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Debt De-risking

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Debt De-risking*

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Abstract

We examine the incentive of corporate bond fund managers to manipulate portfolio risk in response to competitive pressure. We find that bond funds engage in a reverse fund tournament in which laggard funds actively de-risk their portfolios, trading-off higher yields for more liquid and safer assets. De-risking is stronger for laggard funds that have a more concave sensitivity of flows-to-performance, in periods of market stress, and when bond yields are high. We provide evidence that debt de-risking also reduces ex post liquidation costs by mitigating the investors' incentive to run ex ante. We argue that, in the presence of de-risking behaviors, flexible NAVs (swing pricing) may be counter-productive and induce moral hazard. (*JEL Codes:* G11, G23, G32, E43)

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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 under-performing managers increase their risk levels, gambling to improve their ranking against other managers. This attempt to manipulate performance is consistent with the economic incentives that are provided by investor behavior. In fact, Chevalier and Ellison (1997) and Sirri and Tufano (1998) find that investor flows are less sensitive to under-performance than to out-performance.[1] This implies that, by taking extra risk, under-performing fund managers face an asymmetric pay-off: the potential upside in terms of climbing in the rankings and attracting new flows is large, whereas the downside risk is more contained.

While there is consensus on how competition influences the risk-taking of *equity* mutual funds, little is known on the implications for corporate *bond* mutual funds. The strategic actions of bond funds in response to looming competitive threats are important for three reasons. First, the bond fund industry has experienced unprecedented growth in recent years, with many new funds launched and incumbent funds growing in size (see Figure 1). This expanding supply of available investment vehicles has put fund managers in a tough spot to deliver out-performance. Second, there is an inherent liquidity mismatch which may pose a threat to financial stability: corporate bonds are an illiquid class, while the funds themselves promise to their shareholders liquidity at all times. Fragilities may then quickly unravel in fire-sale episodes.[2] Finally, bond funds can be used as a laboratory to improve our understanding of competitive incentives for other market participants (such as banks and hedge funds) that share a similar liquidity mismatch but are more complex and

[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), or the remarks given in June 2019 at the Bank of England by the former governor Mark Carney, according to whom investment funds that hold illiquid assets but offer daily redemptions to investors are "built on a lie."

somewhat less transparent.

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 for the decrease in assets under management (AUM) 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 generates 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. Corporate bonds are notoriously difficult to trade, requiring a significant amount of intermediation by dealers. To find a matching opposing interest at a fair price may sometimes take several days, if not weeks. Offloading large portfolio positions to dealers can therefore be difficult. This means that sudden investor withdrawals may therefore force the fund manager to execute fire sales that impose severe negative externalities on slow-moving investors. This, in turn, magnifies outflows in response to bad performance giving rise to a flow-to-performance sensitivity (FPS) that has *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 holdings tend to be more liquid. By contrast, in the context of corporate bond funds, both relative fund performance and possible share value dilution are important determinants of investor flows. 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: Out-performance only rewards the fund with mild inflows, whereas under-performance leads to large-scale redemptions.[3] The main

[3]Notably, most mutual funds charge fees on the assets under management rather than on performance. Therefore, the best strategy from a profit-maximizing perspective is that of attracting as much dollar flows as possible (irrespective of actual performance).

goal of our paper is to explore how these considerations impact risk-taking decisions by bond fund managers.

We begin our analysis by exploring how bond fund managers adjust their asset allocation on the basis of relative performance. Our core finding is that laggard funds, i.e., funds that under-perform their peers, actively de-risk their debt portfolio. This is achieved by tilting portfolio allocation towards securities that pay lower yields but are more liquid and have better ratings. We confirm our findings providing transaction-level evidence that laggard funds purchase (sell) bonds that are of higher (lower) liquidity than the average bond in their portfolio. The flip side of the coin is that this demand for liquidity forces laggard funds to hold lower-yielding bonds. This gives rise to a reverse tournament: As realized under-performance leads to investor redemptions, fund managers attempt to alleviate ex ante liquidation costs accepting to hold less profitable securities. Notably, these dynamics are the exact opposite of those documented in equity mutual fund tournaments, whereby loser funds increase risk-taking and winner funds de-risk. In the bond fund context, the threat of investor runs appears to dominate over the desire to increase performance, in line with the incentive structure created by the concave shape of the sensitivity of flows to performance.

Next, we explore how fund characteristics and market conditions influence the incentives of laggard funds to de-risk. First, we document that de-risking is inversely U-shaped. Both the top- and the worst-performing funds decrease risk levels. However, they do that asymmetrically: under-performers decrease risk-taking significantly more than top performers. Second, we show that young funds and retail funds—which tend to have more concave FPS—de-risk more in response to bad performance. Third, funds that have lower precautionary cash buffers de-risk more, as the incentive to flee for havens is mitigated. We also show that the strength of these effects depends on market conditions: our results are significantly stronger in periods of market stress and when the level of bond yields is higher.

We provide evidence that the decision by corporate bond fund managers to de-risk ex-ante is generally quite effective in averting investor runs. In particular, we document that laggard funds that decrease risk-taking more decisively, experience milder subsequent outflows. This finding suggests that investors take into account fund portfolio's riskiness when deciding whether to pull their money out. Back-of-the-envelope calculations indicate that a one-standard-deviation decrease in risk-taking corresponds to a decrease of net outflows from laggard funds by 50%. 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 by itself 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 reduce risk-taking thereby making runs less likely. Notably, even in the case in which runs on funds do occur, fund managers end up holding more liquid assets. This helps to avert the risk of an adverse feedback loop scenario in which funding liquidity shocks and evaporating asset liquidity reinforce each other in a downward spiral (see, e.g., Brunnermeier and Pedersen (2009)). Such inherent de-risking incentives in turn raise the hurdle for regulatory intervention. These findings are consistent with the anecdotal observation that, outside of periods of market turmoil, actual runs on bond mutual funds have been infrequent events with limited repercussions on other market participants.[4]

Our findings have policy implications. In October 2016, the U.S. Securities and Exchange Commission (SEC) adopted 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 non-redeeming investors. We find that swing pricing may reinstate the moral hazard problem documented for equity funds, i.e., under-performers end up having an incentive to take more risk. In line with this argument, we show that managers of poorly-performing bond funds maintain high risk levels (or further increase them), as the

[4]The most notable exception is that of the Third Avenue Focused Credit Fund (FCF). FCF was forced to halt redemptions and close down 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).

sensitivity of flows to under-performance is mitigated. Overall, in equilibrium, adverse industry shocks may have more serious consequences in a scenario with swing pricing, as the most vulnerable funds end up holding riskier and more illiquid assets.

This paper contributes to three strands of literature. First, our paper fits into the large 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 destabilizing effects of runs on non-bank institutions, such as, for instance, money market funds (e.g., 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)). Closely related to our paper, Morris, Shim, and Shin (2017) show that funds hoard cash in response to redemptions, which amplifies fire sales, whereas Chernenko and Sunderam (2020) find that fund cash buffers are not enough to fully internalize the cost of outflows. In this regard, 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 research adds to a large literature on mutual fund tournaments. In particular, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998), among others, provide evidence of convexity in the sensitivity of flows-to-performance for equity funds. Convex flows-to-performance creates an incentive for laggard funds to engage in tournaments, as it provides an option-like pay-off from gambling. Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Kempf and Ruenzi (2008) provide empirical evidence for tournament behaviors in the equity fund industry by showing that under-performing funds take more risk than out-performing funds. Schwarz (2011) argues that the results supporting the tournament hypothesis may arise mechanically, as an effect of considering changes in the standard deviation of fund returns instead of changes in holdings. However, the author confirms the presence of tournament behaviors after correcting for this sorting bias. We contribute to this literature by exploring tournament dynamics for bond mutual funds. Specifically, we focus on portfolio-level measures of risk-taking that are immune to the concerns raised by Schwarz (2011). We find that bond mutual funds risk-taking behavior is the exact opposite of that of equity mutual funds, as laggard funds de-risk their portfolio rather than increase risk-taking.

Finally, our results contribute to the growing literature on bond mutual funds. Bond mutual funds are relevant from a financial stability perspective. For example, Manconi, Massa, and Yasuda (2012) show that fixed income investors contributed to propagate the effects of the 2008 Financial Crisis. Ellul, Jotikasthira, and Lundblad (2011) find that regulation-induced bond sales create asset price dislocations, and Shek, Shim, and Shin (2015) show that discretionary selling by emerging market bond mutual funds reinforces the effect of fire sales. Furthermore, Becker and Ivashina (2015), Barbu, Fricke, and Moench (2016), Hau and Lai (2016), Di Maggio and Kacperczyk (2017), and Choi and Kronlund (2018) show in different settings that the low-rate environment leads asset managers to reach for yields. Closely related to our paper, Jiang, Li, and Wang (2017) document the existence of a pecking order for liquidating assets in response to investor redemptions. While the authors investigate asset manager decisions *after* the fund is hit by investor redemptions, our focus is on what happens *before*. We make sure in several ways that our results are not driven by outflows-induced sales. Although not the main focus of their paper, Choi and Kronlund (2018) explore the effect of fund performance on reaching for yields at the end-of-the-year mark. They find weak evidence of increased reaching for yields. Our focus is different, as we examine the strategic response to relative under-performance to mitigate the risk of runs. To the best of our knowledge, we are the first to document a strong demand for liquid assets by under-performing bond funds.

II. Hypotheses development

The presence of complementarities among investors gives rise to a multiplier effect that amplifies the impact of under-performance 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 *static* 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 attempt to predict each others actions. Notably, runs on the fund are costly for fund managers because large outflows negatively impact reputation, career opportunities and, in the worst-case scenario, may lead to contract termination and job loss. If under-performing fund managers are rational, they should act promptly to diffuse the risk of large-scale redemptions. We hypothesize three scenarios:

- *H0: No risk manipulation for competitive reasons.* There is mounting evidence that asset managers reach for yields in a low interest rate environment (Becker and Ivashina (2015), Barbu, Fricke, and Moench (2016), Hau and Lai (2016), Di Maggio and Kacperczyk (2017), and Choi and Kronlund (2018)). Under this view, managers compensate for the subdued yield environment by moving further out in the credit and maturity spectrum. *H0* states that the incentive to hunt for yields created by the low rate environment overshadows any effects stemming from competitive considerations. This implies that, once we control for common determinants of risk-taking at the macro level, the *relative* position of a fund manager against its peers plays no role in determining the risk she takes on.

- *H1: Shrouding risk.* As under-performance triggers large-scale redemptions, laggard funds may choose to artificially inflate their returns by increasing risk-taking. If investors cannot fully distinguish *alpha* from *beta*, fund managers can "fool" investors and move up in the rankings by tilting their portfolios toward riskier assets. For instance, fund managers could replace safer assets with assets that fall within the same rating bucket but offer higher yields — 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 are notoriously hard to price. The relative opaqueness of the asset class, in turn, makes it harder for investors to monitor manager's 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 (2019)). All in all, managers of funds that are ex ante more exposed to fragility concerns may engage in deceptive behaviors that increase the risk of the debt portfolio but might attenuate investor concerns about performance and, in turn, dissuade them from leaving the fund.

- *H2: Debt de-risking.* Alternatively, laggard funds could de-risk their portfolio when they foresee a run, shifting asset allocation towards liquid securities that would suffer lower liquidation costs in the case of forced sales. Divesting illiquid securities and replacing them with liquid securities *before the run occurs* has two advantages. First, if the run does happen, the fund manager is able to redeem exiting investors by selling liquid assets for which there is no fire-sale discount. By doing that, the manager minimizes both the negative externalities to the remaining investors and the resulting under-performance of the fund. Second, portfolio de-risking has the added benefit of mitigating the first-mover advantage among exiting investors, in turn alleviating the incentive of investors to run in the first place. In fact, 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 (as long as the de-risking trades are not crowded). In fact, 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 need data on mutual fund performance, fund portfolio allocations, and asset risk. We obtain data for our analysis from a variety of sources. For corporate bond fund portfolio allocations, we rely on Thomson Reuters Lipper eMAXX. 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. eMAXX retrieves this information from compulsory disclosure to the regulator. Our sample spans from January 2004 to December 2017. To assess the quality of the data, we compare eMAXX with the Federal Reserve Economic Data (FRED). 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 2). The difference between the eMAXX and the FED data stems from the fact that eMAXX does not include the holdings of most banks, hedge funds, proprietary trading firms, and retail investors. This percentage of bonds not covered by eMAXX has been decreasing over time, as banks have been shrinking their corporate bond inventory as they reduced market making activities. We compare a number of randomly selected snapshots of portfolio holdings with regulatory filings to confirm the quality of the data.[5] The eMAXX 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).[6]

We match fund portfolios in Reuters eMAXX with fund information from CRSP mutual funds by fund name. The sample is restricted to funds that hold only or mostly corporate bonds.[7] We impose a number of additional filters. First, for a fund to be included, we require

[5] Notably, we use information on portfolio holdings from eMAXX rather than from CRSP, as reported portfolio holdings in the latter appear unreliable (see Figure A.1 in the Online Appendix).

[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",

at least two years of history, a minimum of 50% of assets invested in corporate bonds, and a number of bonds that exceeds the 5th 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 aggregate information and performance from different share classes at the fund level.[8] We use CRSP to obtain information on the assets under management, inception date, fund fees, fund clientele, performance, and rear loads (as, different from the information on portfolio holdings, these variables appear consistent across databases). Overall, we have data on 702 unique U.S.-domiciled corporate bond funds in the 2004–2017 period for a total of 2,106 different share classes.

We exploit regulatory filings collected by eMAXX and transaction-level data from TRACE to construct our measures of riskiness and liquidity of fund portfolio holdings. More specifically, we use the eMAXX data to obtain ratings, issue, and maturity date. We use market-level information from TRACE to gather information on yields, market prices, and volumes. The exact procedure to build each liquidity measure is described in detail in the Online Appendix.[9]

"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 must be in the set "CBD", "CHY".

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

[9]Notably, as TRACE and Mergent FISD cover corporate bonds only, our measures of risk that focus on yields and bond liquidity are based on corporate bond holdings only. This is a limitation of our approach that is common to other papers as well (see, e.g., Jiang, Li, and Wang (2017)). Conversely, measures of risk based on ratings and maturity consider all bonds (government securities included), as we rely on eMAXX.

B Fund flows and performance

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

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

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. As it is standard in the literature, we winsorized this variable at the 1% and 99% level. We confirm in subsection C of the Online Appendix that the flow-performance sensitivity is concave for the bond funds in our sample in line with Goldstein, Jiang, and Ng (2017).

To measure mutual fund performance, we compute the average risk-adjusted monthly fund return (*alphas*) in a 24-month window. We define a fund as *Laggard Fund* when its two-year monthly average risk-adjusted return at the beginning of a quarter-period is below the quarter median.[10] Following Goldstein, Jiang, and Ng (2017), we estimate fund alphas by regressing monthly fund share class excess returns on the excess returns on the Vanguard Total Bond Index Fund and the value-weighted equity market portfolio. We then aggregate share classes' alphas at the fund level by computing the value-weighted average risk-adjusted return, weighted by the assets under management at the beginning of the month for each share class. The reasons why we use these benchmarks are mainly two: first, we want to be consistent with the empirical approach adopted in Goldstein, Jiang, and Ng (2017); second, recent research shows that common risk factors drive both stock and bond returns (e.g., Koijen, Lustig, and Van Nieuwerburgh (2017)). Naturally, any method to account for risk is exposed 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

[10] In the Online Appendix, we consider alternative cut-offs.

driven by past fund performance adjusted by the market benchmark, and investors rarely use more sophisticated models to account for risk (see Barber, Huang, and Odean (2016) and Berk and Van Binsbergen (2016) for equity funds, and Dang, Hollstein, and Prokopczuk (2019) for bond funds). 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 a number of alternative specifications, length of the performance windows considered, and benchmarks (see the Online Appendix).

C Measuring corporate bond fund 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 of the year (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)).[11] 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: a) the average riskiness of the portfolio at time $t-1$ and b) 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 final measure arise entirely from variations in the weight given to different bonds. In this way, we make sure that our measure does not vary due to changes in the riskiness of the assets that are outside of the fund manager's control (e.g., if a bond is downgraded by

[11] This problem is arguably going to be magnified in our setting, as under-performing 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 her portfolio allocation.

some notches). Formally,

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

where $\Delta Risk_{i,t}$ measures the *active* rebalancing of the portfolio of fund i during quarter t to increase or decrease risk. $Riskiness_{j,t-1}$ is a proxy of the riskiness of bond j in quarter $t-1$ computed using i) bond ratings, ii) bond yields, iii) bond maturity, or iv) bond liquidity. $w_{i,j,t} = \frac{P_{j,t_0} Q_{i,j,t}}{\sum_j P_{j,t_0} Q_{i,j,t}}$ 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. $P_{j,t_0} Q_{i,j,t}$ represents the par amount in units of \$1,000. Notably, an advantage of our data is that eMAXX reports the notional amounts rather than the market value of assets held by the funds. Therefore, we do not need to adjust for changes in relative weights resulting from price fluctuations rather than from manager's decisions.

Importantly, this measure is flow-neutral: 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 not change.

To define $Riskiness_{j,t-1}$, we resort to several measures. *Rating* is the highest credit rating among those assigned by Standard and Poor's, Moody's, and Fitch (similar to Hand, Holthausen, and Leftwich (1992)); *Yield* is the average bond yield; and *Maturity* is the average remaining bond maturity in months. Furthermore, we consider four measures of portfolio liquidity: the inter-quartile range (IQR), the Amihud (2002)'s and Roll (1984)'s liquidity measures, and the Bid–Ask spread. Additionally, we present results using the first principal component of these four liquidity measures (see the Online Appendix).

Summing up, our measure of risk-taking presents four key advantages with respect to alternative measures used in the literature. First, it is not affected by sorting bias of the type described in Schwarz (2011). Second, it is not 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 riskiness that are outside of the fund manager's control. Fourth, it is not mechanically affected by flows into and out of the fund. Overall, our measure is similar in spirit to previous measures of active rebalancing for portfolios of stocks (see, e.g., Huang, Sialm, and Zhang (2011), Curcuru, Thomas, Warnock, and Wongswan (2011), and Greenwood and Thesmar (2011)).

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 $1.72 billion in assets, has a track record of 16 years, and offers more than 3 share classes. Funds in our sample invest mostly in corporate debt and government securities, with the average fund investing 66% and 24% of the AUM in corporate and government bonds, respectively. Bond funds have received an average 1% net inflow per quarter over our sample period. Fund alphas are slightly positive, the median fund earns an average 0.04% a month in the previous 24-month window, which is in line with recent results reported in Clare, O'Sullivan, Sherman, and Zhu (2019).[12] Notably, the average change in risk-taking of bond funds from one quarter to the next is small. For example, on average, funds actively decrease their portfolio yields by 0.02% percentage points. The average change in risk-taking measured by bond ratings is -0.02, i.e., for a hypothetical portfolio of 1,000 bonds with the same nominal value all rated BB, 20 bonds are replaced with bonds rated BBB.[13] 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.

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

[13]Recall that $\Delta Rating = 1$ would suggest that the entire portfolio is replaced with bonds which are one notch lower rated (e.g. from BBB to BB).

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 10 (i.e., BBB). Furthermore, corporate bonds have on average a yield of 5.72%, pay a coupon rate of 6.29%, and have a nominal outstanding amount of almost $1 billion. Overall, our sample statistics are in line with the related literature (see, e.g., Jiang, Li, and Wang (2017)).

IV. Empirical results

A Reverse tournaments: risk shrouding vs. debt de-risking

Main results. Even in the presence of fixed compensation of fund managers, the concavity of the flow-performance relation gives rise to an asymmetric incentive structure. Bond funds' pay-off resembles that of selling a put option where the underlying asset is fund performance and the reward is additional net flows: A higher performance in the gain domain leads to mild increases in inflows. By contrast, a lower performance in the loss domain gives rise to large-scale redemptions. To meet such outflows, managers may need to liquidate bonds at fire sale prices, thereby bringing down further fund performance and leading to more outflows. This, in turn, may set in motion an adverse feedback loop whereby outflows and under-performance reinforce one another. The incentive of fund mangers to avoid this downside risk is even magnified when their compensation is tied to performance (which is the most common case in practice, see Ma, Tang, and Gómez (2019)).

In this section, we explore whether this put-like feature of bond fund pay-off gives rise to strategic allocation decisions depending on how the fund ranks against competitors. Specifically, we contrast three hypotheses as laid out in Section II. First, the ranking of the fund is irrelevant for risk-taking (*H0: No risk manipulation*). Second, laggard funds have an incentive to tilt portfolio allocation towards high-yield securities while hiding risk (*H1: Shrouding risk*). Third, laggard funds flee to havens, actively de-risking their debt portfolios

(*H2: Debt de-risking*). To disentangle between these hypotheses, we run the specification below:

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

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. We measure risk based on the actual portfolio composition in terms of, respectively, i) bond yields, ii) ratings, iii) liquidity, and iv) maturity. $Laggard\ Fund_{i,t-1}$ is a dummy variable that takes a value of 1 if the fund's 24 months average risk-adjusted performance is below the median of the distribution in quarter $t-1$.[14]

We include in our specifications a number of co-determinants of risk-taking and performance, $X_{i,t-1}$. We consider the same variables as in Goldstein, Jiang, and Ng (2017) with the exception of time invariant controls, which are redundant in our specifications as we include fund fixed effects δ_i. Fixed effects are important in our setting. Year-quarter fixed effects, δ_t, account for common factors to which all funds are exposed in a given period (e.g., state of the economy, interest rates level, yield curves). Fund fixed effects absorb fund invariant unobservables that may influence risk-taking (e.g., investment mandate, fund manager compensation contract features, the presence of rear loads). We present results obtained excluding fund fixed effects in the Online Appendix.

We are especially interested in assessing how fund managers manipulate risk-taking when their fund starts to under-perform. The coefficient β_1 captures how risk-taking responds to a change in its relative performance over and above its average risk-taking. A coefficient $\beta_1 = 0$ would indicate that bond funds do not respond to competitive incentives on average, in line with *H0*. A positive coefficient $\beta_1 > 0$ would signal that laggard funds increase portfolio

[14] Notably, we do not focus on the 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 updates on the performance achieved, 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 that there is no strong adjustment in risk-taking in the last semester of the year.

risk, consistent with *H1*. Notably, a $\beta_1 > 0$ for all measures of risk would indicate that bond funds act analogously to equity funds: under-performing funds take relatively more risk. 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 increasing underlying expected portfolio returns. Finally, a negative coefficient $\beta_1 < 0$ would indicate that laggard funds de-risk their portfolio, in line with *H2*.

Table II reports our main finding: competitive forces lead laggard funds to actively de-risk their portfolios. Column 1 shows that portfolio managers tilt their portfolios towards lower-yielding assets, consistent with *H2*. This is achieved by increasing the average quality of the assets held as measured by their ratings (see Column 2), and by tilting portfolio holdings to more liquid securities (see Columns 3 to 6). By contrast, the average effect on maturity is not significantly different from zero (Column 7). This set of results suggest that the documented flight-to-quality is driven by the attempt to reduce liquidation concerns—as both liquid and high-rated securities are less affected by liquidity shocks (Chen, Lesmond, and Wei (2007)). By contrast, an attempt to reduce interest rate risk would arguably also trigger a shift towards lower maturities as well. The magnitude of the de-risking is large, laggard funds decrease the average portfolio yield by 5.7 basis points, which corresponds to 9.5% of one standard deviation in our sample (statistically significant at the 1% level) or to slightly more than twice the average change in risk levels. This finding shows that the incentive structure is different from the equity money management industry, where the worst-performing managers gamble to improve their rankings. Overall, the incentive to mitigate ex ante the cost of potential investor runs dominates over the incentive to improve fund performance. This sets the stage for a "reverse tournament" in which losing funds are willing to trade higher yields for reduced liquidation costs, thereby mitigating the first-mover advantage.

De-risking or liquidation pecking order? Notably, in our setting under-performance 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 asset allocation due to competitive pressure is confounded with the asset liquidation decisions. For example, a safer portfolio at time t may result by either a flight-to-quality to avoid large liquidation costs or by the fact that the fund manager sells 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 her 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 under-estimating the extent of de-risking. The problematic scenario for our setting is the one in which fund managers sell illiquid assets first. Jiang, Li, and Wang (2017) investigate empirically the selling behavior of corporate bond funds hit by redemptions. They find that fund managers liquidate asset 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 reinforce our analysis in two ways. First, we control parametrically for fund flows in all our regressions by including separately inflow and outflow controls. Second, we address this issue non-parametrically by retaining in our sample only funds that experience positive net flows and, therefore, by construction are not forced to sell assets for liquidity reasons (see Table A.3 in the Online Appendix). All the main results remain qualitatively similar. Overall, we conclude that, in the bond space, under-performing funds actively de-risk their portfolios.

Shape of the risk-taking—performance sensitivity. In Figure 3, we illustrate the relation between risk-taking and fund alpha. We do so by fitting a quadratic function. This figure reveals the relation between risk and performance to be inversely U-shaped: risk levels are unaffected by past returns as long as they meet or just exceed market benchmarks. However, large deviations from benchmarks (both positive and negative) lead to meaningful reductions in risk-taking, which are significantly larger in the loss domain. Interestingly, the relation between performance and risk-taking for out-performers is similar to that documented for equity funds: star funds have a limited benefit from further increasing returns and, therefore, decrease risk-taking to consolidate their position.

Absolute vs. relative performance. In practice, due to the inclusion of time fixed effects, our analysis compares how funds manipulate performance in response to their relative performance *against that of other funds*. In Table A.6 of the Online Appendix, we examine whether the documented de-risking is mostly driven by relative or absolute under-performance. This analysis is useful to understand whether competitive considerations are important or fund managers decide risk levels "in isolation," based only on their returns and regardless of how peer funds perform. To do that, we exclude time fixed effects and compare the effects of fund alpha and relative fund alpha (i.e., fund alpha minus the average fund alpha in the quarter). Both variables are standardized to make coefficients comparable. We find that both variables are economically and statistically significant, thereby suggesting that both competitive considerations and absolute under-performance lead laggard funds to de-risk. In the Online Appendix, we present a large number of robustness tests.[15]

Transaction-level evidence. We further zoom in on our previous results and conduct an analysis of fund de-risking at the transaction level. Specifically, we investigate the asset selling and buying behavior of laggard funds conditional on asset liquidity and yields. This analysis is useful to gather further insight into how laggard funds achieve a lower exposure to risk. In principle, a shift towards a more liquid portfolio may be achieved in a number of ways. Fund managers could i) purchase liquid assets, ii) sell illiquid assets, or iii) do both. Alternatively, fund managers could simply expand cash reserves or stop reinvestments in illiquid bonds that are close to maturity.[16] Our main focus is on liquidity,

[15]In Table A.2, we include additional control variables to our baseline specification. In Table A.4 we exclude fund fixed effects (maintaining time fixed effects) and in Table A.5 we include fund-style × time fixed effects. In Table A.3, we limit the sample to funds which currently experience inflows, to rule out possible concerns that our results are driven by sales in response to outflows. In Table A.8, we report our results obtained changing benchmarks to compute risk-adjusted returns, considering a different length of the performance window, using raw unadjusted fund returns, and cumulating risk-adjusted returns (rather than using averages). In all cases, results remain qualitatively similar.

[16]Evidence from non-financial firms indicates that corporations respond to concerns about mounting competition by expanding their cash holdings (Hoberg, Phillips, and Prabhala (2014)) or lengthening debt maturity (Parise (2018)).

as the most direct strategy to mitigate the cost of redemptions-induced fire-sales is to tilt fund portfolio towards liquid assets (regardless of their maturity and rating). However, we also provide results for the effect on yields to capture the trade-off between liquidity and returns. To assess fund manager's allocation decisions, we run the following specification at the transaction level:

$$\begin{aligned} Change_{i,j,t} = \beta_0 + \beta_1\, Laggard\ Fund_{i,t-1} \cdot Liquid\ Bond_{j,t-1} \\ + \Gamma' X_{i,t} + \Lambda' \Pi_{j,t} + \delta_i + \delta_t + \delta_j + \varepsilon_{i,j,t}, \quad (4) \end{aligned}$$

where we define the dependent variable $Change_{i,j,t}$ in three alternative ways. First, as a dummy variable that takes a value of 1 if asset j is bought by fund i in quarter t and value of 0 if the asset is either sold or the position is kept unchanged ($Bought_{i,j,t}$). Second, as a dummy variable that takes a value of 1 if asset j is sold by fund i in quarter t and value of 0 if the asset is either sold or the position is kept unchanged ($Sold_{i,j,t}$). In the third column, we consider the relative change in holdings, measured as the net change in one position divided by the overall trading activity by the fund. $X_{i,t}$ and $\Pi_{j,t}$ are, respectively fund and bond time-varying controls, and δ_i, δ_t, and δ_j are fund, time, and bond fixed effects.

Table III reports our results. Panel A confirms that laggard funds actively shift portfolio allocation towards liquid securities. Notably, this is achieved especially by purchasing liquid assets. Column 1 shows that the probability that laggard funds are 1.3 percentage points more likely to buy liquid securities (as $0.013 = 0.008 + 0.005$). Column 2 indicates that laggard funds are likely to sell securities (regardless of their liquidity). As a result, Column 3 indicates that the relative weight of liquid securities in their portfolio increases. Panel B shows the flip side in terms of yields. Laggard funds are more likely to sell higher-yielding securities and to buy lower-yielding ones, thereby reducing the average portfolio yield. This evidence is consistent with our main results on debt de-risking presented in the previous section. This result is particularly interesting as we do not find an economically meaningful effect of fund under-performance on cash holdings. All in all, laggard funds decrease portfolio risk by both purchasing liquid assets and divesting risky assets.

B Heterogeneous risk-taking: the role of fund characteristics and macroeconomic conditions

Guided by previous research, we conjecture that fund characteristics and market states affect the behavior of under-performing fund managers. Goldstein, Jiang, and Ng (2017) document that fund characteristics and market liquidity influence the shape of the flow-to-performance relation. Furthermore, Choi and Kronlund (2018) find that the low-interest rate environment induces bond fund managers to reach for yields. A natural implication of our previous results is that a more concave sensitivity of flows to performance should generate a stronger incentive for laggard funds to flee to havens. Likewise, market states that give rise to reach-for-yield behavior should attenuate the incentive to de-risk. We test these conjectures below.

Table IV, Panel A reports the effect of fund characteristics on risk-taking. We find that debt de-risking is stronger when most of a fund's share classes are offered to retail investors (Columns 1 and 2), for younger funds (Columns 3 and 4), and for funds that lack a precautionary liquid buffer (Columns 5 and 6). The former finding is consistent with the argument that strategic complementarities matter more for funds oriented towards 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, both a younger fund age and the lack of a precautionary liquid buffer translate into a more concave flows-to-performance relation (Goldstein, Jiang, and Ng (2017)). This, in turn, creates a stronger incentive to de-risk fund portfolios in response to poor performance.

Table IV, Panel B investigates the impact of macroeconomic conditions. Columns 1 and 2 indicate that market states that foster a search for yields mitigate the extent of de-risking. Columns 3 and 4 show that funds are more likely to de-risk in response to under-performance in turbulent times when liquidity dries up (as measured by the TED spread). 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)).

C Averting investor runs

Does the decision of the fund manager to de-risk feed back into investor outflows? From a theoretical perspective, after observing the realized under-performance, fund investors should run if the cost of the negative externalities generated by the outflow-induced sales exceeds the costs of exiting the fund. Exit costs include back-end and rear loads, as well as search costs to find a new investment opportunity.

A critical question to understand whether corporate bond funds pose a threat to financial stability is indeed whether they can to some extent prevent fund runs by de-risking their portfolio. If fund managers are able to decrease the expected cost of outflow-induced sales, investors may be better off choosing not to run. Importantly, the strategic complementarities among investors that trigger runs on the fund are exacerbated by bond illiquidity. If the fund manager could cover investor redemptions by selling *liquid* assets that experience no fire-sale discount, incumbent investors' shares in the fund would not be diluted. This, in turn, would eliminate the incentive to run on the fund in the first place. Notably, investors can infer whether portfolio holdings are safer by either observing a less volatile realized returns or thanks to public portfolio disclosure.[17] While it seems implausible that investors are able to assess the liquidity of the assets held by the fund manager, a significant shift towards high-rated securities may credibly signal that the fund portfolio is more liquid.

In Table V, we explore whether laggard managers may mitigate redemptions pressure by tilting portfolio holdings towards more liquid assets. We find that a shift towards more liquid securities reduces the magnitude of future outflows. Specifically, laggard funds face future outflows of 0.4 percentage points on average. However, when fund managers decrease risk-taking by one standard deviation, net outflows are halved (0.004-0.003+0.001=0.002

[17]Mutual funds are obligated to disclose their holdings at a quarterly frequency. However, in practice, most mutual funds disclose online their top positions and their weights every month.

vs 0.004), see Columns (1)-(3). When we measure liquidity using the inter-quartile range (see Column 4), we find an even larger effect: a decrease of risk-taking by one standard deviation reduces outflows by 75%.

Overall, this finding suggests that the corporate bond money management industry has a natural tendency to reduce risk exposures: the riskier funds, on average, shift portfolio allocation towards liquid securities, thereby minimizing the threat of runs. This behavior likely reduces ex ante the risk of fire sales and liquidation spirals that can cause market dislocations. Yet, more research is needed to comprehensively evaluate the asset pricing implications.

V. Policy implications

Concerns about the risks to financial stability posed by corporate bond mutual funds have recently been voiced prominently. Regulators and academics alike have expressed fears that the liquidity mismatch of bond funds may induce bank-run-like scenarios with severe repercussions on the bond market.[18] The main regulatory measure to ease these concerns has been the introduction, in October 2016, of flexible end-of-day net asset value (NAV), commonly referred to as swing pricing. 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-October 2016 (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 (2019) show that swing prices allow U.K. corporate bond funds to successfully reduce redemptions during stress periods. From a theoretical standpoint, swing pricing is an imperfect solution to the first-mover advantage. Zeng (2017) shows that, even with flexible NAVs, outflows induce predictable voluntary sales

[18] In a similar spirit, in October 2016, the U.S. money market fund reform became effective, which had a primary goal of reducing the risk of runs on prime money market funds.

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 swing pricing affects debt de-risking. In the previous section, we have shown that, even in the absence of regulation, it is in the best interest of laggard fund managers to de-risk when redemption risk looms. This strategic behavior reduces the need for investors to run and may contribute to explain why, anecdotally, runs outside periods of intense market stress have been infrequent. Notably, this is a market-led corrective mechanism that disciplines the manager. Under-performing managers who increase risk in an attempt of gambling for resurrection face a magnified redemption risk. This, in turn, eliminates the moral hazard problem. In the following, we provide evidence for the effect of the introduction of swing prices on the incentive of laggard fund to de-risk. As a flexible NAV reduces withdrawals in case of under-performance, its introduction may re-introduce moral hazard dynamics and weaken the incentive to de-risk.

In Table VI, we consider a difference-in-difference setting in which we compare the effect of under-performance on risk-taking before and after the introduction of the swing pricing regime. We consider laggard funds as treated by the introduction of swing pricing, whereas we use out-performing funds as control group (as these funds are unlikely to suffer large redemptions that require to "swing" prices). We estimate the following specification:

$$\begin{aligned}\Delta Risk_{i,t} = \beta_0 + \beta_1\ Laggard\ Fund_{i,t-1} \times Swing\ Pricing\ Regime_t \\ + \beta_2\ Laggard\ Fund_{i,t-1} + \gamma' X_{i,t-1} + \delta_t + \delta_i + \epsilon_{i,t}, \quad (5)\end{aligned}$$

where $Swing\ Pricing\ Regime_t$ is a dummy variable that takes a value of 1 from the last quarter of 2016 onwards (swing pricing was introduced in the U.S. in October 2016). The coefficient β_1 measures how the incentive to de-risk for laggard funds changes with the introduction of the swing pricing regime. We run this analysis both on the full sample (Panel A) and on a symmetric sub-sample that includes the same number of time periods before and after the event (Panel B).

Results in Table VI suggest that the introduction of the swing pricing regime leads laggard funds to maintain high levels of portfolio risk even as redemption risk looms. The aggregate effect of under-performance on risk-taking post 2006 becomes slightly *positive* in most specifications. This evidence suggests that the precautionary mechanism described in this paper may be weakened – if not completely altered – by the introduction of flexible NAVs. In other words, swing pricing has unintended effects, as fragile funds appear more willing to maintain or even increase risk levels. In a nutshell, swing pricing appears to weaken the market-driven discipline on under-performing bond fund managers who, as a result, tend to behave similarly to equity fund managers. This is, in all likelihood, due to the perception that large outflows in response to poor performance are less likely, which attenuates the motive for precautionary measures and reinstates the moral hazard problem.

It is possible that this outcome may actually magnify the systemic risk of the industry in the case of adverse external shocks. Indeed, in the case where flexible NAVs do not fully prevent outflows, the funds most exposed to fragility will be holding assets that are comparatively illiquid. Notably, our results are not inconsistent with those of Jin, Kacperczyk, Kahraman, and Suntheim (2019) who make the point that swing pricing reduces outflows. Whether these two effects (high portfolio risk vs reduced outflows) balance each other out and which one dominates during periods of severe market stress are open questions. Overall, the consequences of flexible NAVs on the financial stability risks posed by the bond fund industry warrant further theoretical and empirical research.

VI. Conclusion

The incentive structure in the *equity* mutual fund industry leads fund managers to engage in tournament behaviors: funds that lag behind in the rankings gamble to improve their standing. The incentive structure in the *bond* fund industry is, however, remarkably different. Because of the concavity of the sensitivity of flows to performance, the pay-off in terms of flows for bond fund managers resembles being short a put option. In equity fund tournaments the winners are highly rewarded — in bond fund tournaments the losers are severely penalized. Even in the (unlikely) scenario in which fund managers receive fixed compensation, large outflows may lead to fund closure with large costs for the manager in terms of reputation, career prospects, or job loss.

In this paper, we show that the incentive structure in the corporate bond industry leads managers to engage in reverse fund tournaments, in which laggard funds actively decrease risk-taking by tilting their portfolios towards more liquid and safer securities. This de-risking is achieved for the most part by selling cheap (high-yield) bonds and, at the same time, purchasing liquid assets that pay lower yields. The de-risking behavior that we document in this paper is therefore opposite of what is observed in the equity fund industry. Furthermore, we provide evidence that the incentive to de-risk intensifies in bad times, at times when money managers have less of an incentive to reach for yield, and with fund features that lead to a more concave flows-to-performance relation (e.g., young fund age, low cash buffers, retail clientele). Notably, some of the strategic behaviors 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. In fact, these institutions share with bond mutual funds a similar mismatch between liquid liabilities and illiquid assets.

Overall, we argue that the incentive structure of the bond fund industry has some desirable features. By de-risking their portfolios, fund managers reduce the risk of investor runs and fire sales exactly for those funds that are the most exposed to fragility ex ante. This precautionary mechanism could reduce the systemic risk of the industry and may contribute to explain why runs on bond funds outside periods of market tension have been so far sporadic events with limited implications for financial stability. Yet, we find that the introduction of swing pricing attenuates this market-enforced discipline and may reinstate the moral hazard problem that afflicts equity funds. Ultimately, this leads to an equilibrium in which fragile funds hold relatively more risk. Further theoretical and empirical research is however necessary to assess how to optimally regulate the bond fund industry.

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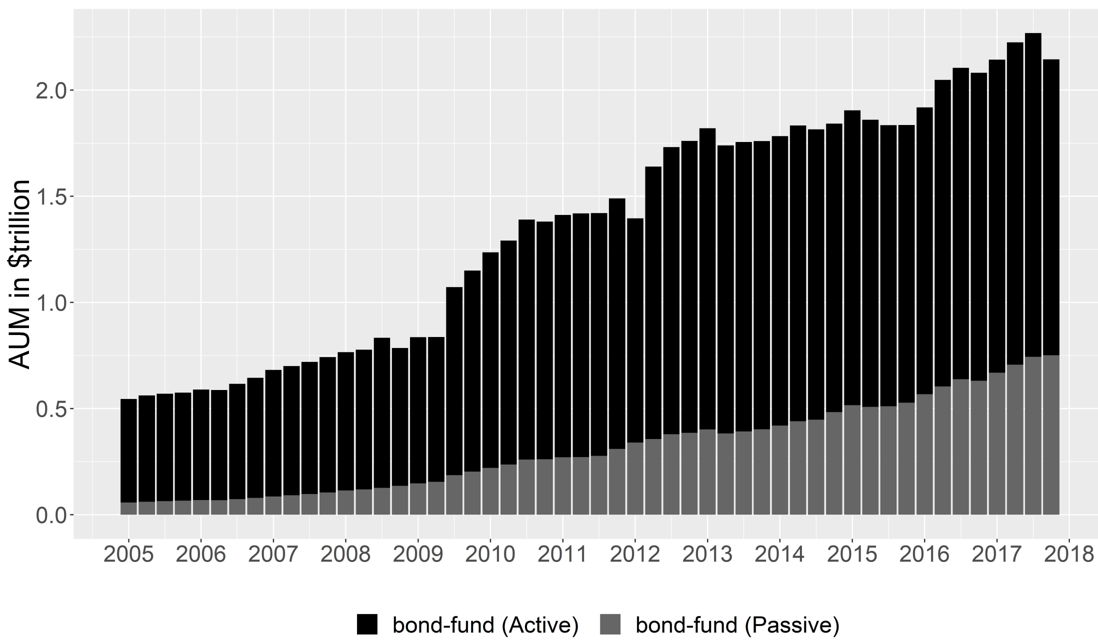
Tables and Figures

(a) Total AUMs of corporate bond mutual funds



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

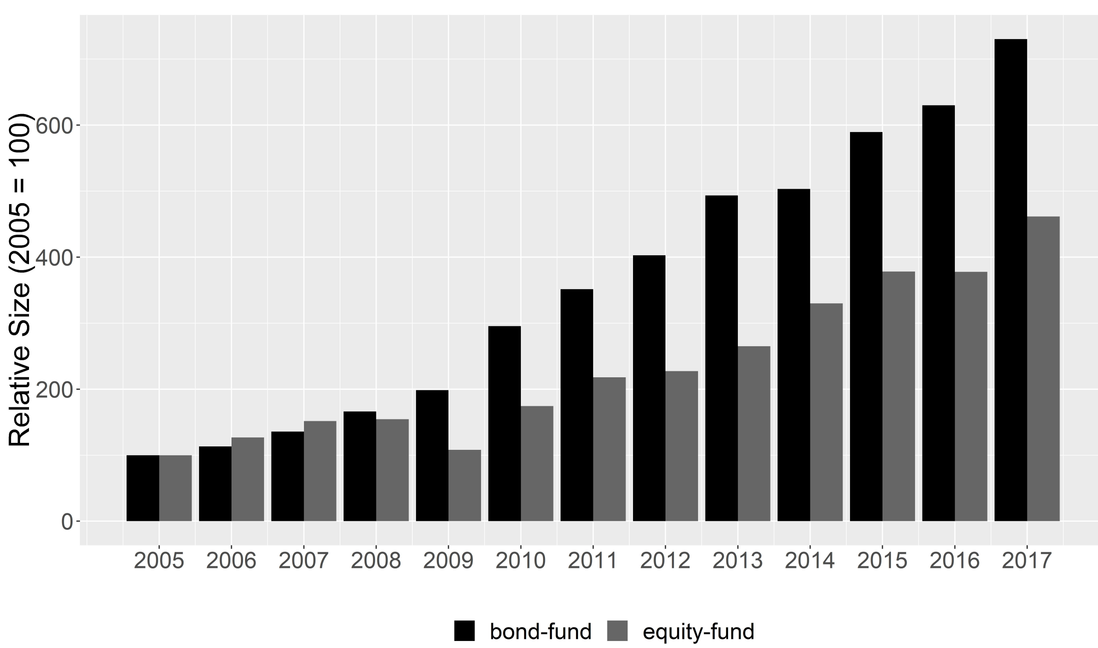


Figure 1: Growth of the corporate bond mutual fund industry

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

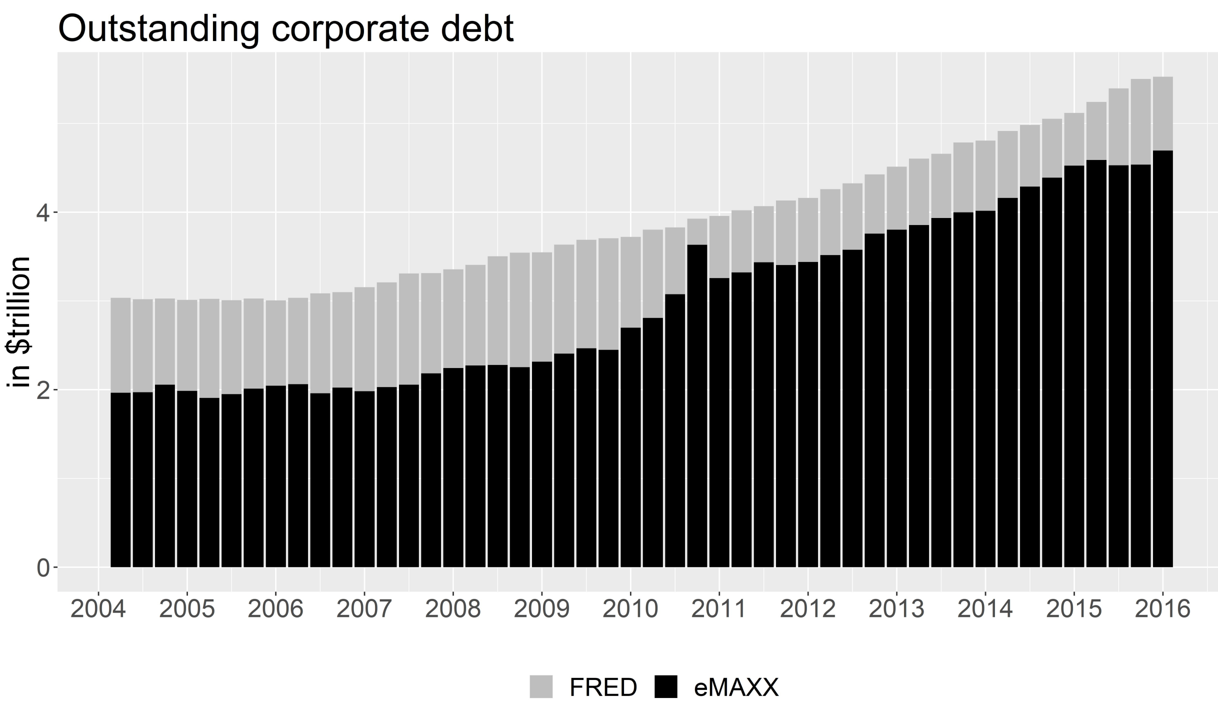
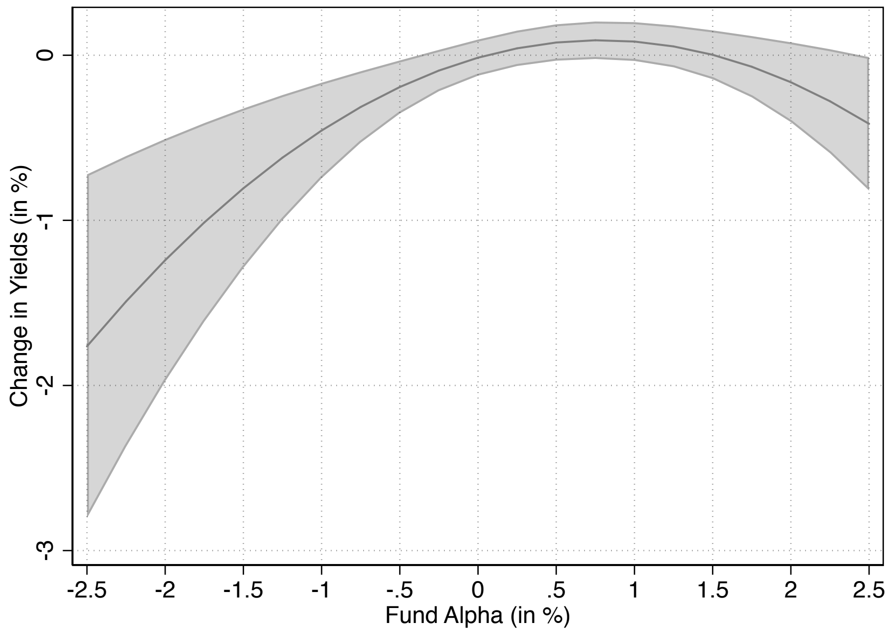


Figure 2: Coverage of the Thomson Reuters eMAXX data set

This figure illustrates the aggregate amount of outstanding non-financial corporate debt in the United States as reported by the Federal Reserve Bank of St. Louis (data series “NCBDBIQ027S” in the FRED database), and the total amount of corporate debt held by institutional investors whose portfolio holdings are covered by Thomson Reuters eMAXX. This latter category includes open-end corporate bond mutual funds as well as pension funds, insurance funds and exchange traded funds, but does not include banks, hedge funds, and retail investors.

(a) Risk-taking based on yields



(b) Risk-taking based on Roll

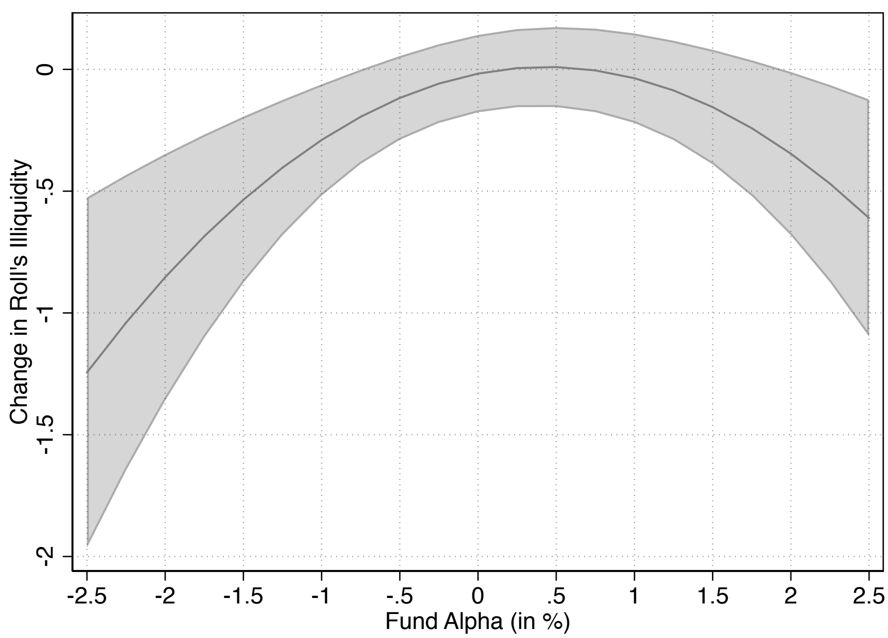


Figure 3: Sensitivity of Risk-taking to Past Fund Performance

These figures show the sensitivity of risk-taking to the average fund alpha achieved in the previous 24 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 Roll illiquidity measure (Panel b), respectively.

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, the 5th percentile, the 25th percentile, the median, the 75th percentile, and the 95th percentile. Panel A shows fund characteristics. *Size* is the total assets under management in millions, *Age* is the age in years of the oldest fund share class, *Expense Ratio* is the weighted-average expense ratio, *Max rear load* is the largest rear load reported for any share class of a fund, *Retail Share* is the fraction of shares owned by retail investors, *Fund Liquidity* is the fraction of cash and government securities held, *Portfolio Illiquidity* is the weighted average of the first principal component of Roll, Amihud, IQR, and bid–ask spread of the corporate bonds held by the fund, *Portfolio Rating* is the weighted average of the rating of all bonds held by the fund, *Government Securities* and *Corporate Bond Holdings* are the fraction of assets invested in government securities and corporate bond, respectively. *Turnover ratio* is the turnover ratio, *Inflow* (*Outflow*) is defined as $Flows \times I(Flows \geq 0)$ $(-Flows \times I(Flows < 0))$, *Alpha* is the average risk adjusted performance in the past 24 months, defined as explained in Section III. *Laggard Fund* is a dummy variable equal to one if the fund's past 24-month risk-adjusted performance is below quarter median of the sample and is equal to zero otherwise. 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 Δ IQR are standarized to have mean 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, *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 $AAA = 0, AA = 1, \ldots, D = 22$.

Panel A: Mutual funds

	N	Mean	Sd.	P5	P25	P50	P75	P95
Size (millions)	22,215	1,723.15	9,088.89	35.00	130.00	376.00	1,095.00	6,088.40
Age (years)	22,215	16.39	10.77	3.67	9.09	14.74	21.02	33.85
# shareclasses	22,215	3.21	2.26	1.00	2.00	3.00	4.00	7.00
Expense Ratio (%)	22,215	0.77	0.30	0.31	0.60	0.74	0.93	1.30
Max rear load (%)	22,215	0.02	0.01	0.00	0.01	0.01	0.02	0.05
Retail share (%)	22,215	60.37	41.23	0.00	12.42	77.85	100.00	100.00
Fund Liquidity	22,215	12.39	15.66	-0.06	3.18	7.10	18.78	41.85
Portfolio Illiquidity	22,215	-0.03	0.27	-0.34	-0.16	-0.06	0.02	0.39
Portfolio Rating	22,215	6.99	4.58	1.76	3.24	5.01	12.68	14.19
Corporate Bond Holdings (%)	22,215	66.00	27.07	25.39	42.82	63.32	95.85	99.45
Government Debt (%)	22,215	23.65	23.85	0.00	0.00	18.59	42.76	65.02
Asset Backed Securities (%)	22,215	4.29	8.23	0.00	0.00	0.00	5.17	21.16
Mortgage Backed Securities (%)	22,215	6.84	12.16	0.00	0.00	0.00	8.74	33.31
Turnover ratio (%)	22,215	1.06	1.45	0.00	0.27	0.57	1.19	4.08
Quarterly Net Fund Flow	22,215	0.01	0.13	-0.13	-0.04	-0.01	0.04	0.18
Inflow (max $[flows_{i,t}, 0]$)	22,215	0.04	0.11	0.00	0.00	0.00	0.04	0.18
Outflow (−min $[flows_{i,t}, 0]$)	22,215	0.03	0.05	0.00	0.00	0.01	0.04	0.13
Fund Return (%)	22,139	0.41	0.51	-0.05	0.19	0.34	0.58	1.09
Fund Alpha (%)	22,212	0.04	0.31	-0.36	-0.09	-0.00	0.11	0.62
Laggard Fund	22,215	0.50	0.50	0.00	0.00	0.00	1.00	1.00
ΔYield (%)	22,215	-0.02	0.60	-0.48	-0.04	0.00	0.08	0.45
ΔRating	22,215	-0.02	0.53	-0.63	-0.11	0.00	0.09	0.53
ΔAmihud	22,215	-0.00	1.00	-1.15	-0.21	-0.02	0.21	1.20
ΔRoll	22,215	0.00	1.00	-1.09	-0.16	0.01	0.17	1.07
ΔBid-Ask	22,215	0.00	1.00	-0.89	-0.10	0.05	0.15	0.78
ΔIQR	22,215	0.00	1.00	-0.23	-0.02	0.01	0.04	0.20
ΔMaturity	22,215	0.26	3.05	-2.40	-0.04	0.09	0.55	3.26

Panel B: Corporate bonds

	N	Mean	Sd.	P5	P25	P50	P75	P95
Residual Maturity (Years)	3,325,354	7.66	6.87	1.50	3.75	6.00	8.50	26.50
Bond Rating	3,325,354	10.04	3.87	4.00	7.00	10.00	13.00	16.00
IQR (%)	3,325,354	0.40	0.48	0.08	0.20	0.30	0.47	1.02
Roll Illiquidity (%)	3,325,354	0.59	0.53	0.15	0.31	0.46	0.69	1.39
Amihud Illiquidity (%)	3,325,354	0.36	0.17	0.16	0.25	0.33	0.43	0.67
Bid-Ask Spread (%)	3,325,354	0.56	0.75	0.09	0.23	0.40	0.67	1.52
Bond Yield (%)	3,325,354	5.72	5.26	1.31	3.36	5.11	6.89	11.38
Bond Quarterly Return (%)	3,325,354	1.85	8.10	-5.62	-0.04	1.46	3.62	9.74
Coupon rate (%)	3,325,354	6.29	2.13	2.50	5.00	6.38	7.75	9.75
Issue Amount Outstanding (M$)	3,325,354	966.21	909.41	200.00	400.00	664.65	1,249.83	2,750.00

Table II: Fund relative performance and de-risking

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

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

where $Riskiness_{j,t-1}$ is a proxy of the riskiness of bond j in quarter $t-1$ computed using bond j's yield, rating, liquidity, or maturity. $w_{i,j,t} = \frac{P_{j,t_0} Q_{i,j,t}}{\sum_j P_{j,t_0} Q_{i,j,t}}$ 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. $P_{j,t_0} Q_{i,j,t}$ 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 24-month risk-adjusted performance is below quarter median and is equal to zero otherwise. $Log(TNA)$ is the natural logarithm of fund assets. $Expense\ Ratio$ is the fund's expense ratio. $Turnover\ Ratio$ is the fund's turnover ratio. $Inflow$ and $Outflow$ are the current inflows and outflows, respectively. We include time and fund fixed effects. 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:	Yield	Rating	Liquidity				Maturity
Liquidity is:			Amihud	Roll	Bid–Ask	IQR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Laggard\ Fund_{t-1}$	-0.057***	-0.046***	-0.062***	-0.055***	-0.095***	-0.032***	-0.049
	(-7.18)	(-7.30)	(-4.73)	(-3.97)	(-6.71)	(-4.29)	(-1.47)
$Log(TNA_{t-1})$	0.019***	0.008	0.001	0.005	0.022*	-0.049	-0.018
	(2.99)	(1.37)	(0.10)	(0.50)	(1.86)	(-0.86)	(-0.72)
$Expense\ Ratio_{t-1}$	-0.058	0.019	-0.073	-0.032	-0.078	-0.411	0.040
	(-1.21)	(0.64)	(-0.86)	(-0.52)	(-1.11)	(-1.08)	(0.26)
$Turnover\ Ratio_{t-1}$	-0.003	0.003	0.004	0.001	0.006	-0.008	-0.012
	(-0.80)	(0.78)	(0.42)	(0.07)	(0.89)	(-0.98)	(-0.33)
$Inflow$ (max $[flows_{i,t}, 0]$)	-0.132	-0.097*	0.025	-0.170	-0.046	-0.032	0.183
	(-1.51)	(-1.71)	(0.14)	(-1.06)	(-0.27)	(-0.60)	(0.90)
$Outflow$ ($-$min $[flows_{i,t}, 0]$)	0.272***	0.489***	0.659***	0.856***	0.496***	-0.223	0.115
	(2.63)	(4.93)	(2.76)	(4.16)	(2.79)	(-0.56)	(0.25)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
R^2	0.078	0.041	0.048	0.052	0.062	0.102	0.026
Observations	21,319	21,319	21,319	21,319	21,319	21,319	21,319

Table III: Transaction-level evidence

This table reports estimates for the effect of relative fund performance on the buying and selling of individual corporate bonds. We run the following panel regression:

$$Change_{i,j,t} = \beta_0 + \beta_1 \ \ Laggard \ \ Fund_{i,t-1} \cdot Liquid \ \ Bond_{j,t-1} + \Gamma' X_{i,t} + \Lambda' \Pi_{j,t} + \delta_i + \delta_t + \delta_j + \varepsilon_{i,j,t},$$

where $Change_{i,j,t}$ is either i) a dummy variable that takes a value of 1 if asset i is bought by fund j in quarter t ($Bought_{i,j,t}$), ii) a dummy variable that takes a value of 1 if asset i is sold by fund j in quarter t and value of 0 if the asset is either sold or the position is kept unchanged ($Sold_{i,j,t}$), or iii) $\Delta Holdings_{i,j,t} = \frac{Net\ Change_{i,j,t}}{\sum_{j=1}^{J} |Net\ Change_{i,j,t}|}$ where $Net\ Change_{i,j,t} = Par\ Amount_{i,j,t} - Par\ Amount_{i,j,t-1}$. We include the same fund-level control variables as in Table II (coefficients unreported). We also include bond-level control variables, namely the outstanding amount, returns, rating, coupon rate, and residual maturity (coefficients unreported). $Laggard\ Fund_{i,t-1}$ is a dummy variable equal to one if the fund's past 24-month risk-adjusted performance is below quarter median and is equal to zero otherwise. *Liquid Bond* is a dummy which is equal to one if the bond is above median liquidity (bond yield) as measured by the first principal component of the four liquidity variables: Roll, Amihud, IQR, and bid–ask spread. If a fund is not trading at all in a quarter, it is not considered for this analysis. We include bond, fund, and time fixed effects. Observations are at the fund–bond–quarter level. 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: Liquidity Dependent variable:	*Bought Dummy* (1)	*Sold Dummy* (2)	*ΔHoldings* (3)
$Liquid\ Bond_{t-1} \times Laggard\ Fund_{t-1}$	0.005**	0.001	0.005**
	(1.97)	(0.65)	(1.98)
$Laggard\ Fund_{t-1}$	-0.002	0.009***	-0.011***
	(-0.67)	(2.91)	(-4.33)
$Liquid\ Bond_{t-1}$	0.008***	-0.001	0.003
	(5.35)	(-1.03)	(1.32)
Time Fixed Effects	✓	✓	✓
Fund Fixed Effects	✓	✓	✓
Bond Fixed Effects	✓	✓	✓
Bond Controls	✓	✓	✓
Fund Controls	✓	✓	✓
R^2	0.082	0.082	0.027
Observations	2,798,805	2,798,805	2,535,881

Panel B: Yields Dependent variable:	*Bought Dummy* (1)	*Sold Dummy* (2)	*ΔHoldings* (3)
$High\ Yield\ Bond_{t-1} \times Laggard\ Fund_{t-1}$	-0.007*	0.009**	-0.015***
	(-1.95)	(2.39)	(-4.13)
$Laggard\ Fund_{t-1}$	0.004	0.005	-0.002
	(1.58)	(1.58)	(-0.62)
$High\ Yield\ Bond_{t-1}$	0.030***	-0.014***	0.012***
	(9.56)	(-5.09)	(3.32)
Time Fixed Effects	✓	✓	✓
Fund Fixed Effects	✓	✓	✓
Bond Fixed Effects	✓	✓	✓
Bond Controls	✓	✓	✓
Fund Controls	✓	✓	✓
R^2	0.082	0.082	0.027
Observations	2,798,805	2,798,805	2,535,881

Table IV: The role of fund characteristics and market states

This table reports estimates for the effect of relative performance on fund risk-taking measured on the basis of bond yields for various sub-samples. In Panel A, we split the sample based on fund characteristics. Funds are classified as institutional (retail) if the retail share is below (above) the median fund in the sample. Funds are classified as old (young) if their age is below (above) the median fund in the sample. Funds are classified as liquid (illiquid) if their percentage holdings of liquid assets (cash and government bonds) is above (below) the median fund in the sample. In Panel B, we split the sample in different periods based on the two measures: the level of the federal funds rate and the TED spread (the difference between the interest rates on interbank loans and on Treasury bills). The control variables are identical to Table II. We include time and fund fixed effects. 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: Fund characteristics

	Fund Orientation		Fund Age		Fund Liquidity	
	Institutional (1)	Retail (2)	Old (3)	Young (4)	Liquid (5)	Illiquid (6)
$Laggard\ Fund_{t-1}$	-0.040***	-0.072***	-0.047***	-0.057***	-0.023**	-0.062***
	(-3.72)	(-5.59)	(-4.22)	(-4.42)	(-2.13)	(-4.18)
$Log(TNA_{t-1})$	0.015**	0.050***	0.013	0.034***	0.006	0.029***
	(2.05)	(3.20)	(1.00)	(3.51)	(0.56)	(2.68)
$Expense\ Ratio_{t-1}$	-0.095	-0.064	-0.134	-0.005	0.004	-0.116**
	(-1.12)	(-0.95)	(-1.45)	(-0.08)	(0.04)	(-2.39)
$Turnover\ Ratio_{t-1}$	-0.005	-0.001	-0.003	-0.005	-0.003	-0.004
	(-0.99)	(-0.17)	(-0.52)	(-0.81)	(-0.60)	(-0.49)
$Inflow$ (max $[flows_{i,t}, 0]$)	-0.130	-0.129	-0.178	-0.119	-0.246*	-0.012
	(-1.31)	(-0.80)	(-0.82)	(-1.32)	(-1.91)	(-0.12)
$Outflow$ ($-$min $[flows_{i,t}, 0]$)	0.159	0.305*	0.197	0.313**	0.161	0.459***
	(1.20)	(1.76)	(1.06)	(2.35)	(1.50)	(2.61)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓
R^2	0.083	0.091	0.087	0.084	0.154	0.088
Observations	10,718	10,568	10,854	10,454	10,617	10,627

Panel B: market states

	Yield (level)		TED Spread	
	low (1)	high (2)	low (3)	high (4)
$Laggard\ Fund_{t-1}$	-0.016*	-0.092***	-0.007	-0.105***
	(-1.92)	(-7.08)	(-0.95)	(-7.91)
$Log(TNA_{t-1})$	0.017	0.028***	0.013	0.031***
	(1.15)	(2.98)	(1.20)	(3.13)
$Expense\ Ratio_{t-1}$	-0.073	-0.079	-0.053	-0.090
	(-0.98)	(-1.19)	(-0.96)	(-1.10)
$Turnover\ Ratio_{t-1}$	0.005	-0.008	0.007	-0.012**
	(0.76)	(-1.54)	(1.35)	(-2.08)
$Inflow$ (max $[flows_{i,t}, 0]$)	-0.055	-0.207	-0.126	-0.122
	(-0.82)	(-1.40)	(-1.50)	(-0.93)
$Outflow$ ($-$min $[flows_{i,t}, 0]$)	0.240**	0.365**	0.084	0.460***
	(2.21)	(2.11)	(0.94)	(2.59)
Time Fixed Effects	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓
R^2	0.106	0.094	0.100	0.102
Observations	9,275	12,028	9,728	11,535

Table V: Does de-risking mitigate future outflows?

This table reports estimates for the effect of the liquidity reallocation of under-performing funds on subsequent outflows. We run the following panel regression:

$$Outflows_{i,t+1} = \beta_0 + \beta_1\, \Delta Risk_{i,t} \cdot Laggard\ Fund_{i,t-1} + \beta_2\, \Delta Risk_{i,t} + \beta_3\, Laggard\ Fund_{i,t-1} + \Gamma \cdot Controls_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t},$$

where $\Delta Risk_{i,t}$ is measured as indicated in Eq. 2 on the basis of the Amihud's liquidity measure (ΔAmihud), Roll's liquidity measure (ΔRoll), the Bid-Ask spread (Δbid-ask), and the interquartile price range (ΔIQR). $Laggard\ Fund_{i,t-1}$ is a dummy variable equal to one if the fund's past 24-month risk-adjusted performance is below quarter median and is equal to zero otherwise. The same control variables as in Table II are included (with the exception of $Inflows_{i,t}$ and $Outflows_{i,t}$ to avoid auto correlation). The dependent variable is $Outflows_{i,t} = -flow_{i,t} \times I(flow_{i,t} < 0)$. $flow_{i,t}$ is defined as $flow_{i,t} = (TNA_{i,t} - (1+r_{i,t}) \cdot TNA_{i,t-1})/TNA_{i,t-1}$ and is winsorized at the 1% level. We include fund and time fixed effects. Observations are at the fund–quarter level. 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.

	$Outflow_{i,t+1} = -\min\,[flows_{i,t+1},\ 0]$			
	(1)	(2)	(3)	(4)
$\Delta Amihud_t \times Laggard\ Fund_{t-1}$	0.003***			
	(3.94)			
$\Delta Amihud_t$	-0.001*			
	(-1.84)			
$\Delta Roll_t \times Laggard\ Fund_{t-1}$		0.003***		
		(3.46)		
$\Delta Roll_t$		-0.001*		
		(-1.68)		
Δ $Bid\text{-}Ask_t \times Laggard\ Fund_{t-1}$			0.002**	
			(2.47)	
$\Delta Bid\text{-}Ask_t$			-0.001**	
			(-2.06)	
$\Delta IQR_t \times Laggard\ Fund_{t-1}$				0.005***
				(2.76)
ΔIQR_t				-0.002**
				(-2.15)
$Laggard\ Fund_{t-1}$	0.004***	0.004***	0.004***	0.004***
	(4.35)	(4.35)	(4.32)	(4.40)
Time Fixed Effects	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓
FundControls	✓	✓	✓	✓
R^2	0.185	0.184	0.184	0.184
Observations	20,457	20,457	20,457	20,457

Table VI: Swing pricing and de-risking

This table reports estimates for the effect of the introduction of swing pricing on the risk-taking of laggard funds. We run the following panel regression:

$$\Delta Risk_{i,t} = \beta_0 + \beta_1 \; Laggard\ Fund_{i,t-1} \times Swing\ Pricing\ Regime_t \\ + \beta_2 \; Laggard\ Fund_{i,t-1} + \gamma' X_{i,t-1} + \delta_t + \delta_i + \epsilon_{i,t},$$

where $Swing\ Pricing\ Regime_t$ is a dummy variable that takes a value of 1 from the last quarter of 2016 onwards (swing pricing was introduced in the U.S. in October 2016). $Laggard\ Fund_{i,t-1}$ is a dummy variable equal to one if the fund's past 24-month risk-adjusted performance is below quarter median and is equal to zero otherwise. In Panel A, we use the entire sample. In Panel B, we restrict the sample to the 2016–2017 period only. We include fund and time fixed effects in all specifications. Observations are at the fund–quarter level. 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	ΔYield	ΔRating	ΔLiquidity Risk				Δ Maturity
Liquidity is			Amidhud	Roll	Bid–Ask	IQR	
Panel A: 2004–2017							
Swing Price Regime$_t$ × *Laggard Fund*$_{t-1}$	0.085***	0.044	0.057	0.078**	0.183***	0.022	-0.001
	(6.22)	(1.07)	(1.62)	(2.55)	(7.42)	(1.56)	(-0.01)
Laggard Fund$_{t-1}$	-0.059***	-0.047***	-0.063***	-0.057***	-0.099***	-0.032***	-0.049
	(-7.27)	(-7.34)	(-4.76)	(-4.03)	(-6.86)	(-4.30)	(-1.44)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
FundControls	✓	✓	✓	✓	✓	✓	✓
R^2	0.078	0.041	0.048	0.052	0.062	0.102	0.026
Observations	21,319	21,319	21,319	21,319	21,319	21,319	21,319
Panel B: 2016–2017							
Swing Price Regime$_t$ × *Laggard Fund*$_{t-1}$	0.271***	0.064	0.156***	0.124***	0.405***	0.099***	-0.024
	(7.83)	(1.50)	(2.83)	(2.79)	(8.22)	(5.01)	(-0.15)
Laggard Fund$_{t-1}$	-0.160***	0.118**	-0.067	0.010	-0.191***	-0.046***	0.198
	(-4.77)	(2.09)	(-1.06)	(0.21)	(-3.30)	(-2.77)	(1.18)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Fund Fixed Effects	✓	✓	✓	✓	✓	✓	✓
FundControls	✓	✓	✓	✓	✓	✓	✓
R^2	0.367	0.260	0.254	0.282	0.326	0.322	0.256
Observations	2,020	2,020	2,020	2,020	2,020	2,020	2,020

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