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Abstract

We examine how corporate bond fund managers manipulate portfolio risk in response to incentives. We find that liquidity risk concerns drive the allocation decisions of underperforming funds, whereas tournament incentives are of secondary importance. This leads laggard fund managers to trade off yield for liquidity, while holding the exposure to other sources of risk constant. The documented de-risking is stronger for managers with shorter tenure and is reinforced by a more concave flow-to-performance sensitivity and by periods of market stress. De-risking meaningfully supports ex post laggard fund returns. Flexible NAVs (swing pricing) may, however, reduce de-risking incentives and create moral hazard.

Keywords: Mutual funds, Incentives, De-risking, Fragility, Bond liquidity.

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"Investment funds that hold illiquid assets but offer daily redemptions to investors are built on a lie." Mark Carney, remarks at the Bank of England — June 2019.

I. Introduction

A large branch of economics investigates how agents adapt their behavior to incentives. In a seminal paper, Brown, Harlow, and Starks (1996) document that equity mutual funds engage in tournament behaviors by which underperforming managers take on more risk to improve their ranking against other managers. This attempt to manipulate performance is consistent with the incentives created by investor behavior: Chevalier and Ellison (1997) and Sirri and Tufano (1998) find that investor flows are less sensitive to underperformance than to outperformance.[1] This implies that, by taking extra risk, underperforming managers face an asymmetric payoff: the potential upside in terms of climbing in the rankings and attracting new flows is large, whereas the downside is contained.

While there is consensus on how rank-chasing incentives influence *equity* mutual funds, the implications for corporate *bond* funds are less clear. This knowledge gap in the literature is unfortunate for several reasons. First, the bond fund industry has experienced unprecedented growth in recent years (see Figure 1): the ensuing expanded supply of investment vehicles has put fund managers in a tough spot to deliver outperformance. Second, there is an inherent liquidity mismatch that may pose a threat to financial stability: corporate bonds are an illiquid asset class, while the funds themselves promise their shareholders liquidity at all times. This fragility may then quickly unravel into fire-sale episodes.[2] Finally, bond funds can be used as a laboratory to improve our understanding of incentives for other market participants (such as banks and hedge funds) that share a similar liquidity mismatch but are more complex and less transparent.

[1]This finding has, however, been challenged by more recent research (see Spiegel and Zhang 2013).

[2]See, for example, the temporary dissonance between the value of corporate bond ETFs and the value of the underlying assets in the midst of the COVID-19 crisis ("The Liquidity Doom Loop in Bond Funds is a Threat to the System," *Financial Times*, March 25, 2020).

To understand why risk-taking dynamics might differ for corporate bond funds, it is helpful to outline the intrinsic source of fragility to which open-end mutual funds are exposed. Standard pricing rules require mutual funds to redeem investors' shares at the daily-close net asset value (NAV). However, the portfolio readjustments necessary to accommodate investor redemptions may take several days. While the first-to-exit investors are liquidated at full price, the costs of these portfolio readjustments are borne by the remaining investors, who face a dilution in the value of their shares. This feature of open-end funds creates strategic complementarities among investors, as it gives rise to a first-mover advantage in the redemption decision (see Chen, Goldstein, and Jiang 2010).

Importantly, mutual fund fragility is exacerbated by the illiquidity of corporate bonds as an asset class. Corporate bonds are notoriously difficult to trade. Offloading large positions to dealers can sometimes take several days, if not weeks. This means that sudden investor withdrawals may force the fund manager to execute fire sales that impose severe negative externalities on slow-moving investors. This risk, in turn, magnifies outflows in response to bad performance, giving rise to a flow-to-performance sensitivity (FPS) that has a *concave* shape: investor outflows are sensitive to bad performance more than inflows are sensitive to good performance (Goldstein, Jiang, and Ng 2017). Notably, fund fragility is somewhat mitigated for equity money managers, as stock markets tend to be more liquid. As a result, while the pay-off structure of equity funds resembles being long a call option (Brown, Harlow, and Starks 1996), that of bond funds is more similar to being short a put option: the benefit of fund outperformance in terms of new inflows is limited, whereas underperformance is heavily penalized with large-scale redemptions.[3] The main goal of our paper is to explore how this different incentive structure impacts the risk-taking decisions of bond fund managers.

We take advantage of precise portfolio holdings information to explore how bond funds

[3]Notably, most mutual funds charge fees on the assets under management rather than performance. Therefore, fund managers may attempt to maximize dollar inflows rather than actual performance. A large literature investigates agency issues in the mutual fund industry (see, e.g., Carhart, Kaniel, Musto, and Reed 2002; Bhattacharya, Lee, and Pool 2013; Eisele, Nefedova, Parise, and Peijnenburg 2020; and Evans, Prado, and Zambrana 2020).

shift asset allocation when performance declines. Our core finding is that both tournament incentives – i.e., the incentive to take additional risk – and precautionary incentives – i.e., the incentive to decrease risk-taking – coexist in bond funds, but the latter set of incentives dominates on average. In particular, we establish that funds that underperform (from now on *Laggard Funds*) de-risk their debt portfolio by reducing the exposure to liquidity risk, while leaving the exposure to credit and interest rate risk unchanged. The flip side of the coin is that the de-risking forces laggard funds to tilt their portfolios towards expensive (lower-yielding) bonds, thereby compromising yield in an attempt to alleviate expected liquidation costs. This gives rise to dynamics that are opposite of those documented for equity mutual fund tournaments, whereby loser funds increase risk-taking and winner funds consolidate their positions (Brown, Harlow, and Starks 1996, Chevalier and Ellison 1997, and Kempf and Ruenzi 2008). We confirm that the effect of performance on risk-taking is causal by running a trade-level analysis that allows us to account for changes in fundamentals at the bond issuer level.

In line with the incentive structure created by the concave shape of the sensitivity of flows to performance, we show that the incentives of laggard funds to de-risk are shaped by market states, fund characteristics, and portfolio illiquidity. Specifically, we document that periods of market stress and illiquid asset holdings amplify de-risking dynamics, whereas a low interest rate environment weakens them by fostering a search-for-yield that conflicts with de-risking incentives. We also show that fund managers with shorter tenure, retail funds, and funds that hold lower precautionary cash buffers – characteristics that tend to be associated with a higher and more concave flow-performance sensitivity – de-risk more in response to bad performance, as they have a stronger incentive to flee to safe havens. Overall, we conclude that de-risking incentives are stronger than rank-chasing incentives in the bond fund space.

We provide evidence that the decision by corporate bond fund managers to de-risk in anticipation of outflows, while costly in terms of lower yield and transaction costs, has a host of positive effects. In particular, we document that laggard funds that decrease risk-taking more decisively experience milder subsequent outflows and deliver higher returns. Back-of-the-envelope calculations indicate that a one-standard-deviation decrease in risk-taking corresponds to 49% lower outflows in the subsequent period. This finding has implications for the financial stability risks posed by bond funds. As it is in the fund manager's best interest to de-risk, the industry exhibits a natural tendency to reduce risk exposures on its own without the need for regulatory intervention. The funds that are more vulnerable to runs, and would trigger the largest negative externalities through fire sales, voluntarily scale back risk-taking. This may help to avert an adverse feedback loop scenario in which redemptions and fire sales reinforce one another. These findings are consistent with the anecdotal observation that, outside of periods of market turmoil when redemption pressures hit several funds simultaneously, actual runs on bond mutual funds have been infrequent events with limited repercussions on other market participants.[4]

Our findings have policy implications. In November 2018, the U.S. Securities and Exchange Commission (SEC) introduced new rules permitting U.S. open-end mutual funds to adopt flexible NAVs, commonly known as *swing pricing*. Swing pricing allows funds to adjust the NAV of redeeming investors depending on the total flows experienced by the fund, thereby minimizing the dilution of investors who remain invested. Yet, only a small subset of asset managers adopted flexible NAVs when the new rules came into effect. We take advantage of this asymmetry in the adoption to examine the effect of flexible NAVs on the risk-taking behavior of laggard funds. We find that, after November 2018, laggard funds affiliated with companies that adopted swing pricing meaningfully increase risk-taking with respect to laggard funds affiliated with companies that (as of now) have not yet adopted swing pricing. Overall, our evidence suggests that flexible NAVs may weaken the precautionary incentive uncovered in our paper, which in turn may reinstate the moral hazard problem typical of equity funds.

[4]One notable exception is that of the Third Avenue Focused Credit Fund (FCF). FCF was forced to halt redemptions and close in December 2015. Yet, the FCF case might not be representative, as the fund was running unusually large and concentrated bets. For instance, Marty Whitman – the founder of Third Avenue – is reported to have argued that "diversification is a damn poor surrogate for knowledge, control and price consciousness" ("How the Third Avenue Fund Melted Down" *The Wall Street Journal*, December 23, 2015).

Our paper contributes to three strands of literature. First, it fits within the large body of literature on the financial stability and systemic risk of financial institutions. While this literature has been traditionally concerned with depositor runs on banks (e.g., Diamond and Dybvig 1983), recent work provides evidence of the destabilizing effects of runs on non-bank institutions (e.g., Bernardo and Welch 2004, Kacperczyk and Schnabl 2013, and Lawrence, Timmermann, and Wermers 2016). More broadly, a large literature documents the implications of mutual fund fragility for asset prices (see, e.g., Coval and Stafford 2007, Greenwood and Thesmar 2011, Christoffersen, Keim, and Musto 2018). We provide evidence for a mechanism that reduces fragility, which emerges from managers acting in their self interest given the incentive structure set by the investors.

Second, our paper contributes to a growing literature on bond mutual funds. Morris, Shim, and Shin (2017), Chernenko and Sunderam (2020), Choi, Hoseinzade, Shin, and Tehranian (2020), Ma, Xiao, and Zeng (2020), Jiang, Li, and Wang (2021), and Jiang, Li, Sun, and Wang (2022) explore how fund outflows affect fund actions and bond pricing *ex post*. By contrast, our paper documents how bond fund managers respond to the incentives created by the concavity of the FPS *ex ante*, when declining performance increases the risk of future redemptions. We are the first to show that lagging performance gives rise to a flight-to-liquidity before actual redemptions hit.[5] Related to our paper, Choi and Kronlund (2018) find a moderate increase in reaching-for-yield behaviors for bottom performers toward the end of the year, which is consistent with the presence of tournament incentives. Our focus is different, as we document the dynamic liquidity risk adjustments of bond funds as a function of past performance and redemption risk. Adding to Choi and Kronlund (2018), we find that, on average, de-risking incentives are stronger than tournament motives, especially for younger managers and in periods of market stress.

Finally, our research adds to a large literature on mutual fund tournaments. In par-

[5]In section IV, we conduct several tests to exclude that our results are driven by redemptions. Notably, our results may help explaining why, empirically, redemption-induced fire sales by bond funds had less severe price implications than fire sales by equity mutual funds (as documented by Choi, Hoseinzade, Shin, and Tehranian 2020) even though corporate bonds are significantly less liquid.

ticular, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998), among others, argue that the sensitivity of flows to performance is convex for equity funds. Convex flows-to-performance sensitivity creates an incentive for laggard funds to engage in tournaments, as it provides an option-like payoff from gambling. Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Kempf and Ruenzi (2008) provide evidence of tournament behaviors by showing that underperforming equity funds take more risk than outperforming ones. We contribute to this literature by documenting that, for bond mutual funds, de-risking incentives dominate rank-chasing motives on average. The net effect of performance rank on risk-taking is therefore opposite to that observed for equity funds.

II. Hypotheses development

The existence of complementarities among investors gives rise to a multiplier effect that amplifies the impact of underperformance on flows and generates the risk of sell-fulfilling runs. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) investigate these mechanisms in a setting in which investors decide to run on the basis of fund performance and perceived liquidation costs. We conjecture that when fund managers decide on their asset allocation they incorporate expectations regarding the future behavior of their investor base. This leads to a situation akin to a dynamic game in which both investors and money managers respond to each others' actions. Notably, runs on the fund are costly for managers because large outflows negatively impact reputation, career opportunities, and, in the worst-case scenario, may lead to contract termination and job loss. If underperforming fund managers are rational, they should act promptly to diffuse the risk of liquidation spirals. Drawing from previous research, we hypothesize the following scenarios:

- *H0: No effects of incentives in the cross-section. H0* states that, in the cross-section, past performance plays no role in determining risk-taking. While there is mounting evidence that fund managers reach for yield in a low interest rate environment (Barbu, Fricke, and Moench 2016, Hau and Lai 2016, Di Maggio and Kacperczyk 2017, and

Choi and Kronlund 2018), the emphasis of this stream of literature is on how changes in macroeconomic factors affect the average demand of yield. By contrast, our focus is on the cross-sectional dimension once the time-series determinants are accounted for.

- *H1a: Tournament incentives.* Laggard bond funds may attempt to improve their position against their peers by increasing overall portfolio risk. This *gambling-for-resurrection*-behavior would be akin to what is documented for equity funds (Brown, Harlow, and Starks 1996, Chevalier and Ellison 1997, and Kempf and Ruenzi 2008). Although the final outcome would be analogous, the incentive mechanism that prompts such actions is different. In the case of equity funds, the reward of extra inflows to top performers incentivizes managers who lag behind in the rankings to take additional risk. In the case of bond funds, it is the additional outflows from underperformers that incentivize them to inflate their returns. Notably, Choi and Kronlund (2018) do find some evidence of additional risk-taking by low-performing bond funds in the periods approaching the end of the year.

- *H1b: Shrouding risk.* A slight variation of H1a applies to a situation where laggard fund managers increase risk-taking *while concealing their behavior*. If investors cannot fully distinguish *alpha* from *beta*, fund managers can "fool" investors and move up in the rankings by tilting their portfolios towards riskier assets in a way that is less evident for their clients. For instance, fund managers could replace safer assets with assets that fall within the same rating bucket but offer higher yield — a behavior documented for insurance companies (Becker and Ivashina 2015). Shrouding risk may prove successful in the case under analysis for two reasons. First, corporate bonds' prices are notoriously stale and, therefore, market valuations of portfolio holdings convey limited information. The relative opacity of the asset class, in turn, makes it harder for investors to monitor managers' behavior. Second, there is no consensus on how bond fund investors should measure risk. In particular, existing evidence suggests that investors are unlikely to employ sophisticated models (Dang, Hollstein, and Prokopczuk 2022). All in all, managers of bond funds that are ex ante more exposed to fragility concerns may engage in deceptive behaviors that might attenuate investor concerns about performance.

- *H2: De-risking.* Alternatively, laggard funds could de-risk their portfolio when they anticipate a run, shifting asset allocation towards liquid securities that would sustain lower liquidation costs in the event of forced sales. Divesting illiquid securities and replacing them with liquid ones *before* redemption pressures from the investor base materialize has two advantages. First, fund managers may sell illiquid assets at a slower pace, to minimize the ensuing price impact. Second, portfolio de-risking has the added benefit of mitigating the first-mover advantage among exiting investors, in turn alleviating the incentive of early redeemers to run in the first place (see Capponi, Glasserman, and Weber 2020). Notably, by selling illiquid assets before the run occurs, the fund manager dilutes all investors equally, thereby avoiding strategic complementarities of the type described by Chen, Goldstein, and Jiang (2010) and Zeng (2017). From a financial stability perspective, this scenario might be preferred. In fact, in the case of fund-specific shocks, the most fragile funds would mitigate the risk of resorting to fire sales without the need for regulatory intervention. This, in turn, reduces the chances that a fund-specific shock propagates to funds holding similar assets through the fire-sale channel (see, e.g., Coval and Stafford 2007 and Anton and Polk 2014).

III. Data and research design

A Data sources

To conduct our analysis, we rely on data on mutual fund performance, fund portfolio allocations, and asset risk. For fund portfolio allocations, we use quarterly filings data from

Thomson Reuters eMAXX.[6] The eMAXX database provides granular information on bond holdings for U.S.-domiciled mutual funds. It also contains detailed information on the characteristics of individual bonds, such as credit ratings and maturity dates. Importantly, the database is free from survivorship bias (as all funds are included, defunct and alive) and reporting bias (as all mutual funds' bond holdings are included). To assess data quality, we compare eMAXX on an aggregate level with data from FRED (Federal Reserve Economic Data). The aggregated volume of corporate bonds covered by eMAXX is fairly close to the total amount of outstanding U.S. corporate debt as reported by the Fed (see Figure A.1 in the Online Appendix). The difference between eMAXX and FRED stems from the fact that eMAXX does not include the holdings of banks, hedge funds, and households. This percentage of bonds not covered by eMAXX has been decreasing over time, as banks have been shrinking their corporate bond inventory (due to their scaling back of market-making activities). We compare a number of randomly selected snapshots of portfolio holdings with regulatory filings to confirm the quality of the data and to exclude the presence of strategic misreporting of the type described in Chen, Cohen, and Gurun (2021).

We match fund portfolios in eMAXX with information from the Center for Research in Security Prices (CRSP) by fund name. The sample is restricted to funds that hold only or mostly corporate bonds.[7] We define fund styles on the basis of Lipper objective codes (lipper_obj_cd).[8] We impose a number of additional filters. First, for a fund to be included, we require at least two years of history and a number of bonds that exceeds the fifth percentile of the sample distribution (42 bonds) to avoid noisy measurement of portfolio risk. Second, we exclude all exchange traded funds (ETFs), exchanged traded notes (ETNs), and index funds. Notably, funds offer several share classes to investors. As all share classes offered by the same fund are based on the same underlying portfolio, we

[6] A number of papers in the literature are based on the same database (e.g., Manconi, Massa, and Yasuda 2012; Massa, Yasuda, and Zhang 2013; and Becker and Ivashina 2015).

[7] To be considered a corporate bond fund, the CRSP lipper_obj_cd variable must be in the set "A" "BBB" "HY" "SII" "SID" "IID"; or the si_obj_cd variable must be in the set "CGN" "CHQ" "CHY" "CIM" "CMQ" "CPR" "CSM"; or the wbger_obj_cd variable must be in the set "CBD" "CHY."

[8] Our results are robust to alternative definitions of style.

aggregate information and performance from different share classes at the fund level.[9] We use CRSP to obtain information on the assets under management, inception date, fund fees, fund clientele, performance, and rear loads. Our sample spans the time period from January 2004 to December 2017. Overall, we have data on 724 unique U.S.-domiciled corporate bond funds for a total of 2,288 different share classes.

We exploit regulatory filings collected by eMAXX and transaction-level data from the Trade Reporting and Compliance Engine (TRACE) to construct our measures of risk and liquidity of fund portfolio holdings. More specifically, we obtain data on ratings, issue, and maturity date from eMAXX when available and Mergent FISD when not available in eMAXX. We use market-level information from TRACE to gather information on yields, market prices, and volumes. The exact procedure to build our different liquidity measures is described in detail in the Online Appendix.[10]

B Fund flows and performance

Following the related literature (see, e.g., Coval and Stafford 2007), we compute net fund flow from CRSP as:

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

where $Flow_{i,t}$ is the net flow to fund share class i during month t. We aggregate monthly flow data from fund share classes to quarterly data at the fund level, as portfolio holdings from eMAXX are reported at a quarterly frequency. Following the literature, we winsorize this variable at the 1% level. We confirm in subsection B of the Online Appendix that the flow-to-performance sensitivity is concave for the bond funds in our sample, in line with

[9]Specifically, we compute value-weighted averages for all the variables of interest, with weights given by the total net assets of each share class at the beginning of the period (to avoid contemporaneous effects).

[10]Notably, as TRACE and Mergent FISD cover corporate bonds only, our measures of risk that focus on yields and bond liquidity are exclusively based on corporate bond holdings, similar to other papers in this literature (see, e.g., Jiang, Li, and Wang 2021).

Goldstein, Jiang, and Ng (2017).

To measure fund performance, we compute the average risk-adjusted monthly fund return (*alpha*) in a 12-month window. In each year-quarter, we then sort all funds on the basis of past alphas. We define as *Laggard Funds* in year-quarter t those funds whose past 12 months average risk-adjusted performance falls in the bottom half of the year-quarter distribution.[11] This choice follows from the fact that funds that underperform their benchmark exhibit a higher sensitivity of flows to performance (Goldstein, Jiang, and Ng 2017). For example, a fund is defined as laggard in the first quarter of 2018 if its average monthly alpha for the year 2017 falls in the bottom half with respect to that of the other funds. This implies that we have the same proportion of laggard funds in every period. Following Goldstein, Jiang, and Ng (2017), we rely on the Vanguard Total Bond Index Fund as the market benchmark for bond funds. Specifically, we estimate fund alphas by regressing monthly fund share class excess returns on the excess returns on the Vanguard Total Bond Index Fund. We then aggregate share classes' alphas at the fund level by computing the average risk-adjusted return, weighted by the assets under management held at the beginning of the month in each share class.

Naturally, any method to account for risk can be subject to critiques, as we do not know the "true" model used by investors. In support of our approach, related research shows that investor flows are mostly driven by past fund performance adjusted by its volatility, and investors rarely use sophisticated models to account for risk (see Dang, Hollstein, and Prokopczuk 2022). Furthermore, in contrast to equity funds, the choice of the model to account for risk has relatively minor effects on the relative performance ranking of bond mutual funds (Blake, Elton, and Gruber 1993). Our results are robust to using alternative risk models when estimating alphas and/or different lengths of the estimation window (see Table A.6 in the Online Appendix).

[11] In the Online Appendix, we consider as alternative cut-offs 33% and 20% (see Table A.5).

C Measuring risk-taking

Most of the literature on fund tournaments explores how relative performance, achieved in the first half of the year, relates to risk-taking, measured as the standard deviation of fund returns in the second half (see, e.g., Brown, Harlow, and Starks 1996 and Chevalier and Ellison 1997). This approach, however, leads to a sorting bias: as returns and risk are related, sorting funds on returns in the first half of the year has mechanical implications for the volatility of returns in the second half of the year (Schwarz 2011).[12] Following Schwarz (2011), we build our main measures of risk-taking based on the actual change of portfolio holdings by mutual funds rather than on the volatility of realized returns.

To gauge how managers manipulate portfolio riskiness, we compute the difference between: i) the average riskiness of the portfolio at time $t-1$ and ii) the average riskiness of the portfolio at time t *had the riskiness of the underlying bonds not changed from the previous quarter*. Note that, as risk for both quantities is measured at time $t-1$, variations in the measure arise entirely from variations in the relative weight assigned to different bonds.[13] With this approach, we make sure that our measure does not vary due to changes that are outside of the fund manager's control (e.g., if a bond is downgraded by a few notches). Formally,

$$\Delta Risk_{i,t} = \underbrace{\sum_{j=1}^{N_{i,t}} w_{i,j,t} \times Riskiness_{j,t-1}}_{Current\ allocation\ of\ past\ risk} - \underbrace{\sum_{j=1}^{N_{i,t-1}} w_{i,j,t-1} \times Riskiness_{j,t-1}}_{Previous\ allocation\ of\ past\ risk}, \qquad (2)$$

where $\Delta Risk_{i,t}$ measures the *active* rebalancing of the portfolio of fund i during quarter t to increase or decrease risk. $w_{i,j,t} = \frac{Q_{i,j,t}}{\sum_j Q_{i,j,t}}$ is the relative weight of bond j in fund i's portfolio at the end of quarter t, out of the $N_{i,t}$ bonds held by the fund. $Q_{i,j,t}$ represents the par

[12] This problem is arguably going to be magnified in our setting, as underperforming bond funds face large future redemptions. Redemptions, in turn, may force the fund manager to sell illiquid assets at a discount, thereby increasing realized return volatility regardless of portfolio allocation.

[13] Results remain similar when we consider bond riskiness measured without a lag or with different time lags (see Online Appendix Table A.8).

amount in units of $1,000. Notably, $\Delta Risk_{i,t}$ changes when bonds mature or are redeemed by the issuer unless the fund manager replaces them with bonds with an analogous risk profile. We show that our results are robust to remove bonds that mature or are redeemed within a quarter so that $\Delta Risk_{i,t}$ is not affected (see Online Appendix Table A.11).

An advantage of our data is that eMAXX reports the notional amounts rather than the market value of assets held by the funds.[14][15] Notably, the market value of a bond changes over time due to a host of determinants outside of the control of the fund manager such as changes in interest rates, time to maturity, and variations in issuers' credit risk. Using market values to determine weights would imply that the relative proportion of risky asset positions in fund portfolios may change from one period to the next even if the manager chooses not to trade. To address this problem, we compute the relative weight of each bond in the portfolio based on notional rather than market values, as measured by par values. As bond par values do not change over time, par-value portfolio weights remain constant *unless the fund manager actively takes a decision to trade and alter portfolio composition.* As a result, changes in our portfolio metrics only capture intentional shifts in allocations by the fund manager from one quarter to the next. To give an example, if a fund's par value-weighted average rating of asset holdings goes from AA in quarter $t-1$ to A in quarter t, it necessarily means that the fund manager actively decreased the quality of bonds in her portfolio. Even if some existing positions were downgraded, thereby decreasing their value relative to other portfolio positions, that would not affect our par value-weighted portfolio metrics (as we keep asset riskiness fixed at time $t-1$). In sum, our risk-taking measures

[14]Similar to us, an increasing number of papers in the literature rely on portfolio measures based on par values (see, e.g., Jiang, Li, and Wang 2021 and Jiang, Li, Sun, and Wang 2022).

[15]It is important to distinguish two types of correlations between performance and risk measures. The first type is the correlation between past fund performance and active changes in portfolio riskiness, which is the focus of our analysis. The second type is a spurious correlation that arises because changes in bond valuations affect both fund performance and the relative *market* weight of bonds in the fund portfolio. This endogenous correlation can bias our coefficients and make it difficult to interpret the estimated beta. If we do not clean our variables from this second type of correlation, we would not be able to determine whether changes in portfolio riskiness (our Y variable) are caused by changes in fund performance (our X variable), or by a third variable Z that affects both X and Y. To avoid these identification issues, our baseline approach uses par values to measure portfolio riskiness, which are not directly affected by changes in bond valuations. Therefore, changes in bond valuations only affect portfolio riskiness through changes in fund performance (i.e. the laggard dummy).

only capture active changes in portfolio allocations.[16]

To define $Riskiness_{j,t-1}$, we resort to a number of metrics. Specifically, we attempt at disentangling the exposure to different sources of risk by relying on specific measures of liquidity, credit, and interest rate risk (considered separately). We consider four measures of liquidity risk: Amihud (2002)'s and Roll (1984)'s illiquidity measures, the Bid–Ask spread, and the inter-quartile price range (in line with Goldstein, Jiang, and Ng 2017). We measure credit risk with *Rating* defined as the highest credit rating among those assigned by Standard and Poor's, Moody's, and Fitch (similar to Hand, Holthausen, and Leftwich 1992). Ratings are translated to a numerical scale from 0 (AAA) to 22 (D). Finally, we proxy interest rate risk with the duration of the bonds in the portfolio. In sum, $Riskiness_{j,t-1}$ is a measure of the riskiness of bond j in year-quarter $t-1$ computed using bond i) liquidity, ii) ratings, or iii) duration.

Importantly, $\Delta Risk_{i,t}$ is flow-neutral, that is, it is not affected by inflows or outflows as long as the fund manager makes investment decisions that maintain the *proportion* allocated to each risky security unaltered. To give an illustrative example, if the assets under management by the fund increase by 10% because of a positive inflow shock, and the fund manager expands every existing position by 10% (or, analogously, buys new securities with the same risk profile), $\Delta Risk_{i,t}$ would be 0.

[16] The following example clarifies the relation between par and market portfolio weights. Consider an asset manager who holds two bonds A and B that trade below their par value of $1,000. Bond A is currently trading at $950 and its bid-ask spread is $0.5, whereas bond B is trading at $600, but is less liquid and its bid-ask spread is $1. The asset manager holds 2 units of bond A and 3 units of bond B, which implies that the *market* weights of the two bonds in the portfolio are 51% and 49%, and the par value weights are 40% and 60%. Now, let's assume that the fund manager wants to rebalance its portfolio to change the relative market weight of the two securities to respectively 44% and 56%, by purchasing 1 more unit of bond B. This decreases the average (market-weighted) liquidity of the portfolio by 0.036 $(0.44 * 0.5 + 0.56 * 1 - 0.51 * 0.5 - 0.49 * 1)$. If we consider par values instead, the active decrease in liquidity is 0.033 $(0.33 * 0.5 + 0.66 * 1 - 0.4 * 0.5 - 0.6 * 1)$. As the fund manager actively decides to trade, both measures reflect a decrease in the average portfolio liquidity (or, equivalently, an increase in the average bid-ask spread). However, we can find an analogous change in the market-weighted measure, 0.036, if bond B increases in value by 33.3% (for instance because of a credit rating upgrade) and the fund manager does not change portfolio composition. Whereas, in this latter case, the change in the par-value weighted portfolio liquidity would be 0, as the par value weight of the bond does not change. We argue that the latter measure is unaffected by price fluctuations and hence better suited for the study of our research question. That said, the measure based on market values is superior in other contexts, e.g., when the portfolio manager seeks to monitor the overall market value of portfolio risk.

As we find that fund managers exhibit high inertia in their portfolio allocations, we need to ensure that $\Delta Risk_{i,t}$ does not change mechanically in response to factors outside of the fund manager's control. In this regard, our measure of risk-taking has four advantages. First, it is not affected by sorting bias of the type described in Schwarz (2011). Second, it is not mechanically affected by changes in the market value of the bonds or by the marking-to-market of securities by the fund. Third, it is immune to shifts in asset riskiness that do not lead the fund manager to change portfolio allocations. Fourth, it is not mechanically affected by flows into and out of the fund. In this way, we ensure that portfolio riskiness remains constant if a fund manager does not actively choose to trade. Overall, our measure is similar in spirit to previous measures of active rebalancing for portfolios of stocks (see, e.g., Curcuru, Thomas, Warnock, and Wongswan 2011, Greenwood and Thesmar 2011, Huang, Sialm, and Zhang 2011, and Schmidt 2019).

D Summary statistics

Table I, Panel A reports descriptive statistics for our bond fund data set. Over the period under analysis, the average active corporate bond fund manages \$1.7 billion in assets, has a track record of 16 years, and offers more than three share classes. Bond funds received an average 1% net inflow per quarter over our sample. Alphas are positive in our sample: funds earn an average 0.43% a month in the previous 12-month window, in line with recent results reported in Clare, O'Sullivan, Sherman, and Zhu (2019).[17] Notably, the average change in risk-taking of bond funds from one quarter to the next is small. For example, on average, funds hold their portfolio yield constant. To ease the interpretation of our findings, we standardize all risk-taking measures based on liquidity to an average of 0 and a standard deviation of 1.

We report the summary statistics for corporate bonds in Panel B. The average bond held by the mutual funds in our sample has a residual maturity of 8 years, and a rating of

[17] Studies on earlier periods find instead a negative average alpha for the bond fund industry, e.g., Blake, Elton, and Gruber (1993).

10 (i.e., BBB-). Furthermore, corporate bonds yield on average 5.50% and have a residual maturity of 8 years. Overall, our sample statistics are in line with the related literature (see, e.g., Jiang, Li, and Wang 2021).

IV. Debt De-risking

A Main results

Even in the presence of fixed fund manager compensation, the concavity of the flow–performance relation gives rise to an asymmetric incentive structure. Funds' payoff in terms of flows is akin to selling a put option where the underlying asset is fund performance. A higher performance in the domain of gains leads to mild inflows, whereas a lower performance in the domain of losses gives rise to large-scale redemptions. To meet such outflows, managers may need to liquidate bonds at fire-sale prices, thereby dragging down performance further and attracting more outflows. This scenario could set in motion an adverse feedback loop whereby outflows and underperformance reinforce one another. The incentive of fund mangers to avoid this downside risk is further magnified when their compensation is tied to performance (as is common in practice, see Ma, Tang, and Gómez 2019).

In this section, we explore whether a concave shape of the flow-to-performance relationship gives rise to strategic allocation decisions depending on how the fund performs. Specifically, we contrast three main hypotheses as laid out in Section II. First, past fund performance is irrelevant for risk-taking in the cross-section (*H0*). Second, laggard funds have an incentive to tilt portfolio allocation towards high-yield securities (*H1a* and *H1b*). Third, laggard funds actively de-risking their debt portfolios (*H2*). To disentangle these hypotheses, we run the following regression:

$$\Delta Risk_{i,t} \;=\; \beta_0 \;+\; \beta_1 \; Laggard\ Fund_{i,t-1} \;+\; \gamma' X_{i,t-1} \;+\; \delta_t \;+\; \delta_i \;+\; \epsilon_{i,t}, \tag{3}$$

where $\Delta Risk_{i,t}$ is the active change in risk-taking of fund i in quarter t with respect to quarter $t-1$, as defined in section III.[18]

We include in our specifications a number of co-determinants of risk-taking and performance, $X_{i,t-1}$, and year-quarter ($Time$) and fund fixed effects ($Fund$). Year-quarter fixed effects, δ_t, account for common factors to which all funds are exposed in a given period (e.g., the state of the economy, the interest rate level, the shape of the yield curve). Fund fixed effects, δ_i, absorb observable and unobservable invariant determinants of risk-taking such as the investment style, the type of investors, or the compensation scheme of the manager. Notably, the fund fixed effects allow us to compare changes in risk-taking within funds, thereby teasing out how fund managers alter portfolio allocation when they underperform as opposed to situations when they outperform.

We are especially interested in assessing how fund managers manipulate risk-taking following underperformance. The coefficient β_1 captures how risk-taking changes when a fund's alpha falls in the bottom half of the cross-section, irrespective of the fund's investment style. A coefficient $\beta_1 = 0$ would indicate that bond funds do not readjust portfolio allocations on the basis of past performance, in line with *H0*. A positive coefficient $\beta_1 > 0$ would signal that laggard funds increase portfolio risk, consistent with *H1*. Notably, a $\beta_1 > 0$ for all measures of risk would indicate that bond funds act analogously to equity funds in that underperforming funds take on relatively more risk (*H1a*). By contrast, a coefficient $\beta_1 > 0$ for risk-taking measures based on yields *and* a $\beta_1 = 0$ for measures based on ratings would indicate that laggard funds are shrouding risk, holding "perceived" risk constant while inflating underlying expected portfolio returns (*H1b*). Finally, a negative coefficient $\beta_1 < 0$ for measures of risk-taking would indicate that laggard funds are de-risking their portfolio, in line with *H2*.

[18] Notably, we do not focus on end-of-calendar-year or second semester adjustments such as in Brown, Harlow, and Starks (1996). Back in 1996, most of the performance assessment was done on an annual basis. Yet, today, funds provide frequent performance updates that include the main portfolio holdings and the AUM. If fund investors make their allocation decisions at any time based on past performance, there is no reason why fund managers should adapt their portfolio risk on a calendar-year basis. Consistent with this argument, in unreported results we find no evidence of a stronger adjustment in risk-taking in the last semester of the year.

Table II reports our main findings: laggard funds actively de-risk their portfolios following underperformance. This is achieved entirely by reducing exposure to liquidity risk. Columns 1-4 show that managers tilt their portfolios towards liquid assets, consistent with *H2*. At the same time, they hold constant the average quality of asset holdings as measured by their ratings (see Column 5) and the average portfolio duration (Column 6). In other words, laggard fund managers reduce exclusively liquidity risk, whereas they do not alter exposure to interest or credit risk. The magnitude of the de-risking is large: when considering Amihud liquidity measure, laggard funds increase the average portfolio liquidity by 10% of one standard deviation, statistically significant at the 1% level (from 8% to 16% of one standard deviation using alternative liquidity measures). However, the increase in liquidity comes at the cost of giving up yield, which decreases by 10 basis points (19% of one standard deviation in our sample) statistically significant at the 1% level (see Column 7).

The empirical evidence presented above establishes that laggard fund managers decrease portfolio risk levels. This decrease in risk-taking is consistent with a fund manager's desire to alter fund risk profiles in response to poor performance. Yet, it does not rule out other motives for trading that endogenously generate the change in portfolio risk. Importantly, if a fund manager modifies portfolio composition for reasons that are unrelated to past performance, those changes would not be captured by the beta estimated in equation (3) but "end up" in the residuals, thereby not affecting our analysis. Our methodology is in line with the literature on fund tournaments where researchers regress fund realized risk on past fund performance (e.g., Brown, Harlow, and Starks (1996)) but it avoids the problem of a mechanical correlation between realized risk and returns documented by Schwarz (2011). We account below for factors that may endogenously generate the relation between fund performance and portfolio composition. Specifically, we examine the role of the two most likely omitted factors: fund flows and changes in asset fundamentals.

Precautionary trading vs tournament incentives. To assess the relative importance of precautionary concerns versus tournament incentives, we run a horse race between risk-adjusted fund performance, $R_{i,t}$, and *style-adjusted* fund performance, $R^s_{i,t}$. Style-adjusted fund performance is the 12-month fund performance in excess of the performance of the funds with the same investment style, i.e., $R^s_{i,t} = R_{i,t} - S_t$, where S_t is the average performance of funds with the same investment style as fund i. Both $R_{i,t}$ and $R^s_{i,t}$ are standardized to make magnitudes comparable. Table III shows that the effects of $R_{i,t}$ and $R^s_{i,t}$ on risk-taking have opposite signs. Underperformance leads fund managers to decrease risk-taking, in line with the presence of precautionary motives regarding liquidity risk. By contrast, *relative* under-performance prompts fund managers to take more risk, which is consistent with the presence of tournament incentives and similar to what is commonly observed for equity funds (see, e.g., Brown, Harlow, and Starks 1996, Chevalier and Ellison 1997, and Kempf and Ruenzi 2008). Importantly, in terms of magnitudes the effect of absolute performance on risk-taking dominates, as it is about six times that of relative performance (when we consider yields).

This set of findings indicates that the incentive structure in the bond management industry is opposite to that of equity funds. In the equity space, laggard fund managers have a strong incentive to gamble to improve their position against their peers. While an analogous incentive does exist for bond funds as well, it is however overshadowed by the incentive to reduce the exposure to liquidity risk when the threat of large investor redemptions looms. In other words, the incentive to mitigate ex ante the cost of (expected) redemptions dominates the incentive to boost fund performance by taking more risk.

Endogeneity. An issue that warrants further discussion is the potential presence of confounding factors that drive a change in portfolio composition even if the fund manager does not intend to alter risk-taking. If an omitted factor drives both the change in risk-taking and the performance of bond funds, our approach would yield biased estimates. For example, this would be the case if asset-level shocks erode fund performance *and* prompt the fund manager to shift portfolio allocation. To tackle this concern, we re-run our analysis at the trade level, which allows us to fully account for security-level shocks by adding to our specification issuer×time fixed effects, $\delta_{J\times t}$. In particular, we estimate the effect of performance on trading behavior within fund, thereby exploring whether a fund is more likely to shun away from risky assets when underperforming. However, we account for the average expectations about a firm fundamentals with the issuer×time fixed effects. The basic idea is that the same firm issues several bonds with different exposure to liquidity risk but that are exposed to the same underlying fundamental risk, which we absorb with the fixed effects. We would expect laggard funds to liquidate the riskiest bonds of a given issuer.[19] Specifically, we run the specification below at the level of individual bond holding:

$$\begin{aligned} Net\ Buying_{i,j,t} \ &= \ \beta_0 \ + \ \beta_1 \ Laggard\ Fund_{i,t-1} \times \ Risky\ Bond_{j,t-1} \ + \\ &\beta_2 \ Laggard\ Fund_{i,t-1} \ + \beta_3 \ Risky\ Bond_{j,t-1} \ + \ \gamma' X_{i,t-1} \ + \ \delta_{J\times t} \ + \ \delta_i \ + \ \varepsilon_{i,j,t}, \quad (4) \end{aligned}$$

where $Net\ Buying_{i,j,t}$ is the number of bonds j, bought by fund i in quarter t minus the number of bonds j, sold by fund i in quarter t scaled by the total number of bonds traded by fund i in quarter t. All numbers are in par amounts of \$1,000. Specifically, $Net\ Buying_{i,j,t}$ will be positive if fund i increases its position in bond j in response to underperformance. We interact $Laggard\ Fund_{i,t-1}$ with the same bond features considered in our main analysis to explore how laggard funds trade assets on the basis of their core characteristics (i.e., yield, liquidity, rating, and duration). Overall, including issuer×time fixed effects ($\delta_{J\times t}$) allows us to fully control for firm-level shocks or expectations, thereby ruling out the possibility that de-risking behaviors are driven by news about asset fundamentals.

Table IV reports our results. Portfolio holding-level results confirm that laggard funds decrease risk-taking by reducing their exposure to “cheap” (high-yield) bonds that are however more exposed to liquidity risk. This rules out the concern that our results may be driven by asset-level shocks. Notably, in this trade-level analysis, we also find an effect on

[19] Our approach is in the same spirit of the methodology commonly used by the banking literature, whereby firm×time fixed effects are used to control for demand level shocks (see, e.g., Khwaja and Mian 2008).

the trading of high-credit-rating and low-duration bonds. However, these have no statistically significant effect when we aggregate the individual trades at the portfolio level. In the following, we present our results at the fund level rather than at the level of bond holdings. This is because fund level results allow us to estimate the aggregate effect on the overall portfolio risk.

In the Online Appendix, we further present results including controls for contemporaneous flows and including issuer×time×laggard fixed effects (see Online Appendix Table A.10). In this way, we account for the possibility that results might be driven by liquidity needs or incorrect beliefs by laggard funds. Furthermore, we present an IV analysis in which we instrument $Laggard\ Fund$ for fund i using the past 12-month risk-adjusted performance of all funds that have the same Lipper investment objective as fund i with the exception of fund i. This analysis confirms that factors that negatively affect the returns of a category of funds, but are exogenous to fund i's actions, still lead to de-risking (see Online Appendix Table A.9). Overall, the analyses confirm our main results.

De-risking or liquidation pecking order? Notably, in our setting underperformance by the fund at time $t-1$ may give rise to forced asset liquidations to meet investor redemptions at time t. These liquidations, in turn, could influence the risk composition of the underlying fund portfolio. In other words, the active change in risk-taking may be confounded with the asset liquidation decisions. A safer portfolio at time t, for instance, may result from either de-risking behavior to avoid large liquidation costs or from the fund manager selling the riskiest assets first to meet investor redemptions. Notably, as explained in Section III, our risk-taking measures are by construction neutral with respect to flows. If a fund manager liquidates assets proportionally to the holdings, this will not affect our measures. By contrast, if fund managers follow a pecking order in which they sell their liquid assets first, that would work against our finding, thereby suggesting that we are underestimating the magnitude of de-risking. The problematic scenario for our setting is the one in which fund managers sell *illiquid* assets first. Jiang, Li, and Wang (2021) investigate empirically the selling behavior of corporate bond funds hit by redemptions. They find that fund managers liquidate assets proportionally in bad times and sell liquid assets first in good times. This suggests that the scenario that would be problematic for our results is unlikely. Nonetheless, we address the concern presented above in two ways. First, we control parametrically for fund flows by including separately controls for contemporaneous inflows and outflows (see Table A.3 in the Online Appendix). Second, we address this issue non-parametrically by retaining in our sample only funds that receive positive net flows over the period and, therefore, are not selling assets to meet redemptions (see Table A.2 in the Online Appendix). All results remain qualitatively similar.

Additional robustness. In the Online Appendix, we present a host of further robustness tests. Namely, we show that our results are robust to employing four alternative risk models to compute alphas: first, a two-factor model that includes the Vanguard Total Bond Index and the value-weighted stock market return; second, a model that includes the return of the government bond index in excess of the one-month T-bill rate and the spread between the high-yield bond index and the investment-grade bond index from Barclays Capital; third, the value-weighted return of funds in the same investment style; and finally, the previous 12-month fund Sharpe ratio. In the first two cases, we estimate multi-factor models using rolling windows of 24 months to have enough statistical power. The effect on risk-taking ranges from -4% to -10% of one standard deviation, and is always statistically significant at the 1% level (Table A.6). Notably, point estimates tend to differ due to a relatively low rank correlation between alphas computed with different models, which directly affects which funds we classify as laggard. Nonetheless, all estimates are economically significant and most of their confidence intervals overlap with that of our baseline measure.

Furthermore, we show that our results are robust to using alternative empirical specifications, fixed effects, control variables, and cut-offs to define laggard funds (Table A.5).

B The role of incentives

Why do laggard bond fund managers de-risk in anticipation of outflows? In Figure 2, we fit a quadratic function to represent the relation between risk-taking and past performance. This figure reveals that the relation between risk-taking and performance is highly asymmetric: funds decrease risk-taking more in the domain of losses ($alpha < 0$) than they increase risk-taking in the domain of gains ($alpha > 0$). This finding mirrors the shape of the flow–performance sensitivity for bond mutual funds, which exhibits stronger sensitivity in the loss domain (Goldstein, Jiang, and Ng 2017).

We conjecture that the shape of the flow–performance sensitivity, the interest rate environment, and the liquidity of portfolio holdings determine the risk-taking behavior of underperforming fund managers. Previous literature documents that fund characteristics and market liquidity influence the shape of the FPS (Chen and Qin 2017 and Goldstein, Jiang, and Ng 2017). Furthermore, Choi and Kronlund (2018) find that a low-interest rate environment induces bond fund managers to reach for yield. If our results emerge from the shape of the FPS, we should observe that states of the world associated with a more concave sensitivity of flows to performance should generate a stronger incentive for laggard funds to de-risk. By contrast, market states that give rise to reach-for-yield behavior should attenuate the incentive to de-risk. We test these conjectures below.

Table V, Panel A investigates the impact of macroeconomic conditions on the risk-taking of laggard funds. Columns 1 and 2 indicate that market states that foster a search for yield mitigate the extent of de-risking. In periods during which the yield of the one-month Treasury bill is below the sample median, the magnitude of de-risking by laggard funds is less than half. This suggests that the motive for reaching for yield conflicts with the incentive to build a precautionary liquid buffer. Columns 3 to 6 show that funds de-risk more in response to underperformance in turbulent times when liquidity dries up (as measured by VIX and TED spread levels above the sample median). This is in line with previous evidence that indicates that flow-to-performance relations are more concave when the overall market is illiquid (Goldstein, Jiang, and Ng 2017).

Table V, Panel B shows the effect of fund characteristics on risk-taking. We find that debt de-risking is stronger when fund managers have shorter tenure (Columns 1 and 2), when most of a fund's share classes are offered to retail investors (Columns 3 and 4), and for funds that lack a precautionary cash buffer ex ante (Columns 5 and 6). The former finding is consistent with the fact that more inexperienced fund managers are more likely to change portfolio allocation in response to low returns (Greenwood and Nagel 2009). The stronger effect for retail funds is in line with the argument that strategic complementarities matter more for funds oriented toward retail investors, because small investors face greater coordination problems and are less likely to internalize the negative externalities of runs (Goldstein, Jiang, and Ng 2017). Likewise, the lack of a precautionary liquid buffer translates into a more concave flows-to-performance relation. This, in turn, creates a stronger incentive to de-risk portfolios in response to poor performance.

Finally, Table V Panel C explores the heterogeneity in portfolio characteristics. Importantly, illiquid holdings exacerbate the first-mover advantage and the consequent negative externality on the fund (Capponi, Glasserman, and Weber 2020). If a fund could fully cover first-movers' redemptions selling liquid securities (that suffer no fire-sale discounts), there would be no need for preemptive precautionary actions. In line with this argument, we find that funds that have an investment mandate that constrains them to hold high quality assets (Column 1) and funds that invest in securities that have better rating (Column 3) or lower yield (Column 5) do not de-risk in response to underperformance.

All in all, the very factors that increase the concavity of the flow–performance relation and the first-mover advantage also increase the incentive for de-risking behaviors. This is in line with the hypothesis that precautionary motives and concerns about liquidity risk dominate rank-chasing incentives in the context of bond mutual funds.

C Effects of de-risking

The economic incentive for actions to defuse the risk of runs is embedded in the structural liquidity mismatch of mutual funds and is analyzed theoretically in Capponi, Glasserman, and Weber (2020). Because of the first-mover advantage, early movers do not bear the cost of their redemptions but pass it on to slower investors.[20] Due to this cost, slower investors earn lower returns, prompting them to redeem more fund shares. This negative externality stirs a spiral in which greater outflows trigger fire sales that, in turn, generate further outflows. In cases of severe stress, this feedback loop can bring down the fund altogether. Crucially, the fund manager can avert this amplification mechanism by diluting all investors equally (a scenario labelled "ideal swing pricing" by Capponi, Glasserman, and Weber 2020). Yet, different from swing pricing, de-risking requires fund managers to act in anticipation of outflows rather than in response to them. By unloading illiquid securities before redemptions hit, de-risking fund managers force all investors to share the asset liquidation costs equally. This, in turn, mitigates ex ante the incentive of first movers to run – as they cannot unload the cost of their exit on other investors – and prevents the ensuing negative externality. Overall, de-risking behaviors by managers should reduce total redemptions and defuse the risk of redemptions–fire sales loops, thereby supporting fund performance.

In Column 1 of Table VI, we test whether laggard managers successfully mitigate redemption pressure by shifting portfolio holdings towards more liquid assets. In line with this reasoning, we find that a shift towards more liquid securities reduces the magnitude of future outflows. Specifically, laggard funds face future outflows of 1.27% on average. However, a one-standard deviation increase in portfolio liquidity reduces outflows by 0.62% (statistically significant at the 1% level), that is, net outflows are reduced to 0.65% (1.27%-0.62%). Notably, this result has important implications for the finding of FPS concavity. In the analysis of Goldstein, Jiang, and Ng (2017), the actions of fund managers are not modeled

[20] As first movers are liquidated at the end-of-day NAV, whereas the corresponding sales of illiquid assets by the fund may take several days.

empirically, an implicit assumption being that managers of poorly performing funds do not (or cannot) prevent investor outflows. However, our evidence indicates that i.) fund managers respond to the risk of looming redemptions, and ii.) their actions are to a large extent successful at reducing fund outflows. In turn, this indicates that the sensitivity of flows to underperformance (the concavity of FPS) may be higher that previously documented, as it is mitigated by fund managers' precautionary actions.

Columns 2 and 3 of Table VI explore the impact of de-risking on fund returns. Note that a-priori the direction of the effect is ambiguous. On the one hand, tilting portfolio holdings towards liquid assets is costly as the fund manager incurs transaction costs when re-allocating and needs to accept a lower yield for greater liquidity. On the other hand, de-risking funds may be able to meet investor redemptions without resorting to fire sales, thereby avoiding the feedback effect of asset sales on outflows. Laggard funds deliver lower excess and risk-adjusted returns on average (-0.14%). Yet, we find that de-risking behaviors successfully mitigate this negative effect which, in turn, provides an economic incentive for precautionary actions by the manager. In terms of magnitude, the average active increase in portfolio liquidity we observe for high-yield funds in our sample (+0.22 see Column 3 of Panel C in Table V) decreases laggard funds' negative performance by 26% in terms of excess returns (0.036/0.14) and by 28% in terms of alpha (0.039/0.14). These effects are economically meaningful and statistically significant at the 1% level. Our evidence thus supports the argument that laggard funds that time illiquid asset sales can meet (reduced) investor redemptions without resorting to fire sales at deeply discounted prices.

Overall, findings in this section indicate that the corporate bond money management industry has a natural tendency to reduce risk exposure: the riskier funds, on average, shift portfolio allocation towards liquid securities, thereby minimizing the risk of looming runs. This inherent tendency reduces ex ante the risk of fire sales and liquidation spirals that can cause market dislocations.

V. Policy implications

Concerns about the risks to financial stability posed by corporate bond mutual funds have recently been voiced prominently (see, e.g., ESMA 2020). Regulators and academics alike have expressed fears that the liquidity mismatch of bond funds may induce bank-run-like scenarios with severe repercussions for the bond market. The main regulatory measure to ease these concerns has been the approval, in October 2016, of flexible end-of-day net asset values (NAVs), commonly referred to as swing pricing. After a compliance period of two years, flexible NAVs were finally adopted in the U.S. in November 2018.

The empirical evidence on the effectiveness of swing pricing to mitigate the first-mover advantage has been mixed thus far. Lewrick and Schanz (2017) compare U.S. funds pre-November 2018 (not allowed to adjust prices) with Luxembourg funds (allowed to adjust prices) and find that swing pricing dampens outflows in reaction to weak fund performance, but has a limited effect during stress episodes. By contrast, Jin, Kacperczyk, Kahraman, and Suntheim (2022) show that swing prices allow U.K. corporate bond funds to successfully reduce redemptions during periods of stress. From a theoretical standpoint, swing pricing is an imperfect solution to curb the first-mover advantage. Zeng (2017) shows that, even with flexible NAVs, outflows induce predictable voluntary sales of illiquid assets post redemptions to rebuild cash buffers. This behavior, which is optimal for the fund, generates a predictable decline in fund NAV and reinstates the first-mover advantage.

In this section, we explore how the introduction of swing pricing affects debt de-risking. In the previous section, we have shown that, even in the absence of regulation, laggard fund managers face a strong incentive to de-risk their portfolio when redemption risk looms. Notably, this is a market-led corrective mechanism that disciplines the manager. Under-performing managers face a magnified redemption risk due to the concavity of the flow–performance sensitivity. This, in turn, mitigates the incentive to gamble for resurrection that is well documented for equity funds (e.g., Brown, Harlow, and Starks 1996). In the following, we provide evidence for the effect of the introduction of swing pricing on the incentive of laggard funds to de-risk. As a flexible NAV reduces withdrawals in case of underperformance, its introduction may reinstate moral hazard and weaken the incentive to de-risk. Importantly, swing pricing has been thus far adopted by few asset managers in the United States. In particular, a committee representing the asset management companies stated that "significant operational challenges exist today which will likely impede the broad adoption of swing pricing by U.S. open-end mutual funds without material changes to the existing mutual fund-related infrastructure."[21] We have manually checked SEC filings and investor letters from U.S. fund companies: only four of them disclose that they have implemented swing pricing mechanisms for funds domiciled in the United States, which corresponds to 1.1% of the laggard funds in our sample.

In Table VII, we explore the effect of swing pricing on risk for laggard funds. Our objective is to compare the riskiness of laggard funds that can adjust NAVs and laggard funds that cannot adjust NAVs. We consider a laggard fund as "treated" by the introduction of swing pricing from November 2018 onward only if the fund company to which it is affiliated has disclosed the adoption of swing pricing policies in the United States. For this analysis, we consider realized risk (intra-quarter fund return volatility) rather than portfolio allocations, as our eMAXX sample does not cover the year 2019.

We estimate the following specification:

$$Risk_{i,t} = \beta_0 + \beta_1 \; Swing \;\; Pricing_{i,t} + \gamma' X_{i,t-1} + \delta_s + \delta_i + \varepsilon_{i,t}, \quad (5)$$

where $Swing\ Pricing_t$ is a dummy variable that takes a value of 1 from the last quarter of 2018 onward for fund groups that adopted swing pricing. We consider a symmetric sample that includes the four quarters before the treatment quarter (Sep. 2017 – August 2018) and the four quarters after (Jan. 2019 – Dec. 2019). We limit our analysis to the 8 quarters around the introduction quarter, in order not to contaminate the analysis with the effects of the COVID-19 crisis, which started in the first quarter of 2020. We account for the

[21]This quote is from File Number S7-16-15 "Response to Proposal to SEC on Swing Pricing and Transparency for Omnibus Accounts."

possibility that laggard funds that adopted swing pricing may have different investment style by including style fixed effects, δ_s. The coefficient β_1 measures how the incentive to take risk for laggard funds changes with the introduction of the swing pricing regime.

Results in Table VII indicate that the introduction of the swing pricing regime leads laggard funds to increase portfolio risk levels. This evidence suggests that the precautionary mechanism described in this paper is weakened by the introduction of flexible NAVs. In the case where flexible NAVs do not fully prevent outflows, the funds most exposed to fragility will be holding assets that are comparatively more illiquid. Notably, our results are consistent with those of Jin, Kacperczyk, Kahraman, and Suntheim (2022), who make the point that swing pricing reduces outflows, since a reduced liquidity risk is a necessary condition to incentivize risk-taking. There are, however, two important caveats to consider. First, our result is driven by a small subset of laggard funds that adopted flexible NAVs. Second, the adoption of swing pricing is possibly not exogenous with respect to fund risk. The interpretation of this set of findings, therefore, warrants some caution.

VI. Conclusion

In this paper, we show that the incentive structure in the corporate bond fund industry leads managers of laggard funds to rebalance away from risky (high-yielding) bonds to increase average portfolio liquidity *before* redemptions hit. These de-risking dynamics are the opposite of what should occur in the presence of the tournament incentives that are prevalent in the equity mutual fund industry. Overall, we show that a concave shape of the flow-to-performance sensitivity attenuates fund managers' rank-chasing behaviors and incentivizes de-risking.

In support of this claim, we provide evidence that the incentive to de-risk intensifies in bad times, at times when money managers are less likely to reach for yield, when the fund manager is inexperienced, and when the fund exhibits features that accentuate the concavity of the flow–performance relation (such as a low cash buffer or a retail investor base). Notably, the strategic behavior that we uncover in this paper may also be important for other institutions (such as banks, money market funds, and hedge funds), in particular when no lock-in provisions or gates are in place. More broadly, our findings may apply to all financial institutions that share with bond mutual funds a similar mismatch between liquid liabilities and illiquid assets.

Overall, we argue that the incentive structure in the bond fund industry has some desirable features, at least in normal times. By de-risking their portfolios, fund managers reduce the cost of investor runs and fire sales exactly for those funds that are more exposed to fragility ex ante. This precautionary behavior by fund managers could alleviate systemic risk and may help explain why runs on bond funds outside periods of market tension have been thus far sporadic events. Yet, the consequences of de-risking may be less benign in periods of market turmoil if the demand for liquidity gives rise to aggregate sales. Furthermore, we find some evidence that suggests that the introduction of swing pricing may attenuate this market-enforced discipline and reinstate the moral hazard problem that afflicts equity funds. Ultimately, this could lead to an unintended equilibrium in which fragile funds hold relatively more risk. We conclude that further theoretical and empirical research is necessary to assess how to optimally regulate the bond fund industry.

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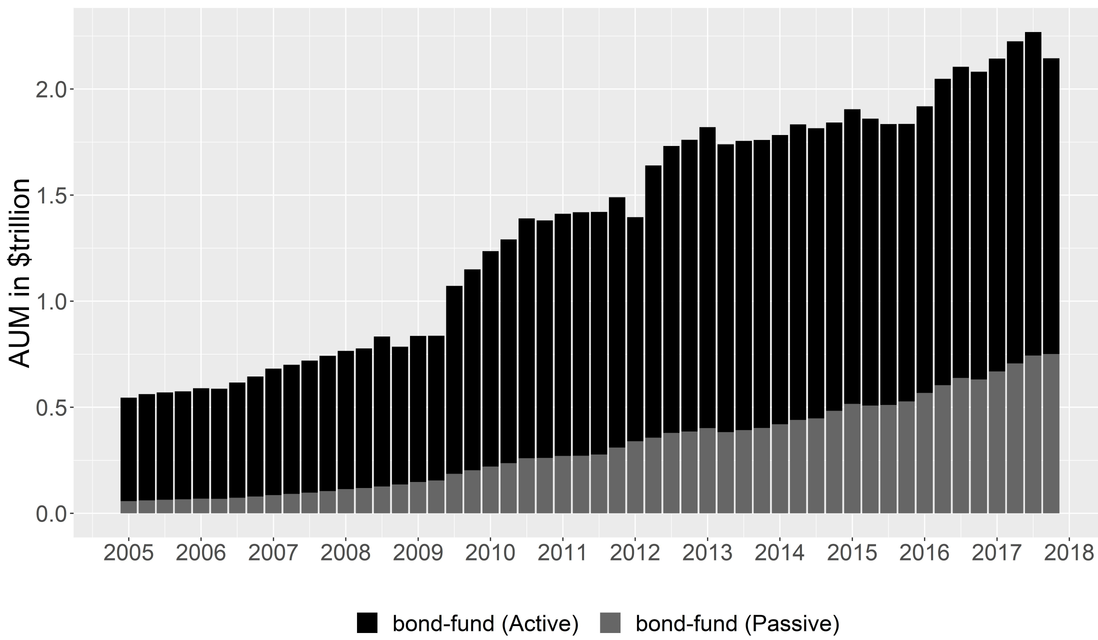
Tables and Figures

(a) Total AUM of corporate bond mutual funds



(b) Relative growth of AUM: equity vs. bond funds

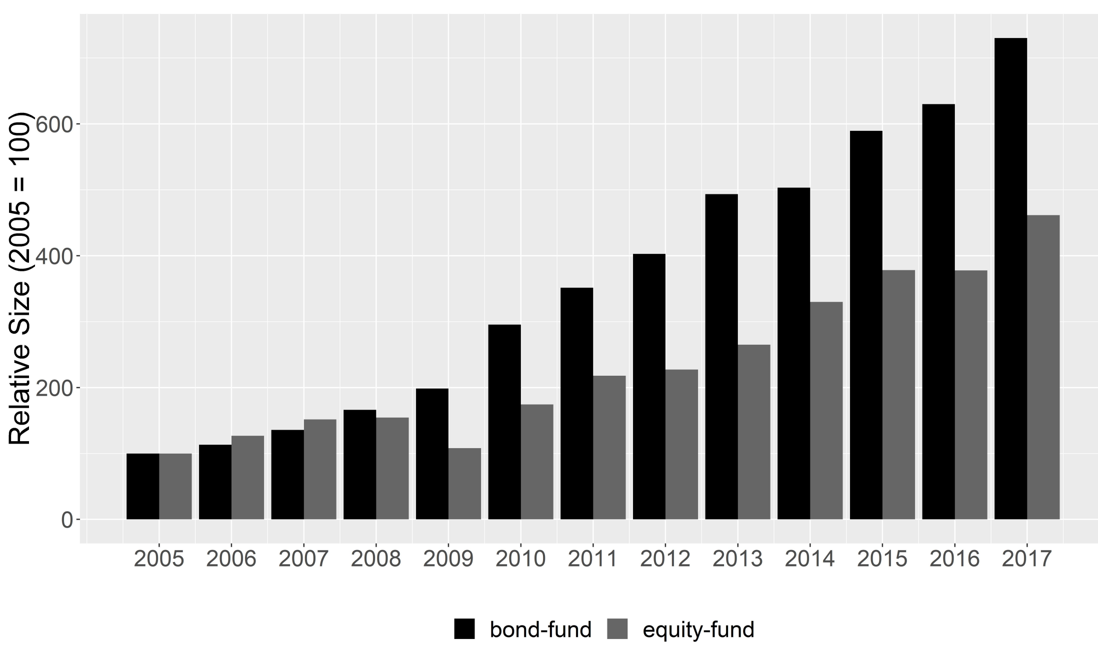
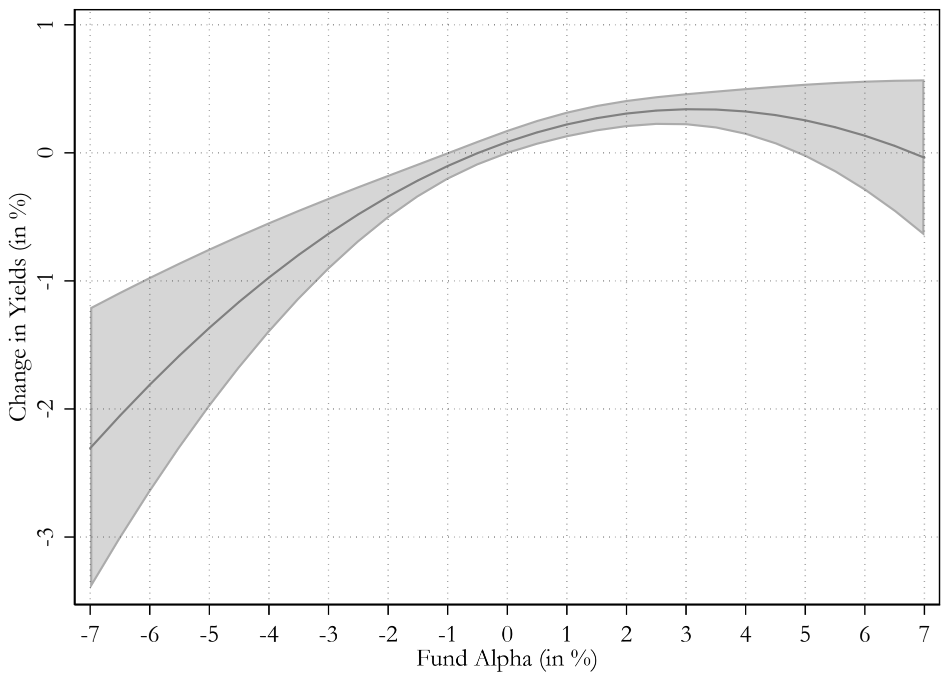


Figure 1: Growth of the corporate bond mutual fund industry

Panel (a) reports the assets under management of active vs. passive corporate bond mutual funds over time. Panel (b) shows the relative growth of the equity and corporate bond mutual fund industry benchmarked against the size in 2005.

(a) Demand for yields



(b) Demand for illiquidity

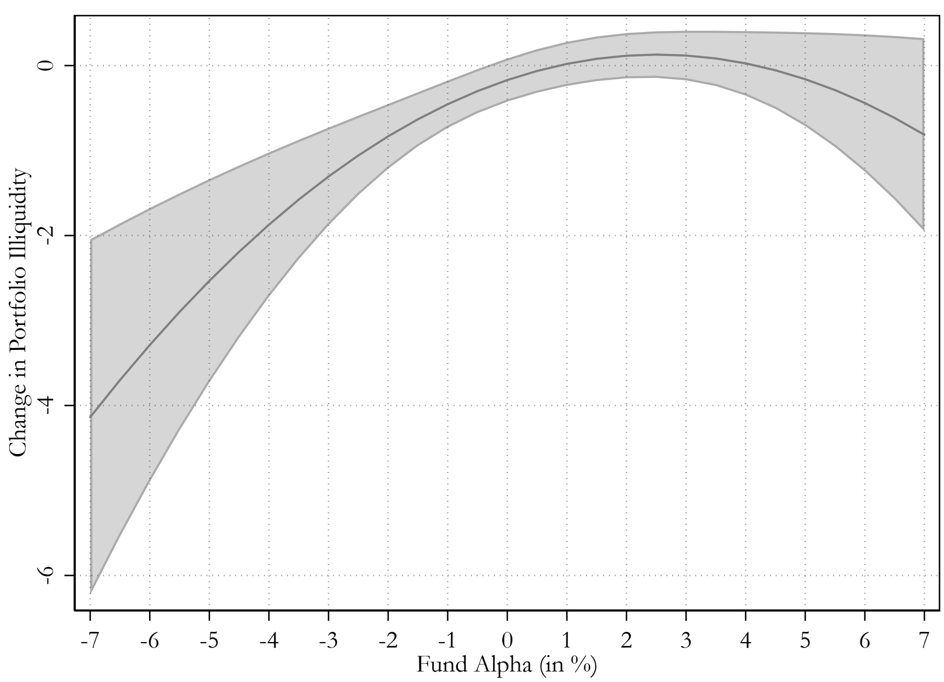


Figure 2: Sensitivity of risk-taking to past fund performance

These figures show the sensitivity of risk-taking to the average fund alpha in the previous 12 months, 95% confidence intervals are plotted. We fit a linear model that relates risk-taking with a second-order polynomial function of fund alpha, the same controls and fixed effects reported in Equation 3 are included. Risk-taking is represented on the vertical axes and computed using Equation 2 on the basis of yields (Panel a), and on the basis of the first principal component of four illiquidity measures: Roll's measure, Amihud's measure, the bid-ask spread, and the interquartile price range (Panel b).

Table I: Summary statistics

This table reports summary statistics for the corporate bond funds in our sample as well as their portfolio holdings. For each variable, we report the number of available observations, the mean, the standard deviation, and the 5th, 25th, 50th, 75th, and 95th percentile. Panel A shows fund characteristics. *Size* is the total assets under management in millions, *Age* is the age of the oldest fund share class in years, *Expense Ratio* is the weighted average expense ratio, *Exit fee* is the rear load charged, *Entry fee* is the front load charged, *Retail Share* is the fraction of shares owned by retail investors, *Cash* is the fraction of cash and government securities held, *Portfolio Rating* is the weighted average of the rating of all bonds held by the fund, *Investment Grade* is the share of funds that invest mostly in low-risk bonds according to Lipper investment objective codes, *Turnover ratio* is the fund turnover ratio, *Fund flows* is the net fund flow in the quarter, *Inflows* (*Outflows*) are defined as $Flows \times I(Flows \geq 0)$ $(-Flows \times I(Flows < 0))$, *Fund excess return* is the quarterly fund return in excess of the risk-free rate, *Fund Alpha* is the quarterly fund risk-adjusted return using the Vanguard Total Bond Index Fund as the risk factor, *Sharpe ratio* is the average 12-month fund excess return over the standard deviation of excess returns, *Realized risk* is the quarterly standard deviation of daily returns, *Laggard Fund* is a dummy variable equal to one if the fund's past 12-month risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. ΔYield, ΔRating, ΔAmihud, ΔRoll, ΔBid–Ask, ΔIQR and ΔMaturity are measures of fund risk-taking computed as explained in equation (2). ΔAmihud, ΔRoll, ΔBid–Ask, and ΔIQR are standardized to have mean of zero and standard deviation of one. Panel B reports the characteristics of the corporate bonds held by the funds in our sample. *Residual Maturity* is the bond residual maturity measured in years, *Duration* is bond duration in years, *Rating* is the best bond rating among those awarded by S&P Ratings, Fitch Ratings, and Moody's. Ratings are converted to a numerical scale where $AAA = 1, AA+ = 2, \ldots, D = 22$.

Panel A: Mutual funds

	N	Mean	Sd.	P5	P25	P50	P75	P95
Size (in millions)	25,037	1,712.01	8,759.75	30.80	121.30	367.30	1,093.70	6,196.90
Age (in years)	25,037	16.32	10.87	3.15	8.83	14.78	21.32	33.91
# share classes	25,037	3.17	2.26	1.00	1.00	3.00	4.00	7.00
Expense ratio (%)	25,037	0.82	0.28	0.37	0.62	0.83	0.99	1.28
Exit fee	25,037	0.01	0.02	0.00	0.00	0.00	0.02	0.05
Entry fee	25,037	0.04	0.01	0.02	0.04	0.04	0.04	0.05
Retail share (%)	25,037	60.12	41.28	0.00	12.24	77.00	100.00	100.00
Cash (%)	25,037	12.75	15.78	0.00	3.27	7.34	19.29	42.66
Portfolio rating	25,037	6.80	4.47	1.73	3.17	4.92	12.09	14.09
Investment grade	25,037	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Turnover ratio (%)	25,037	1.14	1.34	0.22	0.48	0.70	1.12	3.94
Fund flows	25,037	0.01	0.13	-0.13	-0.04	-0.01	0.04	0.18
Inflows (max $[flows_{i,t}, 0]$)	25,037	0.04	0.11	0.00	0.00	0.00	0.04	0.18
Outflows ($-$min $[flows_{i,t}, 0]$)	25,037	0.03	0.05	0.00	0.00	0.01	0.04	0.13
Fund excess return (%)	25,037	0.96	3.29	-2.86	-0.26	0.84	2.26	5.26
Fund alpha (%)	25,037	0.43	3.10	-3.08	-0.30	0.23	1.20	4.48
Sharpe ratio (%)	25,034	0.35	0.44	-0.31	0.03	0.31	0.66	1.09
Realized risk	25,033	0.22	0.29	0.06	0.13	0.19	0.26	0.46
Laggard fund	25,037	0.50	0.50	0.00	0.00	0.00	1.00	1.00
ΔAmihud	25,037	-0.00	1.00	-1.34	-0.29	-0.06	0.22	1.40
ΔRoll	25,037	-0.00	0.99	-1.31	-0.23	-0.02	0.18	1.28
ΔBid-Ask	25,037	-0.00	0.99	-1.27	-0.18	0.03	0.18	1.10
ΔIQR	25,037	0.00	1.00	-1.17	-0.13	0.02	0.18	1.03
ΔRating	25,037	-0.00	0.57	-0.72	-0.11	0.00	0.13	0.64
ΔDuration	25,037	-0.04	0.29	-0.45	-0.11	0.00	0.04	0.30
ΔYield	25,037	-0.00	0.53	-0.44	-0.05	0.00	0.08	0.44

Panel B: Corporate bonds

	N	Mean	Sd.	P5	P25	P50	P75	P95
Residual Maturity (Years)	3,032,521	7.65	7.01	1.25	3.75	6.00	8.50	27.00
Duration	3,032,521	5.24	3.28	1.10	3.18	4.67	6.40	13.00
Bond Rating	3,032,521	9.94	3.85	4.00	7.00	10.00	13.00	16.00
IQR (%)	3,032,521	0.38	0.50	0.08	0.19	0.29	0.44	0.94
Roll Illiquidity (%)	3,032,521	0.54	0.45	0.14	0.29	0.43	0.64	1.25
Amihud Illiquidity (%)	3,032,521	0.36	0.16	0.15	0.25	0.33	0.42	0.65
Bid-Ask Spread (%)	3,032,521	0.53	0.66	0.09	0.22	0.37	0.63	1.41
Bond Yield (%)	3,032,521	5.50	6.04	1.25	3.11	4.78	6.50	10.86

Table II: Laggard funds and risk-taking

This table reports estimates for the effect of performance on fund risk-taking. Risk-taking is defined as:

$$\Delta Risk_{i,t} = \underbrace{\sum_{j=1}^{N_{i,t}} w_{i,j,t} \times Riskiness_{j,t-1}}_{Current\ allocation\ of\ past\ risk} - \underbrace{\sum_{j=1}^{N_{i,t-1}} w_{i,j,t-1} \times Riskiness_{j,t-1}}_{Previous\ allocation\ of\ past\ risk},$$

where $Riskiness_{j,t-1}$ is a proxy of the riskiness of bond j in quarter $t-1$ computed using bond j's liquidity (Columns 1 to 4), rating (Column 5), duration (Column 6), or yield (Column 7). $w_{i,j,t} = \frac{Q_{i,j,t}}{\sum_j Q_{i,j,t}}$ is the relative weight of bond j in fund i's portfolio at the end of quarter t, out of the $N_{i,t}$ bonds held by the fund. $Q_{i,j,t}$ represents the par amount in units of $1,000. We run the following panel regression:

$$\Delta Risk_{i,t} = \beta_0 + \beta_1\ Laggard\ Fund_{i,t-1} + \gamma' X_{i,t-1} + \delta_t + \delta_i + \epsilon_{i,t},$$

where $Laggard\ Fund_{i,t-1}$ is a dummy variable equal to one if the fund's past 12 months average risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. X is a vector of controls: $Log(TNA)$ is the natural logarithm of fund assets; *Expense Ratio* is the fund's expense ratio; *Turnover Ratio* is the fund's turnover ratio. Standard Errors are clustered at the fund level, and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Riskiness is:	Liquidity				Credit	Duration	Yield
	Amihud (1)	Roll (2)	Bid–Ask (3)	IQR (4)	(5)	(6)	(7)
$Laggard\ Fund_{t-1}$	-0.104***	-0.084***	-0.160***	-0.154***	-0.003	0.002	-0.100***
	(-6.95)	(-5.40)	(-9.34)	(-8.78)	(-0.39)	(0.65)	(-10.60)
$Log(TNA_{t-1})$	0.023*	0.029**	0.025**	0.028**	0.019***	0.004	0.020***
	(1.88)	(2.55)	(1.98)	(2.51)	(3.01)	(0.71)	(3.96)
$Expense\ Ratio_{t-1}$	0.077	0.029	-0.007	0.014	0.042	-0.016	-0.015
	(1.04)	(0.36)	(-0.09)	(0.20)	(1.09)	(-0.55)	(-0.36)
$Turnover\ Ratio_{t-1}$	0.001	-0.001	0.004	-0.006	0.001	-0.005	-0.006
	(0.16)	(-0.06)	(0.53)	(-0.90)	(0.16)	(-1.13)	(-1.62)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
R^2	0.070	0.069	0.064	0.065	0.084	0.147	0.063
Observations	25,037	25,037	25,037	25,037	25,037	25,037	25,037

Table III: Tournament incentives vs precautionary concerns

This table reports estimates for the effect of fund performance and relative fund performance on fund risk-taking. Risk-taking is defined as:

$$\Delta Risk_{i,t} = \underbrace{\sum_{j=1}^{N_{i,t}} w_{i,j,t} \times Riskiness_{j,t-1}}_{Current\ allocation\ of\ past\ risk} - \underbrace{\sum_{j=1}^{N_{i,t-1}} w_{i,j,t-1} \times Riskiness_{j,t-1}}_{Previous\ allocation\ of\ past\ risk},$$

where $Riskiness_{j,t-1}$ is a proxy of the riskiness of bond j in quarter $t-1$ computed using bond j's liquidity (Columns 1 to 4), rating (Column 5), duration (Column 6), or yield (Column 7). $w_{i,j,t} = \frac{Q_{i,j,t}}{\sum_j Q_{i,j,t}}$ is the relative weight of bond j in fund i's portfolio at the end of quarter t, out of the $N_{i,t}$ bonds held by the fund. $Q_{i,j,t}$ represents the par amount in units of \$1,000. We run the following panel regression:

$$\Delta Risk_{i,t} = \beta_0 + \beta_1\ R_{i,t-1} + \beta_2\ R^S_{i,t-1} + \gamma' X_{i,t-1} + \delta_t + \delta_i + \epsilon_{i,t},$$

where $R_{i,t-1}$ is the fund's past 12 months average risk-adjusted performance and $R^S_{i,t-1}$ is the fund's past 12 months average risk-adjusted performance minus the 12 months average risk-adjusted performance of the funds in the same investment style. Both variables are standardized to ease the comparison of coefficients. X is a vector of controls: $Log(TNA)$ is the natural logarithm of fund assets; *Expense Ratio* is the fund's expense ratio; *Turnover Ratio* is the fund's turnover ratio. Standard Errors are clustered at the fund level, and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Riskiness is:	Liquidity				Credit	Duration	Yield
	Amihud (1)	Roll (2)	Bid–Ask (3)	IQR (4)	(5)	(6)	(7)
$R_{i,t-1}$	0.098***	0.079***	0.166***	0.163***	0.024***	-0.002	0.121***
	(6.28)	(4.33)	(7.70)	(7.64)	(4.18)	(-0.73)	(10.53)
$R^S_{i,t-1}$	-0.035**	-0.022	-0.063***	-0.041**	-0.015***	-0.003	-0.021*
	(-2.30)	(-1.47)	(-3.79)	(-2.25)	(-2.83)	(-1.10)	(-1.87)
$Log(TNA_{t-1})$	0.020	0.027**	0.020	0.024**	0.018***	0.004	0.017***
	(1.60)	(2.33)	(1.54)	(2.05)	(2.81)	(0.69)	(3.34)
$Expense\ Ratio_{t-1}$	0.079	0.031	-0.004	0.022	0.043	-0.017	-0.007
	(1.06)	(0.40)	(-0.05)	(0.31)	(1.11)	(-0.58)	(-0.16)
$Turnover\ Ratio_{t-1}$	0.002	-0.000	0.005	-0.006	0.001	-0.005	-0.006*
	(0.22)	(-0.03)	(0.65)	(-0.85)	(0.23)	(-1.11)	(-1.66)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
R^2	0.071	0.070	0.067	0.069	0.085	0.147	0.074
Observations	25,037	25,037	25,037	25,037	25,037	25,037	25,037

Table IV: Transaction-level evidence

This table reports estimates for the effect of performance on fund net bond buying. We run the following panel regression:

$$\begin{aligned} Net\ Buying_{i,j,t} \ = \ & \beta_0 \ + \ \beta_1 \ Laggard\ Fund_{i,t-1} \times \ Risky\ Bond_{j,t-1} \ + \\ & \beta_2 \ Laggard\ Fund_{i,t-1} \ + \beta_3 \ Risky\ Bond_{j,t-1} \ + \ \gamma' X_{i,t-1} \ + \ \delta_{J \times t} \ + \ \delta_i \ + \ \varepsilon_{i,j,t}, \end{aligned}$$

where $Net\ Buying_{i,j,t}$ is the quantity of bond j bought by fund i over year-quarter t minus the quantity of bond j sold, scaled by the total quantity of bonds traded by fund i over the same period. Quantities are in par amount units of \$1,000 and the variable is expressed as a percentage. *Laggard Fund* is a dummy variable equal to one if the fund's past 12 months average risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. $Risky\ Bond_{j,t-1}$ is a dummy variable that takes value of 1 if bond j's illiquidity (Columns 1 to 4), credit risk (Column 5), duration (Column 6), or yield (Column 7) in the previous year-quarter is in the top decile. X is a vector of controls: $Log(TNA)$ is the natural logarithm of fund assets; *Expense Ratio* is the fund's expense ratio; *Turnover Ratio* is the fund's turnover ratio. Observations are at the fund–bond–quarter level. Standard errors are clustered at the fund level and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Riskiness is:	Liquidity				Credit	Duration	Yield
	Amihud (1)	Roll (2)	Bid–Ask (3)	IQR (4)	(5)	(6)	(7)
$Laggard\ Fund_{t-1} \times Risky\ Bond_t$	-0.014**	-0.014***	-0.017***	-0.011**	-0.026***	-0.016***	-0.027***
	(-2.54)	(-3.59)	(-3.80)	(-2.33)	(-3.37)	(-2.78)	(-4.95)
$Laggard\ Fund_{t-1}$	0.003	0.003	0.004	0.003	0.004	0.004	0.004
	(1.12)	(1.07)	(1.19)	(0.95)	(1.25)	(1.21)	(1.22)
$Log(TNA_{t-1})$	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.76)	(0.76)	(0.75)	(0.75)	(0.76)	(0.77)	(0.75)
$Expense\ Ratio_{t-1}$	-0.025	-0.025	-0.025	-0.025	-0.025	-0.025	-0.025
	(-1.23)	(-1.23)	(-1.23)	(-1.23)	(-1.22)	(-1.23)	(-1.22)
$Turnover\ Ratio_{t-1}$	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.000
	(-0.31)	(-0.30)	(-0.31)	(-0.30)	(-0.32)	(-0.33)	(-0.32)
Risky Bond Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Issuer × Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
R^2	0.117	0.117	0.117	0.117	0.117	0.117	0.117
Observations	3,032,521	3,032,521	3,032,521	3,032,521	3,032,521	3,032,521	3,032,521

Table V: Heterogeneous de-risking

This table reports estimates for the effect of fund performance on fund risk-taking (measured using Amihud's illiquidity measure). In Panel A, we split the sample in different periods based on the level of 1-month Treasury bill yields, the Cboe volatility index (VIX), and the TED spread. In Panel B, we split the sample on the basis of the length of fund manager's tenure, the fund orientation, and fund cash holdings. Funds are classified as institutional (retail) if the retail share is below (above) the median fund in the sample. Fund cash holdings are classified as high (low) if cash and government bonds as a percentage of total assets are above (below) those of the median fund in the sample. In Panel C, we split the sample on the basis of the Lipper investment objective code, the average bond portfolio rating, and the average bond portfolio yield. IG (HY) indicates funds that hold predominantly low-risk (high-risk) assets. Portfolio averages are value weighted and measured at the end of the previous quarter. We run the following panel regression:

$$\Delta Amihud_{i,t} = \beta_0 + \beta_1\ Laggard\ Fund_{i,t-1} + \gamma' X_{i,t-1} + \delta_t + \delta_i + \epsilon_{i,t},$$

where $Laggard\ Fund_{i,t-1}$ is a dummy variable equal to one if the fund's past 12 months average risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. The control variables are the same as in the baseline specification. Errors are clustered at the fund level, and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Panel A: Market states

	Treasury (yield)		VIX		TED spread	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Laggard fund	-0.063***	-0.144***	-0.029	-0.136***	0.016	-0.201***
	(-2.75)	(-6.86)	(-1.55)	(-6.31)	(0.74)	(-9.20)
Fund Controls	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓
R^2	0.096	0.092	0.114	0.085	0.113	0.081
Observations	11,726	13,290	12,151	12,864	12,119	12,857

Panel B: Manager and fund characteristics

	Manager's Tenure		Fund Orientation		Cash holdings	
	Long (1)	Short (2)	Institutional (3)	Retail (4)	High (5)	Low (6)
Laggard fund	-0.059**	-0.156***	-0.062***	-0.140***	-0.056**	-0.178***
	(-2.30)	(-4.97)	(-3.02)	(-6.18)	(-2.53)	(-7.26)
Fund Controls	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓
R^2	0.114	0.095	0.080	0.079	0.098	0.107
Observations	7,828	7,487	12,513	12,511	12,469	12,494

Panel C: Portfolio characteristics

	Investment Objective		Portfolio Rating		Portfolio Yield	
	IG (1)	HY (2)	Safe (3)	Risky (4)	Low (5)	High (6)
Laggard fund	-0.000	-0.108***	0.010	-0.126***	0.029	-0.219***
	(-0.00)	(-2.98)	(0.47)	(-3.71)	(1.61)	(-6.47)
Fund Controls	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓
R^2	0.098	0.092	0.104	0.116	0.114	0.128
Observations	13,196	11,824	12,509	12,501	12,494	12,490

Table VI: Effects of de-risking

This table reports estimates for the effects of de-risking on quarterly fund outflows, excess returns, and alphas. All dependent variables are multiplied by 100. We run the following panel regression:

$$y_{i,t} = \beta_0 + \beta_1\ \Delta Liquidity_{i,t} \times Laggard\ Fund_{i,t-1} + \beta_2\ \Delta Liquidity_{i,t} + \beta_3\ Laggard\ Fund_{i,t-1} + \gamma' X_{i,t-1} + \delta_i + \delta_t + \varepsilon_{i,t},$$

where $\Delta Liquidity_{i,t}$ is the active change in portfolio allocation towards liquid assets based on the Amihud liquidity measure as defined in Section III. *Laggard Fund* is a dummy variable equal to one if the fund's past 12 months average risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. *Flows* are net fund flows over the period, *Excess return* is the quarterly fund return in excess of the risk-free rate, *Alpha* is the quarterly fund risk-adjusted return using the Vanguard Total Bond Index Fund as market factor. X is a vector of controls: *Log*(TNA) is the natural logarithm of fund assets; *Expense Ratio* is the fund's expense ratio; *Turnover Ratio* is the fund's turnover ratio. Errors are clustered at the fund level, and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Dependent variable:	Flows	Excess return	Alpha
	(1)	(2)	(3)
$\Delta Liquidity_t \times Laggard\ Fund_{t-1}$	0.618**	0.165***	0.177***
	(2.07)	(2.70)	(2.96)
$\Delta Liquidity_t$	0.041	0.040	0.032
	(0.20)	(1.25)	(1.05)
$Laggard\ Fund_{t-1}$	-1.274***	-0.140***	-0.141***
	(-5.09)	(-4.84)	(-4.93)
$Log(TNA_{t-1})$	-3.514***	-0.181***	-0.185***
	(-11.24)	(-4.21)	(-4.36)
$Expense\ Ratio_{t-1}$	-6.975***	-0.348*	-0.339
	(-3.64)	(-1.72)	(-1.61)
$Turnover\ Ratio_{t-1}$	0.517***	0.013	0.014
	(2.59)	(0.67)	(0.74)
Time Fixed Effects	✓	✓	✓
Fund Fixed Effects	✓	✓	✓
R^2	0.149	0.509	0.509
Observations	25,037	25,037	25,037

Table VII: Swing pricing and fund risk

This table reports estimates for the effect of the introduction of flexible NAVs (swing pricing) on realized risk. We run the following regression:

$$Risk_{i,t} = \beta_0 + \beta_1 \; Swing\ Pricing_{i,t} + \gamma' X_{i,t-1} + \delta_s + \delta_i + \varepsilon_{i,t},$$

where $Risk_{i,t}$ is the standard deviation of daily fund returns in year-quarter t. The time window includes the four calendar quarters before and after the introduction date (November 2018). $Swing\ Pricing_{i,t}$ is a dummy variable that takes a value of 1 from the last quarter of 2018 onward for funds that disclosed the adoption of swing pricing. *Only laggard funds are included.* Laggard funds are funds whose past 12 months average risk-adjusted performance ranks in the bottom half at the beginning of the year-quarter. X is a vector of controls (the same control variables as in the main specification are included). Errors are clustered at the fund level, and t-statistics are reported in parentheses below the coefficients. ***, **, *, indicate statistical significance at the 1%, 5%, and 10% respectively.

Dependent variable:	Risk (in %)	
	(1)	(2)
$Swing\ Pricing_t$	0.018***	0.032***
	(4.16)	(4.55)
$Log(TNA_{t-1})$	0.003**	-0.013**
	(2.05)	(-2.54)
$Expense\ Ratio_{t-1}$	-0.026*	-0.238***
	(-1.91)	(-4.33)
$Turnover\ Ratio_{t-1}$	0.000	-0.013***
	(0.27)	(-7.74)
Style Fixed Effects	✓	✓
Fund Fixed Effects		✓
R^2	0.379	0.759
Observations	2,166	2,166

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