allows for a detailed analysis of these channels. Findings reveal that new issuances absorb a large portion of yield changes, highlighting the competition between public and private bond issuances and the necessity of considering real sector responses in monetary policy assessments.

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1 Introduction

Central banks usually control short-term interest rates directly. However, they are more concerned with long-term rates, as these are closely tied to the borrowing costs for businesses and consumers. This, in turn, affects investment decisions, consumer spending, and overall economic activity. Understanding how central bank actions on short-term rates impact long-term rates is essential, as it shows how these actions influence the broader economy.

Despite its importance, the transmission mechanism of monetary policy through the bond market is not well understood. A longstanding puzzle is that long-term government bond yields are, on average, overly sensitive to short rates, relative to the predictions of standard models (Shiller, 1979; Hanson and Stein, 2015; Brooks et al., 2018; Hanson et al., 2021). Several theories have been proposed to explain this puzzle.

First, the "reaching-for-yield" channel suggests that institutional investors take on more risks when interest rates are low, shifting from cash to riskier bonds, which lowers yields. Second, the asset duration hedging channel indicates that falling rates shorten mortgage durations, leading investors to buy longer-term bonds, thereby reducing yields. The liability duration hedging channel posits that lower rates extend the durations of annuities and pensions, prompting insurers and pension funds to invest in longer-term bonds. Additionally, mutual fund flows, driven by expectations of further rate drops or high returns, could also push yields downward. Finally, QE-induced changes in the supply of government bonds may shift demand to corporate bonds, raising their prices and issuances. Although there is evidence for these channels, their relative quantitative importance remains unclear.

In this paper, we address the following questions: Which channels are important? How important are they? What determines their relative importance? We explore these questions using the demand system of Koijen and Yogo (2019), applied to the U.S. bond market. The key idea is to model bond market instruments as a vector of characteristics, such as

yield, risk, and duration. Major investors in the bond markets, such as mutual funds, banks, and insurance companies, exhibit heterogeneous and potentially time-varying preferences for these characteristics due to different institutional constraints. Policymakers set the yields of short-term bonds through conventional monetary policy and influence the supply of long-term bonds through unconventional policies like quantitative easing. The various channels proposed in the literature can be evaluated by counterfactually changing the relevant institutional preferences.

We assemble a large, granular dataset of the U.S. bond market, covering four major classes of U.S. dollar-denominated bonds: Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities (MBS). These classes represent nearly the entire bond market, with tightly linked yields that should be jointly determined in equilibrium. This diverse sample allows us to capture various transmission channels, such as MBS convexity, that might otherwise be overlooked. One of our key contributions is the assembly of such a comprehensive dataset, which is essential for our demand system analysis and understanding of the bond market's transmission mechanisms.

We find that mutual fund flows, bank deposit flows, and duration demand changes are quantitatively important, contributing to 29%, 13%, and 23% of the total sensitivity of the 10-year Treasury yield to the 1-year Treasury yield, respectively. These same factors contribute 56%, 18%, and 15% to the sensitivity of the 10-year BBB yield to the 1-year Treasury yield, respectively, while changes in credit risk appetite contribute little to the monetary sensitivity of either Treasury yield or corporate yield.

We also find that new issuances by governments and corporations absorb a large portion of yield movements. This highlights the need to account for responses by the real sector, rather than just observed interest rates themselves, when evaluating monetary policy transmission. Interestingly, the results imply a competition between public vs private bond issuances, where more Treasury issuances may crowd out issuances by corporations.

This paper relates to the large literature on bond market transmission of monetary policy. Section 2 describes in detail the channels that have been proposed in the existing literature. This paper also relates to the growing literature that employs asset demand systems and granular portfolio holdings to understand asset pricing (Koijen and Yogo, 2019, 2020; Koijen et al., 2021; Bretscher et al., 2021; Darmouni et al., 2024). Our main contribution is an empirical decomposition of long-term bond yield sensitivity to monetary policy. In order to do this, we rely on a new comprehensive dataset that covers the near universe of all U.S. bonds and a new framework with random demand coefficients. These innovations allow us to capture channels such as mortgage duration hedging (Hanson, 2014) that would have been silent in a framework with only straight bonds.

2 Channels of Monetary Transmission to Bond Yields

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

Firstly, there is a large literature on institutional reaching for yield – institutional investors take more risks at lower interest rates (e.g. Choi and Kronlund, 2018; Anadu et al., 2019). As a result, monetary easing can lead to lower bond yields because investors tilt their portfolios away from cash and towards bonds, especially those with lower ratings, longer duration and worse liquidity. On the other hand, Li (2024) shows that insurers may instead decrease credit risk-taking in response to monetary easing, as a result of regulatory capital constraint.

Secondly, a growing literature shows that long-term bond yields are affected by duration hedging. Hanson (2014) and Hanson et al. (2021) show that mortgages have large negative convexity and therefore large swings in their effective duration in response to interest rate changes. When rates fall, mortgage duration decrease, and mortgage investors tilt towards longer-term bonds to maintain overall portfolio duration, causing lower bond yields. We call this channel asset duration hedging.

Long-term bond yields are also affected by duration hedging activities on the liability side. Domanski et al. (2017) show that annuities and pension liabilities have large positive convexity – when rates fall, the duration of annuities and pension liabilities increases. Ozdagli and Wang (2020) show that this induces insurers and pension funds to tilt their portfolios more towards longer-term bonds to lengthen duration on the asset side. Greenwood and Vissing-Jorgensen (2018) and Jansen (2023) show evidence on the impact of pension funds and life insurers on long-term bond yields.

Thirdly, there is growing evidence that extrapolative mutual fund flows contribute to the monetary sensitivity of long-term bond yields (Brooks et al., 2018; Hanson et al., 2021; Fang, 2023; Darmouni et al., 2024). When the Fed lower rates and bonds realize large returns, mutual fund investors invest more into bond funds in the expectation that rate drops or high returns will persist, and therefore these flows further push down bond yields.

Lastly, in terms of unconventional monetary policy, changes in the supply of government bonds may affect demand on other bonds, through the portfolio rebalancing channel. Selgrad (2024) shows that investors with larger exposure to QE purchases switch more to corporate bonds, leading to higher prices and more issuances of corporate bonds.

3 Data

We assemble a large granular dataset of the U.S. bond market. We cover four classes of U.S. dollar-denominated bonds: Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities (MBS).[1] These four bond classes represent virtually the entire bond market. Their yields are tightly linked and should be jointly determined in equilibrium. Having a diverse sample 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 when deciding the universe of bonds (e.g. why we exclude foreign bonds) is the availability of data on amount outstanding, which is required to derive equilibrium through market clearing.

Data on Treasury bonds come from CRSP U.S. Treasury Database.[2] Data on agency debt and corporate bonds come from Mergent FISD (for characteristics) and TRACE (for pricing).[3] Data on municipal bonds come from Mergent Municipal (for characteristics) and MSRB (for pricing). Data on agency MBS come from Refinitiv.[4] These four classes together virtually cover the entire U.S. bond market. We do not include foreign-currency bonds, loans, or private (non-144A) bonds because of lack of data on amount outstanding, trading, or other key characteristics that are essential for our demand system analysis.

The core of our analysis relies on a comprehensive dataset of bond holdings. We focus on four types of investors for which we have granular holdings data: mutual funds and ETFs (both domestic and foreign), insurance companies, banks, and the Federal Reserve. Data on mutual fund holdings come from CRSP (for U.S.-domiciled funds after 2010) and

[1] We treat agency debt (direct obligations) as corporate bonds with high credit ratings. Results are similar if we treat them as Treasury bonds or stand-alone bond class.

[2] We focus on Treasury notes and Treasury bonds. Treasury bills are treated as cash. We exclude strips and flower bonds.

[3] We include private bonds under Rule 144A or Reg S. We exclude convertible bonds, equity-linked bonds, preferred securities and puttable bonds.

[4] We focus on agency pools and TBAs. We exclude collateralized mortgage obligations.

Morningstar (pre-2010 U.S. funds and foreign-domiciled funds). Data on insurance company holdings come from NAIC statutory filings (Schedule D). Data on bank holdings come from call reports. Data on the Fed holdings come from SOMA (for Treasury and agency securities) and SMCCF (for corporate bonds).

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

4 A Demand System of Bonds

We build a demand system of bonds in the spirit of Koijen and Yogo (2019). The demand system framework is particularly suited to analyze bonds. First, many bond investors have direct demand for bond characteristics – for example, life insurance companies prefer bonds of certain duration that match with their liabilities. Second, demand is heterogeneous – for example, a short-term bond mutual fund can have drastically different demand for duration than a life insurer. Lastly, many bond investors buy-and-hold and are therefore price inelastic, so quantity changes (e.g. fund flows) can have large price impacts.

One key innovation that we are in the process of making relative to Koijen and Yogo (2019) is to incorporate random coefficients that accommodate flexible portfolio substitution patterns. This is important to capture some monetary policy transmission channels that would be mechanically silent under the original framework. For example, suppose there are only two types of bonds, short-term vs long-term, and an investor invests them 50-50. The original framework implies that investors do not care about duration, so increase in supply of long-term bonds relative to short-term bonds (e.g. due to MBS duration changes) would not affect

their relative prices. Random coefficients allow for relative inelasticity across ST vs LT, so demand for LT bonds is relatively fixed, and increase in LT supply would lead to large price impacts.

4.1 Environment

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, coupon, duration, callability, and bid-ask spread. We focus on yield instead of price because bonds with different coupon rates can mechanically have different prices while having the same expected returns. For callable bonds, floating-rate bonds, and other bonds without definitive cash flows, we calculate yield using simulation. We do not use spread because that assumes an exogenous Treasury yield curve, which we try to endogenize.

Instead of individual bonds, we focus on bond portfolios. This is because we are primarily interested in aggregate bond yields (e.g. the yields on BBB-rated 5Y bonds), and papers have shown that investor elasticities vary at different aggregation levels (Li and Lin, 2024; Chaudhary et al., 2022). In our baseline framework, bonds are grouped by 4 classes (Treasury, corporate, municipal and MBS), 6 rating groups (AA or higher, A, BBB, BB, B, CCC or lower), 11 coupon groups (0%, 1%, ..., 10% or higher) 29 maturity groups (2 years or less, ..., 30 years or longer), and callability (yes vs no).[5] We focus on this level of portfolio aggregation to strike a balance between having a big enough cross section to estimate investor demand and capturing investor elasticities at the aggregate level.

We treat cash and cash equivalents as the base bond ($n = 0$).[6] Cash carries the one-year Treasury yield that is directly controlled by the Fed (and not through market clearing). Cash

[5] We group by coupon and maturity instead of just duration. Daniel et al. (2021) shows that coupon can directly affect investor demand.

[6] This includes deposits, money market instruments, Treasury bills, and Treasury bonds with less than one year to maturity.

has AAA rating, 0% coupon, and 0 year to maturity, not callable, and 0% bid-ask spread.

Other bonds (e.g. foreign bonds) and other assets (e.g. equities) are not modelled in our framework. Instead, we will treat investors' allocation between U.S. bonds and other assets as an exogenous parameter and study the effect of changing this parameter for equilibrium bond yields.

Investors are indexed by $i = 1, ..., I$. We focus on four classes of institutional bond investors for which we have detailed data on portfolio holdings: mutual funds (both domestic and foreign), 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 based on amount outstanding.

4.2 Demand

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

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

The portfolio weight of a bond n depends on its yield $y_t(n)$, its characteristics $\boldsymbol{x}_t(n)$, and its latent demand $\epsilon_{i,t}(n)$ relative to other bonds. Latent demand for cash $\epsilon_{i,t}(0)$ is normalized to zero. Notice how portfolio weight of a bond $w(n)$ depends on not only its own yield $y(n)$ but also yields of all other bonds $\{y(m)\}$

This original form of demand specification implies a restrictive form of portfolio substitution pattern. Specifically, we can derive yield elasticity of portfolio weight as:

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

This means that, when the yield of one bond changes, changes to other bonds' portfolio weights depend entirely on existing portfolio weights. However, in reality, we should expect changes to be larger for other bonds with similar characteristics (Chaudhary et al., 2022).

To allow for more flexible substitution pattern, we follow Berry et al (1994) and introduce random coefficients of demand: $\boldsymbol{\beta}_{i,t} \sim N(\mu_{i,t}, \Sigma_{i,t})$. Portfolio weights in Equation 1 then become an integral over the distribution of $\boldsymbol{\beta}$:

$$w_{i,t}(n) = \int \frac{\exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\}}{1 + \sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\}} dP(\boldsymbol{\beta}_{i,t}) \tag{2}$$

This modeling technique allows demand across bonds to be correlated based on characteristics, with the correlation controlled by Σ. The elasticity of portfolio weight to yield is then:

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

with conditional portfolio weight $\tilde{w}(n) = \exp\{\alpha_{i,t} y_t(n) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(n) + \epsilon_{i,t}(n)\} / (1 + \sum_m \exp\{\alpha_{i,t} y_t(m) + \boldsymbol{\beta}'_{i,t} \boldsymbol{x}_t(m) + \epsilon_{i,t}(m)\})$. We can see that the cross elasticity now depends on the covariance of the existing portfolio weights of the two bonds, where the probability space is over the random coefficients. Therefore, if two bonds have similar characteristics, their portfolio weights will have higher covariance, and their substitution will be more closely linked.

This flexible substitution pattern is important to capture portfolio substitution channels such as Hanson (2014). Suppose there are three bonds, one short-term and two long-term that are otherwise identical. Suppose that demand for duration is on average zero, so portfolio weight is 50% short-term and 50% long-term. In the case of fixed coefficient, 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, in the case of random coefficients, β has both high and low values, and,

when β is high, a decrease in the price of one long-term bond will significantly increase the portfolio weight of the other long-term bond, while the portfolio weight of short-term bond is small to begin with and does not change much.

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 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, coupon, duration, bid-ask spread are within one standard deviation of the target bond's.

Our second set of instruments are flow-induced trading by other investors. 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. Other investor flows, after residualized against common factors, are therefore plausibly exogenous shocks to yields for the target investor. Formally, mutual fund i's idiosyncratic flows at time t are given by residuals from a principal component regression:

$$InvestorFlow_{i,t} = a + \sum_k b_k PC_{k,t} + \tilde{InvestorFlow}_{i,t}$$

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:

$$\tilde{BondFlow}_t(n) = \sum_i \frac{AmountHeld_{i,t}(n)}{AmountOutstanding_t(n)} \tilde{InvestorFlow}_{i,t} \tag{3}$$

Figure 3 confirms that flow-induced trading has large effects on bond yields. In other words,

the first stage is strong. Similar to characteristics, we include both the bond's own flow-induced trading and its peers' flow-induced trading.

4.4 Estimation

We estimate $\theta_{i,t} = (\alpha_{i,t}, \mu_{i,t}, \Sigma_{i,t})$ for each investor at each time, using a procedure similar to Berry et al. (1995). Given a guess of θ, we can solve the system of nonlinear equations for the vector δ which equates observed and predicted portfolio weights $w(n) = w(n \mid \delta, \theta)$, which simplify to $\delta = \log(w(n)) - \log(w(0))$ for fixed coefficients specification. We can then perform a linear IV GMM regression of the form:

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

The moments are constructed by interacting the predicted residuals $\hat{\epsilon}(n)$ with instruments $z(n)$ to form:

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

The GMM problem is:

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

where $g(\theta)$ are moments constructed above and W is the weighting matrix.

One practical challenge is that some investors hold a small number of bonds, which make it difficult to produce robust estimation. We deem 100 or less non-zero holdings of bond portfolios as non-robust. Some investors also do not report cash holdings. For these investors, we pool them together by groups (country of domicile x Morningstar Category x AUM decile for funds, filer type x AUM decile for insurers, headquarter state x AUM decile for banks).

Figure **??** shows estimated demand for different investor groups, transformed to have a more

straightforward interpretation of yield semi-elasticity or price elasticity. At the micro level across bonds within a bond class, the weighted average yield semi-elasticity (price elasticity) is 0.5 (10), meaning that if a bond has 1 bps higher yield (1% lower price), its portfolio weight is predicted to increase by 0.5% (10%). The flip side of this is that 1% flow to a bond predicts 2 bps increase in yield (0.1% increase in price).

There is substantial variation in elasticities across investors. Bond funds have the highest micro elasticities but the lowest macro elasticities. This is consistent with the fact that, relative to other investors, bond funds actively monitor the bond market and act aggressively on arbitrage opportunities across very similar bonds. However, they are constrained by investment mandates on rating and duration, which prevent them from acting aggressively on arbitrage opportunities across bond classes.

In contrast, mixed funds have the lowest micro elasticities but the highest macro elasticities. This is consistent with the fact that mixed funds are relatively less constrained on allocating across asset classes, but they are not as attentive to arbitrage opportunities within a specific asset class as other more focused investors.

Insurers' elasticities are between those of bond funds and those of mixed funds. Life insurers' rank of yield semi-elasticities appear to be much higher than their rank of price-elasticities. This is because life insurers hold bonds that have much longer duration than bonds held by other investors. For the same 1 bps change in yield, life insurers' bonds have much bigger price change, which dampens the estimate of price elasticities.

4.5 Equilibrium

In equilibrium, market clears, meaning that the demand by investors equals market supply for each bond. Given monetary policy rate (one-year Treasury yield, y^{T1Y}), bond outstanding

($\{S\}$), bond characteristics $\boldsymbol{x}$, investor AUM A, investor allocation to bonds ξ, investor demand coefficients $\boldsymbol{\beta}$, investor latent demand ϵ, and equilibrium bond yields y, the market clearing condition is:

$$S_t(n)e^{c(n)-y_t(n)T} = \sum_{i=1}^{I} A_{i,t}\xi_{i,t}w_{i,t}(n) \tag{4}$$

where left-hand side is market value of bond outstanding, and right-hand side is total demand across all investors. Market clearing applies to all bonds except for one-year Treasuries, where the supply is controlled by the Fed.

If we treat bond yields y as the only exogenous variable, we can solve for equilibrium bond yields as a implicit function:

$$y(y^{T1Y}, S, \boldsymbol{x}, A, \xi, \boldsymbol{\beta}, \epsilon)$$

This implies that The demand system framework allows us to derive counterfactual bond yields for any given values of environment variables. However, since we treat parameter values (e.g. investor AUM) as given, the resulting market-clearing bond yields are only partial equilibrium. In reality, these parameter values are endogenous – indeed, as discussed in 2, we think all these parameter values are affected by monetary policy rates. Nonetheless, these partial-equilibrium bond yields allow us to isolate the effect coming from a particular parameter, as we discuss further below.

The numerical method to derive counterfactual bond yields is as follows. First, 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 $\{\boldsymbol{\beta}(n)\}$, and latent demand $\{\epsilon(n)\}$, we can calculate the relative portfolio weights $\frac{w_{i,t}(n)}{w_{i,t}(0)}$. Since portfolio weights sum to one ($\sum w_{i,t}(n) = 1$), we can derive actual portfolio weights $w_{i,t}(n)$. From AUM A, allocation to bonds ξ, and portfolio weights $w(n)$, we can derive the total investor demand for bond n as $\sum A_{i,t}\xi_{i,t}w_{i,t}(n)$, the right hand side of equation (4). 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.

Following Koijen et al (2023), we allow investor AUM to depend on bond yields. TBD

4.6 Decomposition

Using the method above, we can perform a decomposition of bond yield changes into orthogonal components:

$$\Delta y_t = \Delta y_t(y^{T1Y}) + \Delta y_t(S) + \Delta y_t(\boldsymbol{x}) + \Delta y_t(A) + \Delta y_t(\xi) + \Delta y_t(\boldsymbol{\beta}) + \Delta y_t(\epsilon) \tag{5}$$

where:

$$
\begin{aligned}
\Delta y_t(y^{T1Y}) &:= y(R_t, S_{t-1}, x_{t-1}, A_{t-1}, \xi_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_{t-1}) \\
&\quad - y(R_{t-1}, S_{t-1}, x_{t-1}, A_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_{t-1}) \\
\Delta y_t(A) &:= y(S_{t-1}, x_{t-1}, R_{t-1}, A_t, \boldsymbol{\beta}_t, \epsilon_t) \\
&\quad - y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_t, \epsilon_t) \\
\Delta y_t(\xi) &:= y(S_{t-1}, x_{t-1}, R_{t-1}, A_t, \boldsymbol{\beta}_t, \epsilon_t) \\
&\quad - y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_t, \epsilon_t) \\
\Delta y_t(\boldsymbol{\beta}) &:= y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_t, \epsilon_t) \\
&\quad - y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_t) \\
\Delta y_t(\boldsymbol{x}) &:= y(R_t, S_t, x_t, R_t, A_t, \boldsymbol{\beta}_t, \epsilon_t) \\
&\quad - y(x_{t-1}, S_t, R_t, A_t, \boldsymbol{\beta}_t, \epsilon_t) \\
\Delta y_t(S) &:= y(R_t, S_t, x_{t-1}, A_{t-1}, \xi_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_{t-1}) \\
&\quad - y(R_{t-1}, S_{t-1}, x_{t-1}, A_{t-1}, \xi_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_{t-1}) \\
\Delta y_t(\epsilon) &:= y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_t) \\
&\quad - y(S_{t-1}, x_{t-1}, R_{t-1}, O_{t-1}, \boldsymbol{\beta}_{t-1}, \epsilon_{t-1})
\end{aligned}
$$

Here are the specific steps we take. For each period, we start with parameter values from the last period, and the resulting market-clearing bond yields would be identical to the last period. We sequentially change the yield on one-year Treasuries, i.e. the outside bond ($\Delta(y^{T1Y})$), investor AUM ($\Delta(y^A)$), investor allocation to bonds ($\Delta(\xi)$), investor demand coefficients ($\Delta(\boldsymbol{\beta})$), bond characteristics ($\Delta(\boldsymbol{x})$), bond outstanding ($\Delta(S)$), and finally investor latent demand ($\Delta(\epsilon)$).

Conceptually, each component of the decomposition measures the contribution to yield changes from a particular channel. For example, $\Delta y_t(S)$ measures how would yields change

if only bond issuances and redemptions occur – and everything else (e.g. investor AUM) is help constant – from time $t-1$ to time t.

There are a few technical issues with this decomposition. Changes in AUM include both changes in valuation and flows. We focus on flows. In the counterfactual exercise, We will adjust an investor's AUM as of quarter-end $t-1$ by its flows from quarter-end $t-1$ to t. We also show the prices effects separately for bond fund flows and for flows to other institutional investors.

$\Delta y_t(\boldsymbol{\beta})$ captures changes in demand for all characteristics, but we are also interested in the effect of each characteristic alone. $\Delta y_t(\beta_1, \gamma_1)$ corresponds to changes in risk-taking, $\Delta y_t(\beta_2, \gamma_2)$ duration hedging, and $\Delta y_t(\beta_3, \gamma_3)$ changes in liquidity sensitivity.

In analyzing changes in characteristics, we exclude the natural shortening of maturity. We instead focus on other changes in bond characteristics (e.g. downgrade). Similarly, in analyzing changes in bond supply, we do not forbid natural redemption at maturity. Therefore, We focus on non-maturity changes in bond supply, such as new issuance and redemption call.

5 Decomposing yield sensitivity to monetary policy

We are interested in how much each channel (e.g. changes in investors' demand for duration ($\boldsymbol{\beta}$)) contributes the sensitivity of bond yields to monetary policy. We measure contribution through the following regression:

$$\Delta y_t(c) = \alpha + \beta \Delta y_t^{T1Y} + \gamma X_t + \epsilon_t \tag{6}$$

where $\Delta y_t(c)$ denotes year-over-year yield changes attributable to channel c which we derived in the previous section, y_t^{T1Y} year-over-year changes in one-year Treasury yield, and X_t control variables including contemporaneous GDP growth, inflation rate, and unemployment rate changes. We focus on year-over-year yield changes because some channels (e.g. fund flows) are at relatively low frequency. Standard errors are adjusted for serial correlation with up to four lags (Newey and West, 1994).

Figure 5 shows the results for 10-year Treasury yield (Panel A) and 10-year BBB corporate yield (Panel B). The black bar shows the total monetary sensitivity, which is directly observed (i.e. with simply Δy_t on the left-hand side of regression 6). In line with existing literature, monetary policy has a significant impact on bond yields, and 1 p.p. increase in one-year Treasury yield is associated with 0.38 p.p. increase in 10-year Treasury and 0.27 p.p. increase in 10-year BBB corporate yield. The other bars show contributions from different channels, where red (blue) indicates positive (negative) contribution.

Investor flows, in particular flows to or from mutual funds and banks, are a leading factor in enhancing the monetary sensitivity of bond yields. During monetary easing (tightening), mutual funds and banks experience large inflows (outflows) of retail capital. This creates large buying (selling) pressure on bonds. At the same time, other investors do not offset price pressure from mutual funds and banks, due to investment mandate and other forms of yield inelasticity. Mutual fund flows increase the monetary sensitivity of 10-year Treasury yield (10-year BBB corporate yield) by 0.14 (0.17) p.p., or 37% (63%) of total monetary sensitivity. For bank deposit flows the contributions are 0.05 p.p., or 13% (19%) of total monetary sensitivity.

Changes in investor demand for characteristics, in particularly duration, is another leading contributor to the monetary sensitivity of bond yields. During monetary easing (tightening), the duration of pension products such as annuities increases (decreases), which induce pension funds and insurers to buy (sell) more long-term bonds in order to minimize the du-

ration gap between assets and liabilities (Domanski et al., 2017; Ozdagli and Wang, 2020). The contribution from changes in demand for duration accounts for 0.09 (0.06) p.p. or 24% (22%) of the total monetary sensitivity of 10-year Treasury yields (10-year BBB corporate yields). Interestingly, contrary to what the reaching-for-yield channel would suggest, demand for credit risk does not play an important role, accounting for a small fraction of total monetary sensitivity.

Changes in the outstanding amount of bonds is a key force in dampening the bond yield sensitivity to monetary policy. During monetary easing (tightening), governments and firms issue more (less) new bonds or decrease (increase) redemption of old bonds (e.g. through tender offer or call options), increasing (decreasing) the total supply of bonds, which raises (lowers) equilibrium bond yields. We estimate that issuances and redemptions by governments and corporations together account for -0.17 (-0.16) p.p., or -45% (-57%) of the total monetary sensitivity of 10-year Treasury yields (10-year BBB corporate yields). Out results highlight the importance to take into consideration how issuances interact with bond yields, rather than focusing on bond yields alone, when evaluating monetary policy transmission.

Interestingly, the results reveal strong substitutability between public issuances by governments and private issuance by corporations. For example, during monetary easing, corporate issuances would have been greater without government issuances. In other words, public issuances can crowd out private issuances. We are in the process of quantifying counterfactual corporate issuance sensitivity to monetary policy without competing government issuances.

Note that the channels do not add up to the total monetary sensitivity. This is because latent demand ϵ drives a large part of the variation in bond yields, similar to the findings in Koijen and Yogo (2019).

6 Conclusion

In this paper, we utilize a demand system framework to assess how monetary policy is transmitted through the bond market. By analyzing granular data on portfolio holdings, we quantify the impact of various transmission channels on bond yield sensitivity to monetary policy. Our findings indicate that mutual fund flows, bank deposit flows, and changes in duration demand play significant roles, whereas shifts in credit risk appetite are relatively unimportant. A considerable portion of yield variations is absorbed by new issuances, with Treasury issuances partially crowding out corporate issuances.

To achieve this, we assembled an extensive dataset of the U.S. bond market, encompassing four major classes of U.S. dollar-denominated bonds: Treasury bonds, corporate bonds, municipal bonds, and mortgage-backed securities (MBS). This comprehensive dataset allows us to capture the interconnected nature of bond yields and the influence of various transmission channels, such as MBS convexity, which might otherwise go unnoticed. Our dataset is crucial for understanding the bond market's transmission mechanisms and provides a detailed view of the bonds' characteristics and holdings.

Our empirical results show that mutual fund flows, bank deposit flows, and duration demand changes account for significant portions of the sensitivity of the 10-year Treasury yield to the 1-year Treasury yield, contributing 29%, 13%, and 23%, respectively. These factors also explain 56%, 18%, and 15% of the sensitivity of the 10-year BBB yield to the 1-year Treasury yield. In contrast, changes in credit risk appetite have minimal impact on the monetary sensitivity of both Treasury and corporate yields. Furthermore, our analysis highlights the importance of new bond issuances by governments and corporations, which play a key role in absorbing yield movements and influencing overall bond market dynamics.

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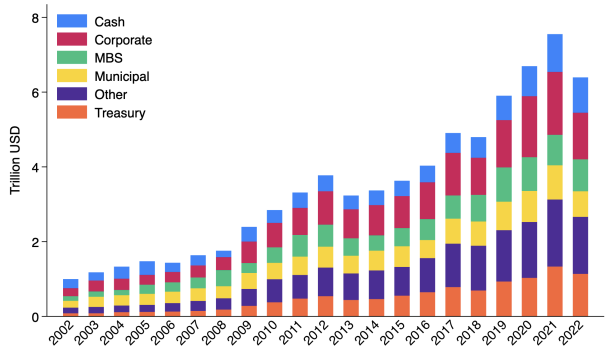
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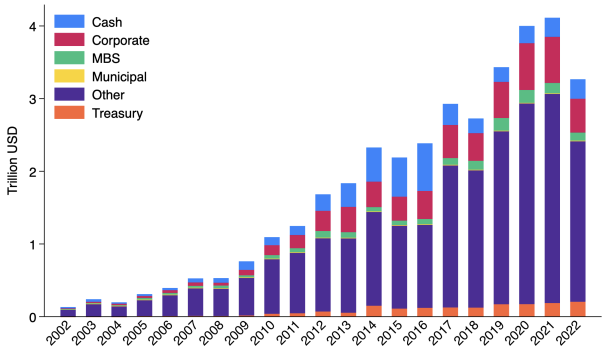
Figures

Figure 1: **Investor Holdings.**

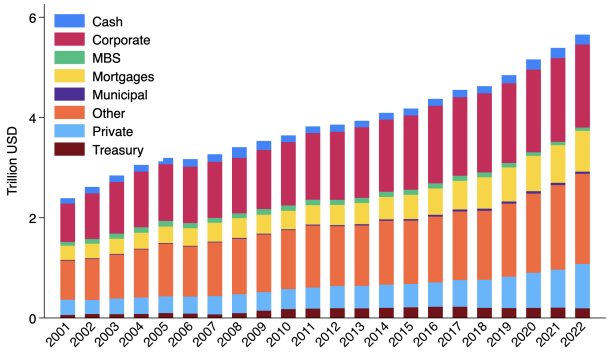
Panel A: Domestic Fund Holdings



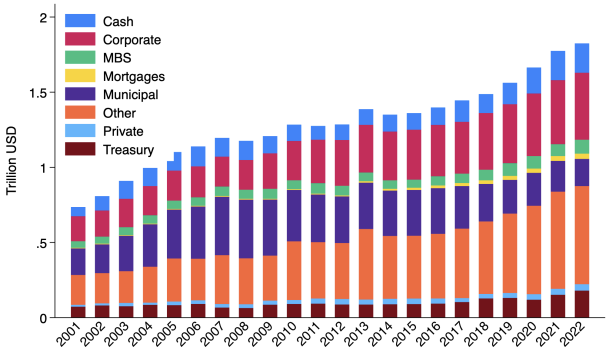
Panel B: Foreign Fund Holdings



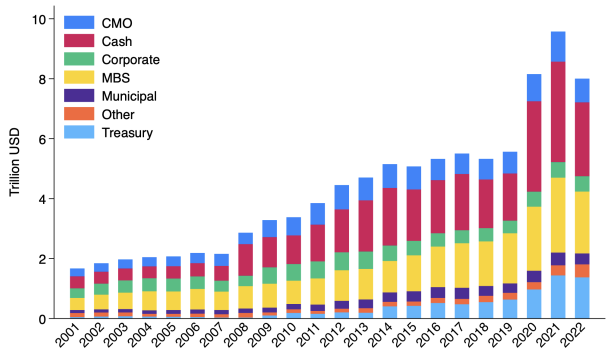
Panel C: Life Insurer Holdings



Panel D: P&C Insurer Holdings



Panel E: Bank Holdings



Panel F: Federal Reserve Holdings

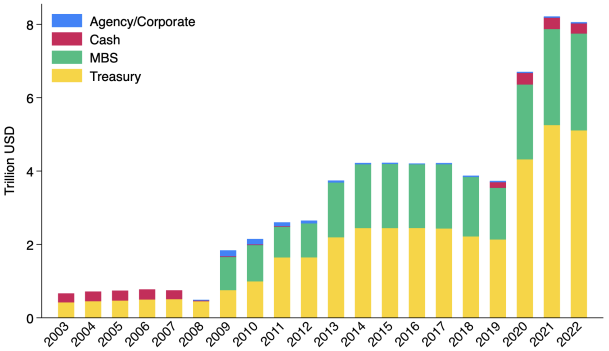
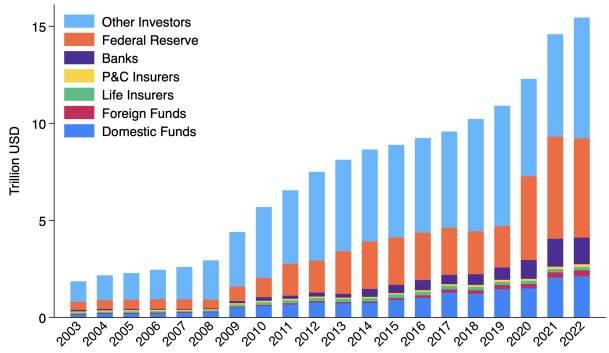
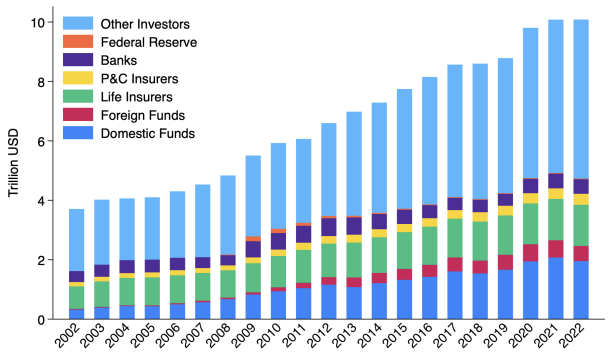


Figure 2: **Bond Ownership.** We restrict to straight USD-denominated bonds with more than one year to maturity.

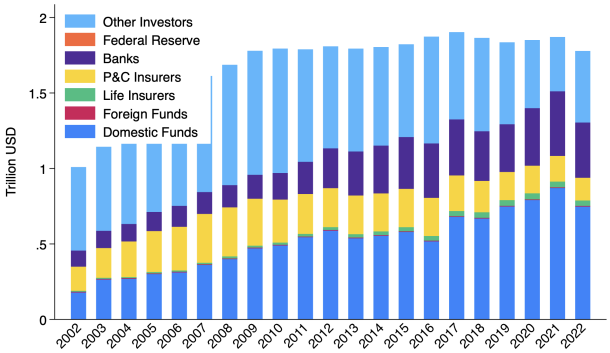
Panel A: Ownership of Treasury Bonds



Panel B: Ownership of Corporate Bonds



Panel C: Ownership of Municipal Bonds



Panel D: Ownership of MBS

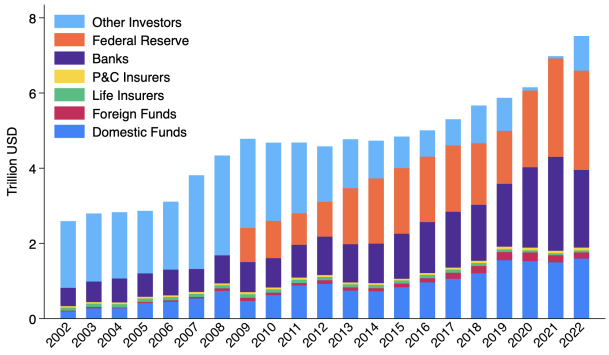


Figure 3: **Yield Impact of Flow-Induced Trading.** This figure plots the response of bonds yields to mutual fund flow-induced trading.

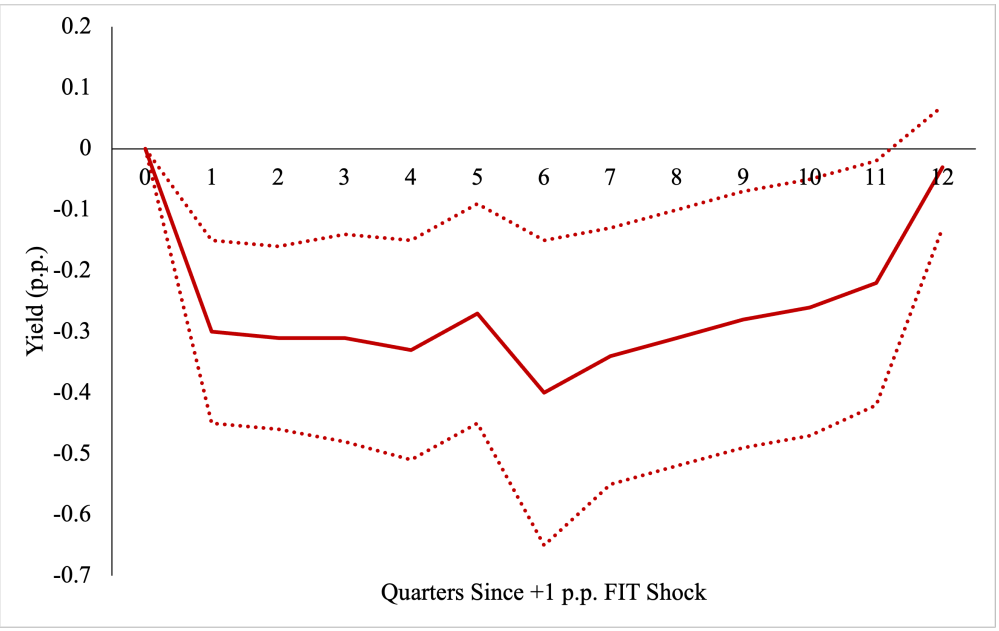
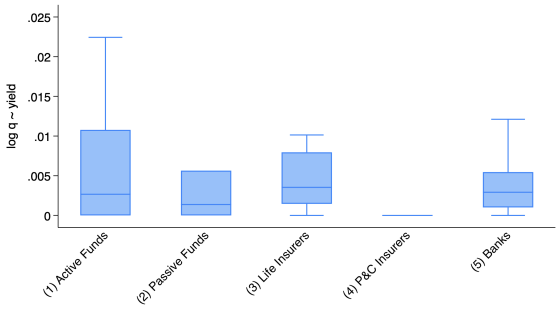
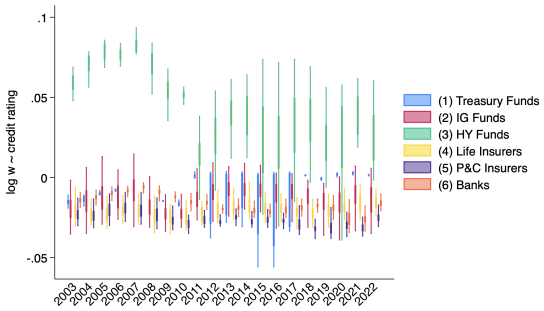


Figure 4: **Estimated Investor Demand.** For investors that hold less than 100 bond portfolios or $10 million assets under management, we group them based on type (e.g. IG funds) and AUM decile.

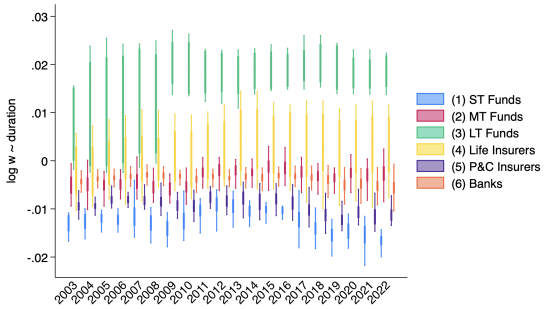
Panel A: Demand on Yield



Panel B: Demand on Rating



Panel C: Demand on Duration



Panel D: Demand on Liquidity

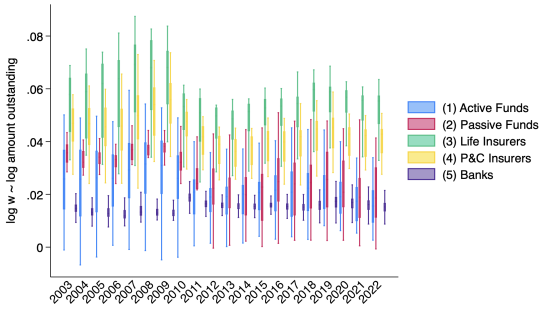
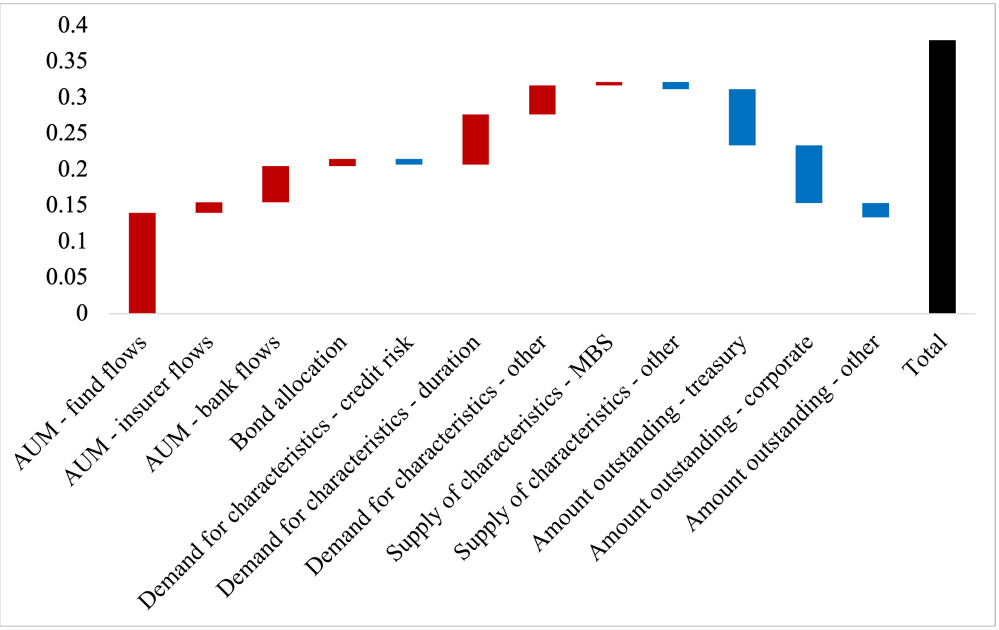


Figure 5: **Decomposition of Yield Sensitivity to Monetary Policy.** Panel A (Panel B) shows decomposition of the monetary sensitivity of 10-year Treasury yield (10-year BBB corporate yield) according to Section 5. The black bar shows the total observed yield sensitivity. The red (blue) bars show positive (negative) contributions from the different channels that we study.

Panel A: YoY Delta 10Y Treasury Yield / YoY Delta 1Y Treasury Yield



Panel B: YoY Delta 10Y BBB Yield / YoY Delta 1Y Treasury Yield

