Reaching for Income and Investor Flows in Corporate Bond Mutual Funds[*]

Gi H. Kim[†] Xu Li[‡]

September 2022

Abstract

A low-interest rate environment induces higher demand for income-generating assets, such as high-dividend stocks and high-coupon bonds. In this paper, we explore the impact of this "reaching-for-income" phenomenon on fund flows of corporate bond mutual funds. We find that high reaching-for-coupon (RFC) funds, i.e., bond funds whose portfolios pay higher coupons than the benchmark, attract more inflows and have fund flows that are less sensitive to past fund performance. More interestingly, they exhibit a less concave flow-performance relation. Further analyses offer evidence that this altered flow-performance relation may result in greater risk-taking on the part of the fund, contributing to higher fund returns. Our results shed new light on the incentive for "reaching-for-yield" behaviours in the fixed-income market.

JEL Classification: E44; G11; G23; G32
Keywords: Reaching For Income; Reaching For Yield; Fund Flow-Performance Relation; Corporate Bond Mutual Funds; Fund Risk-Taking; Low Interest Rates

[*]Any errors are our own.

[†]Warwick Business School, University of Warwick, Scarman Road, Coventry CV4 7AL, United Kingdom. Email: Gi.Kim@wbs.ac.uk

[‡]Warwick Business School, University of Warwick, Scarman Road, Coventry CV4 7AL, United Kingdom. Email: phd17xl@mail.wbs.ac.uk

1 Introduction

Since the global financial crisis, the world has experienced a prolonged period of low-interest rates. This trend has drawn increasing interest recently from academics and practitioners, who question whether and how a low-rate environment affects investor behaviour. Several extant studies provide theoretical frameworks and empirical evidence that it tends to increase investors' appetite for risk-taking and can lead to chasing high-yield assets, referred to as the reaching-for-yield (RFY) phenomenon (e.g., Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018). However, there has been less attention paid to whether low rates increase investor demand for income-generating assets such as high-dividend stocks in order to obtain predictable future cash flow streams (e.g., Jiang and Sun, 2020; Daniel et al., 2021).

In this paper, we focus on fixed income markets, and explore the impact of a related concept, the reaching-for-income (RFI) phenomenon, on corporate bond mutual funds. Do bond funds respond to declining interest rates by tilting their portfolios toward high-coupon bonds (which we refer to as "reaching-for-coupon (RFC)")? Will they indeed attract more inflows? And how would RFC alter the flow-performance relationship, and thus the risk-shifting behaviour, of fund managers? To address these questions, we create a fund-level measure of RFC in a spirit similar to that of Choi and Kronlund (2018). We explore to what extent a fund tilts its portfolio toward bonds that pay higher coupons than their peers of similar yield and maturity.[1] Higher (positive) RFC would indicate a stronger tendency of a fund to "reach for income."

Once we have constructed the RFC measure, we relate it to fund flows, and uncover some interesting results. We use bond holding data of 677 unique corporate bond mutual funds for

[1]We denote the benchmark coupon rate as the average coupon rate of all available bonds with comparable yields and duration to the bond we consider. This is done in order to mitigate concerns that fund managers' portfolio decisions are motivated by either achieving higher yields or by hedging against interest rate (or duration) risk.

the 2002-2018 period that come from Lipper eMAXX. First, bond fund flows, in aggregate, are negatively related to the interest rate, especially for funds with higher RFC. Our fund-month panel analyses show that, for a 1-standard deviation (SD) lower interest rate, funds with higher-than-median RFC measurements obtain an additional 0.185% of fund flows than those with lower RFC. This equates to an approximately 18% increase in the mean monthly flows. Second, RFC tends to weaken the overall sensitivity of fund flows to a fund's past performance. Our fund-month-level panel analyses also show that a 1-standard deviation (SD) higher RFC is related to a 0.369% decrease in flow-performance sensitivity (or about a 30% reduction in overall flow-performance sensitivity) when fund performance is measured using the two-factor model proposed by Goldstein et al. (2017). More importantly, third, RFC alters the shape of the flow-performance relationship, making it less concave. The outflows of RFC funds thus become 3 times less sensitive to poor performance, instead of their inflows becoming 1.5 times more sensitive to good performance. The results of RFC on flow sensitivity are also more pronounced for the low-interest rate period.

We interpret our results on RFC fund flows to mean that investors' tendency to reach for income affects their redemption decisions. For the "rule of thumb" investors, who live off their investment income stream, it is not only the return but also the level of current income that matters to their consumption (Daniel et al., 2021). Hence, all other things being equal, the stronger RFI (or RFC), the less return-chasing behaviour. And a reduced incentive for income-seeking investors to chase returns makes them relatively less responsive to fund performance when making an investment (or redemption) decision. This leads to high-RFC funds showing overall smaller flow sensitivity to performance.

However, RFI can alter not only the level of flow sensitivity, but also the shape of the flow sensitivity to performance. Looking at the fund's bad performance separately from its good performance, bond fund flows exhibit a greater sensitivity to the former than the latter (e.g., Chen and Qin, 2017; Goldstein et al., 2017). This *concave* flow-performance relationship (in contrast to the convex relation for equity funds (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998)) is attributable to strategic complementarities among fund investors, as noted by Chen et al. (2010) and Zeng (2017). That is, the illiquid nature of fund holdings creates first-mover advantages in redemption decisions that amplify fund outflows in response to poor performance.[2] It is conceivable that RFI investors, who seek predictable and stable income streams over longer periods, would value such payoff complementarities less when making redemptions. Hence, we would not expect to see a large amplification in fund outflows due to poor performance. This leads to less concavity in the flow-performance relation for high-RFC funds.

Once we determine the impact of RFC on fund flows, we next explore its implications for fund risk-taking and returns. Funds' risk-taking incentives are positively associated with the convexity in the flow-performance relation (e.g., Brown et al., 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Koski and Pontiff, 1999; Lynch and Musto, 2003; Basak et al., 2007; Schwarz, 2012). The intuition is that fund managers have stronger incentives to maximise their compensations by taking a higher risk since investors penalty less for bad performance. With a concave relation, it is not clear whether bond funds engage in any form of risk-taking. However, we posit that high-RFC fund managers, due to less concavity (or more convexity) of the flow pattern, may have stronger incentives to take on risk.

We test this conjecture, and find that high-RFC funds do tend to hold riskier portfolios, as measured by the fund return volatility and credit ratings of their bond holdings. They also have greater exposure to redemption risk due to a lower liquidity buffer. More specifically, a 1-SD higher RFC is associated with an 0.043% increase in fund return volatility (4.214% of the average sample fund return volatility). Furthermore, we find that RFC is associated with holding lower-rated bonds, as well as lower amounts of cash and Treasury holdings,

[2]Withdrawing money from a fund can lead to high liquidation costs for the fund to adjust their portfolio, especially for illiquid funds. This cost will transfer to the remaining investors. Hence, expecting that other investors would withdraw, resulting in a decrease in the expected return from remaining, each investor has stronger incentive to withdraw as well.

when analyzing the dynamic portfolio composition. RFC funds also tend to generate higher fund (raw) returns, in line with their higher levels of risk-taking.

We note that our paper is closely related to Choi and Kronlund (2018), who study bond mutual funds' reaching-for-yield (RFY) behaviour during low-interest rate periods. The authors find that bond mutual funds tilt their portfolios into higher-yield bonds and take greater risks in order to boost fund performance. RFY and RFC are related concepts, as both involve investing in a certain type of bond (e.g., a high-yield for RFYs vs. a high-coupon for RFCs) and attract fund inflows, but their incentives differ (e.g., a return boost for RFY vs. income-seeking for RFC). Although RFCs can partially increase overall bond yield,[3] we find that only RFCs affect flow-performance sensitivity. Moreover, it is noteworthy that we attempt to filter out the effect of RFY in constructing our measure of RFC by comparing the bond's coupon against that of a peer with similar yield and maturity.

Our paper contributes to three strands of the literature in several key ways. First, our study belongs to the literature on the effect of low-interest rates on investor behaviour in the fixed-income market. A growing body of research has provided empirical evidence that low-interest rates lead to increased investor preferences for high-yield bonds, which is referred to as the "reaching-for-yield" (RFY) phenomenon (e.g., Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018). However, the incentives for RFY have been underexplored, and deserve further investigation. Much of the extant work has focused on greater risk-taking to boost investment returns as the motive for RFY, but has overlooked investors' desire to earn higher coupon income in order to ensure a predictable income stream, referred to as the "reaching-for-income" (RFI) phenomenon.[4] Because high-yield bonds are not necessarily risky, but may be safe and high-coupon-bearing, it is important to distinguish between the two components (i.e., coupon yields and capital gain yields) to fully understand

[3]Bond yields are determined by three different components: current price, coupon, and maturity. Therefore, high-coupon bonds do not necessarily translate into high-yield ones, and they may exhibit low yields if their current price is disproportionately high.

[4]See, e.g., Daniel et al. (2021), Jiang and Sun (2020), and Harris et al. (2015) for studies on RFI.

RFY. Therefore, our paper contributes by demonstrating the presence of a "reaching-for-coupon" (RFC) tendency even after controlling for bond yields.

Second, our paper expands the literature on the flow-performance relation for corporate bond mutual funds. It is well documented that equity funds exhibit a convex relation, where investors send more money to funds with better performance but penalize proportionately less for poor performance. (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Huang et al., 2007). In contrast, corporate bond funds tend to exhibit a concave relation due to payoff complementarities among fund investors. That is, their outflows are sensitive to poor performance more than their inflows are sensitive to good performance. This concave relation results in high redemption risk and fragility in corporate bond markets (e.g., Chen and Qin, 2017; Goldstein et al., 2017). The literature has focused largely on fund illiquidity (e.g., Chen et al., 2010; Goldstein et al., 2017) as cross-sectional determinant of this concave shape. But we argue it is also somewhat dependent on the fund's coupon income.

Last, we also contribute to the literature on mutual fund risk-taking. For equity funds, the convex flow-performance relation induces agency problems between fund managers and investors. The managers thus have an incentive to engage in high risk-taking (e.g., Brown et al., 1996; Chevalier and Ellison, 1997; Koski and Pontiff, 1999; Basak et al., 2007; Schwarz, 2012).[5] However, little is known about the risk-taking behaviours of corporate bond funds. The flow-performance relation is usually concave (rather than convex), it is not clear whether bond funds engage in risk-shifting or tournament-like behaviours given that the illiquid nature of fund holdings makes the cost of redemption risk very high (e.g., Capponi et al., 2020; Choi et al., 2020). Choi and Kronlund (2018) briefly touch on this issue, and provide indirect evidence that bond funds' risk-taking depends on the shape of a flow-performance relation. Our results corroborate their findings by showing that high-RFC funds (those exhibiting a less concave flow-performance relation) tend to hold riskier assets.

[5]Christoffersen et al. (2014) provide a detailed literature review on flows in equity mutual funds.

The remainder of this paper is organized as follows. We describe our data and sample construction in Section 2. We then present our main results as follows: the impact of RFC on fund flow-performance sensitivity (Section 3), fund risk-taking (Section 4), and fund returns (Section 5). Section 6 concludes.

2 Data and Variable Construction

2.1 Data

Our paper uses data from several sources. Quarterly holding data on open-ended corporate bond mutual funds come from the Thomson Reuters/Lipper eMAXX fixed-income database.[6] We obtain monthly data on fund returns and flows, and quarterly fund characteristics from the CRSP Survivorship-Bias-Free Mutual Fund database. Corporate bond characteristics come from Mergent FISD. We calculate bond liquidity measures using bond transaction data in TRACE. We focus only on fixed-rate coupon bonds.

Following Choi and Kronlund (2018), we first select corporate bond mutual funds from the CRSP Survivorship-Bias-Free Mutual Fund database, using CRSP S&P fund style category codes (I, ICQH, ICQM, ICQY, ICDI, ICDS, or IC). We calculate the asset-weighted average of these characteristics across all share classes that belong to the same fund in order to conduct our analysis at a fund level. Because there is no common identifier between eMAXX and the CRSP database, we manually match them by fund name (we lose about 50% of

[6]The database contains detailed fixed income holdings for nearly 20,000 entities, including U.S. and European insurance firms, U.S., Canadian, and European mutual funds, and leading U.S. banks and public pension funds. It provides information on quarterly holdings of more than 40,000 fixed income issuers, with USD $5.4 trillion in total fixed income at par value. We focus on U.S.-issued corporate bonds held by U.S. institutions. The sample contains approximately 1,200 institutional investors who hold a total face value on average of USD $1.8 billion. For these institutions, eMAXX reports holdings based on regulatory disclosures to the National Association of Insurance Commissioners (NAIC) for insurance companies, and to the Securities and Exchange Commission (SEC) for mutual funds, asset managers, and public pension funds. It also reports voluntary disclosures by major private pension funds. A detailed description of the data is provided in Dass and Massa (2014).

observations in this step). Once we have linked the two databases, we merge funds' bond holding data in eMAXX with fund characteristics and returns in CRSP. We then add bond-level information (e.g., coupon, yield, maturity, duration, and liquidity) using 8-digit CUSIP numbers from Mergent FISD (we lose 13.717% of observations in this step). Next, we merge the quarterly fund characteristics and holdings data with monthly bond flows obtained from CRSP. Finally, we limit our sample to non-index funds, following Jiang et al. (2021a) (we lose 946 observations in this step). Our final sample consists of 677 unique corporate bond mutual funds, and 49,892 fund-month observations from July 2002 to March 2018.

2.2 Variable Construction

2.2.1 Measurement of Reaching-for-Coupon

In this section, we outline our construction method for the RFC fund-level measure. In a similar spirit to the RFY measure in Choi and Kronlund (2018), we aim to capture the extent to which the fund tilts its portfolio toward corporate bonds whose coupon rates are higher than the benchmarks. Such funds will be attractive to income-seeking investors, since the fund is required to distribute all of its coupon income regularly to investors.[7] To this end, we first determine the benchmark coupon rate each quarter. Although a bond's coupon rate is predetermined based on prevailing market interest rates at the time of issuance, it is correlated with the bond's current yield and duration.[8] To mitigate any concern that fund managers' portfolio choices may be driven by either achieving higher yields or hedging against interest rate (or duration) risk, we calculate the benchmark coupon rate as the average coupon rate of all available bonds with similar yields and durations to the bond we consider.

[7] See "Mutual Funds and ETFs", page 22. Accessed Jan. 16, 2022, U.S. Securities and Exchange Commission.

[8] Coupon rates are positively related to bond yields, and negatively related to bond duration (or maturity).

More specifically, for each quarter, we double-sort all available bonds in TRACE and NAIC based on their yields and durations to form 5-by-5 portfolios. We then calculate the average coupon rate of all bonds contained in the twenty-five portfolios. For each bond j held by fund i for quarter t, we compute a deviation of bond j's coupon rate from the benchmark rate, $C_{j,t}^{y,d}$. This is defined as the average coupon rate of the portfolio to which bond j belongs. Last, we compute the measure of RFC for fund i and quarter t, $RFC_{i,t}$, as the holding-weighted average of the deviation in coupon rates:

$$RFC_{i,t} = \sum_{j} \omega_{j,i,t}(C_j - C_{j,t}^{y,d}), \tag{1}$$

where $\omega_{j,i,t}$ is the weight of bond j's amount to the total amount of bonds held by fund i at the end of quarter t.

This RFC measure captures mutual fund managers' tendency to tilt their portfolios toward bonds with higher coupon rates than their peers with similar yields and maturities. Bond fund investors expect to receive higher coupon income from high-RFC funds. This holdings-based measure allows us to investigate fund managers' dynamic portfolio decisions on high-coupon bonds. However, we note one caveat with this measure. Although it will be highly correlated with the actual amount of coupon payments that fund investors receive each quarter (Figure 1.1),[9] the two may differ due to the time mismatch. That is, coupons are paid on different dates for different bonds, and the payments are not always received every quarter.

[9]Comparing the cross-sectional mean of RFC with the dividend income yields of the funds in our sample over time, Figure 1.1 shows a fairly high correlation between the two. We expect a certain amount of discrepancy, because the variable of dividend income yields we use from CRSP includes not only bond coupons, but also stock dividends.

2.2.2 Measurement of Fund Flows and Performance

The key variables in our empirical analyses are mutual fund flows and performance. We define monthly fund flows of fund i in month t, $Flow_{i,t}$, as follows:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + Ret_{i,t})}{TNA_{i,t-1}}, \tag{2}$$

where $TNA_{i,t}$ is fund i's total net assets at the end of month t, and $Ret_{i,t}$ is fund i's return during month t.

To measure bond fund performance, we first use the two-factor regression model proposed by Goldstein et al. (2017) to estimate risk-adjusted α as follows:

$$Ret_{i,t} - RF_t = \alpha + \beta_1(BOND_t^{Mkt} - RF_t) + \beta_2(STOCK_t^{Mkt} - RF_t) + e_t \tag{3}$$

where $Ret_{i,t}$ is the return on fund i in month t, RF_t is the risk-free rate proxied for by the one-month T-bill rate in month t,, $BOND_t^{Mkt}$ is aggregate bond market returns in month t, proxied for by the return of the Vanguard Total Bond Market Index Fund, and $STOCK_t^{Mkt}$ is aggregate stock market returns in month t, proxied for by the CRSP value-weighted market return (Goldstein et al., 2017). We estimate the bond fund's α by using a twenty-four-month rolling window. We then estimate the bond fund's average alpha over the past eighteen months in order to measure the performance of corporate bond funds. We use average fund raw returns over the past eighteen months as a second measurement of fund performance. [10]

[10] In Appendix 1.B, we estimate alpha using a one-factor model with only aggregate bond market returns in a twenty-four-month rolling window (instead of using both aggregate stock and bond market returns). We use average alpha estimated through this one-factor model over the past eighteen months as an alternative performance measure. Moreover, for robustness, we also measure performance by using average fund excess raw returns (fund raw returns minus the risk-free rate) over the past eighteen months.

2.3 Summary Statistics

We provide summary statistics in Table 1. Breaking down fund holdings into asset classes, we note that corporate bonds make up the largest asset class held by mutual funds in our sample. Thus, 48.389% of their holdings are in corporate bonds, while 2.447% are in cash, 10.567% are in government bonds, 0.544% are in equity, and 38.053% are in other asset classes, including foreign securities and structured products.

The sample average RFC is 0.343% (the average coupon rate in the sample is 5.854%). This indicates the fund's tendency to reach for coupon, that is, corporate bond funds on average hold higher-coupon bonds than their yield- and duration-matched benchmarks. There is also large heterogeneity in RFC, as evidenced by the interquartile range of -0.090% to 0.777%, and the large standard deviation of 0.687%. As Figure 1.1 shows, our RFC measure is highly correlated with the fund's dividend income yields, indicating that high-RFC funds pass through greater amounts of coupon payments to fund investors.

In our sample, the average of monthly fund flows ($Flow$) is about 1.027%, with a monthly flow volatility ($FlowVolatility$) of 11.600%. These are quantitatively similar to the bond fund flows in Goldstein et al. (2017). Similar to the average bond fund returns in Goldstein et al. (2017) and Chen and Qin (2017), we find that average monthly fund return (Ret) is 0.405%, and average fund return volatility ($RetVolatility$) for the past twelve months is 1.027%. These are 3.963% lower than those documented in Shu et al. (2012) for equity funds, due to the relatively stable nature of bond markets. For fund performance, the average raw returns and two-factor alphas during the past eighteen months are 0.432% and 0.008%, respectively. Idiosyncratic volatility ($IdioVolatility$) is as small as 0.542%, which suggests that more than 70% of the total variation in fund returns can be attributed to systematic volatility with respect to two risk factors.[11].

Overall, on average, fund size ($FundSize$), defined as the log of total net assets (TNA), is

[11]The fraction is calculated as:$1 - (0.542\%)^2/(1.027\%)^2 = 72.15\%$

5.511, and the maturity of the fund's bond holdings ($FundTtm$) is 7.117 years. The fund has a mean expense rate ($FundExpense$) of 0.723% of TNA, and its average age ($FundAge$)is 12.351 years. The difference between the fund's fifty-two-week highest and lowest net asset values ($DiffNAV$) is \$0.709 million.

3 RFC and Fund Flow-Performance Relation

In this section, we examine the impact of RFC on fund flows. We first explore whether high-RFC funds attract more fund inflows, especially when interest rates are low. We then turn to detailed analyses of fund flow-performance sensitivity. Finally, we investigate how the impact of RFC affects the shape (or curvature) of the flow-performance relation of bond mutual funds.

3.1 Interest Rates, RFC and Fund Flows

Bonds as a whole may be *relatively* less attractive than stocks during periods of low interest rates, when income-seeking (or RFI) investors would prefer higher stock dividends over limited coupon payments (e.g., Jiang and Sun, 2020). Within bonds, however, high income-generating types would nevertheless have some comparative appeal to income-seeking investors when interest rates are declining, as shown in Daniel et al. (2021). We argue that RFI investors prefer high-coupon bonds because they generate relatively higher income than their low-coupon counterparts. To test this conjecture, we examine the relation among interest rates, RFCs, and fund flows at both the aggregate (Equation 4) and fund (Equation 5) level:

$$Flow_t = \alpha + \beta_1 InterestRate_t + \beta_2 InterestRate_t * AggRFC_t + \beta_3 AggRFC_t + \gamma Controls_{t-1} \tag{4}$$

$$Flow_{i,t} = \alpha + \beta_1 InterestRate_t + \beta_2 InterestRate_t * HighRFC_{i,t} + \beta_3 HighRFC_{i,t} + \gamma Controls_{i,t-1} \quad (5)$$

where $Flow_t$ is the aggregate sum of fund flows in month t, $InterestRate_t$ is the interest rate at month t, and $AggRFC_t$ the aggregate sum of the fund's RFCs in month t. We use the aggregate sum of lagged flows $LagFlow$ and lagged fund returns $LagRet$ in month $t-1$ as our control variables in Equation 4. Similarly, $Flow_{i,t}$ is monthly fund flow for fund i in month t. $HighRFC_{i,t}$ is a dummy variable that equals 1 if fund i has higher-than-median RFC in month t. We include several characteristics for fund i in month $t-1$ as our controls (see the caption of Table 2 for details).

Columns 1 and 2 in Table 2 present the results of the effect of interest rates and RFC on fund flows at the aggregate level. For Column 1, the coefficient of $InterestRate$ is -0.297 (with t-statistic -4.685), and it is significantly negative at the 1% significance level. This indicates that, for a 1% decline in the interest rate, bond funds receive an additional 0.297% monthly inflow, which translates into a 28.919% increase in the sample mean of fund flows.[12]

Interestingly, when we interact $InterestRate$ with $AggRFC$ in Column 2, we observe that the regression coefficient of this interaction term is significantly negative (coefficient = -0.003, t-statistics = -2.054). This suggests that, during the low-rate period, bond funds attract more investor flow when they engage in higher RFC. It is noteworthy that the coefficient on $InterestRate$ loses its significance when we interact it with RFC. These findings are consistent overall with those of Daniel et al. (2021). They use impulse response analyses, and find that a decline in the fed funds rate leads to an increase in fund flows for bond funds with higher income (but not for funds with lower income). The coefficient for control variables is also consistent with findings in the bond fund literature, where past fund performance

[12]Historically, U.S. households tend to allocate their funds more heavily into stocks than bonds during periods of low interest rates (e.g., Jiang and Sun, 2020). Hence, we may expect a positive coefficient on $InterestRate$. However, Daniel et al. (2021) show that bond funds that generate higher income experience an increase in fund inflows in response to interest rate declines. We therefore interpret our finding of a negative coefficient on $InterestRate$ to mean that our sample of funds is comprised of funds with relatively high coupon payments, as evidenced by the sample mean of RFC being positive..

positively predicts future flows, and higher past fund flows are positively related to future flows (due to fund flow persistence) (e.g., Goldstein et al., 2017; Chen and Qin, 2017). The results are qualitatively similar for the fund-level analyses in Columns 3 and 4.[13]

Collectively, our results suggest that bond funds tend to attain more inflows during a low-interest rate environment. This pattern is more prominent for funds investing in high income-generating assets, or for high-RFC funds that tilt their portfolios toward higher coupon bonds than their yield- and maturity-adjusted benchmarks. We interpret this as evidence of the impact of an RFI phenomenon on corporate bond mutual fund flows.

3.2 RFC and Fund Flow-Performance Sensitivity

We have shown that high-RFC funds attract more inflows during low-interest rate periods, and linked our finding to the reaching-for-income tendency of fund investors. In this section, we provide more direct evidence on the link between RFI and fund flows by examining the impact of RFCs on the response of bond mutual fund flows to past fund performance. If investors' objective is to receive a stable and predictable stream of income, rather than to boost fund returns, we expect their investment/redemption decisions to differ dramatically from those of otherwise comparable investors.

We argue that a greater emphasis by RFI investors on income than capital gains would lead to a lower sensitivity of fund flows of RFC funds to past performance. To test this conjecture, we estimate the following panel regression:

$$Flow_{i,t} = \alpha_i + \eta_t + \beta_1 Perf_{i,t-1} + \beta_2 Perf_{i,t-1} * RFC_{i,t} + \beta_3 RFC_{i,t} + \gamma Controls_{i,t-1} \quad (6)$$

where $Flow_{i,t}$ is fund i's flow in month t, and $Perf_{i,t-1}$ is average fund performance over the

[13]We include month fixed effects in Column 4 to absorb unobservable macroeconomic conditions following Daniel et al. (2021)

past eighteen months.[14] We measure fund performance by both raw returns and risk-adjusted ones, estimated as the intercept from a regression of excess fund returns on two risk factors, namely, excess aggregate bond market and aggregate stock market returns, for the past twenty-four month period. $RFC_{i,t}$ is fund i's reaching-for-coupon in month t. $Controls_{i,t-1}$ includes a number of fund characteristics: $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$.[15]

Table 3 presents the results of the regression in Equation 6. As documented in the mutual fund literature for both equity and bond funds (e.g., Jain and Wu, 2000; Berk and Green, 2004; Chen and Qin, 2017), our results show a significantly positive relationship between fund flows and past performance, whether using raw or risk-adjusted returns[16] proxying for performance, or whether fund fixed effects are included. This suggests fund investors exhibit return-chasing behaviour. Specifically, we observe a significantly positive coefficient on $Perf$, that is, coefficient = 0.902 (1.228), t-stat = 4.049 (3.735) for raw (risk-adjusted) returns in Column 1 (Column 2) for the model without fund fixed effects, and coefficient = 0.978 (1.309), t-stat = 3.964 (3.900) with both month and fund fixed effects in Column 3 (Column 4), even after controlling for various fund characteristics.

More importantly, the regression coefficient of the interaction term $Perf_{i,t-1} * RFC_{i,t}$ is negative and highly significant for all model specifications, that is, coefficient = -0.680 (-0.547), t-stat = -3.702 (-2.256), for raw (risk-adjusted) returns in Column 3 (Column 4). We interpret this, for the case in Column 4, to mean that a 1-standard deviation increase in RFC is associated with a decrease in flow-performance sensitivity of 0.376 (0.547*0.687).

[14] Our results remain quantitatively unchanged if we estimate average fund performance over the past twelve or twenty-four months. The results are untabulated but are available upon request.

[15] To examine how current RFCs affect the flow to past performance, we use $Flow_{i,t}$ and $RFC_{i,t}$ at concurrent month t, where $Perf_{i,t-1}$ is at month $t-1$. This is similar to the regression specification in Goldstein et al. (2017).

[16] We use the two-factor model proposed by Goldstein et al. (2017) to proxy for risk-adjusted fund returns. For robustness, we also use two alternative measurements to capture abnormal fund performance: one-factor alphas, e.g., the intercept from a regression of excess corporate bond fund returns on the excess aggregate bond market, and excess fund returns. Our results remain unchanged (Appendix Table B.1) .

This corresponds to a 28.7% (= 0.376/1.309) reduction in flow-performance sensitivity.

In sum, our results in Table 3 suggest that high-RFC funds exhibit a weakened sensitivity of fund flows to fund performance. This is in line with our conjecture that return-chasing behaviour is somewhat decreased for income-seeking investors.

A recent study by Choi and Kronlund (2018) shows that corporate bond mutual funds engage in RFYs in order to attract more inflows from investors who seek higher-yielding assets, and to boost fund performance. Bond coupon rates tend to be positively related to bond yields. Thus, we must disentangle RFCs from RFYs when investigating fund flow-performance sensitivity and controlling for the effect of bond yields. First, when constructing our RFC measure, we calculate the benchmark coupon rate based on coupons of peer bonds within similar yields and maturities (see Section 2.2.1).Second, we investigate whether RFYs affect flow-performance sensitivity in a similar manner as RFCs by replacing RFC with RFY in Equation 6. The result, reported in Appendix Table B.2, shows that we do not observe any significant coefficient on the interaction term, $Perf_{i,t-1} * RFY_{i,t}$, regardless of model specifications. Therefore, our RFC results are unlikely to be driven by investors' reaching-for-yield tendency, but rather their desire to chase high income.

3.3 RFC and the Shape of the Flow-Performance Relationship

A number of studies have documented asymmetry in the fund flow-performance sensitivity for open-end mutual funds. That is, the sensitivity of outflows to poor performance differs from that of inflows to good performance. For equity, mutual funds tend to have a convex flow-performance relation: Good performance attracts disproportionately large investor flows; poor performance leads to smaller outflows (e.g., Chevalier and Ellison, 1997; Huang et al., 2007). In contrast, bond mutual funds tend to have a concave relation, meaning a greater sensitivity of outflows to poor performance (e.g., Chen and Qin, 2017; Goldstein et al., 2017). This is attributable to strategic complementarities among fund investors. In other words, the liquidity mismatch between illiquid bond holdings and liquid daily redemption creates the first-mover advantage for fund investors to withdraw money from bond mutual funds. As a result, fund outflows in response to poor performance are amplified .

We conjecture that payoff complementarities would arise to a lesser extent among RFI investors, as they tend to emphasize current income as well as capital gains. This may lead to a weakened sensitivity of fund outflows to poor performance for RFC funds (or a less concave relation between fund flows and performance). To test our hypothesis, we investigate how RFC moderates the flow-performance relationship in the realm of negative and positive fund performances by running the following piecewise linear regression. We follow Goldstein et al. (2017), but augmented with a triple interaction term:

$$
\begin{aligned}
Flow_{i,t} = \alpha + \beta_1 Perf_{i,t-1} + \beta_2 Neg_{i,t-1} + \beta_3 HighRFC_{i,t} + \beta_4 Perf_{i,t-1} * HighRFC_{i,t} \\
+ \beta_5 Perf_{i,t-1} * Neg_{i,t-1} + \beta_6 Neg_{i,t-1} * HighRFC_{i,t} \\
+ \beta_7 Perf_{i,t-1} * Neg_{i,t-1} * HighRFC_{i,t} + \gamma Controls_{i,t-1},
\end{aligned}
\tag{7}
$$

where $Flow_{i,t}$ is fund i's flow for month t; $Perf_{i,t-1}$ is average fund performance over the past eighteen months; $Neg_{i,t-1}$ is a dummy variable that equals 1 if $Perf_{i,t-1}$ is negative, and 0 otherwise; and $HighRFC_{i,t}$ is a dummy variable that equals one if fund i's RFC is above the sample median across funds with the same CRSP S&P fund style code in month t, and 0 otherwise.[17]. $Controls_{i,t-1}$ is as defined before. The positive sign on β_5 is consistent with a concavity of the flow-performance relation, as shown in Goldstein et al. (2017). The sign of the coefficient on β_7, which is our main focus, should be negative.

Table 4 presents the results of the regression in Equation 7, which confirm our conjecture overall that RFC weakens the concavity of the shape of the flow-performance relationship for corporate bond funds. More specifically, and consistent with Goldstein et al. (2017),

[17] Our results remain unchanged if we alternatively define $HighRFC_{i,t}$ as a dummy variable that equals 1 if fund i has an above sample median RFC across *all* funds in month t, and 0 otherwise. The results are untabulated, but available upon request.

fund flows show greater sensitivity to fund performance when performance is poor (or when they are negative). This is shown in Column 2 by the significantly positive coefficient on $Perf * Neg$ (coefficient = 3.727, t-stat = 4.304). More importantly, the highly significantly negative coefficient on the triple interaction term, $Perf * Neg * HighRFC$, (coefficient = -2.238, t-statistics = -2.444) is in line with lower sensitivity of fund outflows to poor performance for high-RFC funds.[18] We show slightly weaker but qualitatively similar results in Column 1 when we use raw returns instead of risk-adjusted returns as a proxy for fund performance.

When we limit our attention to the negative performance regime (Columns 3 and 4), we observe that the diminished concavity of the flow-performance shape becomes more visible. In Column 4, the regression coefficient for $Perf * HighRFC$ is significantly negative (coefficient = -2.394, t-stat = -2.915), indicating that flow-performance sensitivity is significantly reduced for funds with higher RFC. Specifically, we find it is 3.716 for funds with low RFC, implying that a 1-standard deviation decrease in $Perf$, measured by the 2-factor alpha,[19] leads to about a 0.632% increase in outflow. However, the sensitivity is 1.322 for high-RFC funds, suggesting that a 1-standard deviation decrease in $Perf$ is only associated with a 0.225% increase in fund outflow. The results in Column 3 based on raw fund returns are qualitatively similar.

Collectively, our results show that RFC diminishes the concavity of the flow-performance relation for corporate bond mutual funds, which we interpret to mean that RFI investors become less sensitive to poor fund performance in their redemption decisions.

[18] For comparison purposes, we compute flow sensitivity to both good and poor performance for high- vs. low-RFC funds, based on the estimated coefficients in Column 2 of Table 4. For low-RFC funds, the flow-to-positive performance sensitivity is -0.243, calculated as the value of the coefficient on $Perf$ when we have $HighRFC = 0$ and $Neg = 0$. The flow-to-negative performance sensitivity is 3.484 (coefficient of $Perf$ when $HighRFC = 0$ and $Neg = 1$). This shows a strong concave flow-performance relation for funds with lower RFC. In contrast, for high-RFC funds, the number is -0.372 for good performance ($HighRFC = 1$ and $Neg = 0$), and 1.117 for poor performance ($HighRFC = 1$ and $Neg = 1$).

[19] The standard deviation of $Perf$ measured by the 2-factor alpha is 0.170% in negative performance regime.

3.4 RFC and Interest Rates

In this section, we extend our line of reasoning and examine how the impact of RFC on the flow-performance relation depends on interest rates. We expect RFC to have a stronger effect on the relation during low-interest rate periods. This is because RFI investors have more incentives to chase high-coupon bonds to make up for losses in other sources of income (Daniel et al., 2021). To test this, we divide our sample into low- vs. high-interest rate regimes, and repeat our analyses from the previous sections separately for each regime.

The results are in Table 5. In Panel A, we find that RFC reduces flow-performance sensitivity only for the low-interest rate regime (i.e., the period for which interest rates are below the sample median value). In Column 1, the coefficient of the interaction term $Perf * RFC$ is -1.013, which is negative at a 1% significance level. Specifically, a 1-standard deviation increase in RFC leads to a 0.696 decrease in flow-performance sensitivity. We do not observe a similar pattern for the high regime (Column 3). With regard to the shape of the relation, a similar pattern emerges (Panel B). The coefficient of $Perf * Neg * HighRFC$ in Column 2 is significantly negative (coefficient = -2.098, t-statistics = -2.003), indicating that investor flows of funds with higher RFC respond less sensitively to negative fund performance than funds with lower RFC.

4 RFC and Fund Risk-Taking

The literature has shown that fund managers of equity mutual funds tend to increase their level of risk-taking. We attribute this to the fact that investor flows into/out of equity funds in response to fund performance are asymmetric. For example, Chevalier and Ellison (1997) and Huang et al. (2007) document a convex flow-performance relation in equity funds, i.e., equity fund investors typically invest in funds with excellent performance. They do not equally penalize funds with poor performance, which leads to stronger incentives for the managers to pursue higher risk.[20]

Less is known about the risk-taking behaviour of corporate bond mutual funds. In contrast to equity funds, bond funds exhibit a concave flow-performance relation due to their illiquid holdings and resulting payoff complementarities among bond fund investors (see Goldstein et al. (2017)). It would be interesting to explore whether an RFC-induced shift of the flow-performance relation toward less concavity (or more convexity) has any bearing on fund risk-taking. Would high-RFC bond funds engage in greater risk-taking, since their investors do not tend to penalize much for poor performance? In this section, we explore this question in two ways. First, we determine whether RFC funds tend to be riskier, as measured by the volatility of their fund returns and the credit ratings of their bond holdings. Second, we turn to liquidity management, and examine whether RFC funds are subject to higher liquidity (or redemption) risk.

We hypothesize that RFC creates incentives for bond mutual funds to increase their appetite for risk. Such incentives are more prominent when interest rates are low, e.g., the period during which RFI investors' demand for high-coupon bonds is stronger. Based on the use of both total and idiosyncratic volatility of fund returns to capture the level of fund risk-taking (e.g., Huang et al., 2011; Shu et al., 2012), we test whether RFC is positively related to fund return volatility.

The results in Table 6 suggest that the two are indeed positively associated. Specifically, the coefficient on RFC is 0.063 (0.036), with a t-stat of 4.374 (4.248) for the regression of total (idiosyncratic) volatility (Columns 1 and 3, respectively). Furthermore, interest rates negatively moderate the RFC fund-return volatility relation, as shown by the significantly negative coefficient on the interaction term between them (coefficient = -0.037 (-0.010) and t-stat = -4.598 (-2.115), see Columns 2 and 4, respectively.

In addition to fund return volatility, we also exploit the credit risk, measured by credit

[20] See, e.g., Brown et al. (1996) and Koski and Pontiff (1999) for a study of the convex nature of the flow-performance relationship and the fund risk-taking of equity funds.

ratings, of funds' bond holdings. The result in Table 7 shows that RFC has a significantly positive relation with the average credit rating ($NumericalRating$),[21] regardless of model specifications: coefficient = 0.142 (0.110) and t-stat = 11.675 (9.378) for Columns 2 and 4, respectively. This result indicates that high-RFC funds tend to invest in lower-rated bonds.

Next, we examine the effect of RFC on funds' liquidity management. Studies have documented that corporate bond funds tend to preserve a certain amount of liquid assets, such as cash and Treasury securities, in order to meet potential future redemptions (e.g., Ma et al., 2020; Jiang et al., 2021a). Hence, we conjecture that RFC relieves fund managers' concerns about the amplified outflow following poor fund performance. As a result, RFC funds may face a reduced risk of redemption, leading to lax management of fund liquidity and a lower liquidity buffer (the amount of cash and Treasuries divided by a fund's total assets). The results are in Columns 1 and 3 of Table 7. We find that RFC is negative relative to a fund's liquidity buffer, especially for Treasuries, suggesting that higher RFC funds tend to engage in less liquidity management.

5 RFC and Fund Returns

We have shown that RFC is associated with greater risk-taking due to the reduced sensitivity of fund outflow to poor performance. Moreover, studies show that higher fund returns can be attributable to holding assets with higher credit risk (e.g., Choi and Kronlund, 2018; Jiang et al., 2021b) and lower cash positions (e.g., Daniel et al., 1997; Wermers, 2000). Thus, we next explore whether greater risk-taking by RFC funds results in higher fund returns, and whether those returns are raw or risk-adjusted. Therefore, we run the Fama-MacBeth

[21] Higher numerical rating scores indicate the worse credit ratings.

regression of monthly fund (raw) returns on the lagged value of RFC:

$$Ret_{i,t} = \alpha + \beta RFC_{i,t-1} + \gamma Controls_{i,t-1}, \tag{8}$$

where $Ret_{i,t}$ is fund i's raw returns for month t, and $RFC_{i,t-1}$ is the fund's RFC during month $t-1$. We control for the same firm characteristics as in previous analyses.We do not use $LagRet$ as a control here to avoid potential serial correlation.

Table 8 gives the results. In Panel A, we see that the coefficient on lagged RFC in Column 1 is significantly positive (coefficient = 0.093, t-stat = 2.461). Specifically, a 1-standard deviation increase in lagged RFC leads to a 0.064% increase in raw fund returns, which corresponds to about 15.802% of the sample mean of fund raw returns. In Column 2, we include lagged RFY, along with lagged RFC, to further control for the potential effect of reaching-for-yield on fund returns documented in Choi and Kronlund (2018). The two may be related. We find that the return predictability becomes weaker with the inclusion of RFY variables, but it remains comparable to that of RFY in terms of both magnitude and statistical significance.

We then repeat the same analysis for the subsample of low and high interest rates (based on the value of the sample median). If a return boost indeed occurs due to RFC-induced risk-taking, we expect the return predictability of RFC funds to be more prominent when interest rates are low. In Column 3, we find that, during low-interest rate environments, RFC strongly predicts higher fund raw returns, with a 1-standard deviation increase in lagged RFC leading to 0.071% higher raw returns (t-stat = 2.686). This corresponds to 17.531% of the sample mean. Interestingly, the coefficient on lagged RFY is no longer significant. During high-interest rate times, neither RFC nor RFY exhibit predictive power for future fund raw returns (Column 4). This pattern (e.g., return predictability observed only for low, not high, interest rates) is in line with our previous finding that RFC would allow bond funds to take on higher risk, especially when interest rates are low.

In Panel B of Table 8, we split our sample further into illiquid vs. liquid, and retail vs. institutional, funds to explore the cross-sectional variation of the RFC effect on fund returns. There are stronger payoff complementarities among bond investors for illiquid (vs. liquid) funds (Chen et al., 2010; Goldstein et al., 2017), and the reaching-for-income phenomenon is more salient among retail (vs. institutional) investors (Daniel et al., 2021). Therefore, we expect the RFC channel to be more binding for illiquid or retail funds, and, hence, the return predictability to be stronger.

In Column 1, we note that the effect is much stronger for illiquid funds: The regression coefficient on lagged RFC is 0.118, with a t-stat = 2.659, meaning that a 1-standard deviation increase in lagged RFC leads to a 0.081% higher raw return (corresponding to about 20% of the sample mean). The coefficient is halved, with much weaker significance, for liquid funds (Column 2). This pattern applies as well to the other subsample, where the effect is more prominent for retail funds (Columns 3 and 4).

Our results thus far show that higher RFC is associated with better fund raw performance. It is logical next to determine the source of high fund returns: Do fund managers exhibit superior skill in picking underpriced bonds? Or are fair returns merely compensation for taking high risk? We therefore test whether the outperformance of high-RFC funds is due to betas (i.e., loading higher risks) or alphas (i.e., superior bond-picking skills).

We present the results in Table 9. We sort all funds into terciles based on lagged RFC at the end of each quarter to construct RFC portfolios, and calculate a return differential between top and bottom terciles each month. Column 1 in Panel A shows that funds in the top tercile tend to generate 0.213% higher returns per month (around 2.594% per annum) than those in the bottom. Moreover, the dominance of the returns of the top tercile is salient only for low-interest rate regimes (Columns 2 and 3).

In Panel B, we present the alphas and factor loadings of the high-minus-low tercile, estimated using three systematic risk factors: 1) the market risk factor, or the CRSP value-weighted stock returns in excess of the risk-free rate, 2) the term factor, or the 30-year Treasury minus 1-year Treasury rate, and 3) the default factor, or the equal-weighted corporate bond return minus the 1-year Treasury rate.

In Column 1, we find that, after controlling for the risk factors, bond funds do not generate significantly positive alphas (coefficient = -0.001, t-stat = -0.289). However, betas are positive and highly significant, especially for default risk and market risk. In Columns 2 and 3, we find that high-minus-low portfolios load only on default risk when interest rates are low.

In sum, our results suggest that the outperformance of high-RFC funds is associated with funds' greater risk-taking rather than managers' superior skills.

6 Conclusion

We study the implication of the reaching-for-income (RFI) phenomenon on the behaviour of investor flows for corporate bond mutual funds. When interest rates are low, rule of thumb investors, who live off current income from their portfolios, have a stronger tendency to chase high-income-generating assets, such as high-coupon bonds. Our analyses find that more money is allocated to funds, dubbed RFC funds, that have larger holdings in high-coupon bonds. Interestingly, RFC funds exhibit less sensitivity of fund flows to performance overall, and a less concave shape of the flow-performance relation. Our results also suggest that RFC funds expect reduced redemption risk following poor performance, and so engage in greater risk-taking, which ultimately boosts fund performance.

Our study should shed new light on understanding the incentives of reaching-for-yield (RFY) in corporate bond mutual funds. RFY is a prominent behaviour in fixed income markets, engaged in by various classes of investors, including money market funds, insurance companies, and bond mutual funds. We do not understand enough yet about why bond mutual funds would engage in reaching for high-yield bonds. Unlike insurance companies, they are not subject to the investment constraints imposed by regulation and mandates. Perhaps they are catering to RFI investors, and thus chase high-coupon bonds that happen to have high yields. Thus, is it truly reaching for yield, or is it reaching for coupon? We believe disentangling these two provides an interesting avenue for future research.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Basak, S., Pavlova, A., and Shapiro, A. (2007). Optimal asset allocation and risk shifting in money management. *The Review of Financial Studies*, 20(5):1583–1621.

Becker, B. and Ivashina, V. (2015). Reaching for yield in the bond market. *The Journal of Finance*, 70(5):1863–1902.

Berk, J. B. and Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, 112(6):1269–1295.

Brown, K. C., Harlow, W. V., and Starks, L. T. (1996). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance*, 51(1):85–110.

Capponi, A., Glasserman, P., and Weber, M. (2020). Swing pricing for mutual funds: Breaking the feedback loop between fire sales and fund redemptions. *Management Science*, 66(8):3581–3602.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Chen, Y. and Qin, N. (2017). The behavior of investor flows in corporate bond mutual funds. *Management Science*, 63(5):1365–1381.

Chevalier, J. and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, 105(6):1167–1200.

Choi, J., Hoseinzade, S., Shin, S. S., and Tehranian, H. (2020). Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics*, 138(2):432–457.

Choi, J. and Kronlund, M. (2018). Reaching for yield in corporate bond mutual funds. *The Review of Financial Studies*, 31(5):1930–1965.

Christoffersen, S. E., Musto, D. K., and Wermers, R. (2014). Investor flows to asset managers: Causes and consequences. *Annual Review of Financial Economics*, 6(1):289–310.

Daniel, K., Garlappi, L., and Xiao, K. (2021). Monetary policy and reaching for income. *The Journal of Finance*, 76(3):1145–1193.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, 52(3):1035–1058.

Dass, N. and Massa, M. (2014). The variety of maturities offered by firms and institutional investment in corporate bonds. *The Review of Financial Studies*, 27(7):2219–2266.

Di Maggio, M. and Kacperczyk, M. (2017). The unintended consequences of the zero lower bound policy. *Journal of Financial Economics*, 123(1):59–80.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*, 126(3):592–613.

Harris, L. E., Hartzmark, S. M., and Solomon, D. H. (2015). Juicing the dividend yield: Mutual funds and the demand for dividends. *Journal of Financial Economics*, 116(3):433–451.

Huang, J., Sialm, C., and Zhang, H. (2011). Risk shifting and mutual fund performance. *The Review of Financial Studies*, 24(8):2575–2616.

Huang, J., Wei, K. D., and Yan, H. (2007). Participation costs and the sensitivity of fund flows to past performance. *The Journal of Finance*, 62(3):1273–1311.

Jain, P. C. and Wu, J. S. (2000). Truth in mutual fund advertising: Evidence on future performance and fund flows. *The Journal of Finance*, 55(2):937–958.

Jiang, H., Li, D., and Wang, A. (2021a). Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis*, 56(5):1622–1652.

Jiang, H. and Sun, Z. (2020). Reaching for dividends. *Journal of Monetary Economics*, 115:321–338.

Jiang, W., Ou, J., and Zhu, Z. (2021b). Mutual fund holdings of credit default swaps: Liquidity, yield, and risk. *The Journal of Finance*, 76(2):537–586.

Koski, J. L. and Pontiff, J. (1999). How are derivatives used? evidence from the mutual fund industry. *The Journal of Finance*, 54(2):791–816.

Lynch, A. W. and Musto, D. K. (2003). How investors interpret past fund returns. *The Journal of Finance*, 58(5):2033–2058.

Ma, Y., Xiao, K., and Zeng, Y. (2020). Mutual fund liquidity transformation and reverse flight to liquidity. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Schwarz, C. G. (2012). Mutual fund tournaments: The sorting bias and new evidence. *The Review of Financial Studies*, 25(3):913–936.

Shu, T., Sulaeman, J., and Yeung, P. E. (2012). Local religious beliefs and mutual fund risk-taking behaviors. *Management Science*, 58(10):1779–1796.

Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, 53(5):1589–1622.

Wermers, R. (2000). Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance*, 55(4):1655–1695.

Zeng, Y. (2017). A dynamic theory of mutual fund runs and liquidity management. *Available at SSRN 2907718*.

Appendix A: Variable Definitions

Variable	Definition
RFC	Reaching for Coupon. Value-weighted average of the deviation of each bond's coupon rate from the benchmark coupon rate in Equation 1.
$Flow$	Bond mutual fund flow in a given month in Equation 2
$LagFlow$	Bond mutual fund flow in the last month.
$InterestRate$	Interest rate. Discount rate for the U.S., obtained from FRED, the Federal Reserve Bank of St. Louis.
$HighRFC$	Indicator variable that equals 1 if the fund has above-median RFC among funds with the same CRSP S&P fund style code, and 0 otherwise.
RFY	Reaching-for-yield measure (within-rating-and-maturity) proposed by Choi and Kronlund (2018).
Ret	Monthly bond mutual fund returns.
$LagRet$	Bond mutual fund returns in the last month.
$WeightCorpBonds$	Bond mutual funds' percentage holding in corporate bonds.
$WeightEquity$	Bond mutual funds' percentage holding in equities.
$WeightCash$	Bond mutual funds' percentage holding in cash.
$WeightTreasury$	Bond mutual funds' percentage holding in Treasuries.
$WeiOthers$	Bond mutual funds' percentage holding other than corporate bonds, equities, cash, and Treasuries.
$FundSize$	Natural log of fund's total net assets.
$FundTtm$	Bond mutual funds' value-weighted time to maturity (in years) across all corporate bonds.
$FundExpense$	Bond mutual funds' expense ratio.
$FundAge$	Bond mutual funds' age in years.
$FlowVolatility$	Fund flow volatility. Standard deviation of fund flows over the past twenty-four months.
$DiffNAV$	Difference between the highest and lowest NAV within the past fifty-two weeks.
$RetVolatility$	Fund return volatility. Standard deviation of fund returns over the past twelve months.

$IdioVolatility$	Idiosyncratic fund return volatility. Standard deviation of the error terms from two-factor model regressions (Goldstein et al., 2017) of excess corporate bond fund returns on excess aggregate bond market and aggregate stock market returns over the past twelve months.
$NumericalRating$	Bond mutual funds' value-weighted numerical bond ratings across all corporate bonds.
$FundDuration$	Bond mutual funds' value-weighted duration across all corporate bonds.
$FundAmihud$	Bond mutual funds' value-weighted Amihud illiquidity measure (Amihud, 2002) across all corporate bonds.

Appendix B: Additional Table

Table B.1
RFC on Flow-Performance Sensitivity: Alternative Measures

This table examines the effect of RFC on the sensitivity of flow to past performance using alternative performance measures. One-factor alpha (Goldstein et al., 2017) is the intercept from a regression of excess corporate bond fund returns on excess aggregate bond market returns. The second measure is excess fund returns. We average these performance measures over the past 18 months. The dependent variable is $Flow$. The independent variables are RFC and $Perf$. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. In Columns 1 and 2, we include month fixed effects. In Columns 3 and 4, both month fixed effects and fund fixed effects are included. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: $Flow$	(1)	(2)	(3)	(4)
Performance Measured by	1-F Alpha	Excess Ret	1-F Alpha	Excess Ret
$Perf$	0.380*	0.885***	0.428*	0.977***
	(1.655)	(3.994)	(1.938)	(4.012)
RFC	0.000	0.001	0.000	0.002*
	(-0.111)	(0.846)	(0.084)	(1.916)
$Perf * RFC$	-0.341*	-0.462***	-0.363*	-0.645***
	(-1.833)	(-2.692)	(-1.918)	(-3.655)
$FundSize$	-0.001***	-0.001***	-0.009***	-0.010***
	(-3.534)	(-4.022)	(-10.840)	(-11.023)
$FundTtm$	0.000*	0.000	0.001***	0.001***
	(1.815)	(0.611)	(3.280)	(3.143)
$FundExpense$	-0.232*	-0.298**	-0.181	-0.242
	(-1.752)	(-2.269)	(-0.511)	(-0.677)
$FundAge$	-0.001***	-0.001***	0.000	0.000
	(-10.334)	(-10.271)	(0.698)	(0.842)
$LagFlow$	0.306***	0.309***	0.228***	0.229***
	(18.968)	(19.067)	(15.615)	(15.746)
$LagRet$	0.040	0.003	0.020	0.007
	(0.647)	(0.042)	(0.344)	(0.115)
$FlowVolatility$	0.005**	0.005**	0.001	0.001
	(2.384)	(2.328)	(0.642)	(0.663)
$DiffNAV$	-0.003***	-0.004***	-0.003*	-0.003*
	(-3.094)	(-3.376)	(-1.919)	(-1.736)
Observations	47,676	47,755	47,673	47,755
R-squared	0.141	0.146	0.200	0.206
Fund FEs	No	No	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Table B.2
The Effect of RFY on Flow-Performance Sensitivity

This table examines the effect of RFY on the sensitivity of flow to past performance. The dependent variable is *Flow*. The independent variable is *RFY*. We use two measures to capture fund performance *Perf*: average fund raw return in the past 18 months and average two-factor model alphas (Goldstein et al., 2017) during the past 18 months. We control for lagged fund characteristics including *FundSize*, *FundTtm*, *FundExpense*, *FundAge*, *LagFlow*, *LagRet*, *FlowVolatility*, and *DiffNAV*. In Columns 1 and 2, we include month fixed effects. In Columns 3 and 4, both month fixed effects and fund fixed effects are included. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: *Flow*	(1)	(2)	(3)	(4)
Performance Measured by	Raw Return	2-F Alpha	Raw Return	2-F Alpha
Perf	0.553***	0.704**	0.417*	0.798***
	(2.722)	(2.427)	(1.832)	(2.808)
RFY	-0.026**	-0.024***	-0.027**	-0.033***
	(-2.567)	(-2.970)	(-2.601)	(-3.782)
$Perf * RFY$	-0.876	-0.460	-1.714	0.632
	(-0.566)	(-0.183)	(-0.973)	(0.236)
FundSize	-0.001***	-0.001***	-0.010***	-0.009***
	(-3.954)	(-3.201)	(-10.979)	(-10.623)
FundTtm	0.000*	0.000**	0.001***	0.001***
	(1.810)	(2.560)	(3.298)	(3.589)
FundExpense	-0.269**	-0.188	-0.250	-0.192
	(-2.064)	(-1.422)	(-0.700)	(-0.528)
FundAge	-0.001***	-0.001***	0.000	0.000
	(-10.300)	(-10.201)	(0.810)	(0.683)
LagFlow	0.309***	0.302***	0.230***	0.225***
	(18.946)	(18.536)	(15.679)	(15.238)
LagRet	0.005	0.014	0.009	-0.010
	(0.078)	(0.229)	(0.139)	(-0.167)
FlowVolatility	0.005**	0.005**	0.001	0.001
	(2.356)	(2.369)	(0.648)	(0.613)
DiffNAV	-0.003***	-0.003***	-0.002	-0.003*
	(-2.688)	(-2.776)	(-1.303)	(-1.889)
Observations	47,755	47,376	47,755	47,374
R-squared	0.146	0.139	0.206	0.199
Fund FEs	No	No	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Figure 1
Cross-sectional RFC and Income Dividends

This figure plots the cross-sectional average of the RFC and the income dividends sourced from the CRSP Survivorship-Bias-Free Mutual Fund database.

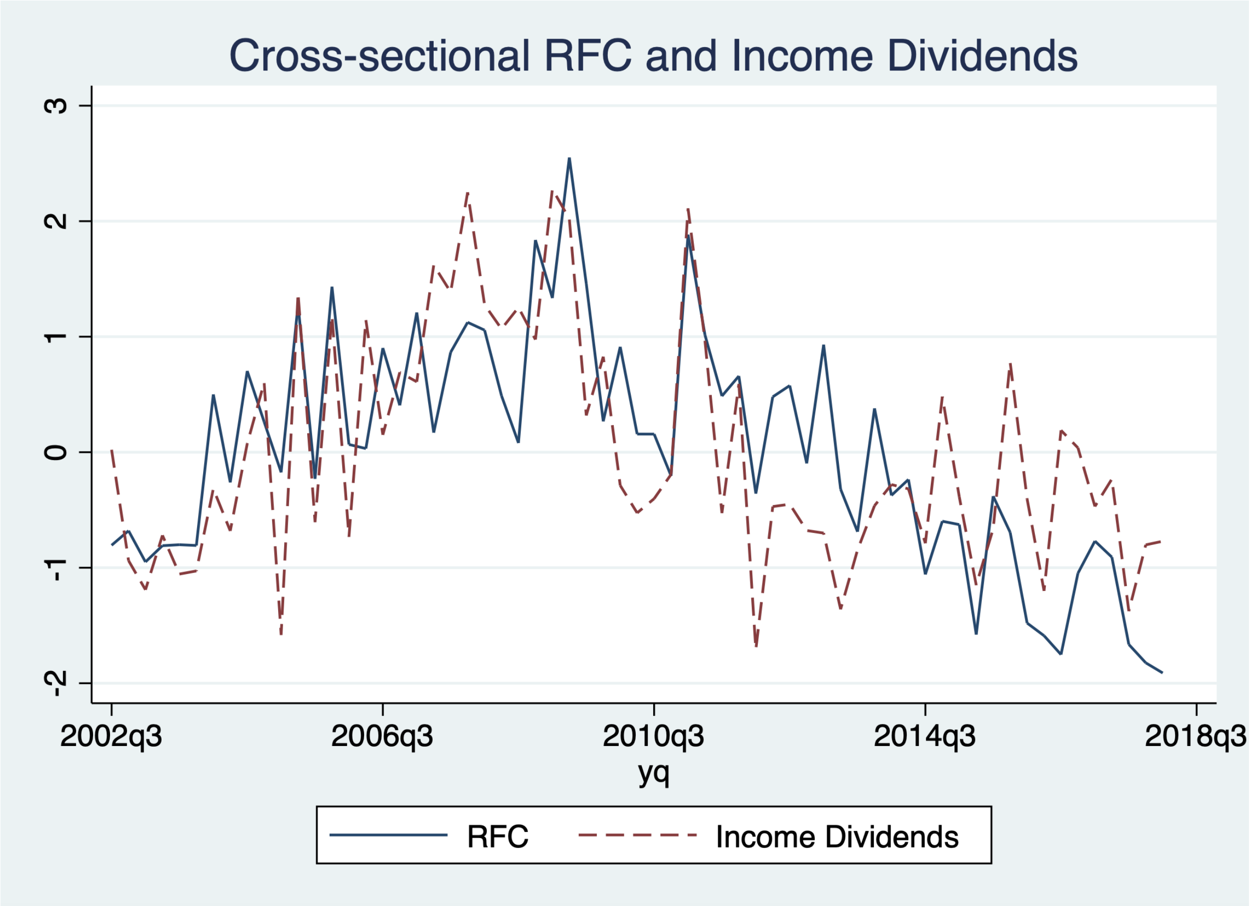

Table 1
Summary Statistics

This table provides summary statistics for variables used in the paper. Definitions of variables are in Appendix A.

	Mean	Std. Dev.	p5	p25	Median	p75	p95	N
RFC (%)	0.343	0.687	-0.828	-0.090	0.356	0.777	1.475	49,892
$Flow$ (%)	1.027	6.247	-5.241	-1.157	0.081	1.860	9.861	49,892
Ret (%)	0.405	1.310	-1.754	-0.118	0.350	1.025	2.508	49,892
$RawRet$ (%)	0.432	0.505	-0.141	0.146	0.348	0.624	1.348	49,422
$2FAlpha$ (%)	0.008	0.272	-0.386	-0.099	-0.007	0.079	0.485	47,982
$RetVolatility$ (%)	1.027	0.730	0.145	0.526	0.835	1.373	2.516	49,892
$IdioVolatility$ (%)	0.542	0.460	0.084	0.185	0.387	0.782	1.458	49,892
$WeightCorpBonds$ (%)	48.389	28.544	0.000	26.370	45.170	73.620	93.600	49,892
$WeightEquity$ (%)	0.544	2.014	0.000	0.000	0.000	0.020	2.730	49,892
$WeightCash$ (%)	2.447	9.672	-12.250	0.170	2.100	5.010	16.440	49,892
$WeightTreasury$ (%)	10.567	14.417	0.000	0.000	1.900	18.950	41.220	49,892
$WeiOthers$ (%)	38.053	29.146	1.120	12.295	34.770	57.333	94.000	49,892
$FundSize$	5.511	1.810	2.517	4.389	5.528	6.690	8.498	49,892
$FundTtm$ (in years)	7.117	3.844	1.777	4.578	6.852	9.049	13.412	49,892
$FundExpense$ (%)	0.723	0.365	0.000	0.501	0.711	0.944	1.363	49,892
$FundAge$ (in years)	12.351	8.646	1.499	5.504	10.917	17.461	28.512	49,892
$FlowVolatility$	0.116	0.391	0.009	0.023	0.043	0.088	0.367	49,892
$DiffNAV$	0.709	0.613	0.078	0.331	0.541	0.880	1.972	49,892

Table 2
Aggregate Flow, Interest Rate and RFC

This table provides results for the impact of interest rate and RFC on fund flows. In Columns 1 and 2, we provide the results at monthly aggregate level. The dependent Variable is monthly aggregated $Flow$. The dependent variable is $InterestRate$ and $AggRFC$ at monthly aggregated level. We control for $LagRet$ and $LagFlow$ at monthly aggregated level. In Columns 3 and 4, we provide fund-month panel regression results. The dependent Variable is fund-month $Flow$. $HighRFC$ is dummy variable equals to one if the fund has above-median RFC among funds with the same CRSP S&P fund style code, otherwise zero. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. Standard errors are two-way clustered by firm and quarter, with the exception of Columns 1 to 2. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: $Flow$	(1)	(2)	(3)	(4)
$InterestRate$	-0.297***	-0.016	-0.136***	
	(-4.685)	(-0.101)	(-4.333)	
$AggRFC$		0.012***		
		(3.580)		
$InterestRate * AggRFC$		-0.003**		
		(-2.054)		
$HighRFC$				0.115
				(0.910)
$InterestRate * HighRFC$				-0.124***
				(-2.718)
$AggLagFlow$	0.528***	0.409***		
	(7.681)	(6.060)		
$AggLagRet$	0.289***	0.294***		
	(3.374)	(3.515)		
Observations	189	189	47,755	47,755
R-squared	0.672	0.706	0.131	0.145
Fund Controls	No	No	Yes	Yes
Month FEs	No	No	No	Yes

Table 3
The Effect of RFC on Flow-Performance Sensitivity

This table examines the effect of RFC on the sensitivity of flows to past performance. The dependent variable is $Flow$. The independent variable is RFC. We use two measures to capture fund performance $Perf$: average fund raw return in the past 18 months and average two-factor model alphas (Goldstein et al., 2017) during the past 18 months. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. In Columns 1 and 2, we include month fixed effects. In Columns 3 and 4, both month fixed effects and fund fixed effects are included. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: $Flow$	(1)	(2)	(3)	(4)
Performance Measured by	$RawRet$	$2FAlpha$	$RawRet$	$2FAlpha$
$Perf$	0.902***	1.228***	0.978***	1.309***
	(4.049)	(3.735)	(3.964)	(3.900)
RFC	0.001	0.000	0.003**	0.000
	(1.231)	(-0.052)	(2.232)	(0.293)
$Perf * RFC$	-0.502***	-0.537**	-0.680***	-0.547**
	(-2.883)	(-2.340)	(-3.702)	(-2.256)
$FundSize$	-0.001***	-0.001***	-0.010***	-0.009***
	(-4.001)	(-3.279)	(-11.019)	(-10.533)
$FundTtm$	0.000	0.000*	0.001***	0.001***
	(0.577)	(1.916)	(3.137)	(3.395)
$FundExpense$	-0.290**	-0.227*	-0.226	-0.161
	(-2.214)	(-1.720)	(-0.633)	(-0.439)
$FundAge$	-0.001***	-0.001***	0.000	0.000
	(-10.287)	(-10.256)	(0.832)	(0.643)
$LagFlow$	0.309***	0.303***	0.230***	0.226***
	(19.062)	(18.578)	(15.745)	(15.256)
$LagRet$	0.003	0.007	0.007	-0.011
	(0.046)	(0.120)	(0.114)	(-0.190)
$FlowVolatility$	0.005**	0.005**	0.001	0.001
	(2.325)	(2.366)	(0.660)	(0.626)
$DiffNAV$	-0.004***	-0.003***	-0.003*	-0.003**
	(-3.412)	(-3.302)	(-1.749)	(-2.269)
Observations	47,755	47,376	47,755	47,374
R-squared	0.146	0.139	0.206	0.199
Fund FEs	No	No	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Table 4
The Effect of RFC on the Shape of Flow-Performance Relationship

This table examines the effect of RFC on the shape of flow-performance relationship. The dependent variable is $Flow$. The independent variable is RFC. We use two measures to capture fund performance $Perf$: average fund raw return in the past 18 months and average two-factor model alphas (Goldstein et al., 2017) during the past 18 months. Neg is an indicator variable equals to one if the performance measure is negative, otherwize zero. $HighRFC$ is dummy variable equals to one if the fund has above-median RFC among funds with the same CRSP S&P fund style code, otherwise zero. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. In Columns 1 and 2, we provide results in the full sample. In Columns 3 and 4, We provide regression results only in negative performance regimes. Both month fixed effects and fund fixed effects are included in the regressions. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: *Flow*	Full Sample		Performance<0	
	(1)	(2)	(3)	(4)
Performance Measured by	*RawRet*	*2FAlpha*	*RawRet*	*2FAlpha*
$Perf$	0.673**	-0.243	0.622	3.716***
	(2.546)	(-0.477)	(0.705)	(4.770)
Neg	-0.006**	-0.003*		
	(-2.375)	(-1.875)		
$HighRFC$	0.001	-0.001	-0.003	-0.003**
	(0.636)	(-0.676)	(-0.590)	(-2.108)
$Perf * HighRFC$	-0.443	-0.129	-1.754*	-2.394***
	(-1.552)	(-0.233)	(-1.842)	(-2.915)
$Perf * Neg$	0.781	3.727***		
	(0.978)	(4.304)		
$Neg * HighRFC$	0.000	-0.001		
	(0.113)	(-0.832)		
$Perf * Neg * HighRFC$	-2.121**	-2.238**		
	(-2.309)	(-2.444)		
$FundSize$	-0.010***	-0.009***	-0.013***	-0.009***
	(-10.930)	(-10.633)	(-3.840)	(-7.838)
$FundTtm$	0.001***	0.001***	0.001*	.001*
	(3.132)	(3.312)	(1.960)	(1.708)
$FundExpense$	-0.226	-0.127	-0.223	-0.272
	(-0.625)	(-0.344)	(-0.150)	(-0.634)
$FundAge$	0.000	0.000	0.000	0.000
	(0.764)	(0.685)	(-0.325)	(1.386)
$LagFlow$	0.229***	0.224***	0.079***	0.189***
	(15.730)	(15.204)	(2.901)	(9.615)
$LagRet$	0.014	-0.021	0.096	0.058
	(0.232)	(-0.356)	(0.980)	(0.916)
$FlowVolatility$	0.001	0.001	-0.006	0.002
	(0.674)	(0.593)	(-0.921)	(0.805)
$DiffNAV$	-0.003*	-0.002	0.000	-0.002
	(-1.761)	(-1.650)	(0.104)	(-1.390)
Observations	47,755	47,374	3,711	24,975
R-squared	0.206	0.200	0.414	0.205
Fund FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Table 5
The Effect of Interest Rate

This table examines the effect of RFC on the flow-performance sensitivity and the shape of flow-performance relationship during low interest rate period. The dependent variable is $Flow$. The independent variable is RFC. We use two measures to capture fund performance $Perf$: average fund raw return in the past 18 months and average two-factor model alphas (Goldstein et al., 2017) during the past 18 months. Neg is an indicator variable equals to one if the performance measure is negative, otherwize zero. $HighRFC$ is dummy variable equals to one if the fund has above-median RFC among funds with the same CRSP S&P fund style code, otherwise zero. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. We define low interest regime if interest rates are lower than the sample median (in Columns 1 and 2), and high interest regime if interest rates are higher than the sample median (in Columns 3 and 4). Panel A examines the effect of RFC on the sensitivity of flow to past performance. Panel B examines the effect of RFC on the shape of flow-performance relationship. Both month fixed effects and fund fixed effects are included in the regressions. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Panel A.	Low Interest Regime		High Interest Regime	
Dependent Var: $Flow$	(1)	(2)	(3)	(4)
Performance Measured by	$RawRet$	$2FAlpha$	$RawRet$	$2FAlpha$
$Perf$	1.517***	1.959***	0.184	0.374
	(4.339)	(4.647)	(0.583)	(0.735)
RFC	0.003**	-0.001	0.000	0.000
	(1.993)	(-0.438)	(0.228)	(0.078)
$Perf * RFC$	-1.013***	-0.939***	-0.076	0.711*
	(-4.299)	(-3.284)	(-0.292)	(1.822)
Observations	31,658	31,424	16,097	15,950
R-squared	0.248	0.236	0.202	0.202
Fund Controls	Yes	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Panel B.	Low Interest Regime		High Interest Regime	
Dependent Var: *Flow*	(1)	(2)	(3)	(4)
Performance Measured by	*RawRet*	*2FAlpha*	*RawRet*	*2FAlpha*
$Perf$	1.034***	0.189	-0.115	-1.524
	(2.976)	(0.358)	(-0.327)	(-1.296)
Neg	-0.007**	-0.002	0.000	-0.005**
	(-2.272)	(-1.087)	(0.053)	(-2.516)
$Perf * Neg$	0.447	4.026***	3.706	3.783**
	(0.544)	(4.141)	(1.349)	(2.071)
$HighRFC$	0.004*	0.000	-0.004*	-0.004*
	(1.856)	(0.191)	(-1.751)	(-1.885)
$Perf * HighRFC$	-0.740**	-0.522	-0.024	0.162
	(-2.145)	(-0.884)	(-0.071)	(0.125)
$Neg * HighRFC$	0.000	-0.002	-0.008	0.000
	(-0.054)	(-0.766)	(-1.022)	(0.169)
$Perf * Neg * HighRFC$	-1.885**	-2.098**	-3.978	-0.469
	(-2.082)	(-2.003)	(-1.351)	(-0.237)
Observations	31,658	31,424	16,097	15,950
R-squared	0.247	0.237	0.203	0.204
Fund Controls	Yes	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Table 6
RFC and Fund Returns Volatility

This table examines the relation between RFC and fund returns volatility. The dependent variables are $RetVolatility$ (in Columns 1 and 2) and $IdioVolatility$ (in Columns 3 and 4). The independent variables are RFC and $InterestRate$. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. Both month fixed effects and fund fixed effects are included. Standard errors are two-way clustered by funds and months. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var:	$RetVolatility$		$IdioVolatility$	
	(1)	(2)	(3)	(4)
RFC	0.063***	0.115***	0.036***	0.050***
	(4.374)	(5.555)	(4.248)	(4.199)
$RFC * InterestRate$		-0.037***		-0.010**
		(-4.598)		(-2.115)
$FundSize$	-0.009	-0.008	-0.010**	-0.010**
	(-1.508)	(-1.266)	(-2.346)	(-2.264)
$FundTtm$	0.011***	0.012***	0.000	0.001
	(3.188)	(3.399)	(0.200)	(0.321)
$FundExpense$	-2.543	-0.903	2.663	3.136
	(-0.827)	(-0.301)	(1.170)	(1.373)
$FundAge$	0.001	0.001	0.004*	0.004
	(0.428)	(0.297)	(1.684)	(1.637)
$LagFlow$	-0.090	-0.094*	-0.165***	-0.166***
	(-1.605)	(-1.670)	(-5.225)	(-5.273)
$LagRet$	0.612	0.547	1.511**	1.494**
	(0.450)	(0.407)	(2.560)	(2.549)
$FlowVolatility$	-0.015	-0.014	-0.017	-0.017
	(-1.057)	(-0.994)	(-1.651)	(-1.636)
$DiffNAV$	0.425***	0.417***	0.295***	0.293***
	(15.155)	(15.105)	(19.313)	(19.155)
Observations	47,591	47,591	47,312	47,312
R-squared	0.807	0.808	0.851	0.851
Fund FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes

Table 7
RFC, Fund Liuqidity, and Bond Ratings

This table provides results of the effect of RFC on fund liquidity and average bond credit ratings. The observations are at fund-quarter level. The dependent variable is RFC. In Columns 1 and 3, we use $CashWeight$, and $TreasuryWeight$ as explanatory variables to measure fund's liquidity buffer. $EquityWeight$ is used to capture the fund's willingness to take higher risk by holding equities. In Columns 2 and 4, the explanatory variables are $NumericalRating$, $FundDuration$, and $FundAmihud$. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $LagRet$, $FlowVolatility$, and $DiffNAV$. Both quarter fixed effects and fund style fixed effects are included. Standard errors are two-way clustered by funds and quarters. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Dependent Var: RFC	(1)	(2)	(3)	(4)
$EquityWeight$	0.038***		0.017**	
	(4.860)		(2.1640)	
$CashWeight$	-0.001		0.000	
	(-0.849)		(-0.398)	
$TreasuryWeight$	-0.009***		-0.007***	
	(-5.121)		(-4.321)	
$NumericalRating$		0.142***		0.110***
		(11.675)		(9.378)
$FundDuration$		-0.003		-0.040**
		(-0.306)		(-2.248)
$FundAmihud$		0.168		-0.061
		(0.451)		(-0.191)
Observations	16,746	16,746	15,987	15,987
R-squared	0.205	0.247	0.295	0.322
Fund Controls	No	No	Yes	Yes
Fund Style FEs	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes

Table 8
RFC and Fund Returns

This table provides results from Fama-MacBeth regressions of monthly fund returns on lagged RFC. The dependent variable is Ret. The independent variable is lagged RFC and lagged RFY. We control for lagged fund characteristics including $FundSize$, $FundTtm$, $FundExpense$, $FundAge$, $LagFlow$, $FlowVolatility$, and $DiffNAV$. In Panel A, we provide results in full sample in Columns 1 and 2. We define low interest regime if interest rates are lower than the sample median (in Column 3), and high interest regime if interest rates are higher than the sample median (in Column 4). Panel B explores the cross-sectional variations. We define Illquid (liquid) funds if funds have cash and treasuries holdings below (above) the median fund in the same CRSP S&P fund style code. We provide results for Illiquid funds (in Column 1), lliquid funds (in Column 2), retail funds (in Column 3) and institution-oriented funds (in Column 4), respectively. We estimate the regressions with Newey-West standard errors with two lags. t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Panel A. Dependent Var: Ret			Low Interest	High Interest
	(1)	(2)	(3)	(4)
RFC	0.093**	0.057*	0.103***	.006
	(2.461)	(1.696)	(2.686)	(0.110)
RFY		1.832*	0.892	2.866
		(1.791)	(1.460)	(1.407)
$FundSize$	0.022*	0.021*	0.019	0.023
	(1.942)	(1.921)	(1.339)	(1.557)
$FundTtm$	0.011**	0.009	0.017*	.001
	(2.005)	(1.466)	(1.872)	(0.094)
$FundExpense$	6.723	3.580	0.347	7.135
	(1.342)	(0.822)	(0.058)	(1.135)
$FundAge$	-0.002	-0.002	-0.001	-0.002
	(-1.346)	(-1.356)	(-0.752)	(-1.410)
$LagFlow$	0.202	0.056	0.227	-0.133
	(1.334)	(0.370)	(1.490)	(-0.493)
$FlowVolatility$	0.042	0.046	-0.035	0.135
	(0.564)	(0.741)	(-1.371)	(1.057)
$DiffNAV$	0.140**	0.092**	0.110	0.072*
	(2.558)	(2.237)	(1.656)	(1.687)
Observations	47,755	47,755	31,658	16,097
R-squared	0.383	0.436	0.419	0.454

Panel B. Dependent Var: *Ret*	Illiquid v.s. Liquid		Retail v.s. institutional	
	(1)	(2)	(3)	(4)
RFC	0.118***	0.059*	0.130***	-0.015
	(2.659)	(1.798)	(2.795)	(-0.203)
$FundSize$	0.034**	0.003	-0.019	0.006
	(2.015)	(0.379)	(-0.482)	(0.335)
$FundTtm$	0.010	0.010	-0.008	-0.003
	(1.536)	(1.619)	(-0.512)	(-0.209)
$FundExpense$	4.776	7.498	8.204	-6.160
	(1.024)	(1.361)	(1.413)	(-0.446)
$FundAge$	-0.003	-0.007	-0.001	-0.002
	(-1.110)	(-1.528)	(-0.475)	(-1.110)
$LagFlow$	0.065	0.113	0.763	0.770
	(0.271)	(0.787)	(1.345)	(1.254)
$FlowVolatility$	-0.191	-0.142	-1.125	-0.002
	(-1.238)	(-0.628)	(-1.644)	(-0.016)
$DiffNAV$	0.172***	0.068	0.111*	0.122**
	(2.737)	(0.943)	(1.869)	(1.982)
Observations	23,927	23,828	17,504	30,251
R-squared	0.443	0.417	0.425	0.453

Table 9
RFC and Fund Returns: Alpha or beta?

This tables provides alphas and betas of monthly high-minus low portfolios sorted on lagged RFC. The funds are sorted into terciles based on lagged RFC at the end of each quarter. We then construct the high-minus low portfolios between the highest tercile and the lowest tercile RFC portfolios. Panel A provides average monthly excess returns on these high-minus-low RFC portfolios. Panel B provides results from time-series regressions of the high-minus-low RFC portfolios returns on common bond risk factors, which are $Market$ (excess market returns), $Term$ (30-year treasury returns minus one-year t-bill returns), and $Default$ (equal-weighted corporate bonds returns minus the risk-free rate). t-statistics are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of variables are in Appendix A.

Panel A. Average returns on high-minus-low RFC portfolios

		Low Interest Regime	High Interest Regime
	(1)	(2)	(3)
Average excess return monthly (%)	0.213*	0.483***	-0.077
	(1.804)	(3.439)	(-0.409)
Observations	189	98	91

Panel B. Alphas and betas of high-minus-low RFC portfolios

		Low Interest Regime	High Interest Regime
	(1)	(2)	(3)
β^{Market}	0.227***	0.145***	0.328***
	(9.969)	(5.694)	(8.829)
β^{Term}	0.000	-0.005	-0.025
	(0.000)	(-0.039)	(-0.272)
$\beta^{Default}$	0.282***	0.409***	0.089
	(4.246)	(5.555)	(0.804)
$Alpha$	-0.001	0.001	-0.001
	(-0.289)	(0.117)	(-0.468)
Observations	189	98	91
R-squared	0.521	0.554	0.552