Monetary Policy Amplification through Bond Fund Flows

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April 2023
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Abstract

I show that the secular rise of bond mutual funds and ETFs ("bond funds") amplifies the bond market transmission of monetary policy. During monetary easing (tightening) cycles, bond funds experience large inflows (outflows) of return-chasing capital and increase (decrease) their corporate bond holdings significantly more than other corporate bond investors such as insurance companies and pension funds. In the cross section of firms, higher bond fund exposure leads to higher firm sensitivity to monetary policy – during monetary easing, more-exposed firms experience larger bond returns, issue more bonds, and increase more on leverage, payout or real investment. To quantify the aggregate effect, I estimate a nested logit demand system with flexible investor elasticity both within and across asset classes. Under a partial equilibrium decomposition, bond fund flows account for a large and increasing share of the aggregate bond yield sensitivity to monetary policy.

Keywords: monetary policy, bond mutual fund, corporate bond, investor elasticity

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1 Introduction

Corporate bonds are an important asset class and an important source of firm financing. Over the past several decades, more and more corporate bonds are financed by a particular group of investors: bond mutual funds and ETFs (henceforth "bond funds"). As shown in Figure 1, the share of corporate bonds held by bond funds has experienced a secular rise from less than 2% in 1980 to over 20% in 2020.[1] This ownership shift matters because bond funds are very different from traditional corporate bond investors such as insurance companies and pension funds. In particular, this paper documents that bond funds' credit supply is much more sensitive to monetary policy than other corporate bond investors. As a result, I show that the rise of bond funds has significantly amplified the bond market transmission of monetary policy.

My results can be summarized in three parts. First, I document new stylized facts on how monetary policy affects credit supply by different corporate bond investors. During monetary easing cycles, bond funds experience large inflows of return-chasing capital and significantly scale up corporate bond holdings, much more so than other corporate bond investors such as insurance companies and pension funds. Next, I demonstrate this bond fund amplification channel of monetary policy in the cross section of firms. In response to monetary easing, firms with higher bond fund exposure experience larger bond returns, issue more bonds, and increase more on leverage, payout or real investment. Lastly, I use a structural model to quantify the aggregate effect and compare bond fund flows to other channels of monetary policy. I estimate a nested logit demand system of bonds, perform a decomposition of the aggregate bond yield sensitivity to monetary policy, and show that the contribution from bond fund flows is large and has risen substantially over time.

I start by documenting new stylized facts on the different monetary sensitivities across corporate bond investors. Net flows to bond funds are highly volatile and strongly negatively correlated with monetary policy rate changes. Due to near-proportional portfolio scaling, bond funds' corporate bond net purchases are equally sensitive to monetary policy. Using local projections with various monetary surprise measures (e.g., Gertler and Karadi, 2015) as instruments, I show that 1 p.p. decrease in the two-year Treasury rate leads to 15 p.p. cumulative increase in net flows to bond funds and their corporate bond net purchases. This high sensitivity to monetary policy is common across bond funds, persistent across time periods, and robust to various macroeconomic controls as well as different monetary surprise

[1] Section 3 gives details on the forces behind the secular rise of bond funds.

instruments. In contrast, traditional corporate bond investors such as insurance companies and pension funds have stable flows and small corporate bond net purchase sensitivity to monetary policy.

What explains bond fund flows' large sensitivity to monetary policy? I show that return chasing plays a key role. First, I perform a decomposition of aggregate bond fund flow beta and find that, among the various channels, return chasing accounts for the largest share of 45%. Next, in the cross section of bond funds, return beta (i.e. Macaulay duration) is the strongest determinant of flow beta, winning horse races against rating, income yield, and yield to maturity. Lastly, across different mutual fund classes, money market funds and loan funds have the opposite return beta and also the opposite flow beta to bond funds. My findings here are consistent with the growing evidence that mutual fund investors chase returns, whether the returns are driven by skill or risk (e.g., Ben-David et al., 2021a).

I show that this heterogeneity in monetary sensitivity across corporate bond investors is an important state variable for monetary policy transmission. I first use a reduced-form approach that exploits cross-sectional firm heterogeneity. Across similar firms, those with higher bond fund exposure are much more sensitive to monetary policy, and I provide an identification strategy to show that the effect is likely causal. To quantify the aggregate effect of bond fund flows and compare with other channels, I use a demand system approach that simultaneously accommodates price inelasticity and direct demand for bond characteristics. After estimating the demand system, I derive counterfactual market-clearing bond yields and decompose the monetary sensitivity of the aggregate corporate bond yield into bond fund flows vs other channels.

I begin with the reduced-form analysis of the cross section of firms. I first establish substantial cross-sectional firm heterogeneity in exposure to bond funds. A typical bond funds holds a small share of the market and near-proportionally scales up (down) existing holdings in response to inflows (outflows). As a result, flows to a bond fund disproportionately affect its portfolio firms, instead of all firms equally. Consequently, if a firm's bonds are held more by bond funds today, it is more exposed to common flows to bond funds tomorrow.

Indeed, I find that, during monetary easing, for firms whose bonds are held more by bond funds, their bondholders experience higher flows and make more purchases of the firms' bonds. These flow-induced trading from existing bondholders are large and stand at around 3% of the firms' bond amount outstanding, creating large buying or selling pressure on these firms' bond prices.

Across corporate bonds with the same rating, same duration and similar other characteristics, those with higher bond fund ownership have significantly higher effective duration: in response to monetary easing, their prices increase much more. Consistent with a price pressure interpretation, the higher prices are temporary and fully revert over time, confirming that the underlying driver is discount rate news rather than changes in fundamental cash flows.

The secondary market price effects spill over to firm activities in the primary market. In response to monetary easing, firms with higher bond fund ownership issue more bonds at lower yields. That price (bond yield) and quantity (bond issuance) move in the opposite direction further supports that the effect is driven by creditor supply instead of firm demand. For the average firm, the additional bond issuance proceeds are mainly used to refinance existing bonds and other debt and to repurchase equity. However, for firms that are financially constrained ex ante, the additional bond issuance proceeds translate into significant increase in real capital expenditures and R&D.

Bond fund ownership is not randomly assigned and my results are subject to endogeneity concerns. After presenting additional evidence against alternative explanations, I focus on an identification strategy that exploits within-firm variation in bond fund ownership due to plausibly exogenous bond fund growth. Specifically, I construct a shift-share instrument based on initial bond fund relationships (the share) and cumulative bond fund flows (the shift). Intuitively, if a firm has more relationships with bond funds that subsequently experience large inflows of capital – due to the secular shift from defined-benefit to defined-contribution pension plans or due to better performance, lower fees, or higher fund family market power – then the firm is going to be more exposed to bond funds over time. My main results remain largely the same, lending further credence to the causal effect of bond fund ownership on firm sensitivity to monetary policy.

The reduced-form results focus on comparing near-identical bonds or firms in the cross section. However, what is the aggregate effect of bond fund flows, especially in comparison to other channels of monetary policy? To answer this, I adapt the demand system of Koijen and Yogo (2019) to allow for different investor elasticities of substitution at the macro level (across bond classes) vs at the micro level (across individual bonds within a given class). The estimated demand system allows me to obtain counterfactual partial-equilibrium bond yields and decompose bond yield changes into various channels. The results show that bond fund flows account for 21% of the aggregate corporate bond yield sensitivity to monetary policy, more important than many other channels, such as changes in institutional risk-taking. This is due to both the large magnitude of bond fund flows in response to monetary policy and the low level of investor price elasticities particularly at the macro level (across bond classes). Moreover, bond fund flows' contribution to the aggregate yield sensitivity to monetary policy has doubled over the past 15 years, reflecting the rise of bond funds and the magnitude of their flows.

My results directly speak to the trade-offs concerning the current monetary tightening. Faced with higher inflation, central banks around the world have increased policy rates at an aggressive pace. However, many observers have cautioned for the recessionary effect of higher interest rates. My results suggest that higher interest rates may decrease bond fund flows, amplifying the increase in corporate bond yields, the decrease in corporate bond issuance, and the slowdown of real activities especially for the constrained firms. Indeed, aggregate bond fund flows have decreased by 20 p.p. since the beginning of 2022. According to my estimates, this means an additional 30 bps increase in the aggregate corporate bond yield. Moreover, according to my cross-sectional analysis, firms with higher exposure to bond fund flows are expected to face particularly severe credit crunches. These are important quantitative effects that can inform policymakers on the future course of monetary policy.

The rest of this paper is organized as follows. Section 2 summarizes this paper's contribution to the literature. Section 3 provides the relevant institutional background and describes the data used in the paper. Section 4 documents new stylized facts on the monetary sensitivity across different corporate bond investors and provide explanations. Section 5 provides reduced-form identification of bond fund amplification using the cross section of firms. Section 6 uses the demand system framework to decompose the aggregate yield sensitivity to monetary policy into various channels. Section 7 discusses broader implications. Section 8 concludes.

2 Literature

This paper contributes to four strands of literature. First, this paper contributes to the large literature on the credit channel of monetary policy. Most of the literature focuses on the bank lending channel, including Bernanke and Blinder (1988), Bernanke and Blinder (1992), Kashyap and Stein (2000), Drechsler et al. (2017), Ippolito et al. (2018), and Supera (2021). In contrast, I study one of the largest and fastest-growing nonbank corporate lenders – the bond mutual funds and ETFs. I show that this bond fund channel matters quantitatively for the transmission of monetary policy, both in the cross section of bond-issuing firms and for the aggregate bond yields. In Section 7, I discuss in detail how bond fund lending is as important – if not more – for monetary policy transmission as bank lending.

Recent work such as Darmouni et al. (2020) and Fabiani et al. (2022) also studies the bond market transmission of monetary policy. Darmouni et al. (2020) studies the European bond market and focuses on the contrast between loans and bonds (in terms of renegotiation cost). Fabiani et al. (2022) studies corporate debt maturity and focuses on overall bond market mispricing (due to investor reaching-for-yield). In contrast, the mechanism of my paper highlights the importance of heterogeneity across corporate bond investors, the secular rise of bond funds, and the inelasticity of institutional investor demand.

A growing literature explores heterogeneity in monetary policy transmission, including Ottonello and Winberry (2020) and Caglio et al. (2022). My paper highlights the important of *investor* heterogeneity – firms held more by bond funds are more sensitive to monetary policy than firms held more by other investors such as insurance companies and pension funds. Other papers have studied the effect of investor heterogeneity for corporate bond liquidity (Li and Yu, 2022), exposure to crises (Coppola, 2022), and valuation (Bretscher et al., 2021).

My approach resonates with recent papers that trace monetary policy transmission to investor flows. Drechsler et al. (2017) show that monetary policy leads to large core deposit flows in and out of the banking system, Xiao (2019) and Supera (2021) show that part of the core deposit flows come from money market funds and time deposits, and Daniel et al. (2021) show that monetary policy leads to large flows in and out of assets with high income yields. My contributions are to give a detailed analysis of flows across different corporate bond investors and across different types of mutual funds and to identify and quantify the effects of these flows on bond pricing and firm financing.

Secondly, this paper contributes to understanding the excess sensitivity of long-term bond yields to monetary policy (Shiller et al, 1983; Cochrane and Piazzesi, 2002; Gürkaynak et al, 2005; Giglio and Kelly, 2018; Kroencke et al, 2021). This surprisingly large sensitivity is one reason behind the explanatory power of the level factor, which is unobserved and commonly taken as given in term structure models. Existing explanations include changes in risk-taking (Hanson and Stein, 2015; Choi and Kronlund, 2018; Lian et al., 2018; Jiang et al., 2022), duration hedging (Hanson, 2014; Domanski et al., 2017; Hanson et al., 2021; Ozdagli and Wang, 2020), and changes in liquidity sensitivity (Drechsler et al., 2018; Lagos and Zhang, 2020; Li and Yu, 2022). Along with Brooks et al. (2018) and Hanson et al. (2021), I emphasize the role of return-chasing investor flows. My contributions are about quantification. First, I provide identification of the impact of monetary-induced bond fund flows in the cross section of corporate bond yields. Then, I use the demand system approach to decompose the aggregate bond yield sensitivity to monetary policy, and show that bond fund flow channel is quantitatively important.

Thirdly, this paper contributes to the growing literature on the role of flows in inelastic asset markets. A growing number of papers speak to bond market elasticity, including Choi et al. (2020), Falato et al. (2021b), Ma et al. (2022), Barbosa and Ozdagli (2022), and Coppola (2022).[2]. My paper shows direct estimates of bond investor elasticities, both at the macro level (across bond classes) and at the micro level (across issues within a bond class). I show that investor elasticities are low enough to make flows a quantitatively important channel of monetary transmission in the bond market. Additionally, I identify firms as an important source of arbitrage capital in reversing the impact of flows (Ma, 2019).

In modeling an inelastic market, I adopt the demand system approach (Koijen and Yogo, 2019, 2020; Koijen et al, 2021; Yu, 2021; Bretscher et al, 2022; van der Beck, 2022). Bretscher et al. (2021) estimate a demand system of corporate bonds using portfolio holdings of mutual funds, insurance companies and pension funds and focus on corporate bond liquidity. I model corporate bond demand as a nested logit framework similar to in Koijen and Yogo (2020), which allows me to capture differential macro vs micro elasticities. My main contribution is to perform a decomposition of the monetary sensitivity of aggregate corporate bond yields.

In additional to asset pricing implications, I show that investor flows have real effects. Similar papers include Bond et al. (2012), Massa et al. (2013), Zhu (2021), Friberg et al (2022), Barbosa and Ozdagli (2022), Coppola (2022), and Zhao et al. (2022). I show that flows to institutional corporate bond investor are a key channel through which firms' leverage, payout, and real investment policies respond to monetary policy.

Lastly, this paper contributes to the understanding of bond mutual funds and ETFs, which have steadily grown to one of the largest lenders to firms. A key distinction between bond funds and other corporate bond investors such as insurance companies and pension funds is their large volatile flows, and a growing literature seeks to understand what drives fluctuations in bond fund flows, such as Chen and Qin (2017), Goldstein et al. (2017), and Falato et al. (2021a). My contribution is to identify monetary policy as a key determinant of bond

[2]Studies on equity market elasticity includes Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012), and Gabaix and Koijen (2022)

fund flows both on the aggregate and in the cross section. My results also imply that part of the secular rise of bond funds can be traced to prolonged accommodative monetary policy and the secular decline in interest rates.

A few recent papers also study how monetary policy affects bond fund flows, including Feroli et al. (2014), Banegas et al. (2016), Brooks et al. (2018), Kuong and Zhang (2020), Hanson et al. (2021) and Li and Yu (2022). This paper makes the following contributions. First, I provide a rigorous documentation of the relationship between monetary policy and bond fund flows, using 30-year of time series and an instrumented local projection framework. Secondly, I show that, among the different explanations, return chasing is responsible for most of the bond fund flow sensitivity to monetary policy, both on the aggregate and in the cross section. Lastly, I show, using both reduced-form and structural approaches, how bond fund flows amplify the transmission of monetary policy to bond pricing and firm financing.

More broadly, this paper also contributes to the understanding of mutual fund flows. Most closely related to this paper are Teo and Woo (2004), Barber et al. (2016), Song (2020), and Ben-David et al. (2021a), which show that mutual fund investors chase simple returns and do not distinguish between alpha vs factor-related returns. Consistent with their results, I show that bond fund investors chase realized returns driven by monetary policy (the factor) and duration (the factor loading).

This paper also contributes to the understanding of bond funds' trading behavior. A large literature emphasizes bond funds' liquidity management, including Choi et al. (2020) and Jiang et al. (2021). I show that bond funds' liquidity management is imperfect, due to information frictions and investment mandates, and as a result investor flows still generate large price pressure.

3 Background and Data

3.1 Corporate bond investors

There is limited direct retail participation in the corporate bond market (e.g., Koijen and Yogo, 2023). Compared to stocks, corporate bonds are very illiquid and sold in large minimum quantities, making them difficult to access by retail investors. On the other hand, there is large retail participation through bond mutual funds and ETFs. According to ICI

Fact Book, over 85% of the bond mutual fund shares are owned by retail investors. I use security-level holdings and verify that there is limited ownership of bond fund shares by institutions such as insurance companies (4%) and other mutual funds (6%), as shown in see Figure A5. Most of bond funds are benchmarked against the aggregate investment-grade or high-yield bond market, holding not only corporate bonds but also Treasury securities, agency securities and foreign bonds, as shown in Figure A6.[3]

Apart from bond funds, insurance companies have traditionally been the largest corporate bond investors. They sell life or P&C insurance policies and invest the premiums in mostly fixed-income securities, due to regulatory incentives.[4] Pension funds are the third largest investors of corporate bonds. Pension funds receive periodic contributions to defined-benefit pension plans (e.g. 401k) and invest in balanced portfolios (e.g., 60 equities / 40 bonds). Banks hold significant corporate bonds as market makers, although their inventory has shrunk significantly due to post-crisis bank regulation (e.g., Wu, 2022). The other corporate bond investors include hedge funds, close-end funds, and foreign entities (e.g., foreign mutual funds).

Figure 1 shows the dynamics of corporate bond ownership over time. There is a secular rise of ownership by mutual funds and ETFs over time, from less than 2% in 1980 to over 20% in 2022. In contrast, pension funds have shrunk steadily over time. Indeed, one key driver of these dynamics is the secular switch from defined-benefit pension plans, where retirement assets are managed by institutional pension funds, to defined-contribution pension plans, where retirement assets are invested in mutual funds by retirees directly. Another important reason for the rise of bond funds is simply their wider adoption over time. As a financial innovation, bond ETFs have experienced particularly large growth not until 10 years ago.

3.2 Data sources

Data on mutual funds and ETFs are primarily from the CRSP Survivor-Bias-Free US Mutual Fund Database. The database contains comprehensive information on the universe of all publicly traded mutual funds and ETFs in the United States, including returns, total net assets, distributions, expense ratios, holdings, and etc. Data are generally available at monthly frequency from January 1990 to December 2020, except for holdings, which only be-

[3] As shown in Figure A6, most of bond funds are active and most of bond funds are categorized by Morningstar as investment-grade intermediate-term bond funds, as known as core bond funds.

[4] Under NAIC statutory rules, equities require significantly higher risk-based capital than bonds.

came reliable in 2010 and are generally available on a quarterly basis.[5][6] Data on Morningstar Categories, Morningstar Ratings and fund holdings from 2005 to 2010 are from Morningstar Direct. I follow Ľuboš Pástor et al. (2015) and use CUSIP and ticker (in this order) to merge CRSP and Morningstar.

I focus on bond funds with significant corporate bond holdings. Following Choi and Kronlund (2018), investment-grade bond funds are defined as by Lipper objective codes A, ARB, BBB, CPB, GB, IID, SII, SID, or USO, and high-yield bond funds ACF, FLX, HY, MSI, SFI, or SHY. I include ETFs and variable annuity funds in the sample, as they are also open-end and their flow sensitivity to monetary policy is very similar to mutual funds. My final bond fund sample contains 1,491 bond funds from 1990Q1 to 2020Q4. Panel B of Table 1 shows summary statistics.

Data on corporate bonds are from Mergent FISD and Enhanced TRACE. Mergent FISD contains information on bond characteristics, such as rating, maturity, amount outstanding, callability, and maturity.[7] Enhanced TRACE contains information on bond trades, which I use to construct variables such as price, yield, duration, trading volume, and bid-ask spread. I closely follow the procedure in Dick-Nielsen (2014) to clean the Enhanced TRACE data.

I focus on straight bonds issued by non-financial firms, to be defined in the next sub-section. I link corporate bonds with Compustat firms by issuer CUSIP and stock ticker (in this order). I exclude convertible bonds, bonds with variable coupons, bonds denominated in foreign currencies, and bonds that are never held by any bond fund (which may reflect some unobserved intrinsic properties). I restrict to bond-quarter observations with non-missing quarter-end price, defined as the trade-weighted daily price closest to the quarter-end date and not more than five days away from the quarter-end date. My final corporate bond sample includes 11,850 corporate bonds from 2005Q1 to 2020Q4. Panel C of Table 1 shows summary statistics of my corporate bond sample.

Data on non-financial firms are from Compustat. I restrict to firms headquartered in U.S. and exclude firms with SIC codes starting with 6. I restrict to firm-quarter observations with at least $1 million market capitalization of equity and at least $1 million bond amount out-

[5] Schwarz and Potter (2016) give detailed description on coverage and quality of the holdings data in CRSP. Parker et al. (2020) make similar restrictions on the CRSP holdings data.

[6] Holdings are generally reported on a quarterly basis but can be on the first, second, or third month of quarter. I use the month that is closest to the end of quarter. For example, if a fund reports holdings in January, April, July and October, I will assign them to Q4 (of previous year), Q1, Q2 and Q3, respectively.

[7] For ratings, I focus on those from S&P, Moody's, and Fitch. If there are multiple ratings for a bond, I take the median.

standing, since I control for equity characteristics (e.g., Tobin's Q) and bond characteristics (e.g., bond rating). My final non-financial firm sample consists of 1,123 firms from 2005Q1 to 2020Q4. Panel D of Table 1 shows summary statistics of my firm sample.

Data on life insurers and P&C insurers are from their regulatory filings with the National Association of Insurance Commissioners (NAIC). In particular, Schedule D filings contain detailed information on insurers' bond holdings. I obtain these filings through SNL Financial. Data on annuity sales are from Beacon Annuity Nexus.

Data on individual U.S. Treasury bonds are from CRSP US Treasury Database, which contains information on characteristics (e.g. maturity) and trading (e.g. yield). Daily data on aggregate zero-coupon treasury yield curves are from Gurkaynak et al. (2007).

Appendix B contains additional details on data cleaning (e.g., error detection) and variable construction (e.g., fund duration and firm profitability).

3.3 Measuring monetary policy

I measure conventional monetary policy by the two-year Treasury rate, denoted as *Rate*. One advantage of using the two-year Treasury rate is that it captures both current and the expected path of future federal fund rates. The literature suggests that two years is roughly the horizon at which the Fed's forward guidance policy operates (Bernanke et al., 2004; Gürkaynak et al., 2005; Swanson and Williams, 2014; Hanson and Stein, 2015). Forward guidance is especially important when the federal funds rates are at the zero lower bound, as was the case during 2008-2015, which constitutes a large portion of my sample (recall that my mutual fund holdings data do not start until 2005).

One disadvantage of using the two-year Treasury rate is that it contains risk premium and central bank information, as discussed in Nakamura and Steinsson (2018). For the analyses that rely on the full sample of 1990-2020 (i.e., not constrained by the mutual fund holdings data), my results are robust to using the federal funds rate.

For identification purpose, I will also use monetary surprise measures from Hanson and Stein (2015), Gertler and Karadi (2015), Nakamura and Steinsson (2018), and Swanson (2021). I will discuss the validity of these measures as instruments later in the paper.

3.4 Measuring flows

One key data issue is to measure net flows in or out of an entity and not confuse them with appreciation or depreciation of value. The primitive is dollar flows:

$$Flow^{\$} = Inflow^{\$} - Outflow^{\$}$$

Dollar flows are directly available in databases such as Financial Accounts of the United States. For mutual funds, the convention is to impute dollar flows using total net assets and returns:

$$Flow^{\$}_{t,t+1} = TNA_{t+1} - TNA_t(1 + Return_{t,t+1})$$

The underlying assumption is that there is no portfolio adjustment until the end of the period. There are a few adjustments needed for this imputation. I subtract ETF purchases by the Federal Reserve's Secondary Market Corporate Credit Facility (SMCCF) following the COVID crisis. I account for fund mergers, which are recorded in the CRSP mutual fund headers file ("merge_fundno"). Specifically, I subtract from the imputed flows the TNAs of acquired funds.

Instead of net flows at the fund level, I am also interested in net flows at the portfolio level, i.e. net purchases. For a portfolio where par values of bonds (or shares of stocks) are given, we can similarly assume that all portfolio adjustments occur at the end of the period and calculate dollar flows as:

$$Flow^{\$}_{t,t+1} = \sum_{n=1}^{N} (Par_{n,t+1} - Par_{n,t}) Price_{n,t+1}$$

where n indexes for the number of bonds.

Dollar flows cannot be studied directly, because they are not stationary. For example, in a time series of aggregate bond fund flows, dollar flows in later periods are mechanically larger than dollar flows in earlier periods because of secular growth in the size of bond funds, and they cannot be directly compared to each other. The convention is to work with percentage flows:

$$Flow^{\%}_{t,t+h} = \frac{Flow^{\$}_{t,t+h}}{Size_t}$$

where $Size$ is usually the entity's own size. Note that $Flow^{\%}$ would simply be the net percentage change in size, or net growth, if the assets have stable value (e.g. deposits). In this paper, we will often compare flows across entities, e.g. between bond funds and other institutional corporate bond investors. To do so, it makes more sense to scale the dollar flows with a common benchmark, e.g. the size of the corporate bond market.

The focus of this paper is how flows respond to monetary policy, i.e. the flow beta:

$$FlowBeta = \frac{\partial Flow}{\partial Rate}$$

4 Monetary Sensitivity across Corporate Bond Investors

In this section, I document new stylized facts on the relative monetary sensitivity across different corporate bond investors. I show that bond funds are much more sensitive to monetary policy than other corporate bond investors such as insurance companies and pension funds – in response to monetary easing, bond funds' net flows and corporate bond net purchases increase much more. I show that return chasing plays a key role in explaining the high monetary sensitivity of bond funds.

4.1 Time series

I begin by visually examining the aggregate time series. The red line in Panel A of Figure 2 plots the year-over-year net flows (scaled by lagged sizes) averaged across bond funds, weighted by corporate bond holdings.[8] It shows that bond fund flows are highly volatile, ranging from 31% in some years to -7% in others – it means that the bond fund sector expands or contracts by as much as 30% over a one-year horizon. More importantly, there is a visibly strong negative correlation between bond fund flows and changes in two-year Treasury rates, as shown by the black dash line. The correlation coefficient is -0.53.

The blue line in Panel A of Figure 2 plots the year-over-year corporate bond net purchases (scaled by lagged corporate bond holdings) averaged across bond funds, weighted by corporate bond holdings. It shows that bond funds' corporate bond net purchases move almost one-to-one with their net flows, suggesting that bond funds near-proportionally scale their corporate bond holdings in response to flows. To confirm this, I follow Lou (2012) and Choi

[8]Since Morningstar holdings data do not become comprehensive until 2005Q1, I use the 2005Q1 holdings as weights for the periods before.

et al. (2020) and analyze how bond funds trade in response to flows at the asset class level:

$$AssetClassFlow_{i,t} = \beta FundFlow_{i,t} + FE + \epsilon_{i,t} \tag{1}$$

where $AssetClassFlow_{i,t}$ denotes bond fund i's net purchases of a particular asset class (e.g. corporate bonds) in year t (scaled by holdings in year $t-1$), $FundFlow_{i,t}$ denotes net flows to bond fund i in year t (scaled by fund size in year $t-1$), and FE includes fund fixed effects and year fixed effects. Panel A of Table 2 shows the results. On an annual frequency, when a bond fund experiences 1% inflow (outflow), its corporate bond portfolio expands (contracts) by almost exactly 1%. This means that cash and cash equivalents (e.g. Treasury securities) play a limited role in absorbing fund flows.[9] This reflects the fact that there are usually targets or mandates on portfolio allocations at the asset class level, e.g. a fixed portfolio weight in investment-grade corporate bonds.

Panel B of Figure 2 highlights how different corporate bond investors react differently to monetary policy rate changes. It plots year-over-year corporate bond net purchases (scaled by lagged corporate bond holdings) for bond funds (in red), insurance companies (in green), and the average corporate bond investor (in blue). To obtain net purchases by the average corporate bond investor, I use aggregate corporate bond net issuance (scaled by lagged aggregate corporate bond outstanding), since firms are the counterparty to all corporate bond investors combined.

It is visible that bond fund net purchases are much more volatile and react to monetary policy rate changes much more than insurers and the average corporate bond investor. The correlation with monetary policy rate changes is high for all corporate bond investors (-0.53 for bond fund, -0.31 for insurers, -0.45 for the average corporate bond investor). However, the beta to monetary policy rate changes is much higher for bond funds (-5.3) than insurers (-0.6) and the average corporate bond investor (-1.2).

The visual evidence above suggests that bond funds' net flows and corporate bond net purchases are highly responsive to monetary policy, much more so than other corporate bond investors such as insurance companies. The sub-section below provides identification and quantification.

[9] The results are different from Choi et al. (2020) since I look at annual flows, which are more relevant to my setting than quarterly flows.

4.2 Local projections

I use an instrumented variation of the local projection approach (Jorda, 2005) to identify and quantify the effect of monetary policy on flows (either total flows or corporate bond flows) to different corporate bond investors. I estimate the following regression:

$$Y_{t,t+h} = \alpha_h + \beta_h \Delta Rate_{t,t+4} + \gamma_h Controls + \epsilon_{t,t+h} \tag{2}$$

where $Y_{t,t+h}$ refers to cumulative aggregate net flows from quarter t to quarter $t+h$ (scaled by size in quarter t), $\Delta Rate_{t,t+4}$ denotes change in two-year Treasury rate from quarter t to quarter $t+4$, controls are specified below, and standard errors are Newey-West with automatically selected bandwidth (Newey and West, 1994). Under this specification, β_h identifies the effect of monetary policy on flows at the h-quarter horizon.

I use one-year change in monetary policy rate to focus on monetary cycle effects, similar to the approach in Xiao (2019) and Daniel et al. (2021). Mutual fund investors, most of whom are retail (see Section 3), are unlikely to respond to rate changes at a high frequency. As will be shown in the next sub-section, one key explanation for bond fund flow beta is return chasing, and return chasing has been shown to operate at a low frequency (Barber et al., 2016). Conveniently, the standard deviation of one-year change in two-year Treasury rate is close to one percentage point (see Table 1), which I will use as the baseline unit of rate change.

I control for observable macroeconomic variables including GDP growth, core inflation rate, and change in unemployment rate. Doing so partials out the part of flows and the part of rate changes that can be explained by observable macro news. To be clear, I do not claim that monetary policy is random. Instead, the assumption I make is that monetary policy can respond to the same macroeconomic news differently over time, and this variation is exogenous to flows.[10]

I control for lags of flows, rate changes, and control variables because all of these variables could be highly persistent. I want to isolate the flows due to new rate changes, not the flows in response to past flows or past rate changes. Olea and Plagborg-Møller (2021) show that controlling for lags makes local projection inference robust to highly persistent data generating processes and obviates adjustment for serial correlation in standard error.

[10] For concreteness, suppose that there is 1 p.p. increase in inflation. In response, the Fed decides how much it should raises the interest rate. I assume that whether the Fed raises interest rate by 25 bps or 50 bps is exogenous to flows.

Despite the controls, one could still come up with endogeneity concerns – there might be some unobservable macroeconomic variables that drive both monetary policy and flows. To address theses concerns, I use the monetary surprises from Gertler and Karadi (2015) as an instrument for monetary policy. The idea is to look at a narrow window (e.g. 30 minute) around an FOMC announcement and treat any rate change there as an exogenous shock to monetary policy, since there is likely no change to any macroeconomic variables over the same narrow window. Since my focus is on one-year rate changes that approximate monetary cycles, I construct the instrument as cumulative monetary surprises over one year, following the approach in Gertler and Karadi (2015). Formally, the identifying assumption is that monetary surprises are large enough and sufficiently correlated with rate changes over the one-year horizon (the relevance condition) but they are orthogonal to any unobservable factors that might drive flows (the exclusion condition).

Panel A of Figure 3 shows the cumulative responses of corporate bond net purchases by the top three corporate bond investors to monetary policy. In response to 1 p.p. drop (hike) in two-year Treasury rate, there is cumulative 15 p.p. increase in net purchases of corporate bonds by bond funds. The response is economically large, since the standard deviation of three-year bond fund net purchases is 17 p.p. In contrast, the effect is much smaller for insurers, pension funds, or the average corporate bond investor, as approximated by the aggregate corporate bond issuance.

Panel B of Figure 3 focuses on the difference between bond funds and insurers at the three-year horizon across various alternative specifications. The difference is large and: 1) robust to using the equal-weighted flow or the panel of bond funds [11], 2) robust to restricting to early periods without the contamination of unconventional monetary policy, 3) similar across monetary easing ($\Delta Rate < 0$) and monetary tightening ($\Delta Rate > 0$)[12], robust to measuring monetary policy with federal funds rates, common across different styles of bond funds (passive vs active, IG vs HY), common across different share classes (retail vs institutional), robust to controlling additionally for concurrent rate changes and fund variables (expense ratio and alpha), robust to using alternative monetary surprises by Nakamura and Steinsson (2018), Swanson (2021), or Bauer and Swanson (2022).

[11] To use the panel data, I use the following regression specification: $Flow_{i,t,t+h} = \beta_h \Delta Rate_{t,t+4} + \gamma_{1,h} MacroControls + \gamma_{2,h} FundControls + FE + \epsilon_{i,t,t+h}$, where FE includes fund fixed effects and standard errors are two-way clustered by fund and by quarter.

[12] Response is stronger with tightening than with easing, likely due to two reasons. First, bond fund flows are more responsive to negative returns than to positive returns, due to strategic complementarity (e.g. Goldstein et al., 2017). Secondly, bond funds scale existing portfolio more proportionally to outflows than to inflows, as shown in Panel A of Table 2.

Nakamura and Steinsson (2018) argue that monetary surprises reflect the Fed's private information about future macroeconomic conditions instead of exogenous shocks to interest rates. I show that my results are robust to using the monetary surprise measures from Jarociński and Karadi (2020) and Cieslak and Schrimpf (2019) that exclude the Fed's private information. In Figure A10 of Appendix A, I show that bond fund flows decrease in response to negative macroeconomic news. As a result, since rate drops reflect the Fed's private information of a weaker economy and bond fund flows increase in response to rate drops, bond fund flows are not likely driven by the Fed information channel.

4.3 Inspecting the Mechanism

Why does monetary policy have much larger effects on bond funds than traditional corporate bond investors such as insurance companies and pension funds? Return chasing is a natural explanation. There is growing evidence that mutual fund investors chase realized returns and do not distinguish between alpha vs factor-related returns (e.g., Ben-David et al., 2021a). When the Fed lowers interest rates, bond funds realize large factor-related returns (monetary policy is the factor and duration is factor loading), which attract large flows from retail investors. In comparison, institutional investors such as insurers should be much less subject to return chasing and other behavioral biases.[13]

I show two pieces of evidence in support of the return chasing channel. First, flows to bond funds largely come from the mutual fund classes that have the opposite return beta as bond funds. I apply the local projection in Equation (2) to the aggregate returns and the aggregate flows of major mutual fund classes: bond funds, money market funds, loan funds and equity funds. Figure A8 shows that money market funds and loan funds have the opposite return beta as well as flow beta as bond funds.[14] The returns on money market instruments and bank loans are indexed to short-term interest rates that mechanically decrease during monetary easing, and return-chasing mutual fund investors pull capital away when this happens.

The second piece of evidence comes from the cross section of bond funds, where bond funds with higher return beta have much higher flow beta. I estimate the following regression in

[13]Return chasing may not be the only channel at play. Brooks et al. (2018) and Hanson et al. (2021) suggest that bond investors extrapolate short rate movement. Lian et al. (2018) suggest that lower interest rates induce higher investor risk-taking due to reference dependence and salience. All these behavioral biases should apply more to retail investors.

[14]These findings are in line with the ones in Xiao (2019) and Nicola Cetorelli (2022).

the cross section of bond funds:

$$Flow_{i,t,t+12} = \beta \Delta Rate_{t,t+4} \times FundCharacteristics_{i,t} + FE + \epsilon_{i,t,t+12} \tag{3}$$

where $Flow_{i,t,t+12}$ denotes cumulative flows to fund i from quarter t to quarter $t+12$ (scaled by fund size in quarter t), $\Delta Rate_{t,t+4}$ denotes changes in two-year Treasury rates from quarter t to quarter $t+4$, fund characteristics include rating, duration, income yield, yield to maturity, log TNA, expense ratio, turnover, return alpha, return volatility and cash ratio, all standardized, and FE includes fund fixed effects as well as style-quarter fixed effects.[15]

Table A1 shows the results. Bond funds with higher return duration have significantly higher flow beta. Given a 1 p.p. decrease (increase) in two-year Treasury rate over the last year, one-standard-deviation increase in fund duration is associated with 0.41 p.p. increase (decrease) in fund flow over the next quarter. The effect is not only statistically significant but also economically meaningful: it is 17% of the mean quarterly bond fund flow. In contrast, rating, income yield and yield to maturity do not affect flow beta to the same extent.[16] This suggests that chasing realized returns is more important than reaching for yield for cross-sectional flow beta.[17]

If return chasing is the main channel that drives bond fund return sensitivity to monetary policy, one might expect similar flow patterns for equity mutual funds, because equity returns are also known to be affected by monetary policy (Bernanke and Kuttner, 2005). Figure A7 and Figure A8 show that the response of equity returns and equity fund flows are much more muted. The reasons is that equity returns are much more sensitive to macroeconomic conditions that tend to be negatively correlated with monetary policy rate changes – when the Fed cuts interest rates, it is usually when the economy is doing well and equity returns are rising. In comparison, bond returns are much more dominated by monetary policy rate changes, the fact that the level factor drives most of bond yield changes.

[15] The regression includes both the interaction term as well as the components of the interaction, e.g. fund characteristics.

[16] Yield to maturity is missing for many fund-quarter observations because I require yield to maturity to be non-missing for at least 50% of the fund's holding. On average, yield to maturity is missing for 66% of the bond fund holdings.

[17] The reasons that I get smaller results for income yield and yield to maturity than Choi and Kronlund (2018) and Daniel et al. (2021) do are as follows. First and foremost, I include return duration in the regression, which I believe is an important omitted variable in their specifications. Secondly, I use a bigger universe of bond funds (1,491 funds) and look at a longer time period (from 1990 to 2022). Thirdly, I conduct my analysis on the fund level, whereas the two papers analyze share-class-level flows, which are subject to the problem of over-weighing funds with many share classes. Lastly, I look at within-style flows by including style-quarter fixed effects, whereas the two papers look at flows across all bond funds, which can be confounded by style-level flows.

5 Cross-Sectional Firm Sensitivity to Monetary Policy

This section demonstrates the bond fund amplification channel of monetary transmission using the cross section of firms. I begin by showing substantial heterogeneity across firms in exposure to bond funds – some firms have stronger relationships with bond funds and are therefore more exposed to changes in bond fund flows and bond fund credit supply. I show that higher bond fund exposure leads to higher firm sensitivity to monetary policy: during monetary easing, more-exposed firms experience larger increase in bond prices, issue more bonds, and increase more on leverage, payout, or real investment, depending on the the firm's financial condition. The effects are economically large compared to the average firm sensitivity to monetary policy. I address potential endogeneity concerns and use a shift-share instrument to show that the effect is likely causal.

5.1 Heterogeneous exposure to bond fund flows

There is substantial heterogeneity in exposure to bond fund flows in the cross section of firms. I first add to the growing evidence of relationship lending in the corporate bond market: bond funds hold concentrated portfolios of firms and near-proportionally scale up (down) existing holdings in response to inflows (outflows). As a result, if a firm has higher bond ownership by bond funds today, it is then more exposed to future changes in bond fund flows and bond fund credit supply. I show large variation in bond fund ownership across near-identical firms and discuss plausibly exogenous sources of variation.

5.1.1 Relationship lending in the corporate bond market

There is growing evidence of relationship lending in the corporate bond market (e.g. Massa et al., 2013; Zhu, 2021; Barbosa and Ozdagli, 2022). Theories on relationship lending include Williamson (1987), Sharpe (1990), Holmstrom and Tirole (1997), and van Nieuwerburgh and Veldkamp (2010), and a common theme is information asymmetry. When there is asymmetric information between lenders and borrowers – e.g., lenders need to pay a cost to acquire information on borrowers – it is optimal for players to form repeated long-term lending relationships. How much information asymmetry there is and whether it matters in the corporate bond market is an empirical question, on which I shed light below.

I first show that bond funds hold concentrated portfolios – they invest in a small fraction of the issuers and corporate bonds that are available on the market. Panel A of Figure 4 shows that, out of the total number of issuers with more than \$1 million bond outstanding conditional on a given corporate bond style (e.g. investment-grade short-term bonds), a typical bond fund holds less than 10%. Panel B of Figure 4 shows that bond funds are even less diversified at the individual bond level.

Not only are bond funds' portfolios concentrated, the concentration is persistent over time. When a bond fund experiences inflows or outflows, it near-proportionally scales up or down its existing holdings. This scaling is more proportional at the more aggregated asset class level, but applies even at the disaggregated bond issuer level. In other words, bond funds do not respond to flows by trading the market or using cash only. To show this, I replicate the exercise in Lou (2012) and Choi et al. (2020), with a different frequency focus and a new counterfactual exercise. Specifically, I run the following regression:

$$IssuerFlow_{i,j,t} = \beta FundFlow_{i,t} + FE + \epsilon_{i,j,t} \tag{4}$$

where $IssuerFlow_{i,j,t}$ denotes flows to a bond issuer j in bond fund i's portfolio in year t (scaled by holdings in year $t-1$), $FundFlow_{i,t}$ denotes flows to bond fund i in year t (scaled by fund size in year $t-1$), and FE includes fund fixed effects and issuer-year fixed effects. By definition, I am looking at the flows to portfolio issuers, whose year $t-1$ holdings are not zero.

Panel C of Table 2 shows the results. When a bond fund experiences 1% outflow, the holdings of its portfolio issuers contract by 0.80%. When a bond fund experiences 1% inflow, the holdings of its portfolio issuers expand by 0.70%. The results suggest that in response to flows, bond funds near-proportionally scale the holdings of its portfolio issuers. The scaling is not one for one, but far above zero, so cash plays a limited role in absorbing flows.

What would the regression coefficients look like if bond funds respond to inflows by buying the market? To answer that, I do the following counterfactual exercise: for each dollar that the bond fund spends on buying a corporate bond, I suppose that the bond instead buys the all the corporate bonds with similar rating and duration, and then I calculate the counterfactual flows to each portfolio bond issuer or portfolio corporate bond. For example, suppose that a bond fund buys \$1 million of a 3-year Apple bond, I spread that \$1 million across the all investment-grade short-term corporate bonds outstanding (weighted by market value), and then calculate the counterfactual flows to the fund's portfolio bond issuers or portfolio corporate bonds. Column 3 shows the results when I run the same regression above with these counterfactual flows. If bond funds were to trade the market in response to flows, the scaling coefficient would have been substantially less, close to zero. This exercise demonstrates that bond funds allocate a disproportionate share of their inflows to issuers that are already in their existing portfolios – they do not trade the market in response to flows.

Panel D of Table 2 repeats the same exercise but at the individual corporate bond level. The results are similar with outflows: when a bond fund experiences 1% outflow, the holdings of its portfolio corporate bonds contract by 0.76%. However, when a bond fund experiences 1% inflow, the holdings of its portfolio corporate bonds expand by only 0.40% – it is still far above zero, but significantly less than the 0.70% at the bond issuer level. The results suggest that, when experiencing inflows, bond funds keep buying from the same bond issuers they have relationship with, but not necessarily the exact bonds that they already hold.

In Appendix C, I allow trading to be affected by liquidity concerns – bonds with higher liquidity should be more likely to be traded in response to flows. Specifically, I follow Ma et al. (2022), construct a ranking of liquidity across bonds in a given portfolio according to rating and maturity, and include an interaction term between fund flow and liquidity rank in regression (4). Bonds with higher liquidity ranks are indeed much more responsive to fund flows.

There are reasons to believe that portfolio concentration and portfolio scaling should be stronger in the corporate bond market, compared to other markets such as the equity market. First of all, there are on average 50,000 bond CUSIPs, which are substantially more than the number of stocks. Secondly, the most liquid corporate bonds are more illiquid than the most illiquid stocks, and therefore it is practically very difficult to trade the entire bond market. Lastly, corporate bonds are highly substitutable to each other – holding a few number of corporate bonds is sufficient to replicate the exposure to the broad bond market.

5.1.2 Measuring exposure to bond fund flows

I want to measure the exposure of each firm to changes in bond funds' credit supply in response to monetary policy. My relationship lending results in the previous section suggests that exposure is sufficiently summarized by the firm's bond fund ownership. Flows to a bond fund do not affect all firms equally, but rather disproportionately affect the firms with high portfolio weights ex ante. Since monetary policy leads to common flows across all bond funds, a firm's total ownership by all bond funds summarizes its exposure to future monetary-policy-induced common bond fund flows.

For example, suppose that Firm A has 50% of its bonds held by bond funds whereas Firm B has 0%. According to my results in Section 4, bond funds would increase their corporate bond net purchases by 10 percentage points more than the average corporate bond investors, in response to monetary easing. Therefore, Firm A's bonds would experience 5% (50% times 10%) higher investor demand than Firm B's bonds.

Concretely, firm j's exposure to common bond fund flows at the end of quarter t is measured by its total ownership by all bond funds:

$$BFOwnership_{j,t} = \frac{\sum_i AmountHeld_{i,j,t}}{AmountOutstanding_{j,t}} \tag{5}$$

where $AmountHeld_{i,j,t}$ denotes bond fund i's holdings of firm j's bonds at the end of quarter t and $AmountOutstanding_{j,t}$ denotes firm j's total bond amount outstanding.

In Appendix C, I take into account the following aspects to more precisely measure exposure to changes in bond funds' credit supply: there is heterogeneity in flow sensitivity to monetary policy across bond funds, bond funds trade bonds differently in response to inflow vs outflow, and bond funds engage in liquidity management and prioritize trading of liquid bonds.

Panel A of Figure 5 shows significant variation in bond fund ownership in the cross section of firms. Part of the variation comes from firm characteristics – bond fund ownership is larger for firms with lower ratings, shorter bond duration, and larger sizes. However, Panel B of Figure 5 shows that significant variation remains even after residualized with a wide set of firm attributes:

$$BFOwnership_j = \gamma FirmAttributes_j + FE + \epsilon_j \tag{6}$$

where firm attributes include log size, cash holdings, profitability, Tobin's Q, bond share, bond rating, and bond duration, and FE includes rating fixed effects and industry fixed effects.

Why is there large variation in bond fund ownership across near-identical firms? One contributing factor is investor base concentration. Figure A9 in Appendix A shows that investor bases are quite concentrated – out of the 1033 bond funds and the 953 insurers, a typical firm only has 144 bond fund or insurer holders. One interpretation is that firms do not exhaustively search for all the potential investors, e.g. due to high information cost van

Nieuwerburgh and Veldkamp (2010). Therefore, two near-identical firms can have very different investor base, due to the randomness in their limited search process for bond investors.

I highlight two important drivers of variation in bond fund ownership. The first is underwriter relationship, as documented in Chakraborty and Mackinlay (2019), Zhu (2021) and Siani (2022). A firm keeps working with a small set of underwriters for primary market issuance and for subsequent secondary market trading, and some underwriters have predominantly bond fund clients whereas others insurer clients. When a firm picks an underwriter, for example one that has branches nearby, and the underwriter has largely bond fund clients, then the firm is going to be more exposed to bond funds.

The other driver of variation in bond fund ownership comes from the secular rise of bond funds. Figure 1 shows that aggregate bond fund ownership has increased steadily from less than 2% in 1980 to over 20% in 2020. As shown in Panel A of Figure 5, there is not only a rightward shift but also a wider spread in the distribution of bond fund ownership. Some bond funds have grown faster than others, due to reasons such as better performance, lower expenses or larger market power. Having relationships with high-growth bond funds means larger increase in bond fund ownership over time.

5.2 Bondholder net flows and net purchases

This sub-section shows that for firms with higher bond fund ownership ex ante, their bondholders indeed experience more inflows and make more purchases of the firms' bonds, during monetary easing. Due to data limitation, I focus on mutual funds and insurance companies, and assume net flows to other bondholders and their net purchases to be zero.

Bondholder net flows are defined as:

$$BHFlow_{j,t,t+h} = \frac{\sum_i AmountHeld_{i,j,t} Flow_{i,t,t+h}}{AmountOutstanding_{j,t}}$$

where $AmountHeld_{i,j,t}$ denotes amount of firm j's bonds held by investor i at quarter end t, $AmountOutstanding_{j,t}$ denotes amount of firm j's total bonds outstanding, and $Flow_{i,t,t+h}$ denotes net flows to investor i from quarter t to quarter $t+h$ (scaled by its size at quarter end t). Intuitively, this measure indicates what would be the net buying or selling of the firm's bonds (scaled by its bonds outstanding) if its bondholders proportionally scale up or down their existing portfolios in response to flows, as elaborated more in Zhu (2021).

Bondholder net purchases are defined as:

$$BHPurchase_{j,t,t+h} = \frac{\sum_i (AmountHeld_{i,j,t+h} - AmountHeld_{i,j,t})}{AmountOutstanding_{j,t}}$$

I run the following regression on the panel data of firm-quarter described in Section 3:

$$Y_{j,t,t+h} = \beta_h \Delta Rate_{t,t+4} \times BFOwnership_{j,t} + \gamma_h Controls + FE + \epsilon_{j,t,t+h} \quad (7)$$

where $Y_{j,t,t+h}$ denotes either firm j's bondholder net flows or bondholder net purchases from quarter t to quarter $t+h$, $\Delta Rate_{t,t+4}$ changes in monetary policy rates from quarter t to quarter $t+4$, and $BFOwnership_{j,t}$ (standardized) bond fund ownership of firm j's outstanding bonds at quarter end t.[18] Controls include the interaction of macro news and bond fund ownership and the interaction of rate changes with firm attributes including log total assets, cash ratio, Tobin's Q, leverage, profitability, bond share, bond rating and bond duration.[19] FE includes firm fixed effects and Fama-French 10 industry by quarteer fixed effects. β_h identifies whether firms with higher bond fund ownership experience bigger changes in bondholder flows or bondholder net purchases in response to monetary policy, at horizon h.

Figure 6 shows the results. In response to 1 p.p. decrease in monetary policy rate, for firms with one standard deviation higher bond fund ownership, their bondholders experience higher flows equal 3.0% of the firms' bonds outstanding and make more purchases of the firms' bonds equal 2.2% of the firms' bonds outstanding.

5.3 Bond pricing

This sub-section shows that for firms with higher bond fund ownership ex ante, their bonds experience higher returns than other bonds with near-identical characteristics, during monetary easing.

I run the following regression on the corporate bond-quarter panel data described in Section 3:

$$Y_{b,t,t+h} = \beta_h \Delta Rate_{t,t+4} \times BFOwnership_{j,t} + \gamma_h Controls + FE + \epsilon_{b,t,t+h} \quad (8)$$

where $Y_{b,t,t+h}$ denotes return on bond b from quarter t to quarter $t+h$, $\Delta Rate_{t,t+4}$ changes in

[18] The regression includes both the interaction term as well as its components, i.e. $\Delta Rate_{t,t+4}$ and $BFOwnership_{j,t}$

[19] see Appendix B for details on variable definitions.

two-year Treasury rates from quarter t to quarter $t+4$, and $BFOwnership_{j,t}$ (standardized) bond fund ownership of all the outstanding bonds by bond b's issuer j.[20]

I include a large set of control variables. I control for the interaction of bond fund ownership and macro news such as GDP growth and inflation rate to control for bond fund flows driven by changes in macroeconomic conditions. I control for the interaction of rate changes with bond characteristics such as callability, bid-ask spread and log amount outstanding.[21] I control for the interaction of rate changes with issuer characteristics such as log total assets, cash ratio, Tobin's Q, leverage, and profitability.[22] See Appendix B for details on variable definitions.

I include rating letter by rounded duration by quarter fixed effects. Effectively, I compare corporate bonds with the same rating and the same duration at the same time. This restriction allows me to focus on near-identical corporate bonds and focus on variations not explained by any non-parametric functions of rating and duration.

Panel A of Table 3 shows the baseline results. Corporate bonds with higher bond fund ownership have significantly higher return sensitivity to monetary policy. In response to 1 p.p. decrease in monetary policy rate, for corporate bonds with one-standard-deviation-higher bond fund ownership, they experience 30 bps higher returns than other bonds with the same rating, same duration, and similar bond-level and issuer-level characteristics.

Comparing Column 2 with Column 1, we see that controlling for additional bond-level characteristics slightly increases the effect of bond fund ownership. The reason is that callable bonds and liquid bonds, which tend to have lower response to monetary policy, tend to correlate with higher bond fund ownership and therefore dampen the identified effect. Controlling for additional issuer-level characteristics in Column 3 does not significantly change the results.

Is the 30 bps abnormal return economically meaningful? As shown in Table B2 of Appendix B, the average investment-grade 5-year (10-year) corporate bond has a return sensitivity – with respect to two-year Treasury rate – of 1.69 (2.23) percentage points. Therefore, the 30 bps effect is economically meaningful when compared with the average monetary sensitivity.

[20]The regression includes both the interaction term as well as its components, i.e. $\Delta Rate_{t,t+4}$ and $BFOwnership_{j,t}$.

[21]Duffee (1998) for example shows that fixed callable bonds have returns that are less sensitive to interest rate changes.

[22]Ottonello and Winberry (2020) for example shows that firms with larger distance to default are much more responsive to monetary policy.

Table A2 in Appendix A shows that the amplification effect of bond fund flows is asymmetric, being bigger in monetary tightening than in monetary easing. This is due to two forces. First, Section 4 shows that bond fund flows are more sensitive to monetary tightening than monetary easing, consistent with the concave flow-performance relationship documented in Goldstein et al. (2017). Secondly, Section 5.1 shows that the correspondence between bond fund flows and bond fund trading is stronger with bond fund outflows, which are more likely under monetary tightening.

Figure 7 shows the full dynamics of abnormal returns. The abnormal return emerges over the same window as rates decline and reaches its peak at the end of rate decline. The abnormal return is temporary and fully reverted by the end of year three, confirming that it is driven by price pressure resulting from temporary supply-demand imbalances, rather than changes in bond fundamentals. In other words, the abnormal return is due to discount rate news rather than cash flow news.

The price effects I identify may seem puzzling, since bond funds engage in liquidity management to avoid price impacts (Choi et al., 2020) and other corporate bond investors should be sensitive to arbitrage opportunities (Becker and Ivashina, 2015). In particular, one might wonder why it takes such a long time for price to revert – if prices become abnormally high, arbitrageurs should sell or short the bonds and prices should revert immediately. There are three main reasons. First, monetary-policy-induced flows are common across all bond funds, and common flows lead to price pressure that is large in aggregate and difficult to be absorbed by other investors, consistent with the findings in Ben-David et al. (2021b) and Coppola (2022).

Secondly, monetary-policy-induced bond fund flows are very persistent, which pose higher limits for arbitrage. As Figure 6 shows, bonds keep experiencing abnormal bondholder flows up to three years since the onset of rate change. Therefore, while arbitrage capital eventually forces bond prices to revert, it can be balanced out by price pressure from additional bond fund flows in the short-term. The delay of reversal and its uncertainty discourages arbitraging activities in the first place. The long-horizon dynamics here are similar to the findings in Lou (2012).

Lastly, while other investors do respond to arbitrage opportunities, their elasticities can be far smaller than we we expect with rational agents in benchmark models, consistent with the findings in Gabaix and Koijen (2022). Similar to bond funds, other investors can have persistent portfolio tilts. For example, insurers face high capital charges on high-yield bonds, and therefore cannot freely arbitrage on high-yield bond mispricings. As another example, even if some issuers' bonds are underpriced, if there is a high cost of acquiring information on this issuer, then bond investors may not purchase the bonds. Insurers and pension plans are buy-and-hold investors that make most of their bond purchases in the primary market. They pay relatively little attention to secondary market mispricings. Table 8 shows my estimates of price elasticities across different types of institutional corporate bond investors. As will be elaborated in detail in Section 6, these estimates are done in a demand system framework as the responsiveness of portfolio weights to price dislocations coming from residual mutual fund flows. Panel A shows price elasticities within a bond class, whereas Panel B shows price elasticities across bond classes. The estimated price elasticities are far lower than their frictionless benchmarks, which are about 6000 for micro elasticities and 20 for macro elasticities (Gabaix and Koijen, 2022).

5.4 Firm financing

In this sub-section, I show that the secondary market price effects above spill over to primary market activities. During monetary easing, for firms with higher bond fund ownership, as their bond prices increase more, they opportunistically issue more bonds. The additional bond proceeds are largely used to refinance old debt and repurchase equities, but translate to significant real investments for the constrained firms.

I run the following regression on the firm-quarter data described in Section 3:

$$Y_{j,t,t+h} = \beta_h \Delta Rate_{t,t+4} \times BFOwnership_{j,t} + \gamma_h Controls + FE + \epsilon_{j,t,t+h} \tag{9}$$

where $Y_{j,t,t+h}$ denotes firm j's gross bond issuance, net bond issuance, net debt issuance, net equity payout, or real investment from quarter t to quarter $t+h$ (scaled by bond amount outstanding in quarter t), $\Delta Rate_{t,t+4}$ changes in two-year Treasury rates from quarter t to quarter $t+4$, and $BFOwnership_{j,t}$ (standardized) bond fund ownership of firm j's bonds outstanding at quarter end t.[23] Controls include the interaction of macro news and bond fund ownership and the interaction of rate changes with firm attributes such as log total assets, cash ratio, Tobin's Q, leverage, profitability, bond share, bond rating and bond duration.[24] FE includes firm fixed effects and Fama-French 10 industry by quarter fixed

[23]The regression includes both the interaction term as well as its components, i.e. $\Delta Rate_{t,t+4}$ and $BFOwnership_{j,t}$.

[24]See Appendix B for details on variable definitions.

effects. The coefficient β identifies whether firms with different bond fund ownership have different sensitivity to monetary policy. I focus on $h = 12$ to capture cumulative effects and defer results on other horizons to the appendix.

Panel A of Table 4 shows the results. Column 1 shows that, given 1 p.p. decrease (increase) in monetary policy rate, firms with one-standard-deviation-higher bond fund ownership increase (decrease) their gross bond issuance by 3.01% of bond amount outstanding more than the average firm. The effect is not only statistically significant but also economically large, as it represents 51% (3.01 / 5.96) of the average monetary sensitivity of gross bond issuance.

What do firms do with the bond issuance proceeds? I find that most of the bond issuance proceeds are used for refinancing old bonds and other forms of credit (e.g. bank loans). Column 2 (3) shows that, in response to 1 p.p. rate drop, firms with one-standard-deviation-higher bond fund ownership increase net bond issuance (net debt issuance) by 1.31% (0.98%) of bond amount outstanding more than the average firm, which is only 44% (33%) of the effect on gross bond issuance. In other words, 56% of the gross bond issuance proceeds are used to refinance old bonds and 11% to refinance other forms of credit.

Despite the large refinancing activity, the 0.98% change in net debt issuance is still economically meaningful, as it represents 37% (0.98 / 2.63) of the average monetary sensitivity of net debt issuance. What do firms do with the net debt issuance proceeds? Column 4 shows that most of the proceeds are paid out to equity holders. Given 1 p.p. monetary easing, firms with one-standard-deviation-higher bond fund ownership increase net equity payout more than the average firm by 0.91% of bond amount outstanding, an amount that closely mirrors the effect on net debt issuance (0.98%). Column 5 shows that there is no significant effect on real investment in CAPX and R&D, confirming that, on average, the higher bond issuance activities are not driven by firm demand related to productive investment opportunities.

My results are consistent with the findings in Ma (2019), who finds that many equity payouts are financed by bond issuance driven by bond mispricing. In comparison, my paper provides a concrete source of bond mispricing: monetary-policy-induced bond fund flows.

5.5 Real effects

What are the real effects, which are the ultimate goal of monetary policy? My baseline results show significant effects on firms' capital structure related to debt refinancing and equity payout. One way to assess the economic magnitude is to compare with well-known determinants of leverage, such as tax. Heider and Ljungqvist (2015) show that one-standard-deviation increase in local tax rate leads to an 40 bps increase in leverage (measured as total debt as a ratio of total assets). Therefore, the effect that I have identified here is roughly 10% of the effect of one of the leading determinants of leverage (bond amount outstanding is roughly a third of total assets for the average firm in my sample). Therefore, monetary easing leads to significant increase in leverage through the bond fund channel, which bears implications for stability of the real economy.

Even though I find limited direct effects on real investment, there can be significant indirect effects. For example, as firms issue more bonds to repay their bank loans and repurchase their equities, banks and equity holders can use the received capital to re-invest in other firms with real investment opportunities. This spillover is not captured by my focus on bond-issuing firms but can be plausibly large.

I show below that there are large direct effects on the real activities of constrained firms, consistent with theories such as Stein (1996) and Ottonello and Winberry (2020). One one hand, unconstrained firms should face less frictions in adjusting their debt issuance policy and therefore be more capable of taking advantage of mispricing of their own bonds.[25] On the other hand, unconstrained firms are likely already at the optimum of their level of investment, and any additional supply of capital would then simply be used to pay out equity distribution. To investigate this potential heterogeneity, I estimate the following regression:

$$Y_{j,t,t+h} = \beta_h \Delta Rate_{t,t+4} \times BFOwnership_{j,t} \times Constrained_{j,t} + \gamma_h Controls + FE + \epsilon_{j,t,t+h} \quad (10)$$

where $Constrained_{j,t}$ is an indicator for whether firm j is constrained at quarter end t, defined as having low payout ratio (relative to earnings), high investment ratio (relative to earnings), low cash holdings (relative to total assets), small size (in terms of total assets), or young age (defined as time since first appearance in Compustat database). The regression includes both the triple interaction term as well as its components, i.e. $\Delta Rate_{t,t+4}$, $BFOwnership_{j,t}$, $Constrained_{j,t}$ and their pair-wise interactions.

Table 5 shows the results. In response to the same monetary easing and given the same exposure to bond fund flows, constrained firms issue less bonds, indicating their lack of ability to arbitrage the market. However, they use the bond proceeds much more towards real investment instead of equity payout. The results suggest that, for these constrained firms, bond funds serve as a channel through which monetary policy can alleviate financial

[25] For example, bank-dependent firms cannot adjust their leverage freely because of covenant restrictions that are prevalent in loan contracts.

constraints and stimulate real activity.

5.6 Endogeneity concerns

Bond ownership by bond funds is not exogenously assigned to firms. Therefore, its effect on monetary sensitivity could be spurious and driven by some other factors. I argue for causality in two steps. First, I describe a host of plausible alternative explanations and provide additional evidence against them. Then, I employ an identification strategy relying on firm-specific variation in bond fund ownership over time. I construct a shift-share instrument that further isolates the exogenous component of the variation.

5.6.1 Additional evidence against alternative explanations

Some bond characteristics are mechanically linked to higher monetary sensitivity (e.g. bonds with longer maturity) and they might be happen to be preferred more by bond funds. However, my baseline analyses control for a large set of bond characteristics and firm attributes – either their interactions with rate changes or their time-interacted fixed effects – so the results are not driven by these observable factors. To further rule out alternative explanations based on observables, I analyze a sub-sample of firms that are matched on their propensity scores for bond fund exposure, and Table 4 shows that my main results remain robust.

Some firms may have higher demand for bond financing in response to monetary easing and they are preferred more by bond funds. However, that I find bond yields and bond issuances move in the opposite direction suggests that the results are driven by creditor supply instead of firm demand. Moreover, unless the firm is financial constrained, the bond issuance translates mainly to debt refinancing and equity payout, not real investment.

One reverse-causality story is that bond funds can identify and prefer bonds with higher effective duration. This preference for implicit duration should come from bond funds that cannot simply buy bonds with higher explicit duration – for example, bond funds that already have high explicit duration relative to what their investment mandates allow. To rule out this constrained demand for implicit duration, I exclude bond funds that are in the top quintile of fund duration for each style and re-do the same bond-level regression (8). Table A2 shows the results, which show that my results are robust to excluding the bond funds that may have high demand for implicit duration.

Following papers such as Choi et al. (2020) and Ma et al. (2022), I exploit heterogeneity across bonds issued by the same firm. This exercise purges out any inherent differences in monetary sensitivity at the issuer level. First, I redefine bond fund ownership at the bond level, instead of the issuer level. I then rerun the bond-level regression (8) with issuer-quarter fixed effects. Table A2 shows the results. Column 1 show that, across near-identical bonds issued by the same firm, higher bond fund ownership is associated with higher effective duration by 11 bps, but the effect is not statistically significant. However, if I restrict the sample to monetary tightening (i.e., when $DeltaRate > 0$), I do find larger effects that are statistically significant. This is because monetary tightening induces outflows from bond funds, and, as I have shown in Section 5.1, portfolio scaling at the bond level is much higher for outflows than for inflows. The effect of 19 bps is still significantly smaller than the baseline results in Table 3, which is unsurprising because these bonds are such close substitutes to each other that we should expect the investor elasticities to be much higher and hence the price impacts to be much smaller.

5.6.2 Firm-specific variation in bond fund ownership over time

Some firms might be inherently more sensitive to monetary policy in ways not captured by any of the observables that I control for, and this higher monetary sensitivity could be spuriously correlated with bond ownership – for example, bond funds like and can identify firms with higher monetary sensitivity. I present an identification strategy that relies on firm-specific variation in bond fund ownership over time that is plausibly exogenous to firm sensitivity to monetary policy. The idea is that the same firm can have different bond fund ownership over time due to, for example, the secular rise of bond funds due to the switch from defined-benefit to defined-contribution pension funds. When the firm's bond fund ownership increases due to these exogenous reasons, any correlated change in monetary sensitivity is arguably causal.

As a first step, I control for firm dummies interacted with rate changes in the bond-level regression (8) and the firm-level regression (9). Results are given in Table A2 and Table A3. For the same firm, higher bond fund ownership is associated with higher monetary sensitivity, where the effect is largely the same as my baseline specification. This exercise rules out any firm-specific time-invariant monetary sensitivity that could be driving my baseline results.

However, one alternative interpretation is that bond funds increase their holdings of a firm precisely when its monetary sensitivity increases. In other words, monetary sensitivity reverse-causes bond fund ownership. To address this, I construct a shift-share instrument that excludes discretionary bond fund trading and zooms in on the change in bond fund ownership due to cumulative bond fund flows:

$$z_{j,t} = \frac{\sum_i AmountHeld_{i,j,t_0} FundFlow_{i,t_0,t}}{AmountOutstanding_{j,t}} \tag{11}$$

where $AmountHeld_{i,j,t_0}$ is bond fund i's ownership of firm j's bonds at the beginning of my sample period t_0, $FundFlow_{i,t_0,t}$ is cumulative flow into bond fund i since the beginning of my sample period t_0 to current quarter t, and $AmountOutstanding_{j,t}$ is firm j's total bond amount outstanding at current quarter t. Intuitively, having ex ante relationships with bond funds that subsequently experience large cumulative inflows leads to higher bond fund ownership over time.

As an illustrative example, Firm A has relationships with bond funds that have received particularly large cumulative inflows and pension funds that have experienced particularly large cumulative outflows, so its bond fund ownership increases from 5% at the beginning to 50% at the end of my sample period. In comparison, Firm B borrows mainly from insurers, and its bond fund ownership is constant at 0% through out my sample period.

Panel B of Table 3 and Panel B of Table 4 show results. The first-stage F-statistics are well above the conventional thresholds against weak instruments. The key estimates of interests remain significant and are in similar magnitudes as the baseline specifications. As a result, this identification strategy brings further credence to the causal effect of bond fund ownership on firm sensitivity to monetary policy.

One might question the exogeneity of cumulative bond fund flows to firm sensitivity to monetary policy. Although unlikely, retail investors might prefer firms with high monetary sensitivity and are able to identify the firms that have increased monetary sensitivity as well as the bond funds that have sticky relationships with those firms. This would mean that firm monetary sensitivity reverse-causes cumulative bond fund flows. To address this, I construct a refined shift-share instrument that focuses on cumulative bond fund flows that can be explained by factors that are fairly certainly exogenous to firm sensitivity to monetary policy:

$$\tilde{z}_{j,t} = \frac{\sum_i AmountHeld_{i,j,t_0} Fund\tilde{F}low_{i,t_0,t}}{AmountOutstanding_{j,t}} \tag{12}$$

where $Fund\tilde{F}low$ is cumulative bond fund flows that can be explained by the secular shift from defined-benefit to defined-contribution pension, fund performance, and fund expense ratios through the following regression:

$$FundFlow_{i,t_0,t} = \beta_1 DB/DC_{t_0,t} + \beta_2 FundReturn_{i,t_0,t} + \beta_3 ExpenseRatio_{i,t_0,t} + \epsilon_{i,t_0,t}$$

The results are presented in Table A2 and Table A3. My main results remain robust.

6 Aggregate Yield Sensitivity to Monetary Policy

The reduced-form analyses above focus on comparing corporate bonds that are near-identical to each other. This approach is good for identification, but makes it difficult to infer the aggregate effect. For starters, it should be easier to arbitrage across similar bonds (e.g. two bonds with the same rating and the same duration) than across different bond classes (e.g. a long-term Treasury bond vs a short-term high-yield corporate bond). In other words, micro elasticities should be higher than macro elasticities.[26] As a result, we should expect bond fund flows to have bigger impact on aggregate bond yields than what is identified in the cross section.

In addition, the reduced-form approach is silent about comparison with other channels through which monetary policy can affect bond yields. For example, one channel that has received increasing attention is duration hedging. In particular, Domanski et al. (2017) and Ozdagli and Wang (2020) show that pension and insurance liabilities have large convexity, and therefore when rates decline, the duration of these liabilities goes up, which induces pension plans and insurers to tilt towards longer-term bonds to increase asset duration, and this pushes down long-term bond yields. In Appendix D, I provide details on three alternative channels that are prominent in the literature: institutional risk-taking, institutional duration hedging, and institutional liquidity sensitivity.

To assess the aggregate effect of bond fund flows and to compare them with other channels, I use the demand system approach pioneered by Koijen and Yogo (2019). This structural framework not only incorporates imperfectly elastic substitution and therefore flow impact on asset prices, but also allows for direct demand for characteristics, which capture the three alternative channels that I focus on. Following Koijen and Yogo (2020), I extend the original demand system framework to allow for different elasticities at the macro level (across bond classes) vs at micro level (across bonds within a given class), accommodating for different

[26] See Gabaix and Koijen (2022), Li and Lin (2022), Chaudhary et al. (2022) for related evidence.

flow impact on cross-sectional vs aggregate bond yields.

To preview my results, I find that institutional bond investors have limited elasticities when substituting across bonds. The weighted average semi-elasticity with respect to yield in basis point across institutional bond investors is 0.1 (0.5) at the macro level across bond classes (micro level across individual bonds), implying a 10 bps (2 bps) yield impact per unit of flow. With the estimated demand system, I calculate counterfactual bond yields and quantify each channel's contribution to the aggregate corporate bond yield sensitivity to monetary policy. Bond fund flows account for 11 bps increase in aggregate corporate bond yields in response to a 100 bps increase in the two-year Treasury rate, or 21% of the total sensitivity. In comparison, institutional risk-taking, institutional duration hedging and institutional liquidity sensitivity account for 5 bps, 10 bps and 8 bps, respectively.

6.1 A nested logit demand system of bonds

I adapt the framework in Koijen and Yogo (2020) and present a nested logit demand system of bonds with flexible substitution both within and across bond classes. This modeling choice is motivated by the following observations. First, investors are imperfectly elastic even for near-identical bonds, as shown by my analysis in Section 5. Secondly, substitution across bond classes (e.g. between investment-grade bonds and high-yield bonds) should be less elastic than substitution across bonds within a bond class – in other words, macro elasticities are expected to lower than micro elasticities. Lastly, investors could have direct demand for bond characteristics because characteristics fulfill certain functions – for example, life insurers prefer bonds of certain duration that can hedge their liabilities.

There are 9 bond classes, indexed by l: Treasury bonds, further separated into short-term (2-5 years to maturity), medium-term (5-10 years to maturity), and long-term (more than 10 years to maturity); investment-grade (BBB- or above) corporate bonds, further separated into short-term, medium-term, and long-term, with the same maturity cutoffs as above; high-yield (BB+ or below) corporate bonds, further separated into short-term and medium-to-long-term (high-yield bonds with maturity more than 10 years are rare). There is one outside bond class ($l = 0$) and I model it as a money market fund: it pays the two-year Treasury yield that is exogenously controlled by the Fed, it is rated AAA, it has two years to maturity, and its bid-ask spread is 0.[27]

[27]In reality, there are many other bonds (e.g. agency securities) and other assets (e.g. equities).

I include Treasury bonds in addition to corporate bonds for the following reasons. First, Treasury bonds are close substitute to corporate bonds. Figure A6 shows that bond funds hold a large share of their portfolios in Treasury bonds. Secondly, there are detailed historical data on the characteristics and yields of Treasury bonds. This data availability is not present for other bonds such as agency securities. Lastly, modeling Treasury bonds allows me to calculate counterfactual Treasury bond yields and in turn counterfactual credit spreads.

Bonds in each bond class l are indexed by $n_l = 1, ..., N_l$. Each bond has par amount outstanding of $S_t(n_l, l)$, a price measured by yield to maturity $y_t(n_l, l)$, and a vector of characteristics $x_t(n_l, l)$, which include rating, maturity and bid-ask spread.[28] There is one outside bond for each of the bond classes, indexed by $(0, l)$. The outside bond represents the bonds that are part of the class (according to their ratings and maturities) but do not have price information available. I assign to the outside bond the weighted average yields and characteristics of the class. In other words, the outside bond is an index fund of the bond class.

Investors are indexed by $i = 1, ..., I$. I focus on four classes of institutional bond investors for which I have security-level data on portfolio holdings: bond funds, mixed funds, life insurers and P&C insurers. I further separate bond funds into government short-term, medium-term, long-term bond funds, general short-term, medium-term, long-term bond funds, and high-yield bond funds, as indicates by the funds' Morningstar Categories.

Investor i's time t portfolio weight in bond n_l of bond class l is:

$$w_{i,t}(n_l, l) = w_{i,t}(n_l|l)w_{i,t}(l) \tag{13}$$

where $w_{i,t}(n_l|l)$ represents the portfolio weight in bond n_l within bond class l and $w_{i,t}(l)$ represents the aggregate portfolio weight in bond class l. The portfolio weights must sum to one within each asset class: $\sum_{n\in l} w_{i,t}(n_l|l) = 1$. The aggregate portfolio weights must sum to one across all bond classes: $\sum_l w_{i,t}(l) = 1$.

I model the portfolio weight in bond n_l within bond class l at time t as:

$$w_{i,t}(n_l|l) = \frac{\delta_{i,t}(n_l, l)}{\sum_{n_l'} \delta_{i,t}(n_l', l)}$$

[28] I follow Bretscher et al. (2021) and use pseudo zero-coupon yields, which have the advantage of faster mapping to bond prices, compared to the usual yields to maturity that need to take into account both bond prices and coupon rates.

where:

$$\delta_{i,t}(n_l, l) = \exp\{\beta_{i,t}(l) y_t(n_l, l) + \mathbf{\Theta}_{i,t}(l)' \boldsymbol{x}_t(n_l, l)\} u_{i,t}(n_l, l)$$

where $u_{i,t}(n_l, l)$ captures latent demand not explained by observed yields or characteristics. For estimation purpose, I re-write portfolio weight as relative to the outside bond:

$$\frac{w_{i,t}(n_l|l)}{w_{i,t}(0|l)} = \exp\{\beta_{i,t}(l)(y_t(n_l, l) - y_t(0, l)) + \mathbf{\Theta}_{i,t}(l)'(\boldsymbol{x}_t(n_l, l) - \boldsymbol{x}_t(0, l))\} \frac{u_{i,t}(n_l, l)}{u_{i,t}(0, l)} \tag{14}$$

Recall that the outside bond represents the average of the bond class. As a result, the equation above has an intuitive interpretation: the relative within-class weight of a bond is determined by its yield and characteristics relative to the class average.

I model the aggregate portfolio weight in bond class l at time t as:

$$w_{i,t}(l) = \frac{\mathcal{D}_{i,t}(l)}{\sum_{l'} \mathcal{D}_{i,t}(l')}$$

where:

$$\mathcal{D}_{i,t}(l) = \delta_{i,t}(0, l)^{\lambda_{i,t}(l)} \exp\left\{\mathbf{\Gamma}'_{i,t} \boldsymbol{x}_t(l) + \xi_{i,t}(l)\right\}$$

$\sum_{n \in l} \delta_{i,t}(n, l)$ is called the "inclusive value" in a nested logit model. To understand the role of the inclusive value, suppose that the coefficient on yield is positive (i.e., $\beta > 0$). An increase in yields across all investment-grade short-term corporate bonds makes that bond class more attractive, reflected by an increase in its inclusive value. $\lambda_l \in [0, 1]$ governs how elastic the investor is in responding to this inclusive value. A higher $\lambda(l)$ means that the investor is more responsive and substitute to (away) from this bond class more when its inclusive value rises (falls).

In addition to the inclusive value, aggregate portfolio weight also depends on class-level characteristics and latent class-level demand $\xi_{i,t}(l)$. I calculate class-level characteristics as the weighted average of all bonds in that class.

For estimation, I re-write the aggregate portfolio weight as relative to the outside money market fund as:

$$\frac{w_{i,t}(l)}{w_{i,t}(0)} = \mathcal{D}_{i,t}(l) = [\sum_n \delta_{i,t}(n, l)]^{\lambda_{i,t}(l)} \exp\left\{\mathbf{\Gamma}'_{i,t} \boldsymbol{x}_t(l) + \xi_{i,t}(l)\right\} \tag{15}$$

6.2 Identification

To estimate demand coefficients on characteristics $\mathbf{\Theta}$ and $\mathbf{\Gamma}$, I make the standard assumption that characteristics are exogenous:

$$E[\frac{u_{i,t}(n_l,l)}{u_{i,t}(0,l)} \mid \boldsymbol{x}_t] = 1 \tag{16}$$

and

$$E[\xi_{i,t}(n,l) \mid \boldsymbol{x}_t] = 0 \tag{17}$$

Using the above as moment conditions in a GMM framework, I can estimate $\mathbf{\Theta}$ and $\mathbf{\Gamma}$ using the cross section of holdings for each investor at each time. In practice, this is done after β and λ are estimated, so that u and ξ can be constructed.

Estimating the yield coefficient β and the substitution across bond classes λ is less straightforward, as they must be jointly endogenous with latent demand. I follow the identification strategy in Gabaix and Koijen (2022) and van der Beck (2022) and use idiosyncratic flows as exogenous shocks to yields and inclusive values. The idea is that idiosyncratic flows to an institutional bond investor creates particularly price pressure on the bond classes and the individual bonds that the investor already owns, due to investment mandate and lending relationship, which I have shown in Section 5.1. These idiosyncratic flows are plausibly exogenous and hence constitute shocks to yields and inclusive values.

Formally, investor i's idiosyncratic flows at time t are given by residuals from a principal component regression:

$$InvestorFlow_{i,t} = \alpha + \sum_k \beta_k PC_k + Inves\tilde{t}orFlow_{i,t}$$

where PC_k denotes the kth principal component of flows across investors over time. These investor-level idiosyncratic flows are then aggregated for each bond class:

$$Clas\tilde{s}Flow_t(l) = \sum_i \frac{AmountHeld_{i,t}(l)}{AmountOutstanding_t(l)} Inves\tilde{t}orFlow_{i,t} \tag{18}$$

or for each bond:

$$Bon\tilde{d}Flow_t(n_l,l) = \sum_i \frac{AmountHeld_{i,t}(n_l,l)}{AmountOutstanding_t(n_l,l)} Inves\tilde{t}orFlow_{i,t} \tag{19}$$

I argue that these idiosyncratic flows are plausibly exogenous shocks to yields and inclusive values and therefore can be used to identify price elasticities β and λ. First, I make the assumption that β and λ are constant over time for each investor. To identify β, I take the log first difference of Equation (14):

$$\Delta \log w_{i,t}(n_l|l) = \beta_i(l)\Delta y_t(n_l, l) + \epsilon_{i,t}(n, l) \tag{20}$$

where $\epsilon_{i,t}(n, l)$ captures both characteristics and latent demand relative to the outside bond. Using idiosyncratic flows as instruments, β can be identified via GMM by the following moment condition:

$$E[\epsilon_{i,t}(n_l, l) \mid Bon\tilde{d}Flow_t(n_l, l)] = 0 \tag{21}$$

Similarly, to identify λ, I take the log first difference of Equation (15):

$$\Delta \log w_{i,t}(l) = \lambda_i(l)\Delta \log \delta_{i,t}(0, l) + \Xi_{i,t}(l) \tag{22}$$

where $\Xi_{i,t}(l)$ captures both characteristics and latent demand relative to the outside money market fund. Using idiosyncratic flows as instruments, λ can be identified via GMM by the following moment condition:

$$E[\Xi_{i,t}(l) \mid Clas\tilde{s}Flow_t(l)] = 0 \tag{23}$$

I show robustness of my results in Appendix E using alternative identification strategies, including one based on investment universe (Koijen and Yogo, 2019) and one based on characteristics-only demand (Koijen and Yogo, 2020).

6.3 Estimation

I first estimate price elasticities β and λ for each investor, using the identification strategies described in the previous section. Specifically, this is done via GMM using equations 20 and 22 with 21 and 23 as moment conditions. I then estimate demand coefficients on characteristics $\mathbf{\Theta}$ and $\mathbf{\Gamma}$ for each investor at each time. This is done via GMM using equations 14 and 15 with 16 and 17 as moment conditions. This last step also yields u and ξ as the residuals.

One practical challenge is that an investor can have zero holdings of a bond class or zero holdings of the outside bond of a bond class. For example, almost all of the Treasury bonds have price information at all time, and therefore the outside bond for the Treasury bond classes rarely exists. For these cases, I assume that the with-in class demand coefficients are the same as those in the closest bond classes. For example, for an investor who has zero holdings of the outside bond in the long-term Treasury bond class, the within-class demand coefficients are given by those estimated from the investment-grade long-term corporate bond class.

Figure 8 shows estimated micro elasticities (across bonds within a bond class) β and macro elasticities (across bond classes) λ 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).

At the macro level across bond classes, the weighted average yield semi-elasticity (price elasticity) is 0.1 (2), meaning that if the bond class has 1 bps higher yield (1% lower price), its portfolio weight is predicted to increase by 0.1% (2%). Note how macro elasticities are significantly smaller than micro elasticities. As a result, the implied flow impacts are also much bigger at the macro level than at the micro level. 1% flow to a bond class predicts 10 bps increase yield (0.5% 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.

6.4 Counterfactual bond yields

Having estimated the demand system, I can derive counterfactual partial-equilibrium bond yields for any given values of exogenous variables. Specifically, for any values of monetary policy rate (i.e. two-year Treasury rate) R, bond characteristics $\boldsymbol{x}$, bond supply S, investor investment in the outside money market fund O, investor demand coefficients $(\boldsymbol{\Theta}, \boldsymbol{\Gamma})$ and investor latent demand (u, ξ), bond yields y are pinned down through the market clearing condition:

$$S_t(n, l)e^{-y_t(n,l)T} = \sum_{i=1}^{I} \frac{O_{i,t}}{w_{i,t}(0; \boldsymbol{y}_t)} w_{i,t}(n_l, l; \boldsymbol{y}_t) \tag{24}$$

where the left-hand side is the market value of the bond, and right-hand side is the aggregate demand all investors. I include yield in the argument of weight to emphasize that it is the equilibriating variable. Market clearing is required for all bonds, including the outside bond in each bond class, except for the outside money market fund, where the supply is controlled by the Fed such that the two-year Treasury rates are as observed. I denote the counterfactual bond yields as $y(R, \boldsymbol{x}, S, O, (\boldsymbol{\Theta}, \boldsymbol{\Gamma}), (u, \xi))$ and derive them through numerical approximation.

6.5 Decomposing yield sensitivity to monetary policy

I follow Koijen and Yogo (2019) and perform a decomposition of bond yield changes into orthogonal components:

$$\Delta y_t = \Delta y_t(R) + \Delta y_t(\boldsymbol{x}) + \Delta y_t(S) + \Delta y_t(O) + \Delta y_t(\boldsymbol{\Theta}, \boldsymbol{\Gamma}) + \Delta y_t(u, \xi) \tag{25}$$

where:

$$\begin{aligned}
\Delta y_t(x) &:= y(x_t, S_t, R_t, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) - y(x_{t-1}, S_t, R_t, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) \\
\Delta y_t(S) &:= y(x_{t-1}, S_t, R_t, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) - y(x_{t-1}, S_{t-1}, R_t, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) \\
\Delta y_t(R) &:= y(x_{t-1}, S_{t-1}, R_t, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) - y(x_{t-1}, S_{t-1}, R_{t-1}, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) \\
\Delta y_t(O) &:= y(x_{t-1}, S_{t-1}, R_{t-1}, O_t, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) - y(x_{t-1}, S_{t-1}, R_{t-1}, O_{t-1}, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) \\
\Delta y_t(D) &:= y(x_{t-1}, S_{t-1}, R_{t-1}, O_{t-1}, (\boldsymbol{\Theta}_t, \boldsymbol{\Gamma}_t), (u_t, \xi_t)) - y(x_{t-1}, S_{t-1}, R_{t-1}, O_{t-1}, (\boldsymbol{\Theta}_{t-1}, \boldsymbol{\Gamma}_{t-1}), (u_t, \xi_t)) \\
\Delta y_t(u) &:= y(x_{t-1}, S_{t-1}, R_{t-1}, O_{t-1}, (\boldsymbol{\Theta}_{t-1}, \boldsymbol{\Gamma}_{t-1}), (u_t, \xi_t)) - y(x_{t-1}, S_{t-1}, R_{t-1}, O_{t-1}, (\boldsymbol{\Theta}_{t-1}, \boldsymbol{\Gamma}_{t-1}), (u_{t-1}, \xi_{t-1})
\end{aligned}$$

Each component of the decomposition measures how would yields change if there were no change in the exogenous variable. For example, $\Delta y_t(S)$ measures how would yields change if there were no change in bond supply – i.e., no issuance of new bonds.

I am interested in how does each specific channel, e.g. changes in investors' demand for duration, contributes the overall sensitivity of bond yields to monetary policy. I measure monetary sensitivity by the following regression:

$$\Delta y_t(\cdot) = \alpha + \beta \Delta Rate_t + \epsilon_t \tag{26}$$

There are a few technical issues with this decomposition. $\Delta y_t(\boldsymbol{x})$ does not forbid natural shortening of maturity. Forbidding maturity shortening is not sensible, and therefore I focus on other changes in bond characteristics (e.g. downgrade). Similarly, $\Delta y_t(S)$ does not forbid natural redemption at maturity. Therefore, I focus on non-maturity changes in bond supply, such as new issuance and redemption call.

$\Delta y_t(O)$ captures both changes in the value of the outside bond class and flows. The former is difficult to measure since data on outside assets (e.g. agency securities) are limited. I focus on flows, which are the main focus of this paper. In the counterfactual exercise, I will change the investors' outside investment amount by the dollar flow that it receives. I will do this separately for bond funds and for the other institutional investors.

$\Delta y_t(\boldsymbol{\Theta}, \boldsymbol{\Gamma})$ captures changes in demand for all characteristics, but we are also interested in the effect of each characteristic alone. $\Delta y_t(\theta_1, \gamma_1)$ corresponds to changes in risk-taking, $\Delta y_t(\theta_2, \gamma_2)$ duration hedging, and $\Delta y_t(\theta_3, \gamma_3)$ changes in liquidity sensitivity.

Figure 9 shows the decomposition results for the weighted average yield of all corporate bonds. The black bar shows the actual observed monetary sensitivity. Consistent with the literature, monetary policy has a high impact on corporate bond yields. On the annual frequency, 1 p.p. increase in two-year Treasury rate is associated with 0.23 p.p. increase in the average yield of all corporate bonds.

Each of the red arrows shows what the monetary sensitivity would have been if the channel is forced shut. For example, the second red arrow shows that yield sensitivity to monetary policy would have been significantly higher if there is no change in bond supply. This is consistent with the extensive evidence that corporate bond supply is very responsive to monetary policy. When short-term interest rates decline, firms issue more bond and increase net bond supply, which push up bond yields, dampening the monetary sensitivity. The second red arrow shows that the contribution of corporate bond supply to aggregate yield sensitivity is -26 bps. In other words, the monetary sensitivity of corporate bond yield would have been 26 bps higher, if firms do not change their bond supply.

Bond fund flows contribute significantly to the monetary sensitivity. Without bond fund flows, the monetary sensitivity would have been 11 bps smaller. When rates decline, bond funds experience large inflows and buy more corporate bonds, which push down corporate bond yields, amplifying the monetary transmission. The 11 bps contribution is large relative to the actual sensitivity of 23 bps, or relative to the total sensitivity of 51 bps, where both bond characteristics and bond supply are forced to be constant.

Among the other channels, duration hedging, and in particular insurers' duration hedging, have the highest effect. This is consistent with the explanations insurers hunt for duration when interest rates drop (Drechsler et al., 2017). Surprisingly, changes in risk-taking do not play an important role. Similar to Koijen and Yogo (2019), the residual latent demand explains most of the bond yield changes.

Panel A of Figure 10 shows the decomposition for different bond classes. Actual observed yield sensitivity to monetary policy is smaller for bonds with lower ratings and longer maturities. The bond supply effect is strong across all bond classes. The bond fund flow channel is strongest for bonds with lower ratings and shorter maturities, consistent with the fact that bond fund ownership is higher for those bonds. Insurer duration hedging slightly dampens yield sensitivity for short-term bonds and significantly amplifies yield sensitivity for investment-grade long-term bonds, consistent with the explanation that insurers hedge the increase in their liabilities duration by tilting their portfolios away from short-term bonds towards long-term bonds.

Panel B of Figure 10 shows the decomposition for different time periods. Whereas actual observed yield sensitivity has decreased over time, total yield sensitivity absent bond supply has actually increased over time. Bond fund flows seem to be a major reason behind the increase, as its contribution has doubled from 7 bps to 14 bps. The rise of bond funds has contributed to a higher sensitivity of aggregate corporate bond yield to monetary policy.

7 Broader Implications

7.1 Comparison with the bank lending channel

How does the bond fund flow channel stand against other established channels of monetary policy, such as the bank lending channel? I first argue that the bond fund flow channel is as important, if not more, as the bank lending channel in terms of amount of lending. First, the amount of bond fund lending through corporate bonds ($1.57 trillion as of 2020) is almost as large as the amount of bank lending through C&I loans ($1.61 trillion). Based on the trajectory, bond funds are likely to soon overtake banks as the bigger lender to firms.

Secondly, in terms of funding source, bond fund flows are as sensitive to monetary policy as deposit flows. Figure A10 shows that savings deposits increase by 21 p.p. in response to 1 p.p. decrease in the two-year Treasury rate, which is higher but on a similar magnitude as the monetary sensitivity of bond fund flows.

Lastly, there is mixed evidence on the bank lending channel of monetary policy. Indeed, papers such as Greenwald et al. (2020) and Supera (2021) show that C&I loans actually contract in response to monetary easing, which I verify in Figure A10.[29] In contrast, bond fund lending moves almost one-for-one with flows (see Section 5.1) and significantly expands during monetary easing (see Section 4).

Apart from amount of lending, another important dimension is the accessibility of bond fund lending vs bank lending. All firms can access bank lending, but not all firms have access to the bond market. Panel A of Figure A2 shows that only about a quarter of the firms have access to the bond market. However, Panel B of Figure A2 shows that firms with bond market access are the largest firms and account for most of the real investment and employment. Therefore, the effects that I identify on these largest firms are important.

Also important is the substitutability of bond fund lending vs bank lending. Indeed, the original motivation of the bank lending channel is that there are significant frictions such as information asymmetry that makes bank lending more sensitive than the bond market to monetary policy. My paper, along with recent work by Barbosa and Ozdagli (2022) and Coppola (2022), shows that the corporate bond market is characterized by the frictions conventionally thought to be confined in bank lending. In Section 5, I have shown that, for

[29] Supera (2021) argues that C&I loans are funded by time deposits, whose flows move in the opposite direction as demand and savings deposits.

the firms with one-standard-deviation higher bond fund exposure, in a monetary tightening cycle, when their bondholder net flows decrease by 3.1 p.p. more than the average firm, their net bond issuance decrease by 1.3 p.p. and their net debt issuance decrease by 0.9 p.p. The results mean that, even for the firms with bond market access, shocks to existing lending can have large impacts on their financing, as they cannot frictionlessly substitute to other bond investors or other forms of debt.

7.2 Mitigating bond market fragility

The rise of bond funds has been an important concern for financial stability. The 2008 financial crisis and the recent COVID crisis show that bond fund flows are highly vulnerable to bad macroeconomic shocks, especially the illiquid bond funds with high run risk (Goldstein et al., 2017; Falato et al., 2021a). Outflows from bond funds have large spillover effects on peer funds (Falato et al., 2021b) and firms' real activities (Coppola, 2022).

My paper shows that monetary policy is potent tool to mitigate bond fund fragility. Whereas bond funds may experience large outflows during economic downturns, monetary easing can mitigate those outflows. Indeed, a back-of-envelop calculation suggests that bond fund outflows would have been 20 p.p. (26 p.p.) more and aggregate bond yields would have been 31 bps (33 bps) higher, had the Fed not aggressively decreased the federal funds rates during the 2008 financial crisis (the 2020 COVID crisis). As bond funds grow and bond market fragility increases, monetary policy also becomes an increasingly important tool to combat the fragility.

At the same time, monetary policy itself can be a source of fragility for bond fund flows. Indeed, the 2013 taper tantrum generated unprecedented bond fund outflows that led to disruptive hike in long-term bond yields. Similarly, the current monetary tightening has lead to significant outflows from bond funds and generated concerns among policymakers. Papers such as Feroli et al. (2014) and Kuong and Zhang (2020) discuss this in greater detail.

8 Conclusion

This paper sheds new light on the question of how monetary policy transmits through credit markets to the real economy. I focus on a large and fast-growing segment of the credit market that has received little research: the bond mutual funds and ETFs. I show that, in response to policy rate changes, bond funds experience large flows that exert large price pressure on bonds. Using a reduced-form approach, I find statistically and economically large differences between firms that are differentially exposed to bond fund flows, in terms of their bond prices, bond issuance, and real activities such as leverage, payout, and investment. Using a demand system approach, I assess the aggregate effect and show that the bond fund flow channel account for a large and increasing share of the aggregate corporate bond yield sensitivity to monetary policy.

My results have direct implications for the current monetary tightening. In the face of high inflation, central banks around the world are increasing interest rates at a historic speed. As a result, year-over-year bond fund flows have decreased by almost 20% and are negative at the end of 2022. My estimates show that this decrease in flows would add 30 bps to the aggregate corporate bond yield, and even more so for firms that have larger exposure to bond fund flows. These are large quantitative effects to be considered by the policymakers as they weigh the trade-offs between inflation and increasing firm financing costs through the bond market.

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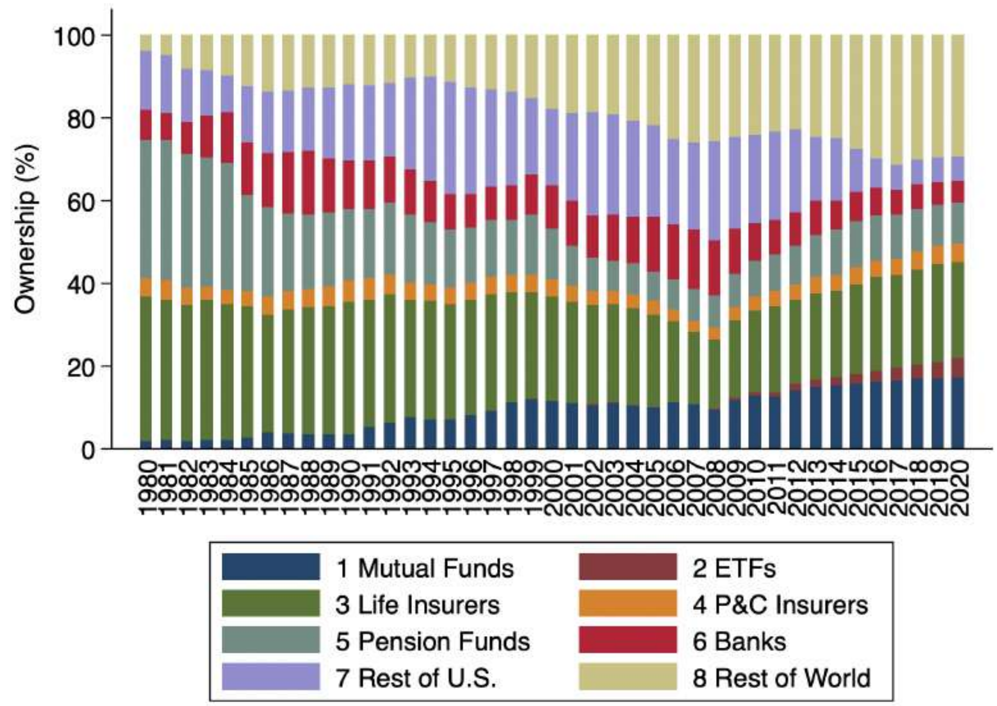
Figures

Figure 1: **Corporate Bond Ownership.** Panel A plots the ownership of corporate and foreign bonds, using data from Financial Accounts of the United States (L.213). Panel B uses security-level holdings data and plots the ownership of U.S. non-financial corporate bonds, defined as straight bonds issued by U.S. non-financial firms and reported in TRACE.

Panel A: Corporate and Foreign Bonds



Panel B: U.S. Non-Financial Corporate Bonds

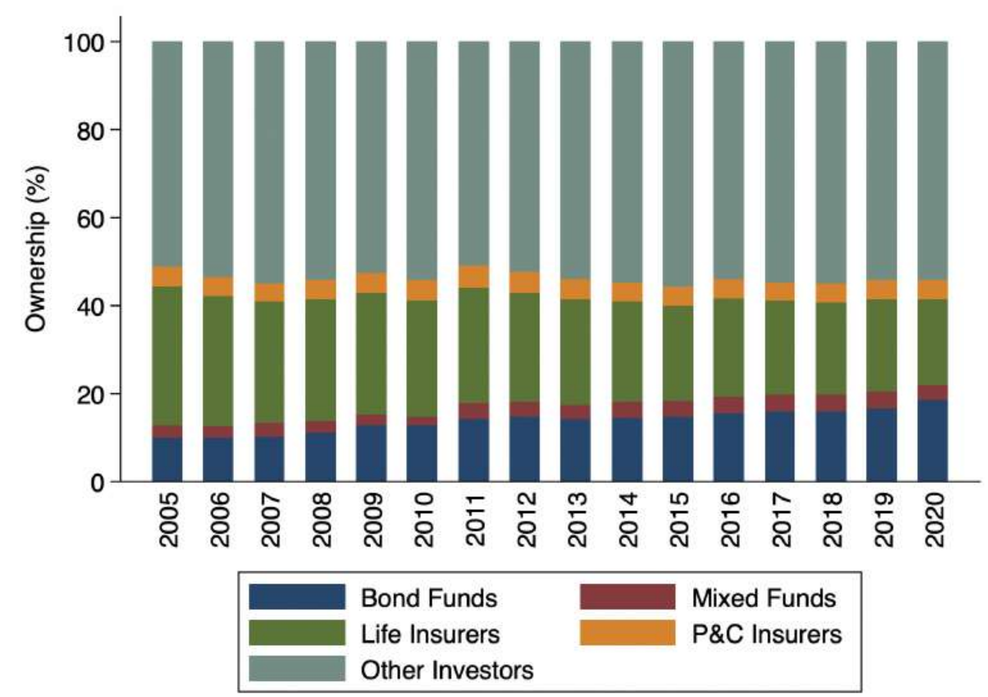
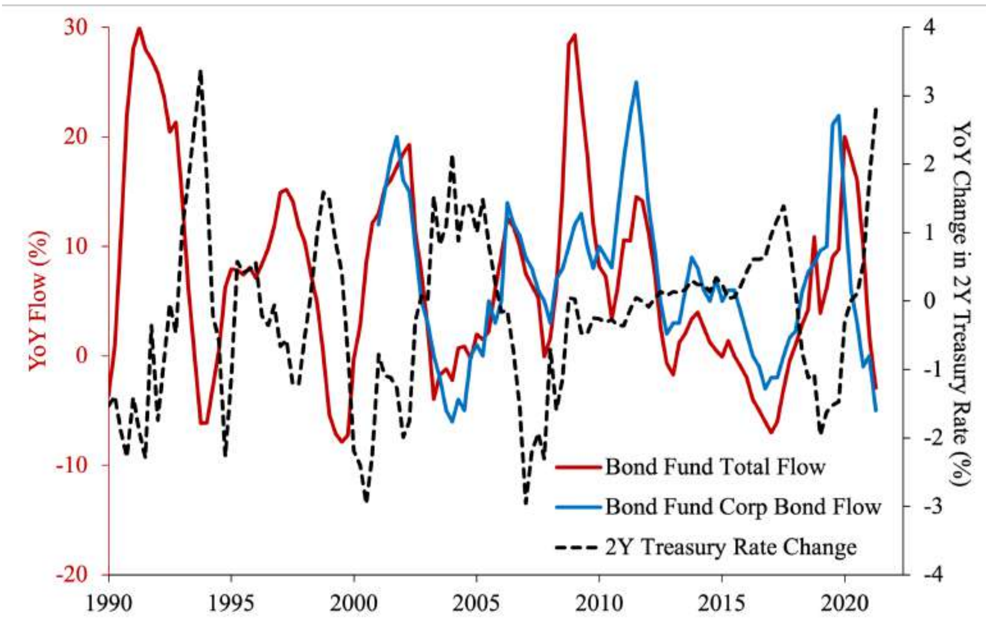


Figure 2: **Monetary Sensitivity across Corporate Bond Investors, Time Series.** Panel A plots year-over-year bond fund net flows (red) and bond fund corporate bond net purchases (blue) as well as year-over-year monetary policy rate changes (black). Panel B plots year-over-year corporate bond net purchases for bond funds (red), insurance companies (green) and the average corporate bond investor (blue).

Panel A: Bond Funds



Panel B: All Corporate Bond Investors

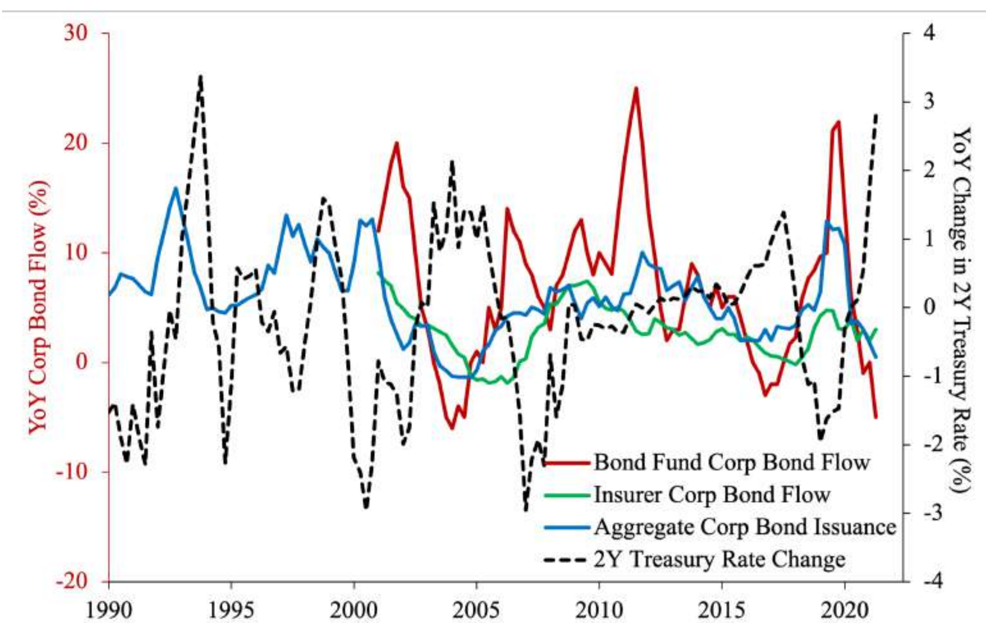
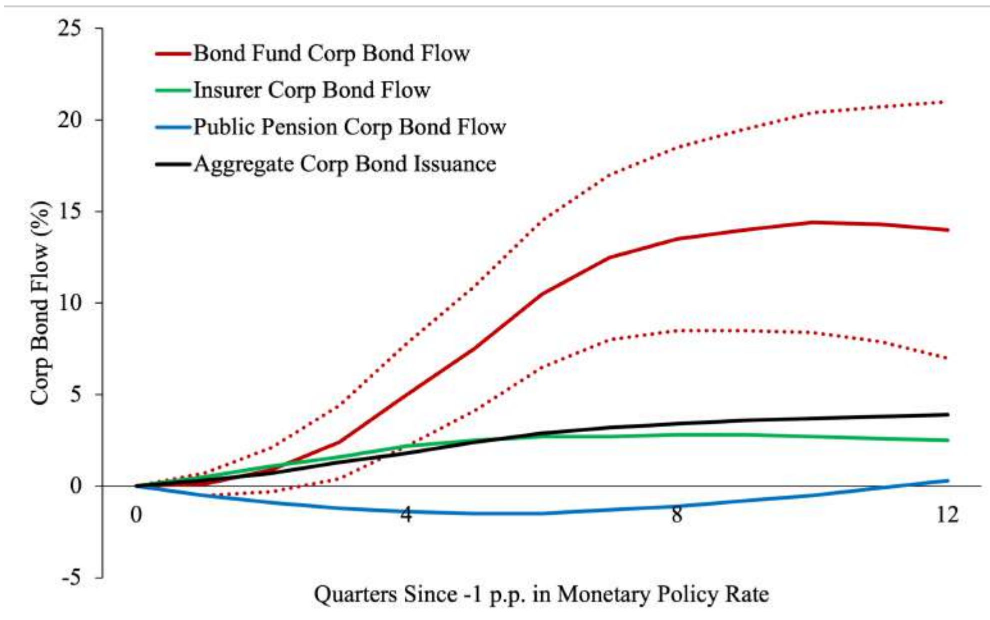


Figure 3: **Monetary Sensitivity across Corporate Bond Investors, Local Projections.** The figures plot cumulative responses of corporate bond net purchases for the largest institutional corporate bond investors to 1 p.p. decrease in two-year Treasury rate with 95% confidence intervals, estimated from Equation (2). Panel A shows the full dynamics of the baseline specification. Panel B shows the difference in three-year response between bond funds and insurers for a battery of alternative specifications.

Panel A: Baseline Full Dynamics



Panel B: Difference in Three-Year Response and Robustness

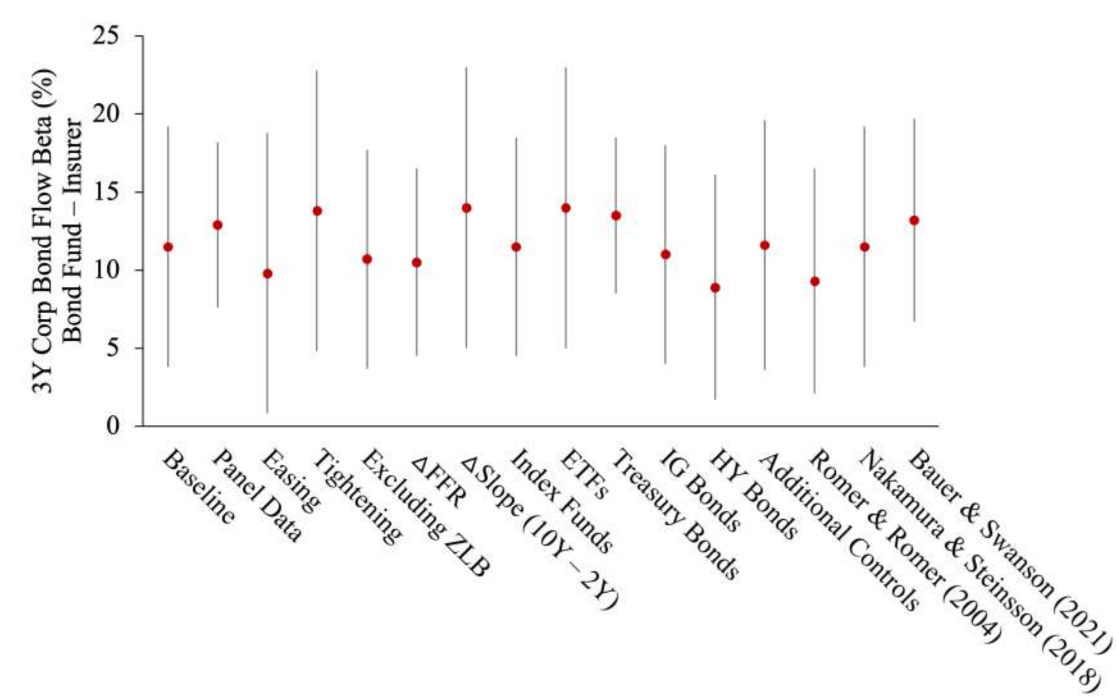
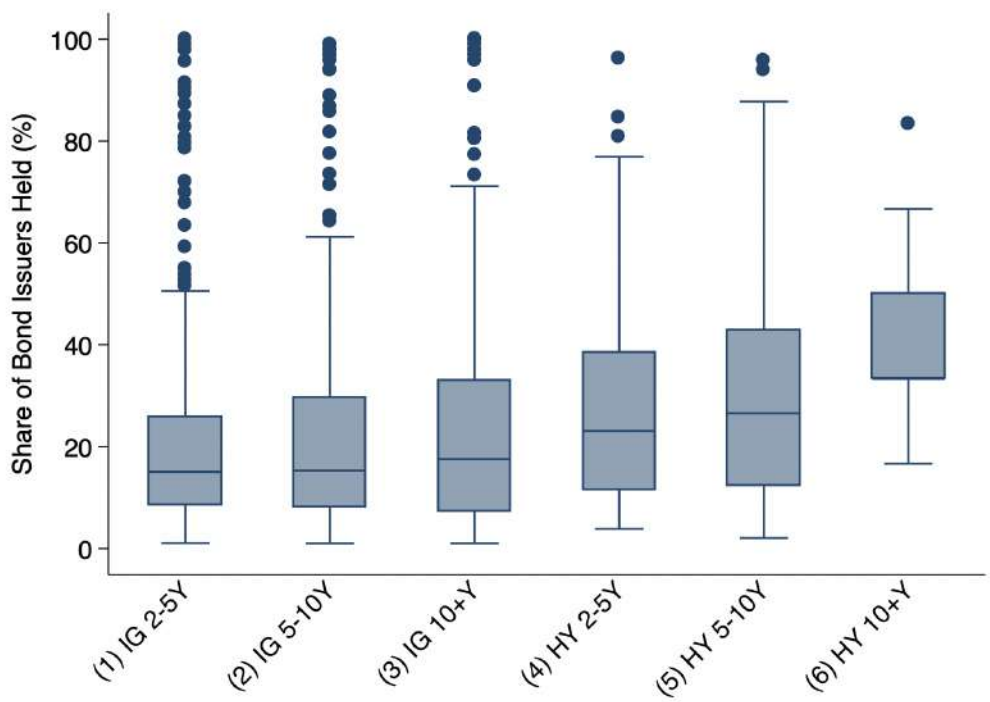


Figure 4: **Bond Fund Portfolio Concentration.** The figures plot distributions of portfolio statistics in the cross section of bond funds with at least $10 million corporate bond holdings at year-end 2015. Panel A (B) plots the relative number of the bond issuers (corporate bonds) held of particular corporate bond style. Bond issuers (corporate bonds) are limited to those with at least $1 million bond outstanding.

Panel A: Share of Bond Issuers Held



Panel B: Share of Corporate Bonds Held

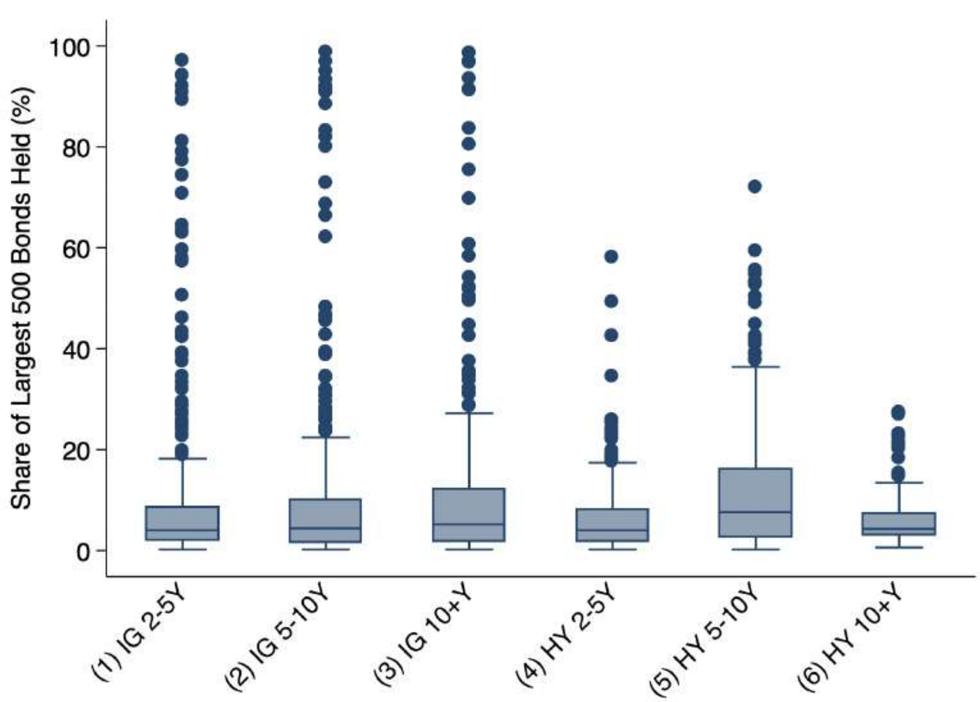
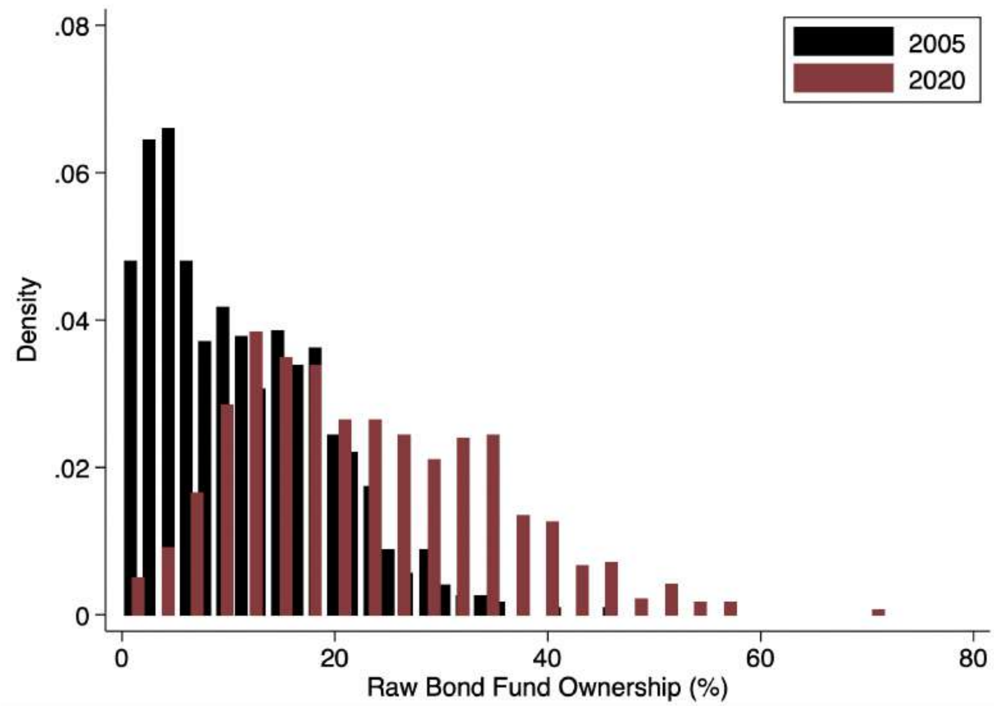


Figure 5: **Cross-Sectional Variation in Bond Fund Ownership.** The figures plot distributions of bond fund ownership across non-financial firms at year-end 2005 and 2020. Panel A shows the raw distribution. Panel B shows the residualized distribution according to Equation (6).

Panel A: Raw Distribution



Panel B: Residualized Distribution

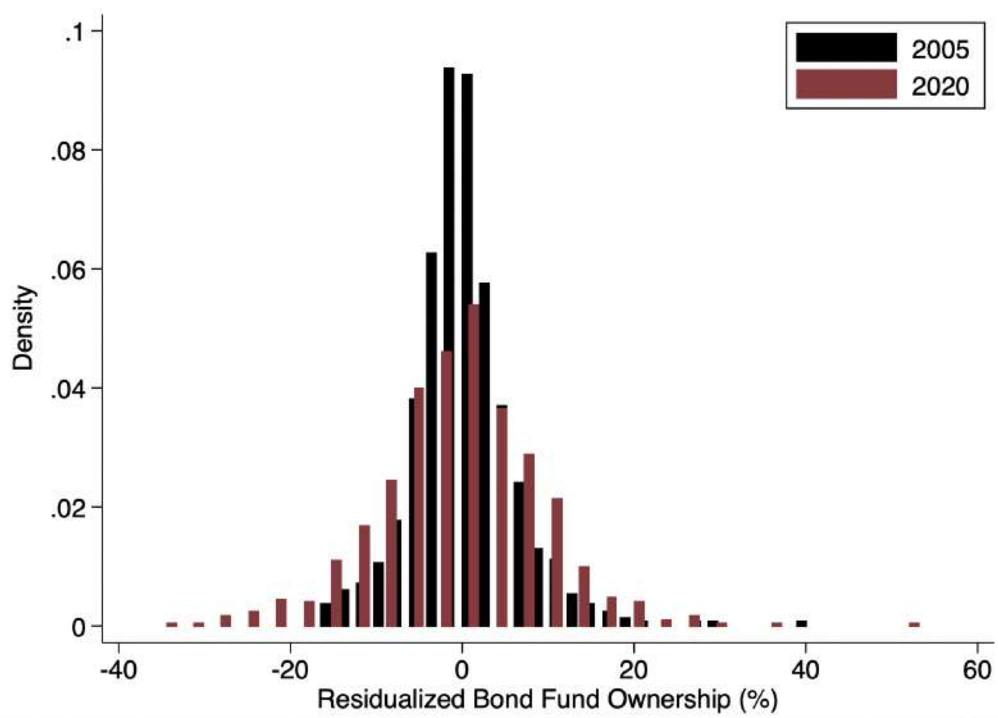


Figure 6: **Cross-Sectional Bondholder Sensitivity to Monetary Policy.** The figure shows whether firms with higher bond fund ownership experience higher bondholder flows and higher bondholder net purchases in response to monetary easing, estimated using Equation (7).

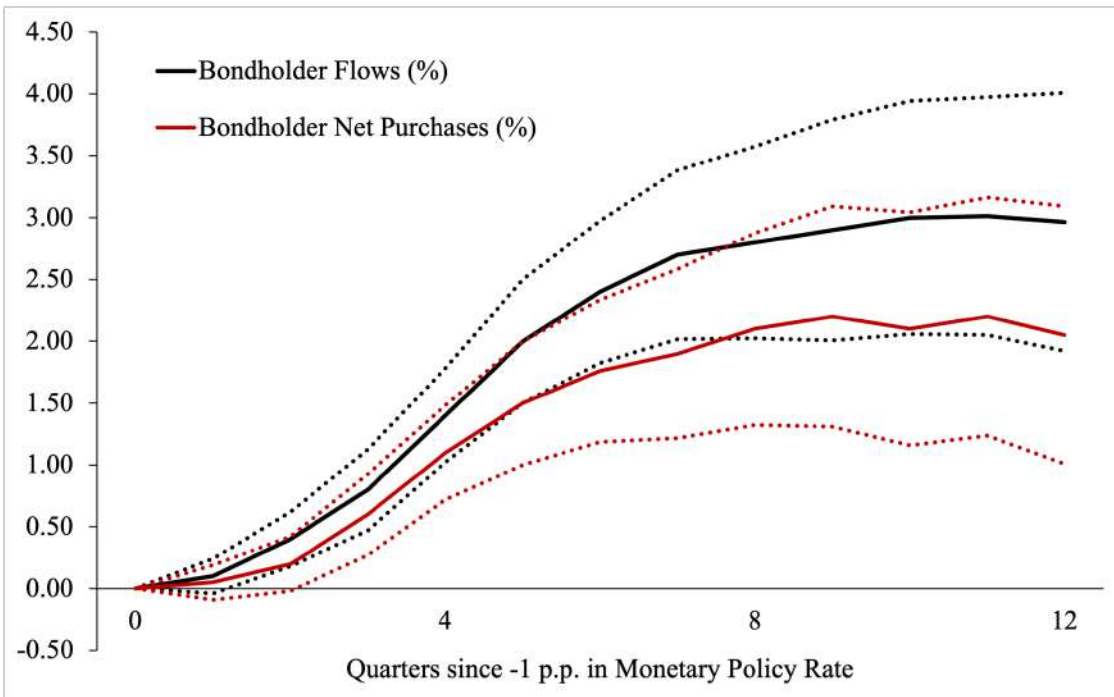


Figure 7: **Cross-Sectional Bond Sensitivity to Monetary Policy.** The figure shows whether bonds whose issuers have higher bond fund ownership experience higher returns in response to monetary easing, estimated using Equation (8).

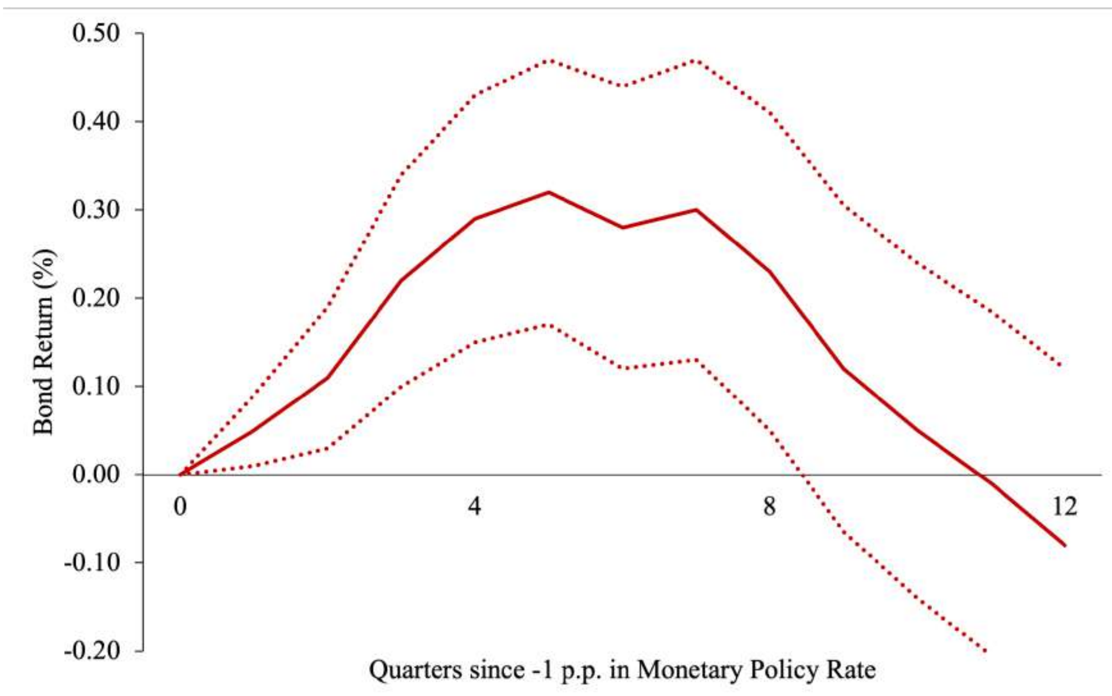
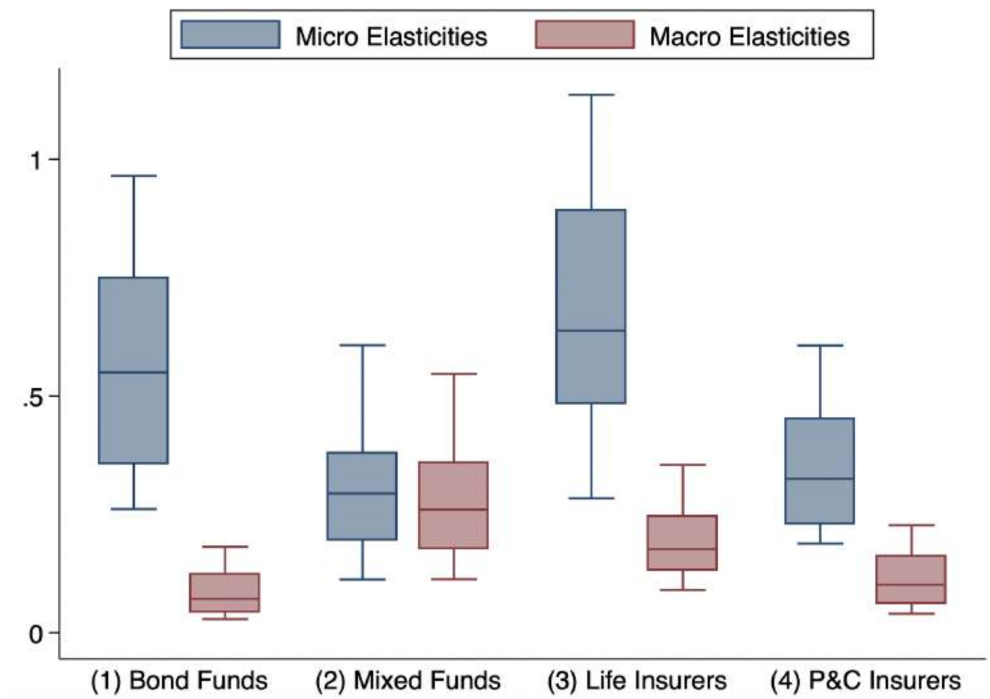


Figure 8: **Estimated Investor Elasticities Within and Across Bond Classes.** The figures show distributions of micro and macro elasticities, estimated from Section 6.3. Panel A shows the semi-elasticity of portfolio weight with respect to yield (in basis point). Panel B shows the elasticity of portfolio weight with respect to price.

Panel A: Yield (bps) Semi-Elasticity $\frac{\partial w/w}{\partial y}$



Panel B: Price Elasticity $\frac{\partial w/w}{\partial P/P}$

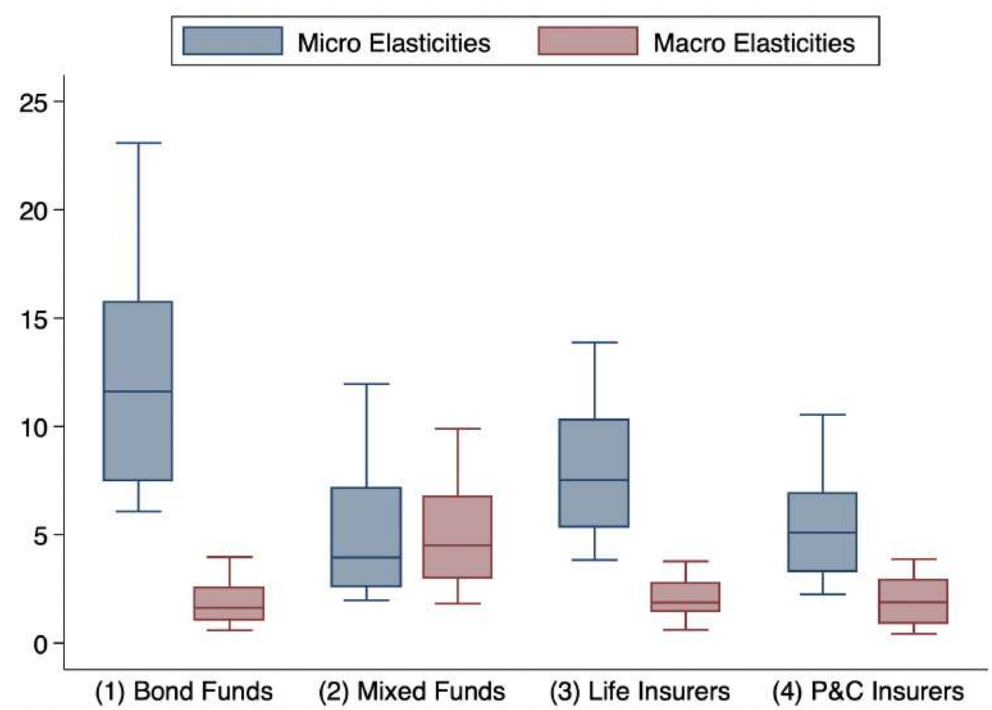


Figure 9: **Decomposition of Aggregate Yield Sensitivity to Monetary Policy.** The figure shows the decomposition of aggregate corporate bond yield sensitivity to monetary policy, according to Section 6.5. The black bar shows the actual yield sensitivity to changes in two-year Treasury rates, over a one-year horizon. The red arrows show what the counterfactual sensitivity would have been if there were no change in the corresponding channel (e.g., if bond funds did not experience any flows).

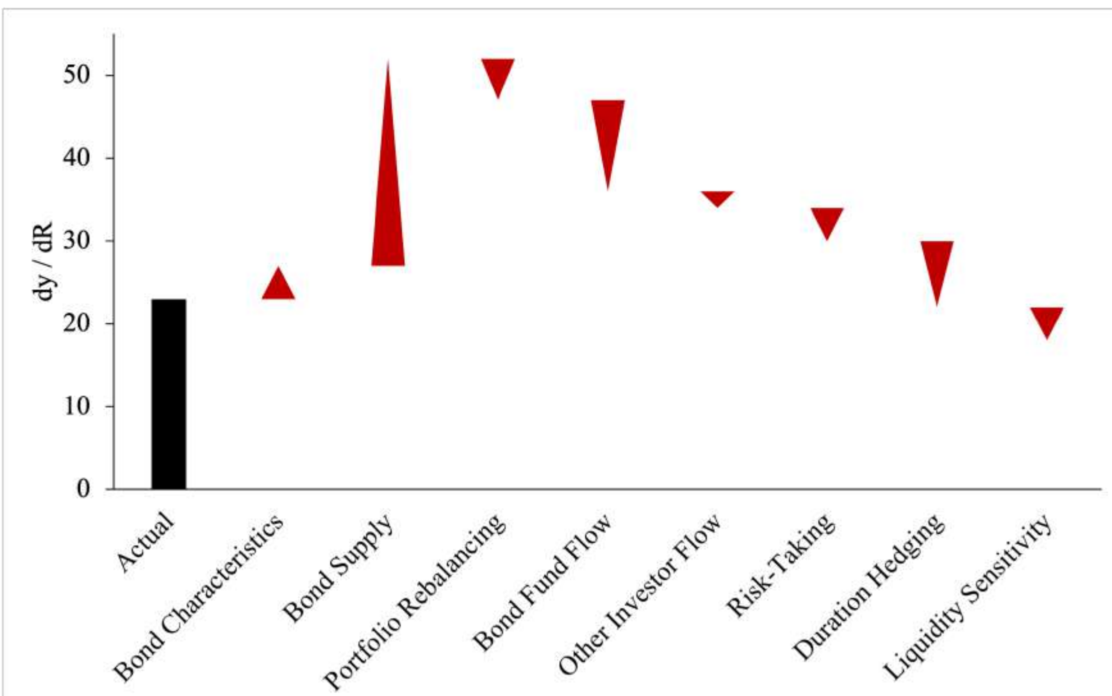
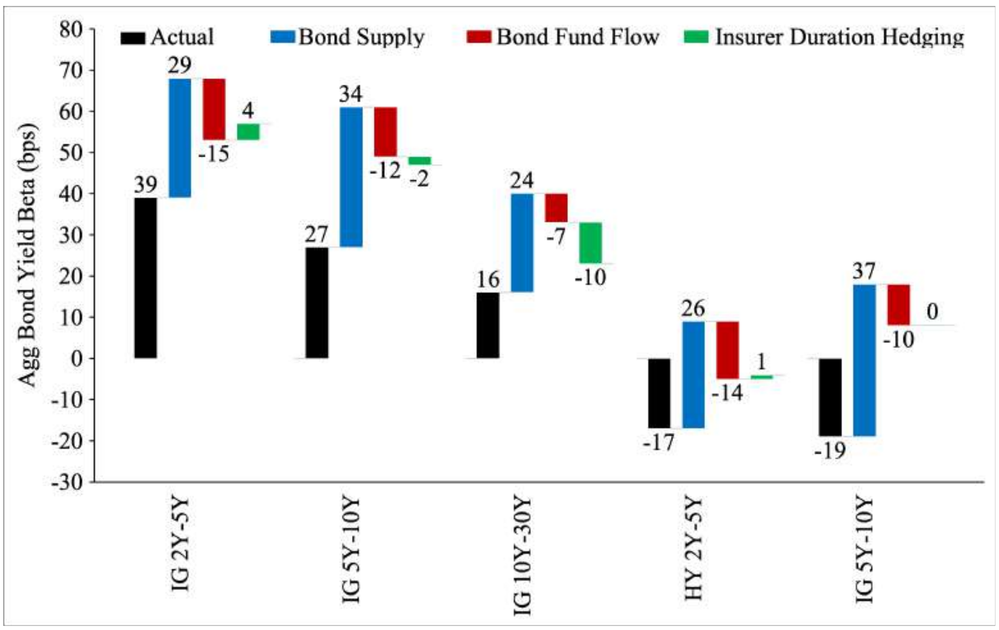
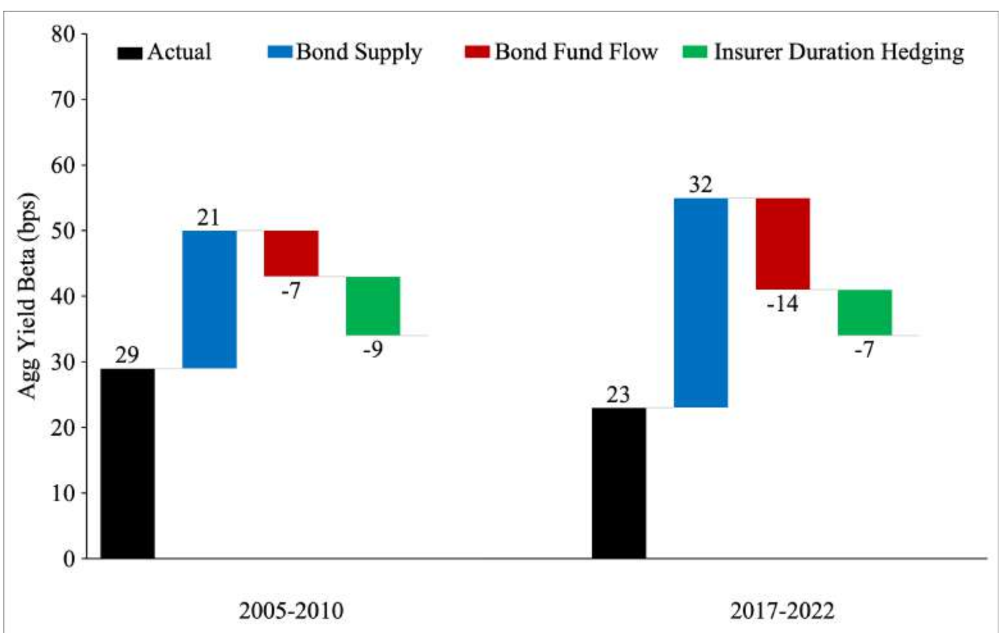


Figure 10: **Decomposition of Yield Sensitivity to Monetary Policy, by Bond Style and by Time.** The figures show the decomposition of the monetary sensitivity of the weighted average yield of different styles of corporate bonds and over different time periods, according to Section 6.5. The black bar shows the actual yield sensitivity to changes in two-year Treasury rates, over a one-year horizon. The green bar, red bar and blue bar show what the counterfactual sensitivity would have been if there were no change in bond issuance, bond fund flows, and insurance companies' demand for duration, respectively.

Panel A: By Bond Style



Panel B: By Time



Tables

Table 1: **Summary Statistics.** Panel A provides summary statistics on aggregate quarterly variables from 1990Q1 to 2020Q4. Panel B provides summary statistics on 1,491 bond funds from 1990Q1 to 2020Q4. Panel C provides summary statistics on 11,523 corporate bonds from 2005Q1 to 2020Q4. Panel D provides summary statistics on 1,123 firms from 2005Q1 to 2020Q4. All variables are winsorized at 1%.

Panel A: Aggregate Quarterly Statistics

	N	Mean	SD	P25	P50	P75
Change in 2Y Treasury Rate (%)						
1Q	123	-0.06	0.53	-0.27	-0.03	0.25
1Y	120	-0.26	1.21	-1.10	-0.12	0.46
Monetary Surprise (%)						
1Q	107	-0.03	0.12	-0.08	-0.03	0.04
1Y	104	-0.10	0.27	-0.24	-0.07	0.06
Bond Fund Flow (% of Own Size)						
1Q	123	1.30	2.36	-0.01	1.24	2.69
3Y	112	17.80	16.64	5.31	16.27	26.79
Life Insurer Flow (% of Own Size)						
1Q	123	1.32	1.15	0.67	1.29	1.88
3Y	112	16.97	5.24	11.81	18.24	21.79
Aggregate Corp Bond Net Issuance (% of Aggregate Corp Bond Outstanding)						
1Q	63	1.67	1.83	0.56	1.48	2.29
3Y	52	19.31	6.20	14.25	21.53	24.29
Bond Fund Corp Bond Net Purchase (% of Aggregate Corp Bond Outstanding)						
1Q	63	0.32	0.60	0.01	0.30	0.52
3Y	52	4.13	2.07	2.53	4.33	5.90
Life Insurer Corp Bond Net Purchase (% of Aggregate Corp Bond Outstanding)						
1Q	63	0.19	0.24	0.02	0.20	0.30
3Y	52	3.00	1.49	1.77	2.44	4.16

Panel B: Bond Fund Quarterly Statistics

	N	Mean	SD	P25	P50	P75
Flow (% of Own Size)						
1Q	100,721	2.40	11.27	-3.81	0.00	5.74
1Y	93,051	13.52	46.23	-13.62	0.18	23.98
3Y	82,015	56.32	162.21	-31.01	0.73	66.97
Flow Duration	100,721	15.73	7.93	9.83	14.90	20.01
Rating (AAA = 1, CCC- = 19)	100,721	7.26	3.31	4.67	6.28	8.85
Duration (Years)	100,721	5.93	3.33	3.92	5.03	8.10
Yield to Maturity (%)	36,251	4.17	2.58	1.95	4.00	5.88
Cash Ratio (%)	100,721	4.95	6.53	1.25	3.34	6.54
Income Yield (%)	100,721	4.27	2.63	2.48	4.02	5.72
1Y Return (%)						
Alpha	100,721	0.96	2.62	-0.01	0.69	1.71
Factor-Related	100,721	2.65	5.80	-0.77	1.86	4.97
Volatility	100,721	4.15	3.01	2.10	3.45	5.01
Age (Years)	100,721	12.66	10.96	4.33	10.00	18.50
Total Net Assets (mn $)	100,721	1,713.92	8,003.62	73.00	265.35	957.80
Expense Ratio (%)	100,721	0.71	0.39	0.45	0.68	0.93
Turnover (%)	100,721	142.81	182.87	41.00	77.00	163.00

Panel C: Corporate Bond Quarterly Statistics

	N	Mean	SD	P25	P50	P75
Bondholder Flow (%)						
1Q	280,509	0.28	0.90	0.00	0.22	0.64
1Y	244,994	0.98	2.42	0.00	0.74	2.04
3Y	172,507	2.72	5.12	0.31	2.28	5.06
Bondholder Flow Duration (%)						
issuer level	280,509	2.45	2.48	0.76	1.72	3.32
bond level	280,509	2.39	2.96	0.51	1.69	3.61
Abnormal Return (%)						
1Q	280,509	0.00	3.56	-1.12	-0.05	1.10
1Y	244,994	0.00	5.03	-1.88	0.11	2.01
3Y	172,507	0.00	7.36	-3.18	-0.26	3.03
Rating (AAA = 1, CCC- = 19)	280,509	8.72	3.06	7.00	8.00	10.00
Duration (Years)	280,509	7.95	4.16	4.59	6.55	11.14
Fixed Callable	280,509	0.24	0.21	0.00	0.00	1.00
Amount Outstanding (mn $)	280,509	609.96	646.70	300.00	500.00	800.00

Panel D: Firm Quarterly Statistics

	N	Mean	SD	P25	P50	P75
Bondholder Flow (%)						
1Q	45,672	0.43	1.79	-0.36	0.33	1.09
3Y	37,101	2.30	5.64	-2.23	1.92	4.39
Bondholder Flow Duration (%)	45,672	2.55	2.61	0.80	1.74	3.49
Gross Bond Issuance (% of TA)						
1Q	45,672	1.66	5.38	0.00	0.00	0.00
3Y	37,101	22.38	31.48	2.46	12.06	27.87
Net Debt Issuance (% of TA)						
1Q	45,672	0.57	3.99	-0.40	0.00	0.53
3Y	37,101	9.01	20.76	-1.48	4.12	13.82
Net Equity Payout (% of TA)						
1Q	45,672	0.77	1.93	0.00	0.41	1.39
3Y	37,101	11.10	18.28	0.37	6.49	18.30
Investment (% of TA)						
1Q	45,672	1.74	1.81	0.65	1.33	2.27
3Y	37,101	22.78	24.09	8.28	16.47	27.54
Total Assets (bn $)	45,672	16.90	30.89	2.49	5.99	15.22
Cash Holdings (% of TA)	45,672	8.85	9.83	2.06	5.04	11.99
Tobin's Q	45,672	3.94	6.90	0.75	1.56	4.31
Leverage (Debt as % of TA)	45,672	39.96	20.36	26.47	35.97	50.68
Net Income (% of TA)	45,672	2.79	9.82	0.96	3.42	6.81
Bond Outstanding (% of Debt)	45,672	67.60	31.37	45.35	69.71	90.08
Bond Rating (AAA = 1, CCC- = 19)	45,672	11.61	3.76	9.00	11.00	15.00
Bond Maturity (Years)	45,672	7.79	3.97	5.04	6.94	9.52

Table 2: **Bond Fund Portfolio Scaling.** Panel A (B) [C] {D} shows how bond funds scale their existing portfolios in response to fund flows on the asset class level (corporate bond style level) [corporate bond issuer level] {individual corporate bond level}, estimated from Equation (1) or Equation (4). The "Counterfactual" columns show what would be the regression coefficients if bond funds were to buy a value-weighted portfolio of all the corporate bonds outstanding (with the same style) in response to inflows. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Asset Class Level

Dependent Variable	Asset Class Flow (%)					
Sample	Outflow			Inflow		
Asset Class	Cash	Treasuries	Corporates	Cash	Treasuries	Corporates
Fund Flow (%)	1.21***	1.05***	0.95***	1.47***	1.10***	0.96***
	(4.21)	(5.35)	(29.42)	(3.68)	(5.93)	(45.67)
Fixed Effects	Fund FE and Year FE					
Standard Errors	Twoway-Clustered by Fund and by Year					
Observations	2,931	2,931	2,936	3,135	3,135	3,139
R2	0.19	0.41	0.60	0.15	0.39	0.73

Panel B: Corporate Bond Style Level

Dependent Variable	Bond Class Flow (%)		
Sample	Outflow	Inflow	Counterfactual
Fund Flow (%)	0.90***	0.93***	0.12***
	(9.52)	(11.32)	(7.93)
Fixed Effects	Fund FE, Bond Class × Year FE		
Standard Errors	Twoway-Clustered by Fund and by Year		
Observations	17,011	20,153	20,153
R2	0.27	0.31	0.14

Panel C: Corporate Bond Issuer Level

Dependent Variable	Issuer Flow (%)		
Sample	Outflow	Inflow	Counterfactual
Fund Flow (%)	0.84***	0.70***	0.08***
	(6.87)	(9.03)	(6.11)
Fixed Effects	Fund FE, Issuer × Year FE		
Standard Errors	Twoway-Clustered by Fund and by Year		
Observations	169,513	170,125	170,125
R2	0.15	0.14	0.10

Panel D: Corporate Bond Issue Level

Dependent Variable	Bond Flow (%)		
Sample	Outflow	Inflow	Counterfactual
Fund Flow (%)	0.81***	0.40***	0.02***
	(9.35)	(10.53)	(5.42)
Fixed Effects	Fund FE, Issue × Year FE		
Standard Errors	Twoway-Clustered by Fund and by Year		
Observations	263,125	295,134	295,134
R2	0.13	0.10	0.09

Table 3: **Cross-Sectional Bond Sensitivity to Monetary Policy.** These tables show how bond fund ownership affects bond sensitivity to monetary policy. Panel A estimate the baseline regression (8). Panel B uses the shift-share instrument in Equation 11. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Baseline

Dependent Variable	1Y Return (%)		
ΔRate × Bond Fund Ownership	-0.29***	-0.35**	-0.35**
	(-4.02)	(-2.41)	(-2.52)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	148127	148127	148127
R2	0.59	0.63	0.63

Panel B: Shift-Share Instrument

Dependent Variable	1Y Return (%)		
Instrumented ΔRate × BFOwnership	-0.33**	-0.50*	-0.53*
	(-2.11)	(-1.76)	(-1.85)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
ΔRate × Issuer Dummies	Y	Y	Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	148127	148127	148127
R2	0.65	0.68	0.69
First Stage F-statistic	103.47	103.47	103.47

Table 4: **Cross-Sectional Firm Sensitivity to Monetary Policy.** These tables examine how bond fund ownership affects firm sensitivity to monetary policy. Panel A estimate the baseline regression (9). Panel B uses the shift-share instrument in Equation 11. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Baseline

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Capital Expenditure
Average Monetary Sensitivity	-5.96	-3.90	-2.63	-2.89	-3.07
ΔRate × Bond Fund Ownership	-3.01***	-1.31***	-0.98**	-0.91*	-0.51
	(-2.71)	(-2.98)	(-2.00)	(-1.83)	(-0.69)
Controls	Macro News × Bond Fund Ownership, ΔRate × Firm Attributes				
Fixed Effects	Firm FE, Industry × Quarter FE				
Standard Errors	Two-way Clustered by Firm and by Quarter				
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.22	0.40	0.57

Panel B: Shift-Share Instrument

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Capital Expenditure
Average Monetary Sensitivity	-5.96	-3.90	-2.63	-2.89	-3.07
Instrumented ΔRate × BFO	-3.61**	-1.07*	-1.50	-1.08*	-0.78
	(-2.42)	(-1.94)	(-1.54)	(-1.68)	(-0.99)
Controls	Macro News × Bond Fund Ownership, ΔRate × Firm Attributes, ΔRate × Firm FE				
Fixed Effects	Firm FE, Industry × Time FE				
Standard Errors	Two-way Clustered by Firm and by Time				
Observations	35372	35372	34546	34546	34546
R2	0.36	0.39	0.26	0.44	0.61
First Stage F-statistic	109.23	109.23	109.23	109.23	109.23

Table 5: **Cross-Sectional Firm Sensitivity to Monetary Policy, Constrained Firms.** This table examines whether the effect of bond fund ownership on firm sensitivity to monetary policy is different for firms that are financially constrained, estimated from Equation (10). t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A:

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Capital Expenditure
ΔRate × Bond Fund Ownership	-3.87***	-1.72***	-0.80**	-1.25*	-0.37
	(-2.98)	(-3.16)	(-2.14)	(-1.91)	(-0.40)
ΔRate × BFO × Low Payout	1.09**	0.79**	-0.39	1.33*	-1.05**
	(2.17)	(2.15)	(-1.49)	(1.78)	(-2.04)
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.23	0.40	0.57

Panel B: High Investment

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Investment
ΔRate × Bond Fund Ownership	-4.09***	-2.25***	-1.39**	-1.54**	-0.46
	(-3.02)	(-2.67)	(-2.36)	(-1.99)	(-0.66)
ΔRate × BFO × High Investment	1.95*	0.59*	-0.21	1.20*	-1.01**
	(1.70)	(1.89)	(-0.55)	(1.89)	(-1.99)
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.23	0.41	0.57

Panel C: Low Cash

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Investment
ΔRate × Bond Fund Ownership	-3.95***	-2.15***	-1.23**	-1.35*	-0.31
	(-3.00)	(-2.80)	(-2.25)	(-1.89)	(-0.19)
ΔRate × BFO × Low Cash	0.91	0.55	-0.01	1.45*	-0.76*
	(1.66)	(1.90)	(-0.05)	(1.84)	(-1.79)
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.23	0.41	0.57

Panel D: Small Size

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Investment
ΔRate × Bond Fund Ownership	-4.21***	-2.37***	-1.41**	-1.45*	-0.44
	(-3.25)	(-3.21)	(-1.99)	(-1.80)	(-0.79)
ΔRate × BFO × Small Size	2.03***	1.02**	0.23	0.78*	-0.98
	(3.03)	(2.03)	(0.59)	(1.69)	(-1.53)
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.23	0.41	0.57

Panel E: Young Age

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Investment
ΔRate × Bond Fund Ownership	-4.00***	-2.51***	-1.17*	-1.59*	-0.49
	(-3.28)	(-2.81)	(-1.96)	(-1.77)	(-0.55)
ΔRate × BFO × Young Age	1.82	1.07*	-0.19	1.21	-0.87*
	(1.64)	(1.89)	(-0.79)	(1.09)	(-1.90)
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.23	0.41	0.57

Table 6: **Estimated Investor Elasticities Within and Across Bond Classes.** This table shows estimated price elasticities from Section 6.3. Panel A shows micro price elasticities within a bond class for different types of investors, estimated from Equation (20) with GMM using Equation (21) as moment condition. Panel B shows macro price elasticities across bond classes for different types of investors, estimated from Equation (22) with GMM using Equation (23) as moment condition.

Within Bond Class

	Treasuries	IG Short	IG Medium	IG Long	High-Yield
Bond Funds					
General Short	14.31	15.62	7.93	7.26	5.56
General Medium	12.19	8.10	10.51	5.71	5.92
General Long	8.99	4.16	6.13	8.56	3.55
High-Yield	12.72	10.01	5.93	1.36	8.45
Mixed Funds	5.98	8.49	5.20	4.16	3.23
Life Insurers	1.51	1.99	3.61	2.68	0.88
P&C Insurers	2.31	3.01	2.00	0.93	0.15

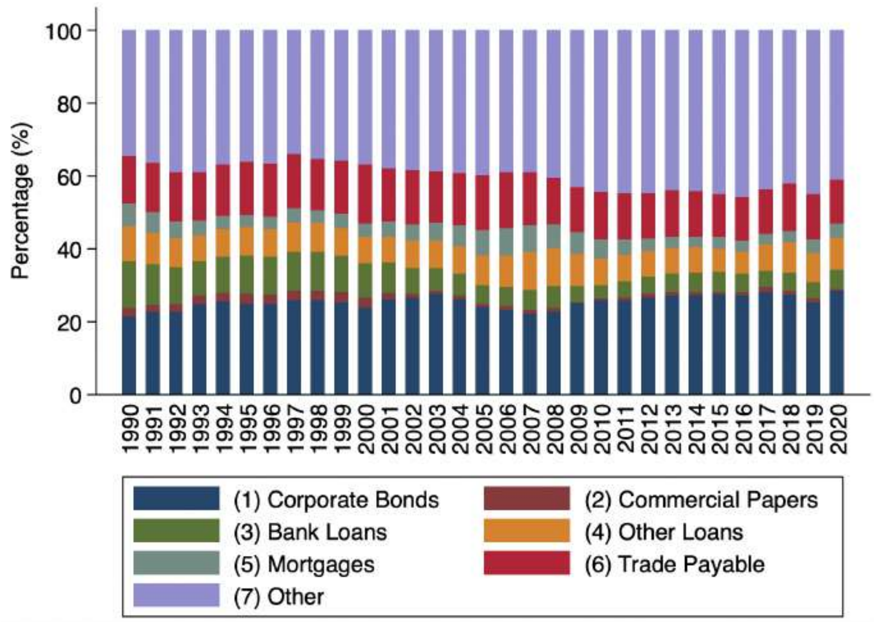
Across Bond Classes

	Treasuries	IG Short	IG Medium	IG Long	High-Yield
Bond Funds					
General Short	6.03	4.53	4.00	1.96	2.44
General Medium	4.94	3.05	4.31	2.95	1.04
General Long	5.98	1.01	2.99	2.23	0.91
High-Yield	2.35	3.61	2.97	1.53	2.13
Mixed Funds	8.56	6.29	5.65	3.99	5.13
Life Insurers	1.66	0.98	1.01	1.59	0.43
P&C Insurers	1.99	1.23	1.21	0.59	0.38

Appendix A Additional Figures and Tables

Figure A1: **Composition of Firm Liabilities.** The figures plot the composition of liabilities for all nonfinancial corporate businesses using data from Financial Accounts of the United States (L.103) in Panel A and for non-financial public firms using data from Compustat in Panel B.

Panel A: Nonfinancial Corporate Business



Panel B: Non-Financial Public Firms

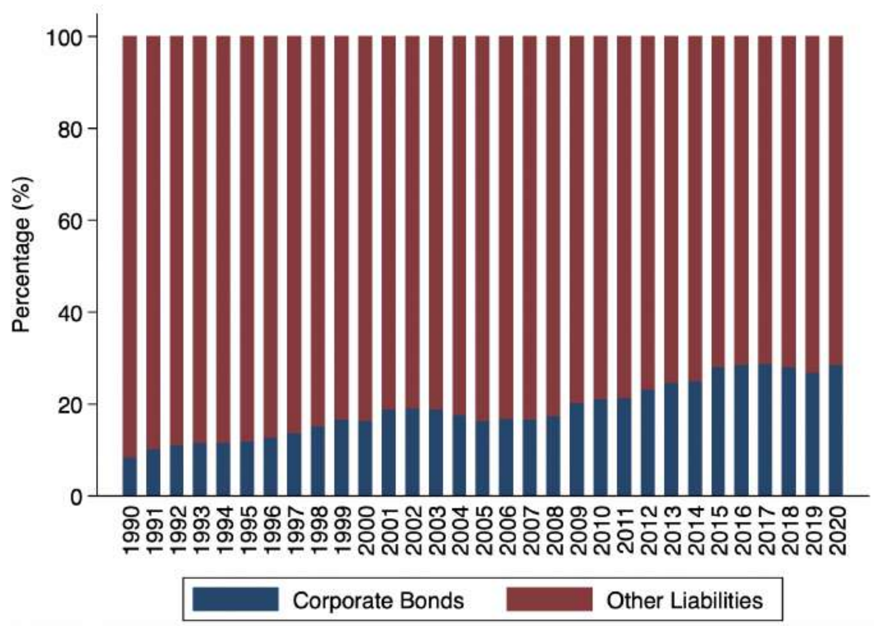
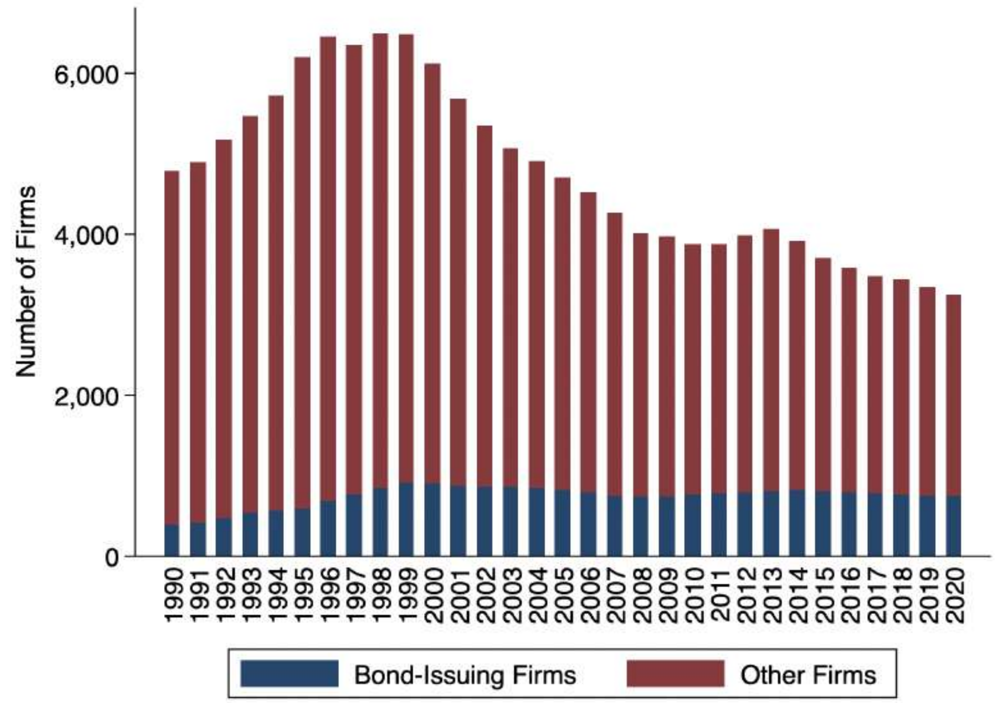


Figure A2: **Composition of Firms.**

Panel A: Number of Firms



Panel B: Total Assets

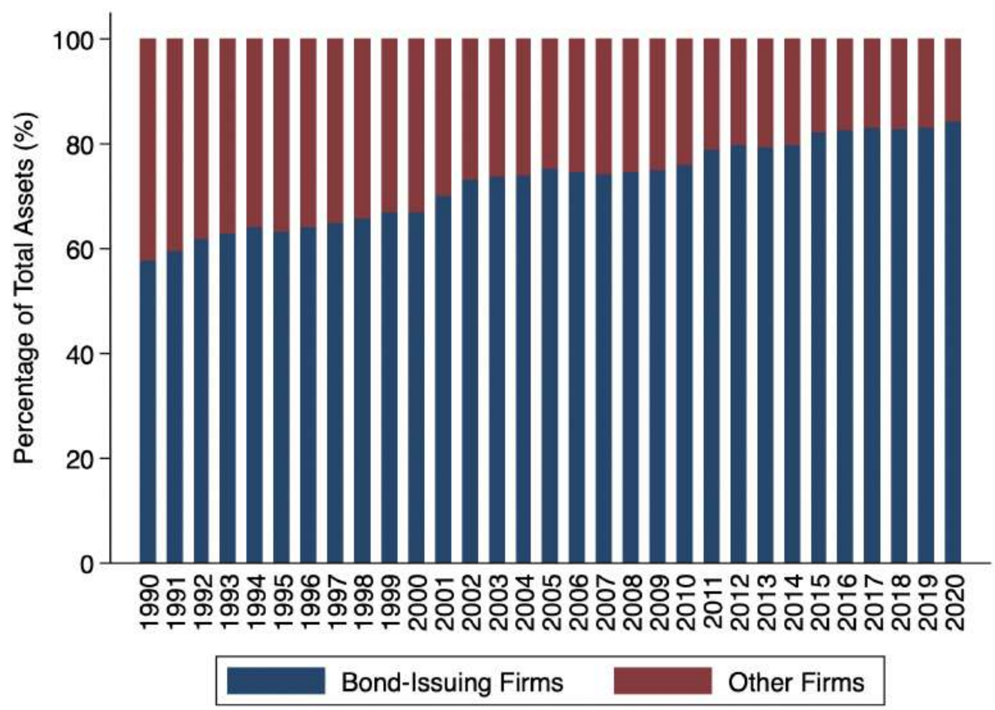
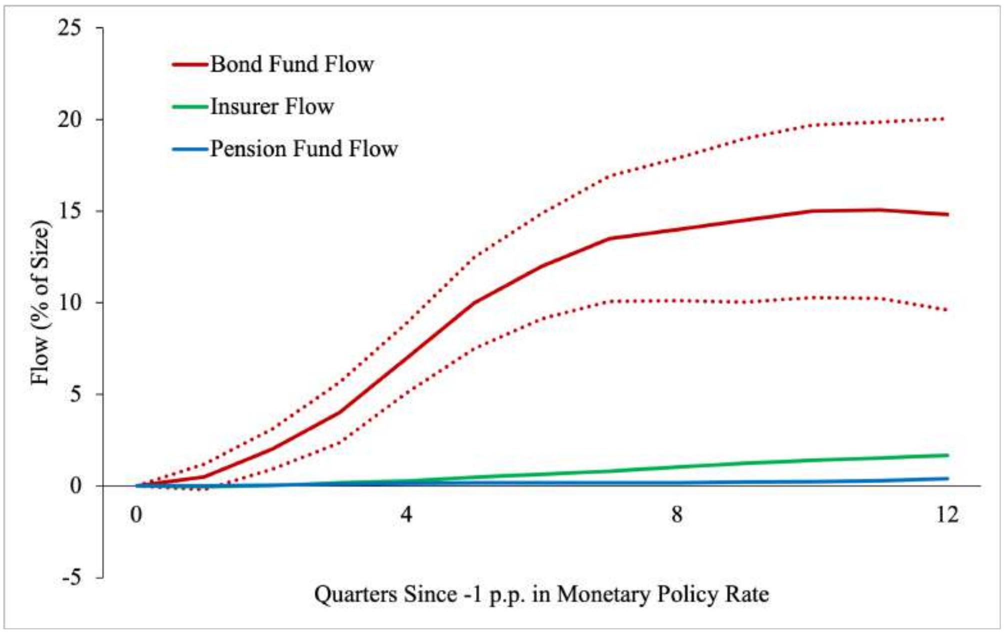


Figure A3: **Monetary Sensitivity across Corporate Bond Investors, Investor Flows.** The figures plot impulse responses of total flows for the largest institutional corporate bond investors to 1 p.p. decrease in two-year Treasury rate with 95% confidence intervals, estimated from Equation (2). Panel A plots the full dynamics with the baseline specification. Panel B shows the difference in three-year response between bond funds and insurers for a battery of alternative specifications.

Panel A: Baseline Full Dynamics



Panel B: Difference in Three-Year Response and Robustness

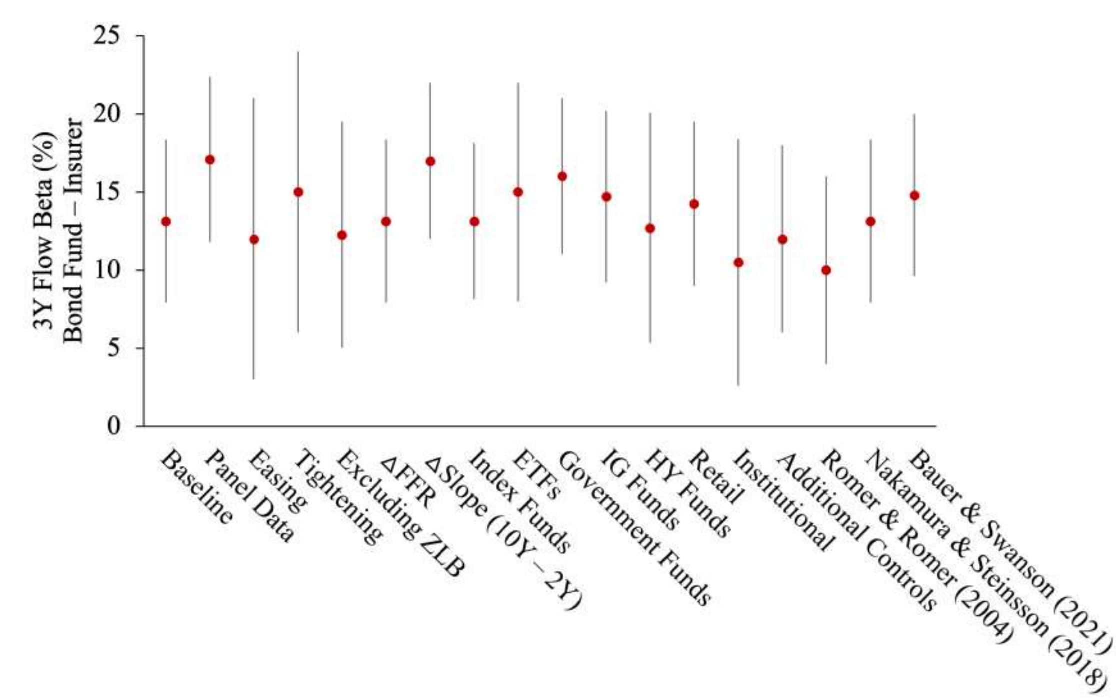


Figure A4: **Treasury Bond Ownership.** Panel A plots ownership of all Treasury securities using data from Financial Accounts of the United States (L.211). Panel B uses security-level data and plots ownership of Treasury securities with more than one year to maturity.

Panel A: All Treasury Securities

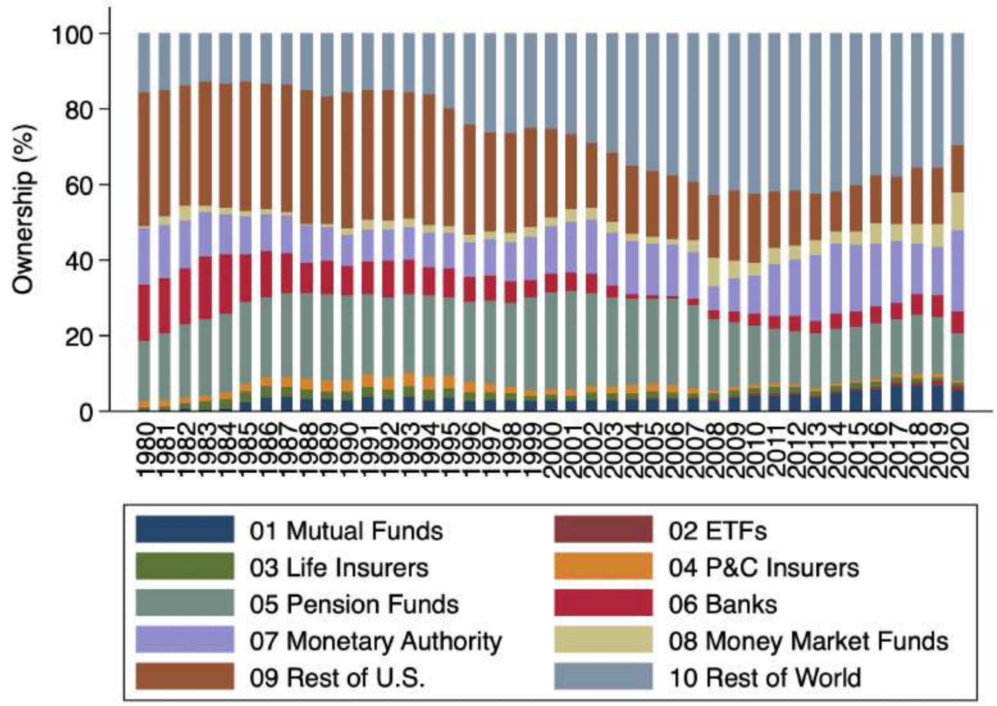
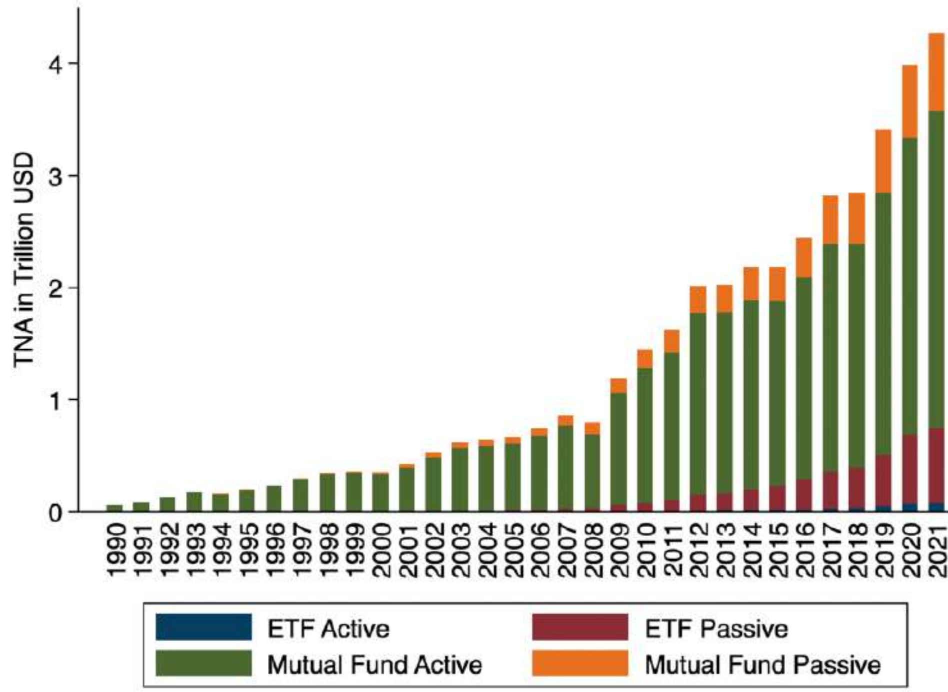
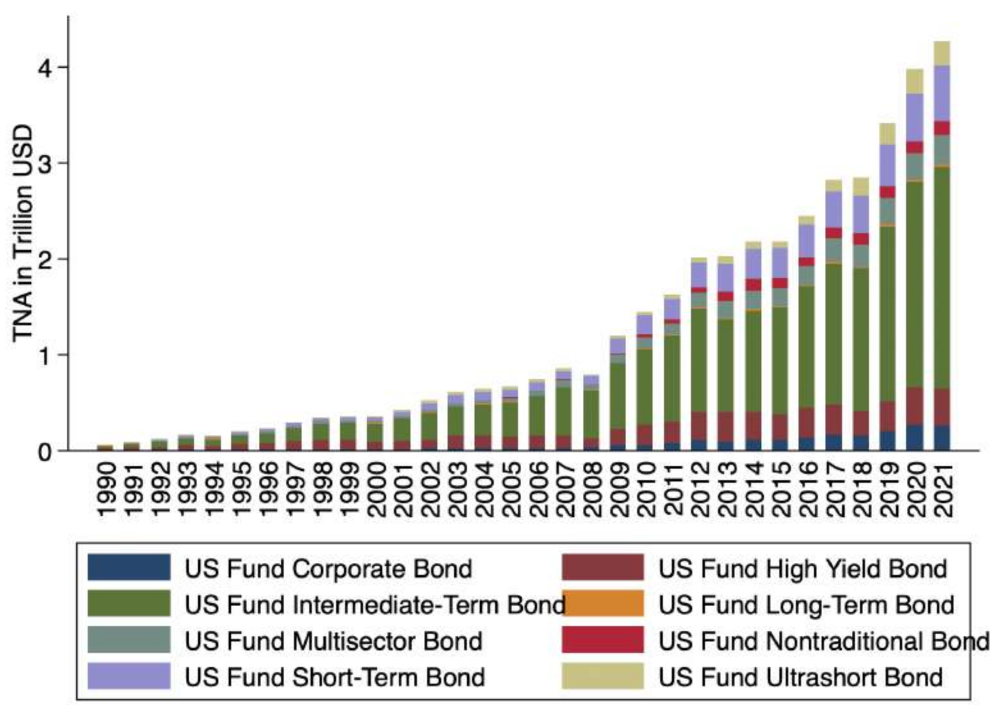


Figure A5: **Composition of Bond Funds.**

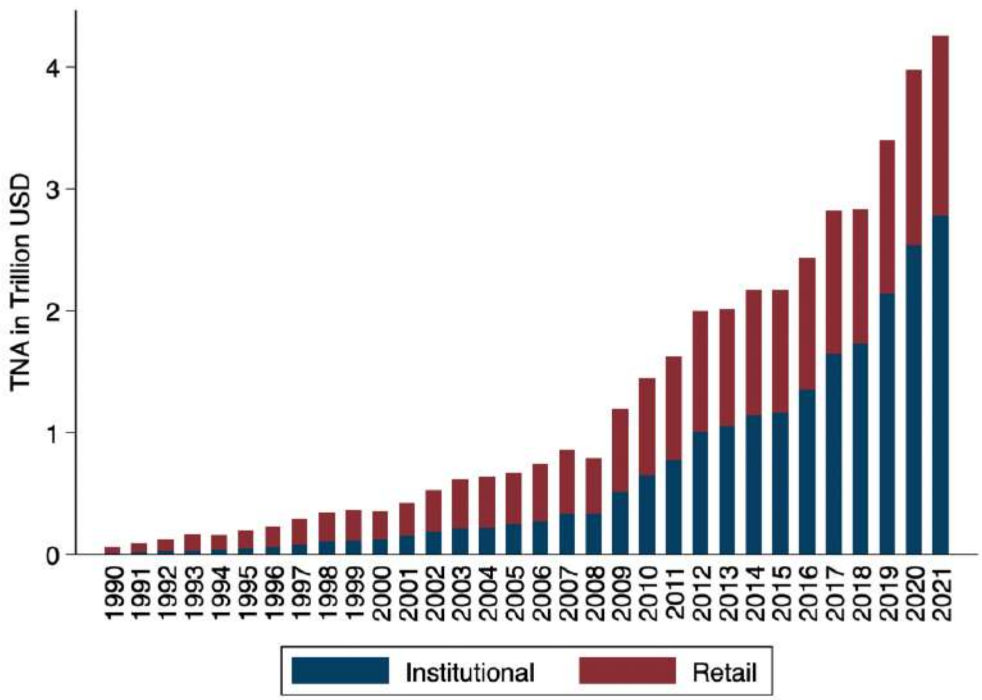
Panel A: By Type



Panel B: By Style



Panel C: By Share Class



Panel D: By Owners

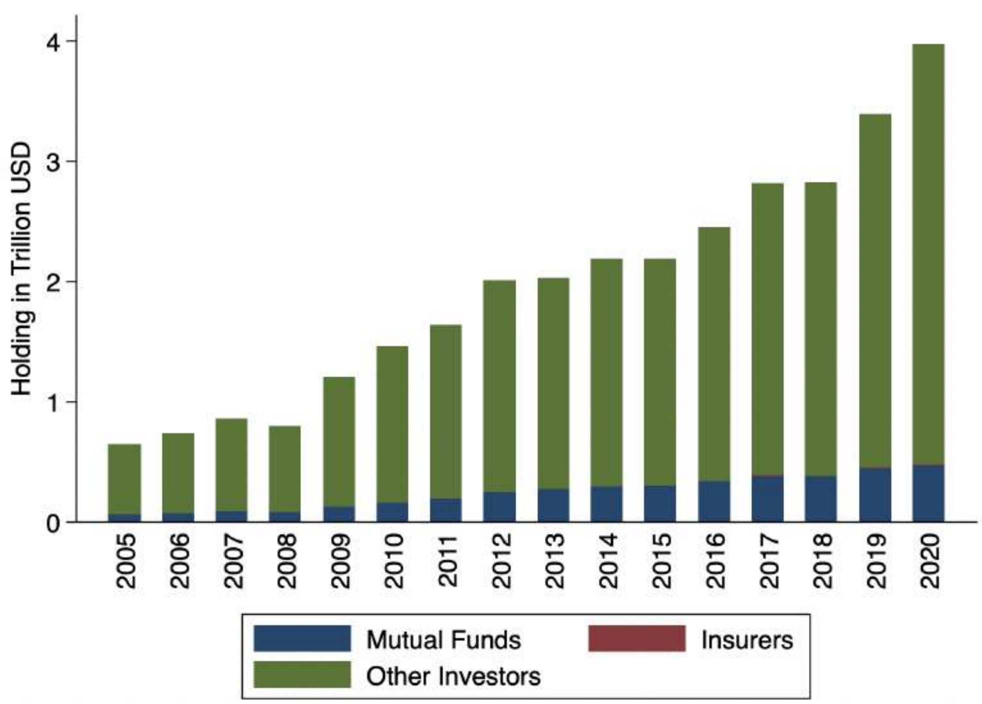
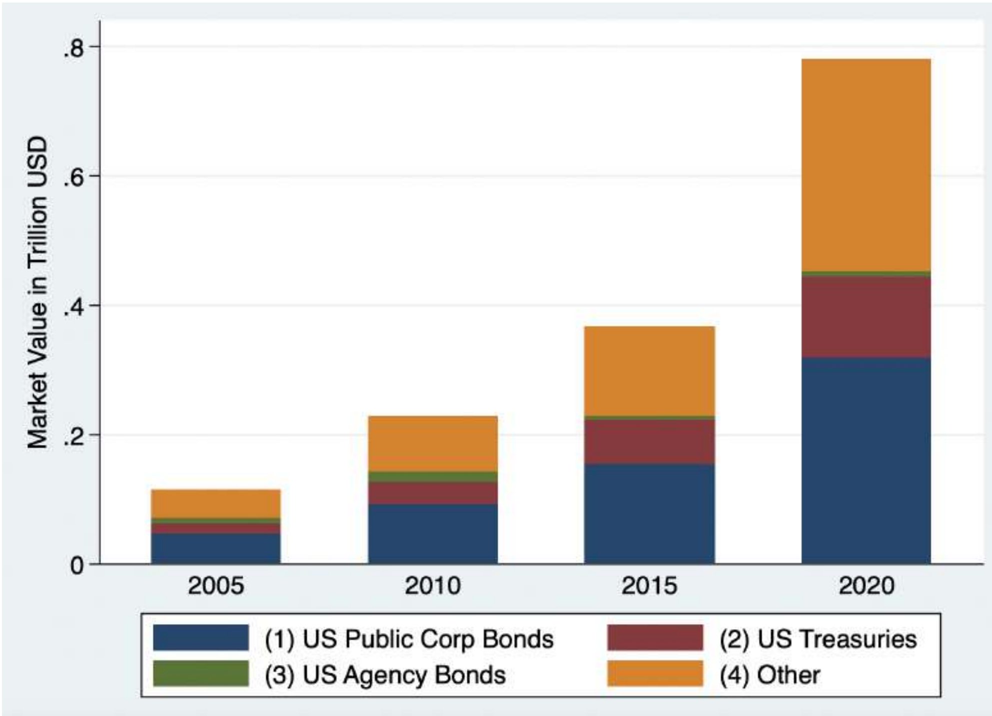
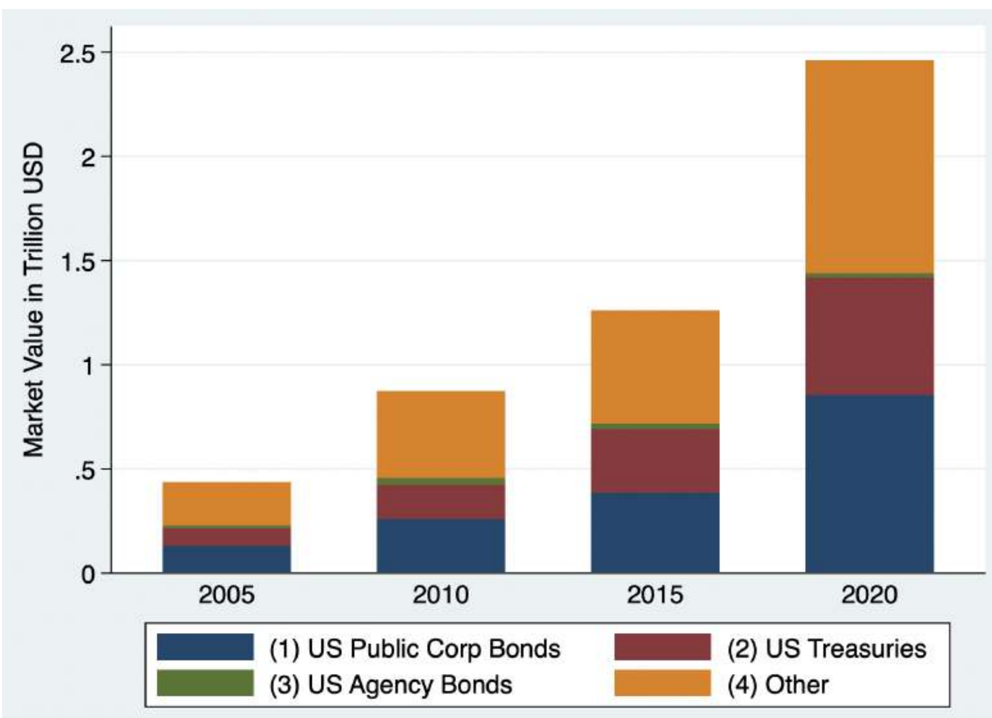


Figure A6: **Holdings by Bond Funds and Insurance Companies.**

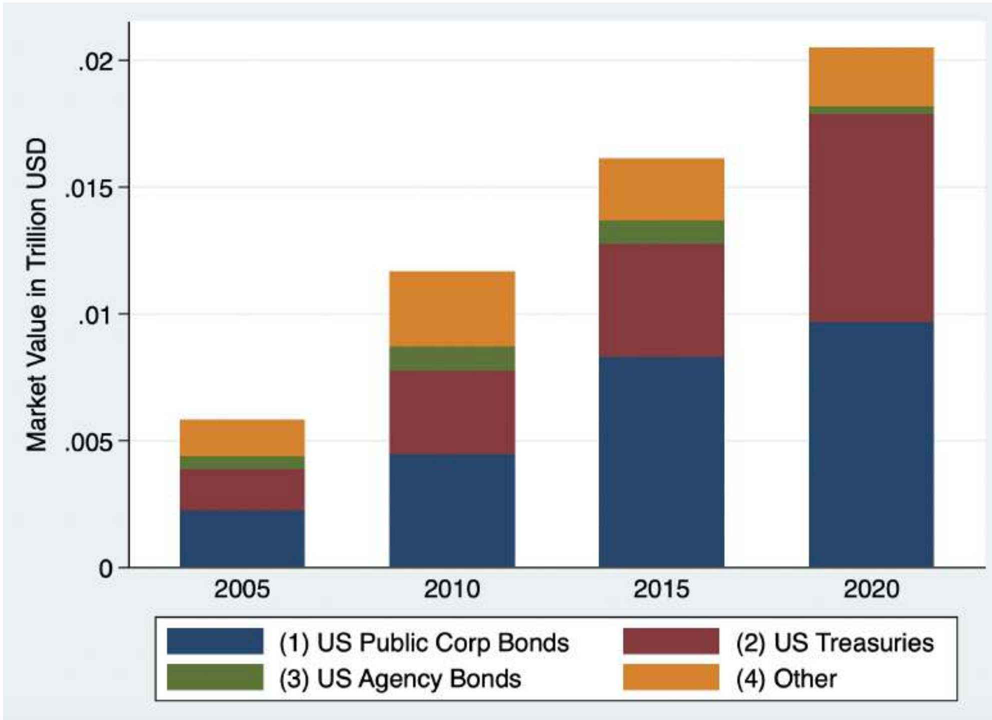
Panel A: General Short-Term Bond Funds



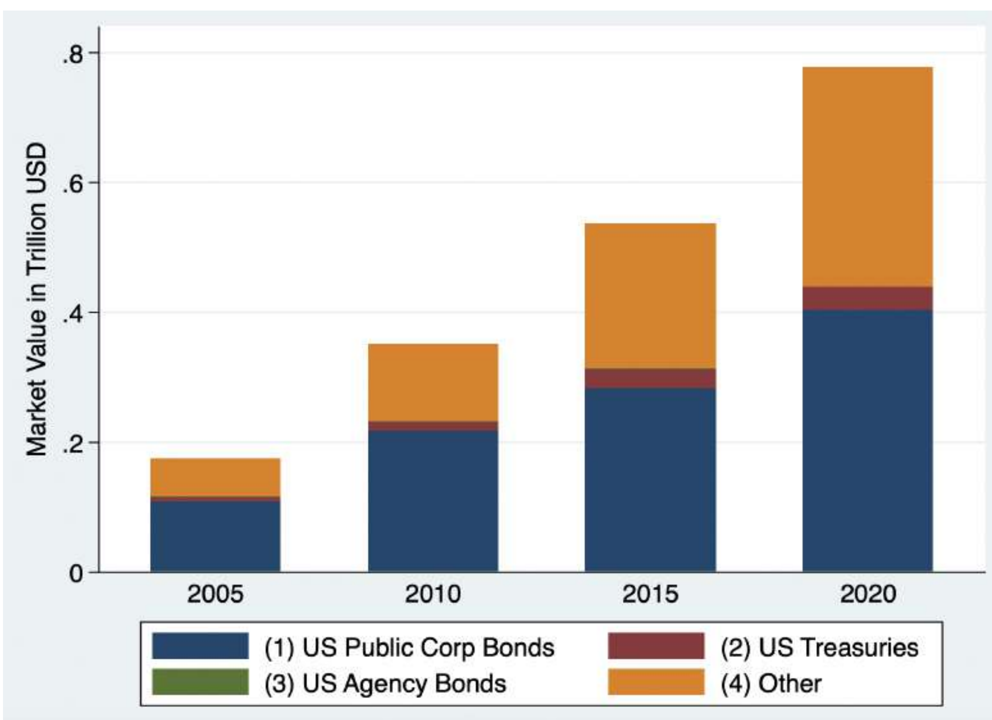
Panel B: General Medium-Term Bond Funds



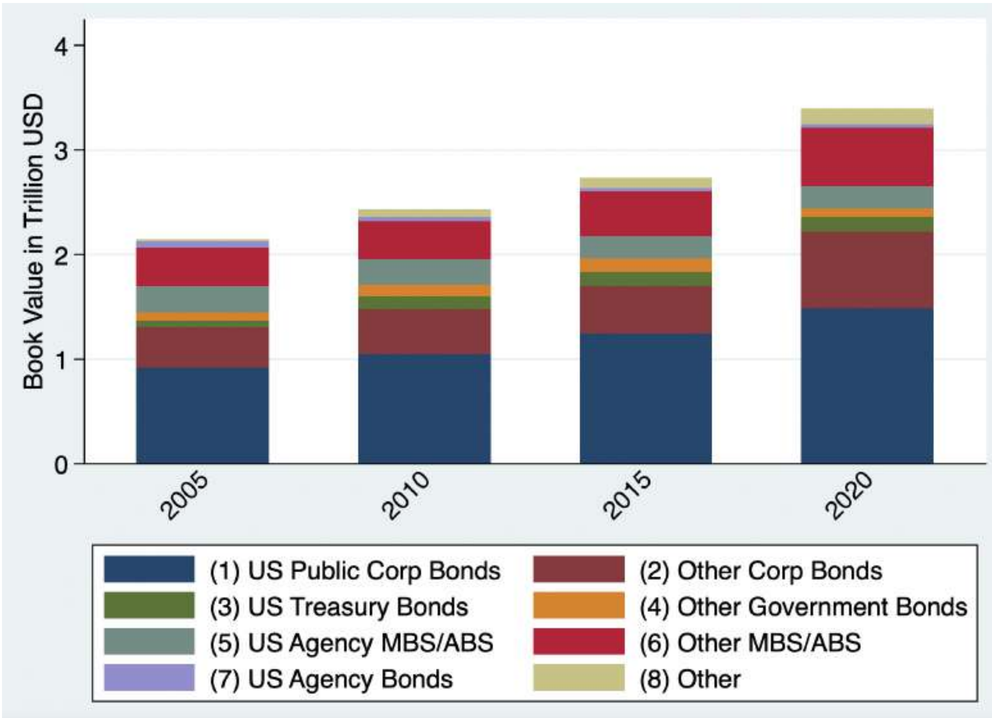
Panel C: General Long-Term Bond Funds



Panel D: High-Yield Bond Funds



Panel E: Life Insurers



Panel F: P&C Insurers

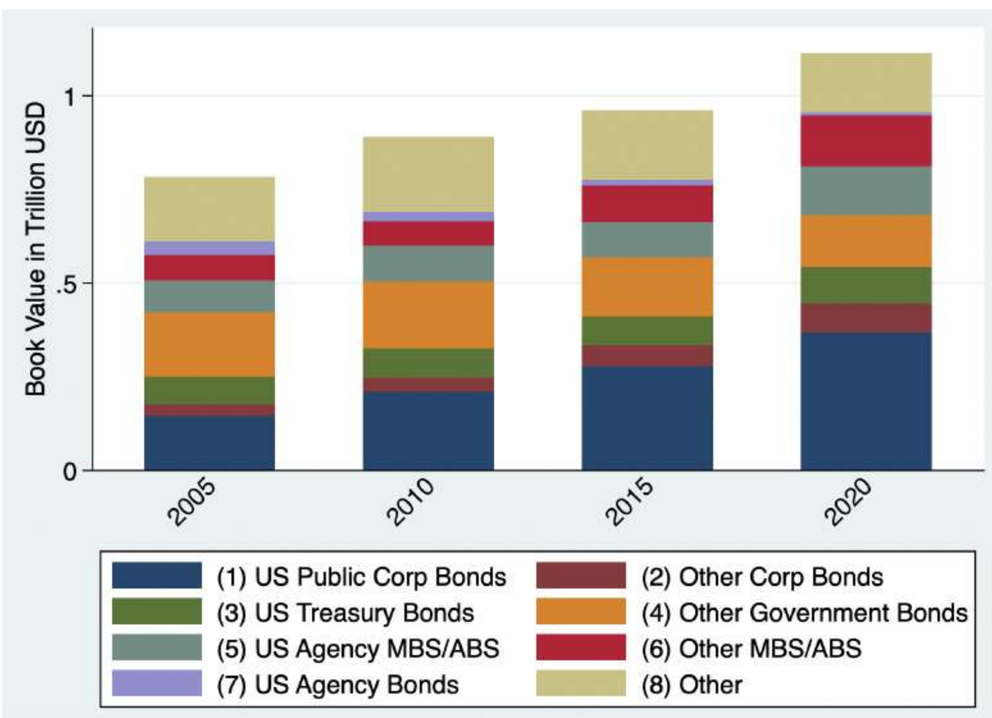
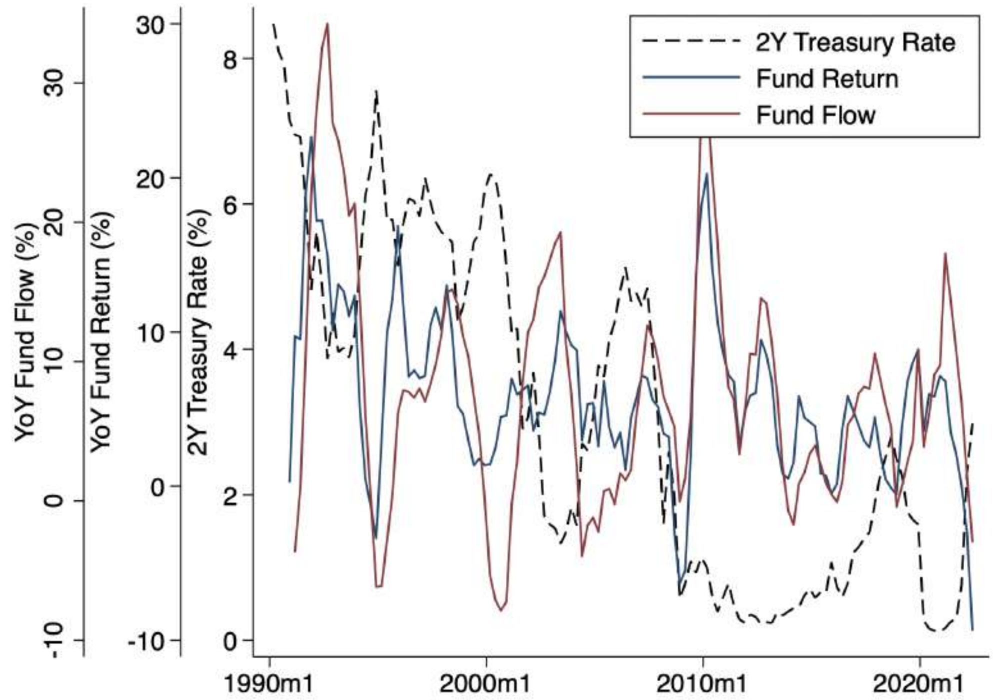
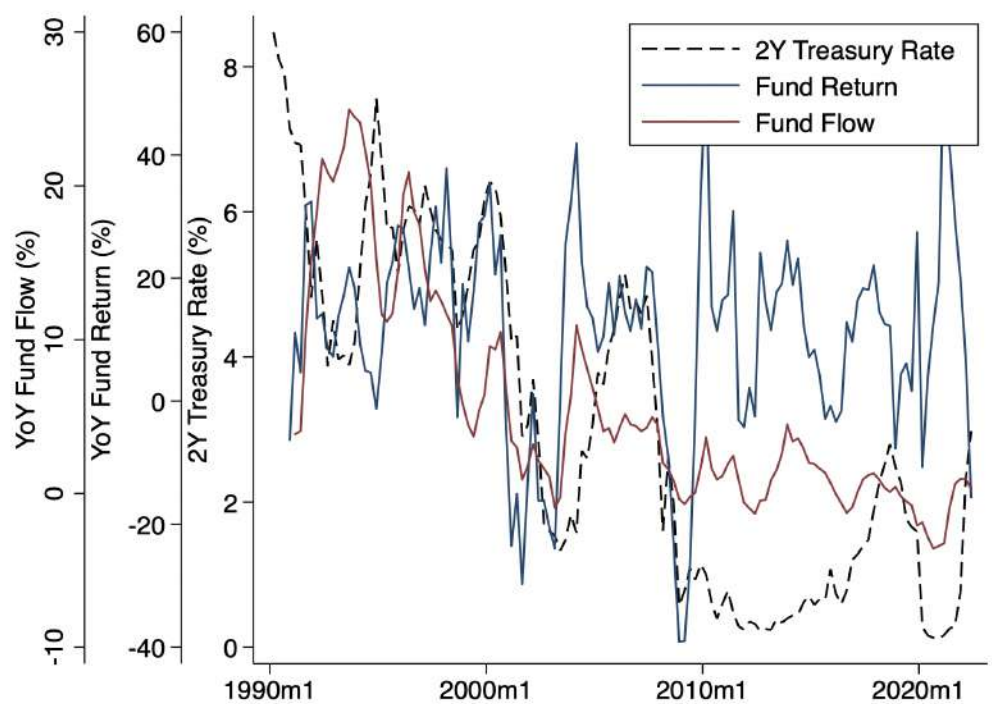


Figure A7: **Monetary Sensitivity across Mutual Fund Classes, Time Series.**

Bond Funds



Equity Funds



Money Market Funds

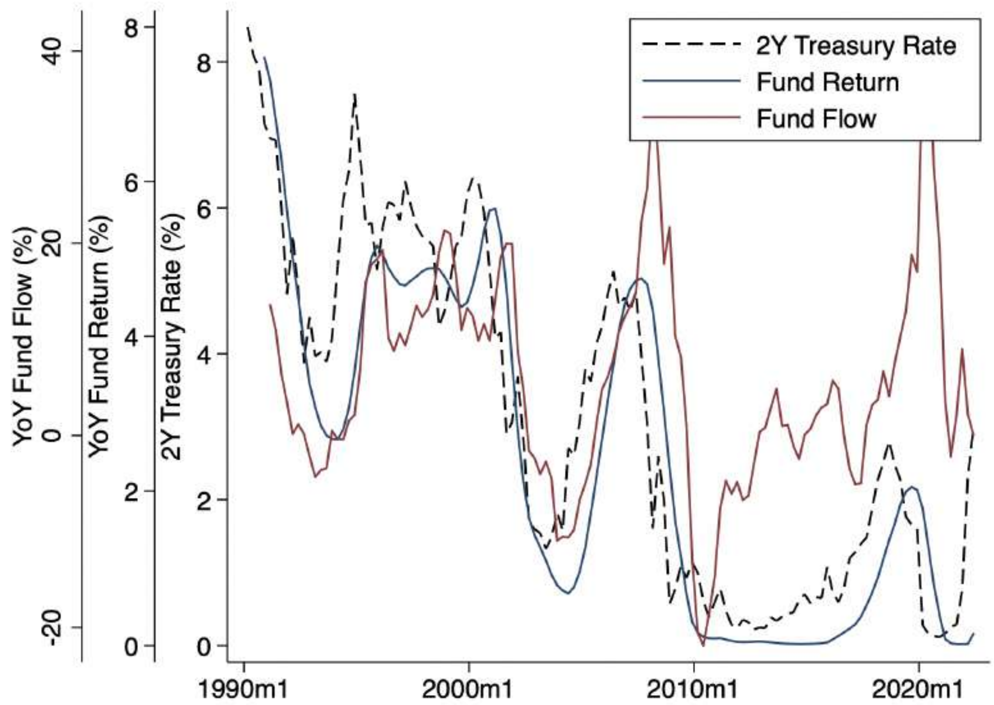


Figure A8: **Monetary Sensitivity across Mutual Fund Classes, Local Projections.** The figure plots the three-year responses of aggregate flows to various classes of mutual funds to 1 p.p. decrease in two-year Treasury rate with 95% confidence intervals, estimated from Equation (2).

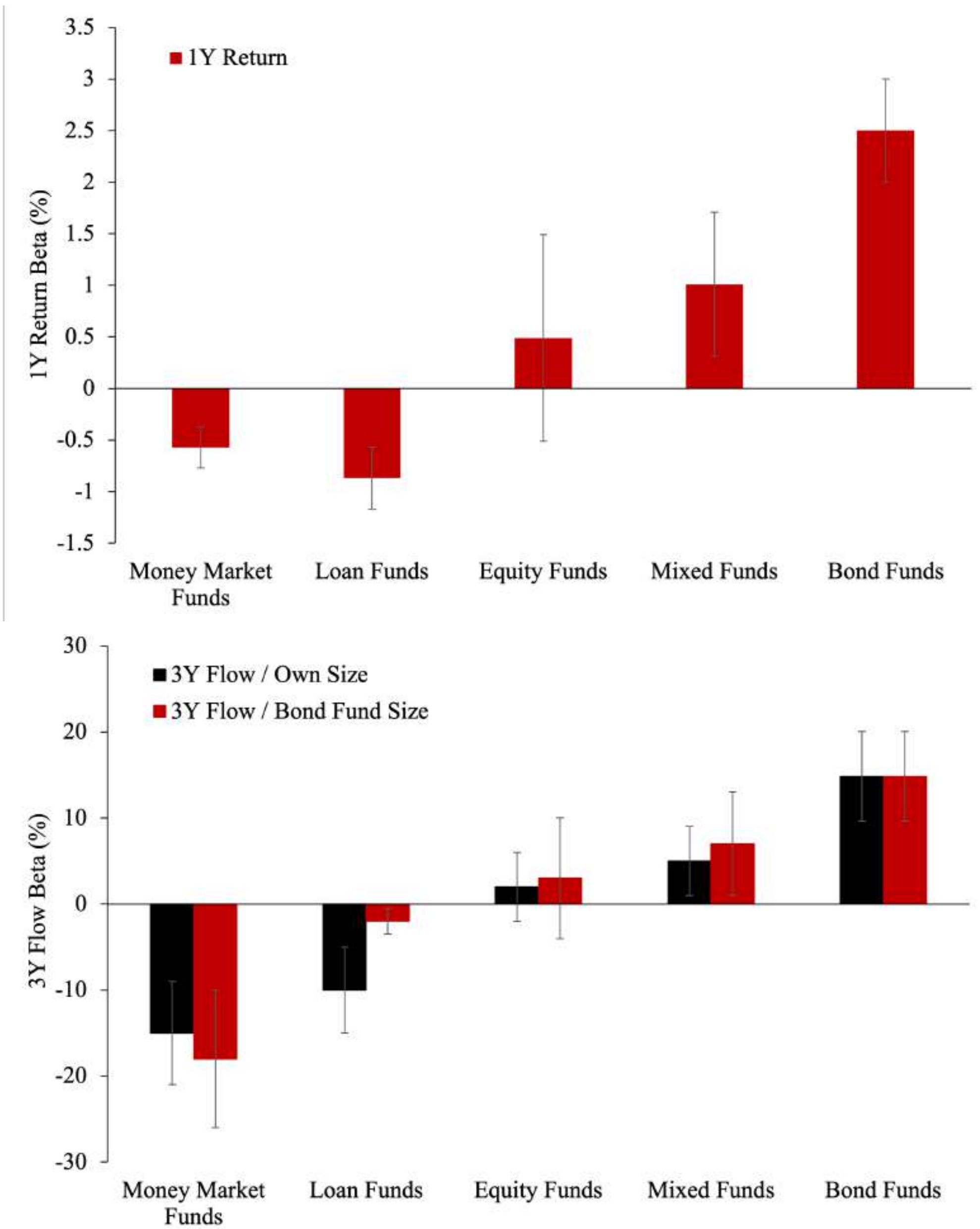


Figure A9: **Investor Base Concentration.**

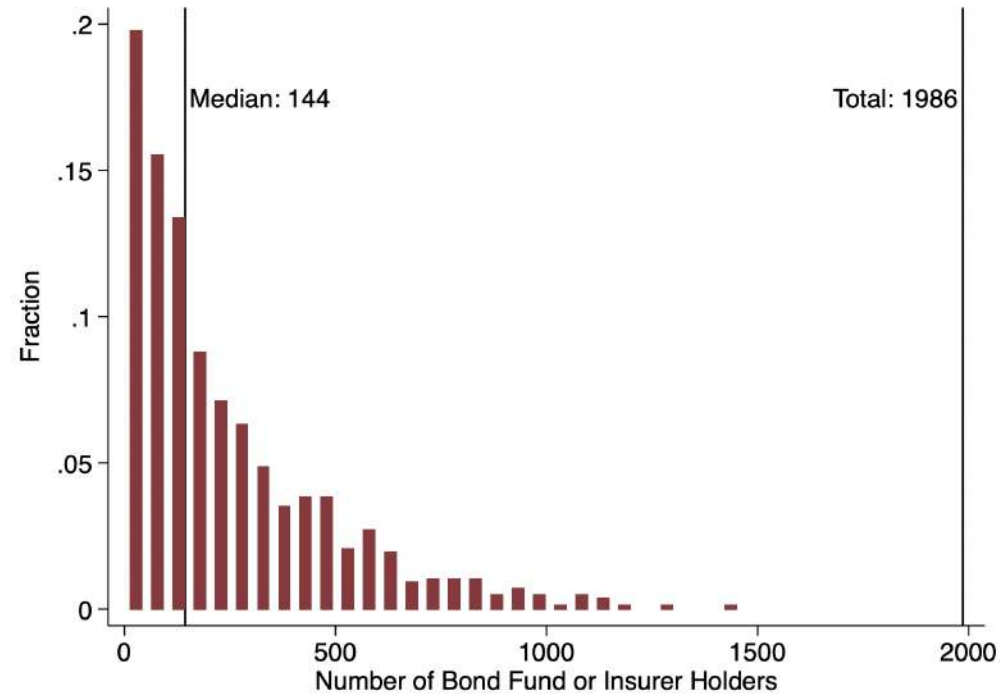
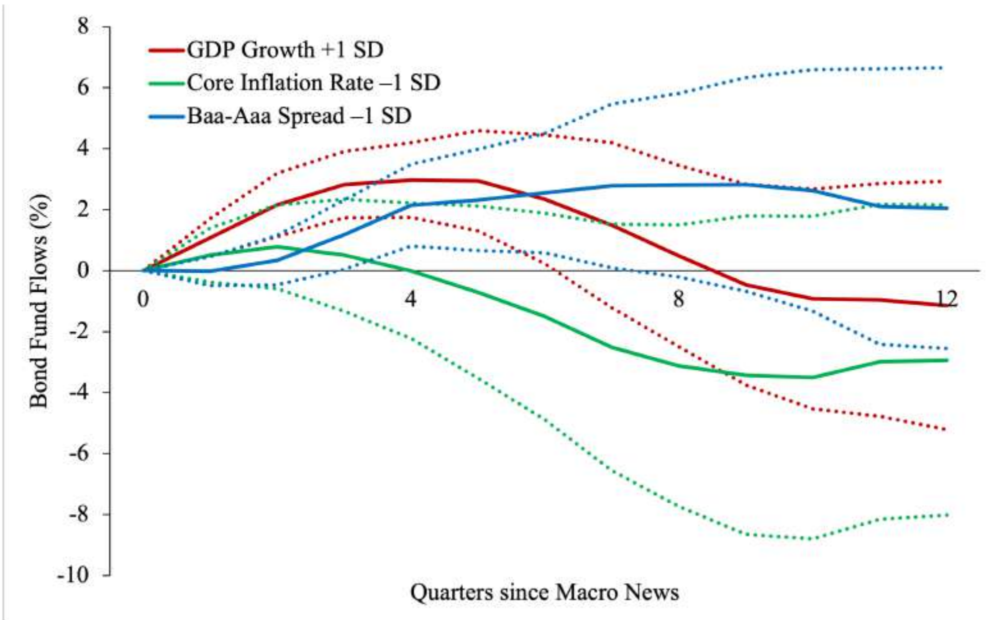
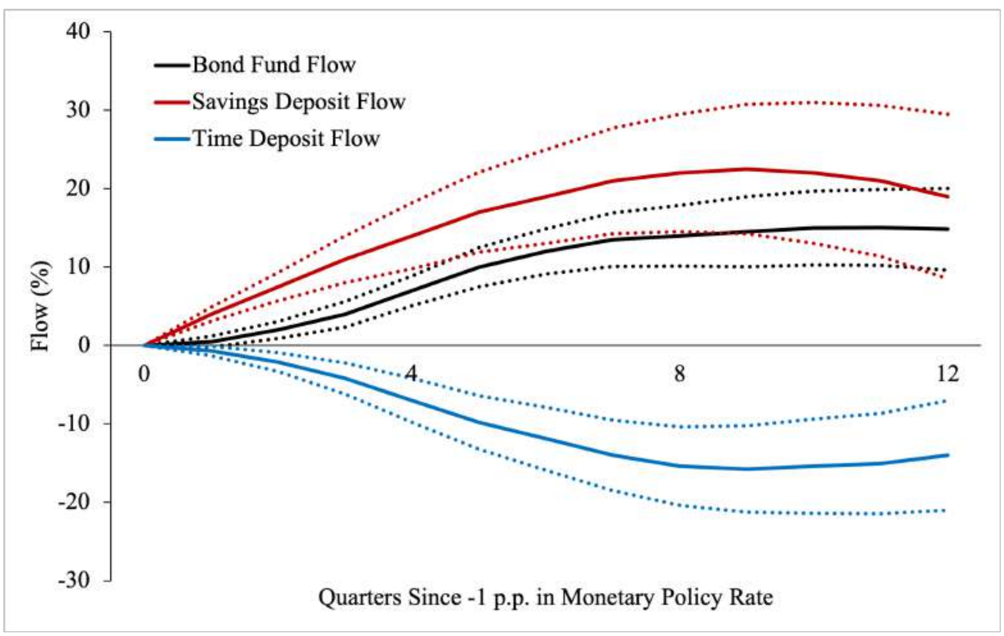


Figure A10: **Impulse Responses.**

Panel A: Macro News and Bond Fund Flows



Panel B: Bank Deposit Flow



Panel C: Bank C&I Lending

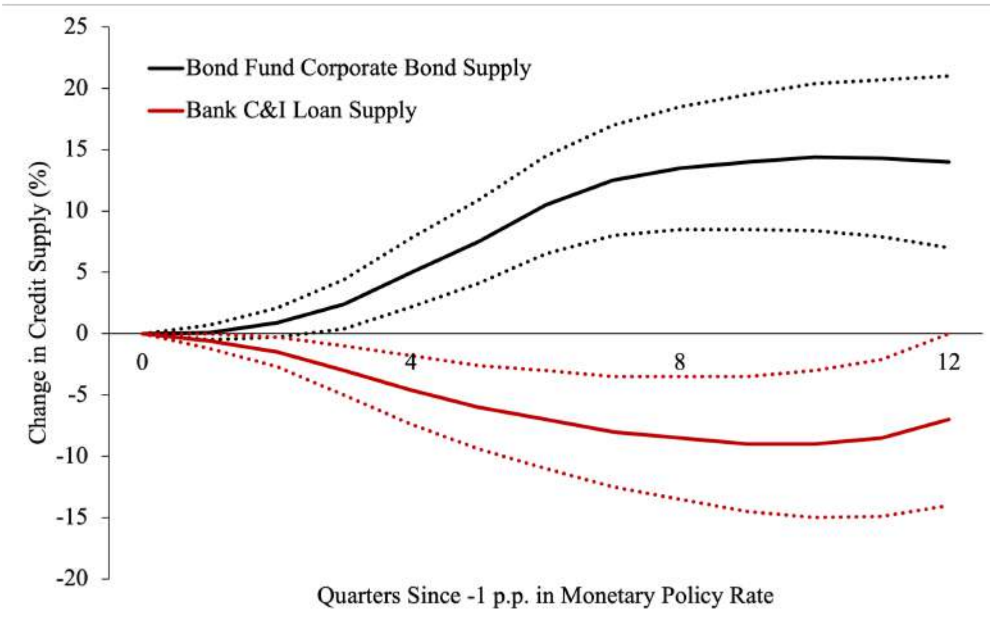


Table A1: **Monetary Sensitivity across Bond Funds.** These tables show what determines flow beta in the cross section of bond funds from Equation (3). t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Baseline

Dependent Variable	Fund Flow (%)	
ΔRate × Rating	-0.50	-0.63
	(-0.91)	(-1.22)
ΔRate × Macaulay Duration	-3.34***	-3.09**
	(-3.91)	(-2.01)
ΔRate × Income Yield	-1.03	-1.25*
	(-1.20)	(-1.71)
ΔRate × Yield to Maturity		0.15
		(0.34)
Controls	ΔRate × (Log TNA, Expense Ratio, Turnover, Return Alpha, Return Vol, Cash Ratio)	
Fixed Effects	Fund FE and Style × Quarter FE	
Standard Errors	Twoway-Clustered by Fund and Quarter	
Observations	93216	29253
R2	0.15	0.12

Panel B: Horse Race

Dependent Variable	1Q Flow	3Y Flow
Mcaulay Duration vs Rating	-0.36***	-3.34***
	(-4.97)	(-3.59)
Mcaulay Duration vs Income Yield	-0.30***	-2.81*
	(-2.81)	(1.93)
Mcaulay Duration vs Yield to Maturity	-0.48**	-3.14**
	(-1.99)	(-2.57)

Panel C: Retail vs Institutional Share Class Flow

Dependent Variable	Total Flow	Retail Flow	Institutional Flow
ΔRate × Rating	-0.05	-0.03	-0.05
	(-0.97)	(-0.25)	(-1.49)
ΔRate × Macaulay Duration	-0.41***	-0.37***	-0.45***
	(-5.73)	(-4.02)	(-6.29)
ΔRate × Income Yield	-0.11*	-0.19**	-0.03
	(-1.69)	-(2.02)	(-0.25)
Controls	ΔR × (Log TNA, Expense Ratio, Turnover, Return Alpha, Return Vol, Cash Ratio)		
Fixed Effects	Fund FE and Style × Quarter FE		
Standard Errors	Twoway-Clustered by Fund and Quarter		
Observations	99163	93501	95239
R2	0.22	0.24	0.20

Table A2: **Cross-Sectional Bond Sensitivity to Monetary Policy, Robustness.**

Easing vs Tightening

Dependent Variable	1Y Return (%)		
ΔRate Hike × Bond Fund Ownership	-0.36***	-0.41***	-0.39**
	(-2.96)	(-2.70)	(-2.41)
ΔRate Drop × Bond Fund Ownership	-0.25**	-0.32**	-0.30**
	(-2.51)	(-2.23)	(-2.00)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	148127	148127	148127
R2	0.59	0.63	0.63

Same Issuer, Different Bonds

Dependent Variable	1Y Return (%)	
Sample	Full	Tightening Only
ΔRate × Bond Fund Ownership	-0.10	-0.16*
	(-1.45)	(-1.81)
Rating × Duration × Quarter FE	Y	Y
Macro News × Bond Fund Ownership	Y	Y
ΔRate × Bond Characteristics	Y	Y
Issuer × Quarter FE	Y	Y
Standard Errors	Two-way Clustered by Bond and by Quarter	
Observations	91260	36235
R2	0.67	0.62

Same Issuer, Different Bond Fund Ownership over Time

Dependent Variable	1Y Return (%)		
ΔRate × Bond Fund Ownership	-0.35***	-0.41*	-0.40*
	(-2.79)	(-1.92)	(-1.90)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
ΔRate × Issuer Dummies	Y	Y	Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	148127	148127	148127
R2	0.59	0.63	0.63

Same Firm, Different Exposure due to Predicted Bond Fund Flows

Dependent Variable	1Y Return (%)		
Instrumented ΔRate × BFOwnership	-0.27*	-0.45*	-0.41
	(-1.93)	(-1.60)	(-1.56)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
ΔRate × Issuer Dummies	Y	Y	Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	148127	148127	148127
R2	0.65	0.68	0.69
First Stage F-statistic	39.66	39.66	39.66

Issuance Yield

Dependent Variable	Issuance Yield (bps)		
ΔRate × Bond Fund Ownership	4.36***	4.97**	4.83*
	(2.87)	(2.07)	(1.94)
Rating × Maturity × Quarter FE	Y	Y	Y
Macro News × Bond Fund Ownership	Y	Y	Y
ΔRate × Bond Characteristics		Y	Y
ΔRate × Issuer Characteristics			Y
Standard Errors	Two-way Clustered by Bond and by Quarter		
Observations	6181	6181	6181
R2	0.73	0.79	0.80

Table A3: **Cross-Sectional Firm Sensitivity to Monetary Policy, Robustness.**

Easing vs Tightening

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Capital Expenditure
Average Monetary Sensitivity	-5.96	-3.90	-2.63	-2.89	-3.07
ΔRate Hike × BF Ownership	-3.15*	-1.41**	-0.95	-1.21*	-0.43
	(-1.95)	(-2.12)	(-1.47)	(-1.70)	(-0.60)
ΔRate Drop × BF Ownership	-3.02*	-1.17*	-1.00	-0.79	-0.95
	(-1.87)	(-1.85)	(-1.54)	(-1.35)	(-0.88)
Controls	Macro News × Bond Fund Ownership, ΔRate × Firm Attributes				
Fixed Effects	Firm FE, Industry × Time FE				
Standard Errors	Two-way Clustered by Firm and by Time				
Observations	35372	35372	34546	34546	34546
R2	0.30	0.32	0.22	0.40	0.57

Same Firm, Different Exposure due to Predicted Bond Fund Flows

Dependent Variable (% of Bond Outstanding)	Gross Bond Issuance	Net Bond Issuance	Net Debt Issuance	Net Equity Payout	Capital Expenditure
Average Monetary Sensitivity	-5.96	-3.90	-2.63	-2.89	-3.07
Instrumented ΔRate × BFO	-3.25*	-1.20	-1.01*	-0.62	-0.20
	(-1.95)	(-1.56)	(-1.71)	(-1.03)	(-0.29)
Controls	Macro News × Bond Fund Ownership, ΔRate × Firm Attributes, ΔRate × Firm FE				
Fixed Effects	Firm FE, Industry × Time FE				
Standard Errors	Two-way Clustered by Firm and by Time				
Observations	35372	35372	34546	34546	34546
R2	0.36	0.39	0.26	0.44	0.61
First Stage F-statistic	46.11	46.11	46.11	46.11	46.11

Change in Cash Holdings

Dependent Variable	3Y Change in Cash Holdings (%)		
Average Monetary Sensitivity	0.53		
ΔRate × Bond Fund Ownership	0.12 (0.50)	0.03 (0.20)	0.09 (0.34)
Firm FE	Y	Y	Y
Quarter FE	Y		
Rating × Quarter FE		Y	
Industry × Quarter FE			Y
Controls	Macro News × Bond Fund Ownership, ΔRate × Firm Attributes		
Standard Errors	Two-way Clustered by Firm and by Quarter		
Observations	35372	35372	35372
R2	0.47	0.52	0.55

Table A4: **Bond Sensitivity to Monetary Policy by Rating and Duration.**

Dependent Variable	1Y Yield / 1Y Return Sensitivity to Monetary Policy					
Rating \ Duration	3-5	5-7	7-9	9-11	11-13	13-15
AAA	0.50	0.50	0.31	0.29	0.29	
	-2.13	-2.95	-3.35	-3.68	-4.61	
AA	0.44	0.38	0.32	0.22	0.37	
	-1.72	-2.17	-2.30	-2.09	-2.69	
A	0.37	0.30	0.29	0.25	0.11	0.12
	-1.41	-1.64	-1.84	-2.00	-2.66	-2.14
BBB	0.24	0.12	0.11	0.15	0.11	0.08
	-1.07	-1.17	-1.16	-1.30	-1.65	-1.51
BB	-0.21	-0.23	-0.08	0.00		
	1.06	1.04	0.72	-0.03		
B	-1.36	-0.74	-0.67	-0.15		
	2.28	1.83	1.61	1.59		
CCC	-3.19	-2.15	-1.98			
	5.51	5.87	4.48			

Appendix B Additional Details on Data and Variables

B.1 Mutual fund data

B.1.1 Correct errors

There are errors on total net assets, returns and expense ratios in the CRSP Survivor-Bias-Free US Mutual Fund Database. I closely follow the cleaning procedures in Ľuboš Pástor et al. (2015). In particular, I merge CRSP with Morningstar at the share class level using CUSIP and then ticker, manually check all cases where there are inconsistencies between the two databases, and set CRSP values to those in Morningstar if I can confirm that CRSP values are errors, or missing if I cannot. Common errors in CRSP include: TNA is reported in dollar instead of in million, TNA is copied from a previous month, and return is reported on a wrong decimal basis.

B.1.2 Consolidate share classes to funds

A fund can have multiple share classes, representing different target investors (e.g., retail vs institutional). The convention is to conduct analysis at the fund level, since all share classes of the same fund have identical gross returns and very correlated flows. In CRSP, share classes are identified by "fundno" and funds are identified by "portno". CRSP provides a mapping between the two, which I use to consolidate returns, flows, and other statistics at the fund level.[30] Note that for most money market funds, holdings are not available and therefore "portno" is not assigned.

B.1.3 Return-implied fund rating and fund duration

For my analysis on the cross section of bond funds, I need rating and duration for a given fund at a given time, which are not directly available in CRSP. One option is to calculate these quantities using portfolio holdings. However, for a lot of the bonds held by bond funds, such as agency securities, foreign bonds and private placements, there is no readily available data. For a typical bond fund in my sample, only 46% of its holdings have ratings, and only 32% of its holdings have information on coupon, maturity and price so that duration can be calculated. In addition, fund holdings are available only starting in 2005.

Therefore, in this paper, I formulate a strategy to estimate fund rating and fund duration using fund returns, which are available on a consistent basis and in high quality. The idea is that funds with worse rating (longer duration) should have higher return betas to changes in

[30]Because of changes in data provider, there was a change of "portno" for most of the funds in 2010. To account for that, I use the most recent "portno" as the identifier for a fund.

the level of credit spreads (changes in the level of interest rates). Specifically, first, I calculate returns on zero-coupon U.S. Treasury bonds of different maturities (1 year to 30 years) and I take the first principal component to represent changes in the level of interest rates. Then, I calculate return spreads of portfolios of corporate bonds over duration-matched U.S. Treasury bonds and I take the first principal component to represent changes in the level of credit spread. Given an asset for which I want to estimate duration and rating, I regress its returns on the interest rate factor and and the credit spread factor and define the factor loadings as duration and rating. I normalize factor loadings so that a 10-year Treasury bond would have an estimated duration of 10 and a 10-year BBB bond would have an estimated numeric rating of 10.

Table **??** reports portfolio-implied and return-implied fund rating and fund duration across different fund styles. To ensure that the portfolio-implied quantities are reliable, I restrict to portfolios where at least 75% of holdings have the relevant information (e.g. coupon, maturity and price). Return-implied rating and duration are highly correlated with the portfolio-implied ones.

B.2 Insurance company data

Data on insurance companies are from NAIC statutory filings. Schedule D filings provide bond purchases (Part 3) and bond disposals (Part 4) at the quarterly frequency and holdings (Part 1) at the annual frequency. I infer quarterly holdings from the previous year's holdings and the transactions in between. I hand correct all cases where the inferred holdings are negative.

B.3 Corporate bond data

I follow Bali et al. (2021) in calculating long-term bond returns. Return on bond i from end of quarter t to end of quarter $t+h$ is:

$$Return_{i,t,t+h} = \frac{Price_{i,t+h} + AccruedInterest_{i,t+h} + Coupon_{i,t,t+h}}{Price_{i,t} + AccruedInterest_{i,t}}$$

I first calculate the daily clean price as the trading volume-weighted average of intraday prices to minimize the effect of bid-ask spreads. I then convert the bond prices from daily to quarterly frequency. Corporate bonds occasionally default prior to reaching maturity. I use the composite default returns from Bali et al. (2021) for these defaulted bonds. Specifically, the composite default returns are -40.17% for defaulting investment-grade issues and -17.67% for defaulting high-yield issues.

There are errors in Mergent FISD. I manually check and correct the following occurrences, which I deem to be abnormal:

- FOREIGN_CURRENCY is N but OFFERING_AMT or AMOUNT_OUTSTANDING is greater than $100 billion.
- ACTION_TYPE is I but AMOUNT_OUTSTANDING is significantly different from OFFERING_AMT.

B.4 Firm data

Firm variables are defined as follows, with Compustat data items in italic:

- Bond amount outstanding: sum of par amounts of all bonds outstanding from Mergent FISD
- Net debt issuance: long-term debt issuance (*dltis*) minus long-term debt reduction (*dltr*)
- Net equity payout: repurchase of common and preferred stock (*prstkc*) minus sale of common and preferred stock (*sstk*) plus dividends (*dvq*)
- Real investment: capital expenditure (*capx*) plus R&D (*xrd*)
- Log total assets: log of total assets (*at*)
- Cash ratio: cash holdings (*che*) divided by total assets (*at*)
- Tobin's Q: debt ($dlc + dltt$) plus market value of equity ($prcc \times csho$) minus current assets (*act*) divided by plant, property and equipment (*ppegt*), following Erickson and Whited (2012)
- Total debt: debt in current liabilities (*dlc*) and long-term debt (*dltt*)
- Leverage: total debt to total assets
- Profitability: net income (*ni*) divided by total assets (*at*)
- Bond share: ratio of bond amount outstanding to total debt
- Bond rating: average of bond ratings weighted by amount outstanding
- Bond maturity: average of bond maturity weighted by amount outstanding

Appendix C Alternative measures of exposure to bond fund flows

C.1 Bondholder flow beta

As I have shown in Section 4, some bond funds (e.g., those with higher return beta) have significantly higher flow beta than others. Therefore, a corporate bond would have higher exposure to bond fund flows if it is owned more by bond funds (extensive margin) and in particular bond funds with higher flow beta (intensive margin). I construct an alternative measure of bond fund exposure to capture the intensive margin. First, for a given bond fund i, its flow beta is defined as the expected cumulative three-year flows (relative to its current size) given 1 p.p. decrease in two-year Treasury rate over the next year:

$$FlowBeta_{i,t} = E_t[Flow_{i,t,t+12} \mid \Delta Rate_{t,t+4} = -1\%] = f(X_{i,t}) \tag{27}$$

where the last equality comes from the regression results in Equation (3), which shows that a bond fund's flow beta is non-trivially affected by its characteristics such as return duration. For a firm j, I define Bondholder Flow Beta as the expected flows to its bond fund bondholders (relative to its bond amount outstanding) given 1 p.p. decrease in two-year Treasury rate:

$$BHFlowBeta_{j,t} = \sum_i \frac{AmountHeld_{i,j,t}}{AmountOutstanding_{j,t}} FlowBeta_{i,t} \tag{28}$$

This measure adapts from the Bondholder Flow measure in Zhu (2021).[31] Suppose that a bond issuer is owned entirely by a single bond fund, then its Bondholder Flow Beta is exactly the flow beta of that bond fund. Suppose that a bond issuer is not owned by any bond fund (e.g., it is owned entirely by insurers), then its Bondholder flow beta is zero.

C.2 Monetary-induced price pressure

A more complicated definition takes into account the differential scaling of bond fund portfolio in response to flows due to flow direction and liquidity concerns (Lou, 2012; Choi et al., 2020; Ma et al., 2022). Specifically, monetary-induced price pressure is defined as:

$$MIPP_{j,t} = \sum_i \frac{AmountHeld_{i,j,t}}{AmountOutstanding_{j,t}} \times FlowBeta_{i,t} \times ScalingFactor_{i,j,t} \tag{29}$$

[31] This measure is also similar to Chodorow-Reich (2013) in the context of measuring relationship-based bank lending supply.

where

$$\begin{aligned} ScalingFactor_{i,j,t} = {} & 1(FlowBeta_{i,t} < 0)(0.80 + 0.12 \times LiquidityRank_{i,j,t}) \\ & + 1(FlowBeta_{i,t} > 0)(0.58 + 0.20 \times LiquidityRank_{i,j,t}) \end{aligned}$$

The scaling factor is similarly defined in Lou (2012) and Ma et al. (2022) and captures the differential effect of inflows vs outflows and liquidity on relationship between fund flows and fund trading. As shown in 2, trading is more mechanically linked to outflows than inflows, and bond funds prioritize trading of more liquid bonds, even at the annual frequency.

Appendix D Other Channels of Monetary Policy Transmission to Corporate Bond Yields

First, there is a large literature on institutional reaching for yield – institutional investors take more risks at lower interest rates (e.g. Hanson and Stein, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018; Anadu et al., 2019). As a result, monetary easing can lead to lower corporate bond yields simply because investors tilt their portfolios more towards corporate bonds as they carry higher risks (e.g. vs the treasuries).

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 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. On the other hand, 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, and insurers and pension funds tilt their portfolios more towards longer-term bonds to lengthen duration on the asset side.[32]

Lastly, a growing literature studies the connection between monetary policy and liquidity premium. Nagel (2016) and Drechsler et al. (2018) shows that liquidity premium comoves strongly with federal funds rates. Drechsler et al. (2018) present a model where leveraged investors become more sensitive to illiquidity risk when short-term interest rates rise. On the other hand, Li and Yu (2022) shows that lower interest rates are associated with higher risk premium in the corporate bond market.

[32] Greenwood and Vissing-Jorgensen (2018) shows direct evidence on the impact of pension funds and life insurers on long-term bond yields.

Appendix E Alternative Strategies for Identifying Investor Elasticity

E.1 Investment universe

The instrument follows Koijen and Yogo (2019) and makes use of investment universe: an investor only invests in a subset of corporate bonds issued by a particular group of firms. This can be due to investment mandate, limited attention, or relationship. I have already shown evidence of investment universe for bond funds in Section 5.1: when a typical bond fund experiences flows, it passes through most of the flows to its portfolio firms, i.e. firms that it already invests in. I define investor i's investment universe at time t as its portfolio at time t. Similar to Bretscher et al. (2021), I consider investment universe at the bond issuer level rather than the bond issue level, because a firm can issue multiple bonds and this stickiness is more likely to be at the issuer level.

Having defined investment universes, I construct the instrument as:

$$\hat{y}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t}\frac{1_{j,t}(n)}{1+\sum_{m=1}^{N} 1_{j,t}(m)}\right)$$

where the indicator function $1_{j,t}(n)$ equals one if the issuer of bond n at time t belongs to the investment universe of investor i. Hence, the instrument depends only on the investment universes of other investors, which are assumed to be exogenous to latent demand as the identifying assumption. Intuitively, when a certain bond issue is included in the investment universes of more investors, particularly those of large investors, it has a larger exogenous component of demand. A large exogenous demand component generates higher prices and, hence, lower yields, which are orthogonal to latent demands.

E.2 Characteristics-only demand

The instrument follows Koijen and Yogo (2020) and is defined as:

$$\hat{y}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t}\hat{w}_j(n)\right)$$

where $\hat{w}_j(n)$ is fitted value from a regression of portfolio weights onto characteristics only. The idea is that bonds held more by large investors (because of these investors' demand for the bonds' characteristics) have higher outside demand and lower yields that are orthogonal to investor i's latent demand.