Bond Funds and Credit Risk

Finance Working Paper N° 639/2019
September 2026

Jaewon Choi
Seoul National University

Amil Dasgupta
London School of Economics

Ji Yeol Jimmy Oh
Korea University

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Jaewon Choi
Seoul National University

Amil Dasgupta
London School of Economics and ECGI

Ji Yeol Jimmy Oh
Korea University Business School

This Draft: July 12, 2026

Abstract

We show that supply-side effects arising from the bond holdings of open-end mutual funds affect corporate credit risk. In our model, open-end funds are reluctant to roll over bonds with weak prospects, fearing future outflows. This lowers rollover prices, enhancing equityholders' default incentives, and increases credit risk. Empirically, we find that in firms with weak prospects, fund holding shares increase CDS spreads, and more so when flows are more sensitive to performance. We provide direct evidence for the relevance of the rollover channel, use two quasi-experiments and an instrument to address endogeneity concerns, and rule out reverse causality via reaching-for-yield.

JEL classification: G23, G32
Keywords: Fund flows, credit risk, flow concerns, bond rollover

* Jaewon Choi, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Korea; telephone: +82 (0)2 880 6379. E-mail: jaewchoi@snu.ac.kr. Amil Dasgupta, London School of Economics, Houghton Street, London, WC2A 2AE, United Kingdom; telephone: +44 (0)20 7955 7458. E-mail: a.dasgupta@lse.ac.uk. Ji Yeol Jimmy Oh, Korea University Business School, 145 Anam-ro, Seongbuk-gu, Seoul, 02841, Korea; telephone: +82 (0)2 3290 2616. E-mail: jyjoh@korea.ac.kr.
Nikolai Roussanov was the editor for this article. We thank an anonymous referee for valuable feedback. We are also grateful to Ulf Axelson, Vikas Agarwal, Hui Chen, Hyun-Soo Choi, Ji-Woong Chung, Alexander Dickerson, Sergei Glebkin, Dirk Jenter, Xin Liu, Jaehoon Lee, Matthew Ringgenberg, and the audiences at AFA 2022, APAD, Bank of England, BI Oslo, Bonn, Canadian Derivatives Institute Annual Conference, CAFM, Cornell, FIRS 2025, FMA Annual Meeting, Georgetown, HKU Summer Finance Conference, INSEAD, KAIST, LSE, MFA Annual Meeting, NHH Bergen, NTU, Ohio State University, Peking University Shenzhen, Rice, Sungkyunkwan University, UNIST, University of Illinois, UNLV, UNSW, University of Texas at Dallas, and Aalto University for helpful comments. We thank the Systemic Risk Centre at the LSE for providing access to data sourced from Markit under license. Dasgupta acknowledges financial support from the ESRC via Research Grant ES/S016686/1. Oh acknowledges financial support from the National Research Foundation of Korea (NRF) grant funded by the Korean government (grant number NRF-2020S1A5A8043041). This work was partially supported by Korea University Business School Research Grant. Send correspondence to Ji Yeol Jimmy Oh, jyjoh@korea.ac.kr.

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Abstract

We show that supply-side effects arising from the bond holdings of open-end mutual funds affect corporate credit risk. In our model, open-end funds are reluctant to roll over bonds with weak prospects, fearing future outflows. This lowers rollover prices, enhancing equityholders' default incentives, and increases credit risk. Empirically, we find that in firms with weak prospects, fund holding shares increase CDS spreads, and more so when flows are more sensitive to performance. We provide direct evidence for the relevance of the rollover channel, use two quasi-experiments and an instrument to address endogeneity concerns, and rule out reverse causality via reaching-for-yield.

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1. Introduction

Since the turn of the century, the U.S. corporate bond market has experienced a large shift in its investor base. As shown in Figure 1, in the two decades between 2002 and 2022, corporate bond holdings of open-end mutual funds and ETFs have increased substantially from 7.4% to 21.2%, displacing both households and other institutional investors.

FIGURE 1 HERE

This shift implies a fundamental change in capital supply in corporate bond markets. In contrast to households and in comparison to other institutional investors, open-end funds are motivated by investor flows. Funds care about investor flows since they are compensated via fees that are proportionate to assets under management: reductions in future flow affect their payoffs directly. Investor flows, in turn, respond to fund performance generating so-called flow-performance relationships.[1] These two factors, combined with the incentives of equityholders, can affect the credit risk of corporations. For example, a negative outlook for a company rolling over its debt may make bond funds reluctant to participate in the rollover, because future underperformance (e.g., a default or downgrade) may impose higher penalties on funds than on other investors. While future underperformance imposes *direct* financial losses on all investors, open-end funds face the additional *indirect* penalty of being exposed to future outflows. Such exposure may reduce the willingness of funds to pay high rollover prices. In turn, a failure to negotiate favorable rollover prices increases the chances of default. In other words, the incentives of the *suppliers* of capital for corporate bonds may affect credit risk.

The literature has not yet examined how changes in the composition of capital supply affects rollover risk, focusing instead either on demand-side (i.e., borrower-level) factors or on the role of aggregate market conditions. The former strand of the literature emphasizes how—in the presence of credit market imperfections—firms may face difficulty rolling over short-term debt when faced with declining collateral values and increasing risk (e.g., Diamond, 1991; Titman, 1992; Gopalan, Song, and Yerramilli, 2014; and Chen,

[1] Papers documenting flow-performance relationships, include Chevalier and Ellison (1997), Sirri and Tufano (1998), Spiegel and Zhang (2013), and Goldstein, Jiang, and Ng (2017) among many others.

Xu, and Yang, 2021). The latter strand emphasizes how changes in market conditions can exacerbate rollover risk and thus affect credit risk (e.g., Acharya, Gale, and Yorulmazer, 2011; He and Xiong, 2012; Valenzuela, 2016; Chen, Cui, He, and Milbradt, 2018; Choi, Hackbarth, and Zechner, 2018; Chen, Michaux, and Roussanov, 2020; and Nagler, 2020). In this paper, we propose a novel *supply-side* (i.e., lender-level) channel through which rollover risk may interact with credit risk. We illustrate theoretically how the incentive schemes of capital suppliers may exacerbate rollover risk and demonstrate empirically that the extent to which a firm's bonds are held by open-end funds is causally associated with an increase in its credit risk.

We begin by examining the link between the presence of flow-motivated investors at rollover and the endogenous default choice of the firm's equityholders using a simple, illustrative model. We consider a firm with some pre-existing debt that must be rolled over today. Equityholders have deep pockets and can bear any rollover losses but—if the equilibrium rollover price is too low—may choose instead to default. Prior to rollover, all potential investors receive an informative signal about the firm's future cash flows. The precision of their information differs and they are unsure about its quality. There are two classes of investors: funds and individuals. What distinguishes funds from individuals is that, in addition to profit or losses—which is the only thing that motivates individuals—funds also derive utility from being perceived to be well-informed by their principals. This is a short hand for flow motivations: since funds' clients prefer to invest with well-informed funds, being viewed as well-informed is likely to enhance future fund inflows. Funds thus contemplate whether their chosen action, i.e., whether to buy the bond at rollover, would enhance or damage their posterior probability of being viewed as being well informed.

We characterize equilibrium bond prices with funds and compare them to benchmark prices with individuals. When funds are present, the equilibrium price carries a component that reflects their flow motivations: when investing in the bond hurts (improves) expected future flows, the funds' equilibrium willingness to pay falls (rises). Thus, rollover prices are more sensitive to the firm's future prospects in the presence of flow-motivated funds. A greater presence of bond funds at rollover thus implies that default risk will be higher for firms whose future cash flow prospects are relatively weak. Funds are reluctant to invest in such firms because of the anticipated negative impact of future underperformance on future fund flows. Such reluctance is relevant in reality because, as we document later on, the average bond mutual fund holds a relatively concentrated portfolio, so that each investment matters for future fund performance. Funds' reluctance to invest reduces the bond price that can be achieved at rollover and increases the chances of default today, leading to a positive association between bond funds' presence at rollover and credit risk. Flow motivations could, of course, also lead funds to overbid at rollover for firms that have strong cash flow prospects; but under such circumstances, default is unlikely in the first place, so there is little impact on credit risk. Thus, the effect of flow-motivated bondholders on credit risk will be clustered amongst firms with relatively weak cash flow prospects.

We empirically examine the link between bond funds and credit risk using data on the bond holdings of mutual funds and the credit default spreads (CDS) of bond issuers between 2002 and 2022. For each firm-month, we compute the share of its bonds held by active bond mutual funds, which we refer to as its fund holding share (FHS).[2] In our baseline OLS specification, we find a significant positive association between FHS and CDS spreads, factoring in a host of controls as well as credit-rating-by-time fixed effects: a one standard deviation increase in FHS is associated with nearly a 13 bps increase in CDS spreads, approximately 8% of the average CDS spread in the sample. Moreover, consistent with the main prediction of our model, the effect is clustered amongst firms with weak cash flow prospects: the positive association between FHS and CDS spreads is only evident among firms rated BBB or below, and much stronger for high-yield firms.

We then provide micro-level evidence on fund trading that supports the relevance of the rollover channel featured in the model. By comparing mutual fund trading in firm-quarters with rollover events versus those without, we find that funds make active portfolio adjustments primarily at bond rollover events. In other words, mutual funds tend to maintain their positions in portfolio firms until rollover dates, even as the firms' cash flow prospects worsen, and concentrate their portfolio decisions at rollover. This reliance on rollover issuances for active position changes appears to be closely related to secondary market illiquidity: the difference in active trading between firm-quarters with and without rollovers is particularly evident for firms whose bonds

[2] For a detailed definition of active mutual funds, see Appendix C.

are relatively illiquid. We also consider several firm-level proxies for rollover risk and examine whether firms with greater exposure to rollover risk observe a stronger relationship between FHS and CDS spread. Firms facing an imminent bond maturity, with shorter average time-to-maturity of their bonds, or with higher concentration of debt maturities are arguably more exposed to rollover risk. We find that the positive FHS-CDS relationship strengthens with higher rollover risk as measured by each of these proxies.

We then turn to the key question of endogeneity. A firm's credit risk and its FHS are likely to be determined simultaneously. For example, mutual funds may invest in firms with higher credit spreads to "reach for yield."[3] To establish the causal link between FHS and CDS spreads, we use a quasi-natural experiment of Adelino, Cheong, Choi, and Oh (2026) to identify plausibly exogenous changes to FHS arising from Morningstar's star rating methodology for fund share classes that turn five years old. Morningstar's overall star rating uses three-, five-, and ten-year star ratings, each of which is constructed using a fund's risk-adjusted return ranking over the specified horizon relative to its category peers. The overall star ratings of funds aged between 36 and 59 months consist exclusively of the three-year rating. When the fund turns five, however, Morningstar begins to use both three- and five-year star ratings with 40% and 60% weights, respectively, to calculate the overall star rating. This means that, a fund's performance between three and five years ago—i.e., purely "stale information"—can raise or lower the overall star rating at the five-year mark. Yet, we find that flows respond strongly to such upgrades. Funds direct over 83% of these flows toward firms they already hold in their portfolios, leading to a significant increase in FHS among firms held by upgraded five-year-old funds compared to their non-upgraded peers.

Exploiting this exogeneous FHS change in a difference-in-difference (DiD) setting, we show that the credit risk of the firms increases in lockstep with their FHS, and that—consistent with our model—that such increase in CDS is clustered amongst high yield firms. Our findings thus support a strong causal link between FHS and credit risk. We further rule out several alternative explanations. First, we find no statistically significant decrease in the holding shares of insurance companies or pension funds for firms held by upgraded funds. Thus,

[3] Reaching for yield has been documented for various types of investors, e.g., for insurance firms (Becker and Ivashina, 2015), money market funds (DiMaggio and Kacperczyk, 2017), and bond mutual funds (Choi and Kronlund, 2018).

our results suggest that the risk mitigating role of institutional investors with stable funding is unlikely to be a first-order impact, complementing those of Chodorow-Reich, Ghent, and Haddad (2021) and Coppola (2025). Second, we find no evidence that upgraded funds channel the part of inflows not allocated to existing portfolio firms toward riskier new firms. Funds do not disproportionately purchase bonds with higher yields or longer maturities, and new purchases are not unduly associated with deteriorating fundamentals either. Instead, upgraded funds' purchases in new firms appear to be driven primarily by their past interactions with the firm and the ease with which these firms' bonds trade in the secondary market.

We further rule out any potential reverse causality arising from bond funds' reaching for yield (RFY) tendencies. We first compute each bond's within-rating-and-maturity RFY coefficient by computing the difference between its month-end yield relative to its rating-and-maturity peers, and then aggregate this measure at the investor-quarter level. On average, and consistent with Choi and Kronlund (2018), we do not find any evidence that bond funds engage in RFY: the average RFY is -4.3 bps. The coefficient becomes even more negative for funds holding more illiquid high yield securities and/or during subperiods of market stress. We then analyze our baseline FHS-CDS regressions across these subperiods and find that the positive effect of FHS on CDS spreads is much stronger when default spreads or VIX is high. This is precisely the opposite of the observed RFY patterns of bond funds, which further helps distinguish our channel from this potential reverse causality channel.

To strengthen the causal link of our baseline findings, we complement the Morningstar DiD setting with an instrumental variable (IV) approach akin to Koijen and Yogo (2019). The IV exploits the fact that a fund's investment mandate is pre-determined and should be exogenous to contemporaneous shocks to firms' credit risk. To capture this idea, we construct hypothetical fund holdings by assuming that each fund allocates its assets under management (AUM) equally across bonds in its investment universe. This IV provides exogenous variation in mutual funds' demand for corporate bonds, which is driven by the cross-sectional AUM distribution of funds that include these bonds in their mandates. The IV results confirm our baseline findings, namely the positive relationship between FHS and CDS spread among firms with weak cash flow prospects.

The model also generates two auxiliary predictions. First, the positive relationship between the FHS and CDS spread should strengthen for funds with greater flow concerns. We proxy for flow concerns using the share of rear load fee classes and management company size. In the absence of rear load fees and within smaller management firms that lack intra-family liquidity provision, funds find it more challenging to mitigate the adverse impact of outflows (Bhattacharya, Lee, and Pool, 2013; Agarwal and Zhao, 2019). In line with this prediction, we find that the holding shares of funds with a smaller share of load fee classes or those belonging to smaller families have more prominent associations with subsequent CDS spreads.

To identify the causal impact of enhanced flow concerns on the relationship between FHS and credit spread, we utilize a second quasi-experimental setting: the unexpected departure of Bill Gross from Pacific Investment Management Company (PIMCO) in September 2014. This event plausibly raised flow uncertainty for PIMCO funds, as many investors had selected these funds based on Gross's track record. Using a matched difference-in-differences design over a [−12, +12] month window, we find that firms with over 0.5% of PIMCO holding share prior to Bill Gross' departure experience CDS spread increases of 27 to 35 bps relative to matched control firms following his departure. Further analysis shows that these effects are driven by heightened concerns regarding flow volatility rather than the fire sales of bonds to meet redemption demands.

Second, the model predicts that concavity in the flow–performance relationship should amplify the FHS–CDS relationship. While our qualitative effects do not rely on concavity, as we illustrate in a simple extension of our model, our *quantitative* results will be strengthened if funds are exposed to greater downside risk via their flow performance relationship. We find that the positive association between FHS and CDS spreads is stronger in funds with higher flow-performance concavity, but the relationship remains even among low-concavity funds. Thus, our results are quantitatively strengthened by concavity but not driven by it.

In the final part of the analysis, we provide several robustness checks. We scale the bond holdings of active funds by total debt, rather than the amount of corporate bonds outstanding. We also use the next-month *change* in the 5-year CDS spread as the dependent variable. In another robustness check, we re-run the Morningstar DiD regressions, focusing on a smaller subset of funds whose three-year ratings (i.e., the overall Morningstar rating under the "old" methodology) remain unchanged at the five-year mark to further sharpen the identification. Finally, we check whether the holding share of funds with greater flow concerns exhibits stronger association with CDS spread in the IV setting. In all instances, our robustness checks confirm our key findings.

Related literature. First, our paper contributes to the literature on rollover risk discussed above. As already noted, in contrast to the prior focus within this literature on demand-side or market-level factors, we highlight a novel *supply-side* factor, namely the flow motivations of mutual funds. More broadly, we extend the vast literature on credit risk, beginning with Merton (1974) and the literature on credit default swaps (see Augustin, Subrahmanyam, Tang, and Wang (2014) for a survey). Second, our study also contributes to the literature on the financial stability and fund flows associated with the open-end structure of mutual funds. Earlier studies document fund flows exert ex-post price effects through flow-induced trading by mutual funds (e.g., Coval and Stafford, 2007). A growing body of studies also show that the open-end structure of mutual funds can exacerbate fund run risk and financial fragility (e.g., Chernenko and Sunderam, 2016; DiMaggio and Kacperzcyk, 2017; Zeng, 2017; Choi, Hoseinzade, Shin, and Tehranian, 2020; Chernenko and Sunderam, 2020; Jin, Kacperczyk, Kahraman, and Suntheim, 2022) and also exert financial and real effects on their stock holdings (Edmans, Goldstein, and Jiang, 2012; Khan, Kogan, and Serafeim, 2012) and bond holdings (Chernenko and Sunderam, 2012; Ben-Rephael, Choi, and Goldstein, 2021; Zhu, 2021). Our contribution to the literature lies in showing that these flows, through their effect on the fund manager's incentives, not only affect fund liquidity and run risk but also the credit risk of firms they hold by depressing their bond rollover prices.

Finally, our study is related to the literature on the asset pricing and corporate governance implications of the flow motivations of asset managers. On the asset pricing side, for equities, Dasgupta, Prat, and Verardo (2011) find that trading behavior consistent with flow motivations is associated with cross sectional return predictability, while for bonds, Cai, Han, Li, and Li (2019) document that herding behavior consistent with flow concerns generates price impact. On the governance side, a growing literature (see Dasgupta, Fos, and Sautner, 2021 for a survey) documents how the flow concerns of equity blockholders can impact firm value. In contrast, we are the first to study the effect of the flow concerns of corporate *creditors* and show how such incentives translate into real impact via their effect on corporate credit risk.

2. A Conceptual Framework

We start with a simplified, two-date version of continuous-time model of endogenous default by equityholders (e.g., Leland and Toft, 1996; Chen, 2010; He and Xiong, 2012), and extend it to introduce flow-motivated institutional bondholders, i.e., bond funds. Consider a firm that generates terminal cash flow $V \in \{0,\ \bar{V}\}$ at $t=2$, where $\bar{V}>1$ and the prior, $\gamma_V = \Pr(V=\bar{V})$, reflects the firm's future *cash flow prospects*. The firm is owned by equityholders with deep pockets but subject to limited liability. Since we are interested in debt rollover, we assume that the firm has pre-existing debt in the form of a bond with face value 1 maturing at $t=1$. There is no cash flow at $t=1$, and so the firm's maturing bond must be rolled over at $t=1$ with a new bond with face value 1 maturing at $t=2$. Investors must decide at $t=1$ whether to purchase this new bond and how much to pay for it. We denote by p the equilibrium price of the new bond.[4] The discount rate is zero and all agents are risk neutral.

To repay pre-existing bondholders, the shortfall of $1-p$ must be borne by the firm's equityholders. As in He and Xiong (2012), there is no constraint to the issuance of new equity at $t=1$.[5] If equityholders decline to provide new equity, the firm defaults and all future cash flows are seized by pre-existing bondholders, so equityholders receive 0 due to limited liability. If they decide to provide more equity shares and bail out the pre-existing bondholders, their expected payoff is given by:

$$\underbrace{\gamma_V(\bar{V}-1)}_{\text{High firm cash flow at } t=2} + \underbrace{(1-\gamma_V)\cdot 0}_{\text{Low firm cash flow at } t=2} - \underbrace{(1-p)}_{\text{Rollover losses at } t=1} \tag{1}$$

Equityholders will default whenever (1) is less than or equal to 0. Thus, we can state:

[4] We assume for simplicity throughout that each investor is small relative to the size of the bond issue, and thus neglects the effect of his own rollover decision on the possibility of default by equityholders.

[5] To avoid frictions in new equity issuance, we abstract from private information of equityholders. If equityholders had private information, they would be *more* reluctant to issue equity to subsidize bondholder at rollover, *enhancing* default. Thus, our simplification works *against* our desired effect. Our assumption that external investors (introduced in sections 2.1 and 2.2) have information incremental to equityholders is in the tradition in the "feedback" literature (see, e.g., Bond, Edmans, and Goldstein's (2012) survey).

Proposition 1 (Interim default). Default occurs at $t = 1$ whenever $p \leq 1 - \gamma_V(\bar{V} - 1)$.

We now endogenize the rollover equilibrium price p. Throughout our analysis, to minimize the number of frictions in the model, we assume that investors are competitive. This implies that, in the rollover game, investors will bid up to their full willingness to pay. Since our interest is in excessively *low* rollover prices, any rent extraction by investors as a result of imperfect competition would simply exacerbate the phenomena.

For expositional ease, we present our rollover analysis in two separate parts. First, in section 2.1, we assume that (all) investors are flow-motivated bond funds. Then, in section 2.2, we shut down flow motivations, so that (all) investors may be interpreted as individuals or more patient institutions. In reality, both flow-motivated and patient investors will be present simultaneously, and the required rollover quantity may affect the identity of the *marginal* investor. Our qualitative findings hold in such settings, as discussed in section 2.5.

2.1. Flow-motivated investors

Suppose first that the population of investors consists of bond funds, i.e., delegated agents, evaluated at $t = 2$ by their principals. Funds conduct research on the firm's terminal cash flow and decide whether to buy the bond issued at $t = 1$. Suppose that each fund can be one of two types, good or bad, denoted $\tau \in \{G, B\}$, with the ex ante probability that the fund is of the good type denoted $\gamma_\tau = \Pr(\tau = G)$. The two types differ in the precision of their information; each fund receives a signal at $t = 1$, denoted s, which satisfies

$$\Pr(s = V^* | V = V^*, \tau = \tau^*) = \sigma_{\tau^*} \text{ for each } V^* \in \{0,\ \bar{V}\} \text{ and } \tau^* \in \{G, B\}. \quad (2)$$

To simplify the analysis, suppose that $\sigma_G = 1$ and $\sigma_B = 1/2$, i.e., good types observe perfect signals, while bad types observe noise. In the tradition of signal jamming models beginning with Holmstrom and Ricart-i-Costa (1986), we assume that funds do not know their own types, i.e., there is residual uncertainty about the quality of the observed signal. While this assumption simplifies the analysis, Dasgupta and Prat (2008) show that incentives in such models are qualitatively similar even if agents have information about their types, other than in the extreme case in which self-knowledge is perfect.[6] Each fund's action is denoted a, with $a = 1$ if the fund chooses to buy the bond or $a = 0$ if not. The variables τ and V are independent of each other. We now state the fund's payoff at $t = 2$, given by:

$$\{\min(1, V) - p\} \cdot I(a = 1) + \kappa \Pr(\tau = G | a, V). \quad (3)$$

The first term of (3) represents the fund's profits if the manager decides to buy the bond. The second term represents the fund's additional gains from taking actions likely to convince the principal, ex post, that she is well-informed. Intuitively, if the fund's buying decision and subsequent cash flows are such that the fund's "reputation" for being well-informed improves, the fund is rewarded by additional investor capital i.e., "flow." The parameter κ measures the intensity of the fund's flow motivation. Microfoundations for such payoff functions can be found in Dasgupta and Prat (2008) and Guerrieri and Kondor (2012).

In reputational cheap-talk models, it is possible for both pooling and separating equilibria to arise. In the former type of equilibrium, funds choose actions that are not contingent on their private signals, while in the latter their actions are informative about their signals. It is only in separating equilibria that funds are rewarded (penalized) for making correct (incorrect) choices, since choices are correlated with information, and information is correlated with underlying ability. Given the evidence on positive flow-performance relationships faced by bond funds (e.g., Goldstein, Jiang, and Ng, 2017), we focus on separating equilibria.[7]

Proposition 2 (Equilibrium with flow-motivated bondholders). There exists an equilibrium where:

(i) The fund chooses $a = 1$ if $s = \bar{V}$,

(ii) The fund chooses $a = 0$ if $s = 0$,

(iii) The firm sets the price of the new bond at:

[6] Our subsequent analysis shows that the key determinant of rollover prices is the incentive of flow-motivated funds to make choices that are likely to be correct ex post. This leads funds to be influenced by the firm's cash flow prospects, i.e., the prior γ_V: if the prior is above a threshold they overpay; if it is below, they underpay (Proposition 4). Dasgupta and Prat (2008) show that even with a degree of self-knowledge, such behavior emerges for sufficiently high or low priors; i.e., in a more complex version of our model with (imperfect) self-knowledge, the over- and under-pricing of Proposition 4 will still arise for sufficiently high or low γ_V.

[7] For interested readers, we show in Appendix B that, under reasonable off-equilibrium beliefs, the key effect of bond funds' flow motivations on corporate credit risk remains qualitatively unchanged even in pooling equilibria.

$$p = \Pr(V = \bar{V}|s = \bar{V}) + \kappa\{E(\Pr(\tau = G|a = 1, V)|s = \bar{V}) - E(\Pr(\tau = G|a = 0, V)|s = \bar{V})\}. \quad (4)$$

All proofs are in Appendix A. In this equilibrium, only funds with high signal ($s = \bar{V}$) participate in the rollover game and buy the bond, while those with the low signal decide not to participate. Knowing that only the high signal funds participate, the firm sets the price equal to their full willingness to pay, which contains two components. The first term in (4) is the high signal funds' expectation of the bond's terminal cash flow at $t = 2$. The second term represents the fund managers' additional willingness to pay arising from their flow motivations. Upon receiving a high signal, funds evaluate how a purchase decision is likely to affect their principals' posterior assessment of their type when the terminal cash flow is realized. If buying the bond (i.e., $a = 1$) increases the funds' likelihood of being viewed as the good type at $t = 2$ compared to staying out of the rollover game, they have an additional reason to participate in the rollover; the reverse holds if funds are less likely to be viewed as being of the good type. The second term in (4) captures the expected reputation gain or loss—i.e., flow payoffs—to high signal funds from participating in the rollover vs. not doing so. Thus, the price in (4) extracts the high-signal funds' full willingness to pay. At the equilibrium price, high-signal funds are thus indifferent between rollover or not. As such, the less optimistic low-signal funds will clearly strictly prefer not to participate, thus completing the equilibrium argument.

Flow vs. performance. We model reputation as a function of observation of trading choices (at $t = 1$) and eventual cash flow outcomes (at $t = 2$). However, it is noteworthy that in the above equilibrium, posterior reputation—and thus, implicitly, flow—is positively correlated with correct trading choices. Funds can only improve their $t = 2$ reputation relative to the $t = 1$ prior by buying at $t = 1$ bonds that subsequently do *not* default at $t = 2$ or by declining at $t = 1$ to buy bonds of companies that do default at $t = 2$.

2.2. Investors without flow motivations

We now consider investors without flow motivations, which corresponds to the case of $\kappa = 0$. These investors are "standard" profit-maximizing agents, whom we casually refer to as individuals to distinguish them from flow-motivated funds in the previous subsection. However, in practice, these investors need not be individuals; any institutional investor with less pronounced short-term flow considerations may behave in a similar manner. The following proposition, then follows immediately by setting $\kappa = 0$ in Proposition 2:

Proposition 3 (Equilibrium with standard profit-maximizers). There exists an equilibrium where:

(i) The individual chooses $a = 1$ if $s = \bar{V}$,

(ii) The individual chooses $a = 0$ if $s = 0$,

(iii) The firm sets the price of the new bond at $p = \Pr(V = \bar{V} | s = \bar{V})$.

2.3. Comparison of equilibria with flow-motivated vs. standard investors

We now compare the equilibrium bond prices derived in the previous two subsections. For ease of exposition, we refer to the equilibrium bond price with flow-motivated investors in Proposition 2 as p_f^*, and the price with standard investors in Proposition 3 as p^*. We show that:

Proposition 4 (Comparing equilibrium bond prices). $p_f^* \leq p^*$ if and only if $\gamma_V \leq \frac{1}{2}(1 - \gamma_\tau)$.

In other words, flow-motivated funds act as punitive buyers at rollover in firms with relatively low cash flow prospects. This is because, as γ_V gets smaller, despite having observed $s = \bar{V}$, high signal funds believe it to be progressively less likely that V will turn out to be $\bar{V}$, and thus—since in equilibrium it is only desirable to be seen to have invested when $V = \bar{V}$—their flow-driven willingness to pay diminishes, progressively reducing p_f^* relative to p^*. The opposite is true as γ_V gets progressively large. Our analysis is illustrated in Figure 2.

FIGURE 2 HERE

2.4. Flow motivations, credit risk, and cash flow prospects

We now show that under natural conditions there is a class of firms *with low cash flow prospects* for which default occurs *if and only if* investors are flow motivated. We begin by assuming, realistically, that default is (unconditionally) relatively rare. Default occurs when equityholders do not perceive sufficient upside to rolling over. Thus, if $\bar{V}$ is small, default occurs frequently, i.e., for a wide range of cash flow prospects, γ_V. We assume that $\bar{V}$ is large enough that the highest value of γ_V for which default can occur is smaller than $\frac{1}{2}(1-\gamma_\tau)$. This is very mild condition: even if, say, a *half* of bond funds are skilled, which in itself is an optimistic assumption, and γ_V is uniformly distributed (i.e., very fat tails) in the population of firms, then we are effectively assuming that unconditional corporate default rates are smaller than 25%, an order of magnitude *higher* than observed corporate default rates.[8] In Figure 2, our assumption ensures that the default threshold is steep enough to intersect the (dashed gray) p^* and (solid black) p_f^* curves to the left of $\frac{1}{2}(1-\gamma_\tau)$. Default arises for a given type of investor if and only if γ_V is to the left of the intersection of the light straight line with the pricing curve corresponding to that type of investor. Whenever the light straight line intersects the pricing curves to the left of $\frac{1}{2}(1-\gamma_\tau)$, the intersection with the dashed gray line is strictly north-west of the intersection with the solid black line. Then, there is a range of γ_V for which default occurs if and only if investors are flow motivated. Further, since the intersections are to the left of $\frac{1}{2}(1-\gamma_\tau)$, for strong cash flow prospect firms, with $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, default never arises with or without flow motivated investors; hence the willingness of flow motivated investors to overpay for such firm's debt at rollover has no impact on credit risk. Formally:

Proposition 5 (Flow motivations and credit risk). There exists a $\hat{V} > 1$ such that for $\bar{V} > \hat{V}$:

(i) There is a positive measure set of γ_V contained in $\left(0, \frac{1}{2}(1-\gamma_\tau)\right)$ for which default arises if and only if investors are flow motivated.

(ii) For $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, flow motivated investors have no impact on default.

Thus, the presence of flow-motivated funds affects credit risk only for firms with *low* cash-flow prospects.

2.5. Flow-motivated and non-flow motivated investors simultaneously present

[8] See https://www.spglobal.com/ratings/en/research/articles/240328-default-transition-and-recovery-2023-annual-global-corporate-default-and-rating-transition-study-13047827

We now discuss how our analysis extends to settings in which flow-motivated and non-flow-motivated investors are simultaneously present. Imagine that the firm needs to roll over K bonds each with face value 1. There is sufficient non-flow-motivated capital to absorb $K_{NF} \geq 0$ of such bonds, while there is sufficient flow-motivated capital to absorb $K_F \geq 0$ of such bonds, where $K_{NF} + K_F > K$. Assuming finite amounts of available non-flow-motivated and flow-motivated capital implicitly requires some friction (e.g., limits to arbitrage or market segmentation), as underpricing or overpricing cannot arise in a frictionless setting. In section 3.1 we discuss why such frictions exist in the primary market for corporate bonds.

Firms with $\gamma_V \leq \frac{1}{2}(1-\gamma_\tau)$ can charge p^* per bond to non-flow-motivated refinancers but only $p_f^* < p^*$ to bond funds. They will sell as much as possible to non-flow motivated investors. Hence, if $K_{NF} > K$, then such firms will sell only to non-flow-motivated investors, rendering such investors marginal buyers. On the other hand, if $K_{NF} < K$, then these firms will first raise $K_{NF}p^*$ from non-flow-motivated investors and will sell the remainder to bond funds raising $(K - K_{NF})p_f^*$. Thus, the total capital that can be raised by the firm is $K_{NF}p^* + (K - K_{NF})p_f^*$, which is decreasing in $K - K_{NF}$ since $p_f^* < p^*$.[9] Thus, the subsidy that equityholders must provide to prevent default *increases* in $K - K_{NF}$, i.e., in the measure of bond funds required at rollover, increasing incentives to default.

2.6. Concave flow-performance relationships

In our framework, learning about funds' ability endogenously generates reputational rewards and punishments, which proxy for an increasing flow-performance relationship. We specify a single parameter κ in (3) to capture the impact of such reputational rewards and punishments on the fund. This specification is tantamount to assuming that reputational rewards are treated symmetrically to reputational punishments. If, for some reason, funds were to experience *asymmetrically* high disutility from reputational losses relative to utility from reputational gains, our results would be quantitatively strengthened.

[9] This discussion assumes that it is possible to engage in differential pricing at rollover. However, the qualitative effects would be similar under uniform pricing. Then, the total capital that can be raised by the firm would be a step function in K_{NF} instead of the linear function shown above but would remain increasing in K_{NF}, as above.

The empirical literature shows that the flow-performance relationship of bond funds is concave (Goldstein, Jiang, and Ng, 2017), suggesting that reputational losses matter more to funds than gains of the same magnitude. The theoretical underpinnings of this effect can be traced to strategic complementarity amongst investors in illiquid bond funds (Chen, Goldstein, and Jiang, 2010). While a full model combining fund-level flow concerns and investor-level complementarity is beyond the scope of this paper, we can illustrate the additional effect of concavity by a two-parameter specification, where reputational gains are captured by a parameter κ_G while losses are captured by a separate parameter κ_L with $\kappa_L > \kappa_G$. This would mean that, in the region where the flow premium is negative, the equilibrium rollover price with funds would decline more steeply in cash-flow prospects than in the baseline case, leading to a *higher* incidence of default. Formally, this is equivalent to the baseline analysis with a contingent κ as follows:[10] $\kappa = \begin{cases} \kappa_G & \text{if } \gamma_V > \frac{1}{2}(1-\gamma_\tau), \\ \kappa_L & \text{if } \gamma_V \leq \frac{1}{2}(1-\gamma_\tau). \end{cases}$

3. Testable Implications, Data, and Variables

3.1. Testable implications

The main implication deriving from our conceptual framework may be summarized as follows:

(i) The presence of mutual funds at the time of rollover increases credit risk for firms with weak cash flow prospects.

Two further implications that emerge from comparative statics on model parameters are as follows:

(ii) Funds with stronger flow concerns will be more reluctant to participate in debt rollovers for firms with weak cash flow prospects, strengthening the effect of fund presence on credit risk.

(iii) A more concave flow-performance relationship will exacerbate the effect of fund presence on credit risk.

Before turning to our empirical analysis, we discuss the empirical relevance of some key aspects of our model.

[10] The statement and proof of Proposition 2 would follow as in section 2.2, replacing κ by its contingent equivalent.

First, the model has only one firm. Discerning readers may wonder if, in reality, bond funds have diversified portfolios so that a default in one firm does not matter quantitatively to them. In our data, however, on average bond funds hold relatively concentrated portfolios of 73 firms, which contrasts with 163 firms for equity funds (see Table 1). Such a high concentration in portfolio holdings implies that, with a 40% percent recovery rate, a default in a single firm can result in a portfolio loss of over 0.8% and even higher losses if defaults are correlated across firms.

Second, our model implicitly assumes some frictions in the primary market, because, in a frictionless market, there will always be sufficient mass of non-flow-motivated investors who would provide rollover capital to firms at fair prices, eliminating underpricing. Such frictions in the primary market can arise from a persistent investor base in the corporate bond market, which makes it difficult for firms to change their capital providers or for investors to participate in new bond issuance in the primary market. This persistence in the investor base can arise because the issuer-underwriter-investor relationships are sticky and costly to switch, facilitating recurring participation in rollover by existing bondholders. It can also arise due to lower information acquisition costs for existing bondholders who may already have conducted necessary research and monitoring of their investments, particularly when firms' credit risk is high and information asymmetry is severe. Using our data, we document that issuer-underwriter-investor relationships are highly persistent. Table A.1 in the Appendix reveals that 91.0% of corporate bond issuances are underwritten by a lead underwriter who has underwritten at least one previous issuance by the same issuer within the past three years. In a similar vein, a staggering 97.0% of funds' primary market purchases involve a lead underwriter that they have previous experience with within the past three years.[11]

Such persistence also helps us to find a proxy for the presence of active funds at the time of bond rollover, which is not directly observable. In particular, given the persistence in issuer-underwriter-investor

[11] Related results can be found in Zhu (2021). DiMaggio, Kermani, and Song (2017), Hendershott, Li, Livdan, and Schürhoff (2020), Nikolova, Wang, and Wu (2020), and Nagler and Ottonello (2022) all show that underwriter/dealer and investor relationships tend to be persistent because of underwriter favoritism, trading network relationships, or costly acquisition of information on issuers. Daetz, Dick-Nielsen, and Nielsen (2018) and Chakraborty and MacKinlay (2019) also show that issuer-underwriter relationships tend to be highly persistent.

relationships, we use the holding share of a firm's outstanding bonds by active mutual funds, which we refer to as fund holding share (FHS), as our main explanatory variable.

Finally, discerning readers may note that in interpreting Proposition 5 in an applied context, we focus on the cross-sectional variation across firms, and do not make direct reference to the time-varying average proportion of good funds, γ_{τ}. In this context, we emphasize that all our empirical results below are robust to controlling for credit-rating-by-time fixed effects, and thus we utilize both firm- and rating-level variation at a given point in time in the data.

3.2. Data

We use five main sources of data: (i) Morningstar Direct for the holdings of U.S. taxable bond funds, (ii) the Center for Research in Security Prices (CRSP) Mutual Funds database for information on fund characteristics, (iii) the Mergent Fixed Income Security Database (FISD), (iv) the Trade Reporting and Compliance Engine (TRACE) for bond trades, and (v) the Markit credit default swap (CDS) database for CDS pricing data.

3.2.1. Mutual fund data

Using the fund holdings data from Morningstar from 2002 through 2022, we first match fund share-class level identifier used by Morningstar (*secid*) with that of the CRSP Mutual Funds database (*crsp_fundno*) using CUSIP in a similar manner to Pástor, Stambaugh, and Taylor (2015). We consider bond funds that are classified as corporate or general according to the CRSP objective code as in Choi and Kronlund (2018);[12] a total of 1,405 funds satisfy the criteria. Over a half of holdings information of these bond funds in Morningstar are in monthly frequency, with the rest mostly in quarterly or semi-annual frequencies, with the latter only in a few isolated instances. Following Elton, Gruber, and Blake (2011), we use the latest available holdings information within the past six months. We obtain further information on each fund using the CRSP Mutual Funds databases.

[12] Specifically, these are funds with CRSP objective codes I, ICQH, ICQM, ICQY, ICDI, ICDS, or IC, which corresponds to Lipper objective codes A, BBB, IID, SII, SID, USO, HY, GB, FLX, MSI, or SFI.

3.2.2. CDS spread data

We measure the credit risk of bond issuers using CDS spreads. Unlike corporate bond spreads, CDS spreads are standardized (e.g., constant maturities) and less subject to market microstructure issues including illiquidity pricing premium and therefore are a cleaner measure of credit risk than bond spreads, which allows us a fair cross-sectional comparison of firms' credit risk. The Markit CDS data provide daily CDS spreads for maturities ranging from 6 months to 30 years. We use monthly five-year CDS spreads on senior unsecured obligations denominated in U.S. dollars as they are the most widely traded contracts.[13]

3.3. Main variable construction

We construct our main explanatory variable, FHS, defined as the fraction of total bond amounts of an issuer held by active bond funds, using our holdings data. At each month-end, we first sum bond amounts held by our sample funds for each corporate bond of a firm, defined as those with Mergent FISD bond type CDEB. We use the mapping provided by Fang (2024) to match corporate bonds with their respective firms. We then aggregate each bond-month observation into firm-month observation and calculate fund holding share by dividing the amount of aggregated active fund bond holdings by the total amount of bonds outstanding for the firm. We use the CRSP Mutual Funds database's index fund identifier, supplemented with the name-based classification of Berk and van Binsbergen (2015), to determine whether a given fund is active or passive.

Using fund returns and total net assets from the CRSP Mutual Funds databases, we calculate the flow of fund i at month t. Share class level data are aggregated at the fund level using the CRSP identifier *crsp_cl_grp* with TNAs at the previous month-end as the weight. For a detailed definition of each variable in our study, refer to Appendix C.

3.4. Summary statistics

[13] We focus on contracts with modified restructuring documentation clause until April 2009 and those with no restructuring clause thereafter in light of the "CDS Big Bang."

Table 1 presents the summary statistics of our sample of 926 firms between January 2002 and December 2022, with firm-level fund holdings data constructed using 1,405 corporate and general fixed income funds. The average five-year CDS spread for our sample is around 170 bps. While the average CDS spread of high investment-grade (AAA to A) firms stands at around 60 bps, those of BBB and high yield firms are in excess of 114 bps and 390 bps, respectively. The FHS of active funds has the mean of 6.4%. We observe substantial variation in FHS, with the standard deviation exceeding 6.5% and the inter-quartile range of over 7.3%.

TABLE 1 HERE

4. Main Results: Fund Holdings and Credit Risk

In this section, we first test our main prediction that a higher FHS increases the credit risk of funds' portfolio firms when firms have weak cash flow prospects. We initially establish a positive association between FHS and credit risk in baseline OLS regressions (Section 4.1) and then examine the importance of the rollover channel in generating this association (Section 4.2). We then employ a quasi-natural experiment exploiting a mechanical upgrade of a fund's Morningstar star rating when it turns five years old to confirm that the relationship is causal (Section 4.3), and rule out reverse causality via reaching for yield (Section 4.4). To further address endogeneity concerns, we use the IV approach of Koijen and Yogo (2019), which exploits stickiness in funds' investment mandates (Section 4.5).

4.1. Fund holdings and credit risk: Baseline OLS analysis

Our first testable prediction states that the presence of flow-motivated funds would significantly increase the credit risk of firms with weak cash flow prospects but it should have little impact on credit risks of firms with good cash flow prospects. Thus, on average, the overall relationship between FHS and CDS spread should be positive in the full sample. To examine this relationship, we run OLS regressions of the next-month CDS spread on FHS. The control variables in the regressions are based on the previous studies on credit risk, for example, Collin-Dufresne, Goldstein, and Martin (2001) and Zhang, Zhou, and Zhu (2009). As firm-level controls, we include the first four moments of stock returns (1-year stock return, volatility, skewness, and kurtosis), log assets, leverage, return on equity, dividend payout per share, and recovery rate. As market-level control variables, we include one-month S&P 500 index return, 3-month T-Bill rate, term spread, and VIX. In an alternative specification, we exclude these market variables but include credit-rating-by-time fixed effects, which allow us to compare the statistical association between FHS and the CDS spread for firms with the same level of credit rating at a given point in time. We use standard errors robust to heteroskedasticity and two-way clustered by firm and time. Table 2 presents our results.

TABLE 2 HERE

In line with our model's predictions, we find a significantly positive association between FHS and the next-period CDS spread. In Table 2, the coefficient estimates on FHS are statistically significant at the 1% level in both columns (1) and (2). In terms of economic magnitude, a one-standard-deviation increase in FHS explains 13 bps (=6.517×1.980) of within-rating variation of the next-month CDS, as indicated in column (2). Given that the unconditional average CDS spread of our sample is around 170 bps, the estimated increase corresponds to approximately 8% of average CDS spread.

We proceed to examine whether the positive relationship between FHS and the CDS spread is indeed concentrated among firms with weak cash flow prospects. To test this prediction, we consider two regression specifications based on proxies for firms' cash flow prospects and examine how the FHS-CDS relationship changes with these proxy variables. First, we employ indicator variables for investment grade (IG) and high yield (HY) firms and interact these indicator variables with FHS. Second, we use past one-year stock returns of the firms as a proxy for cash flow prospects and also interact them with FHS. Table 3 presents our results.

TABLE 3 HERE

As predicted by our model, column (1) of Table 3 reveals that the relationship between FHS and the next-period CDS spread is noticeably stronger among HY firms compared with IG firms, though the coefficient difference is not statistically significant. When we further split the indicator for IG firms into those for firms rated A or above versus firms rated BBB, the results in column (2) reveal a clear pecking order: While the coefficient on the interaction between FHS the indicator for firms rated A or higher is statistically indistinguishable from zero, we find strong and positive statistical significance for the interactions with the indicators for BBB-rated and HY firms, with the latter interaction term exhibiting a noticeably larger point estimate compared with that for BBB-rated firms. Using an F-test, we compare the coefficients on the interactions for firms rated A or above and HY firms and find the coefficient difference to be statistically significant at the 5% level (*F*-stat=4.49).

Column (3) of Table 3 reveal a pattern similar to those in columns (1) and (2): the relationship between FHS and the CDS spread becomes more positive for firms with negative recent stock returns, as indicated by a significantly negative point estimate on the interaction term.[14] The magnitudes of the estimated coefficients in column (3) show that, for a firm with its one-year stock return at the third quartile of our sample (30.1%), a one-standard-deviation increase in FHS is associated with an increase in the next-period CDS spread by approximately 11 bps ($= 6.517\times(2.323 - 2.123\times0.301)$). In contrast, for a firm with its latest one-year stock return at the first quartile (-6.2%), the corresponding figure is 16 bps ($= 6.517\times(2.323 + 2.123\times0.062)$). Taken together, Table 3 highlights the statistical association between mutual funds' holding share on the credit risk of their portfolio firms is particularly pronounced among firms with weak cash flow prospects.

4.2. Fund holdings and credit risk: The relevance of the rollover channel

The previous subsection establishes a strong positive association between FHS and CDS spread, most notably among weak cash flow prospect firms, consistent with our conceptual framework. We now dig deeper into the micro-level evidence by zooming in on rollover events, thus providing a tighter link between the empirics and theory. We do so in two different ways. First, we demonstrate the key role played by rollover events in funds' trading decisions for firms with weaker fundamentals. Other than in a minority of such firms with relatively liquid bonds, we show that mutual funds reduce their holdings of such firms primarily at rollover events. Second, we show that the positive association between FHS and credit risk becomes stronger when

[14] In Table A.2, we consider shorter return horizons of one and six months, respectively, and re-estimate Table 3 column (3). Results are qualitatively unchanged.

firms face greater rollover risk. To this end, we use three firm-level proxies for rollover risk: a proximate rollover event, short average maturities for outstanding debt, and the presence of a "maturity tower."

Fund trading around bond rollovers. The connection between the preceding results and our theory rests on a key ingredient of the model—namely, funds' reluctance to roll over bonds issued by firms with deteriorating cash flow prospects. We establish the relevance of this channel by showing that funds make active portfolio adjustments primarily at bond rollover events. In particular, mutual funds maintain their positions in portfolio firms until rollover dates, even as firms' cash flow prospects worsen, and concentrate their portfolio decisions at rollover. What accounts for such inertia? One possibility is that the high degree of illiquidity in the corporate bond market (e.g., Bao, O'Hara, and Zhou, 2018; Choi, Huh, and Shin, 2024), particularly for stressed bonds, makes it costly and often impractical for funds to reduce their positions through secondary market trading. If so, bond rollovers may provide funds with an important natural opportunity to scale back exposure to firms with deteriorating fundamentals.

In order to examine active trading, we define a benchmark trading case where a fund trades rather passively, which we construct as follows. First, motivated by prior studies,[15] we assume that the fund allocates flows proportionally across all bonds that it held at the previous quarter-end. Second, if a fund holds a firm's bond that is retired either in whole or in part due to early calls, tender offers, or maturity, we reduce its position accordingly.[16] Third, when a firm engages in a rollover issuance, namely an issuance occurring in the same quarter or the quarter preceding a bond retirement, we assume the fund retains the same position in the firm by buying back the retired position.[17] This creates a simple benchmark where the fund trades only in response to bond retirements, rollovers, and flows. The difference between the fund's actual position change and the benchmark, divided by the par amount held in the previous quarter, yields our measure of active fund trading.

[15] See Lou (2012) for equity funds and Choi, Hoseinzade, Shin, and Tehranian (2020) for bond funds, who document that funds scale positions approximately one-for-one with fund flows.
[16] For example, if a bond's amount outstanding declines from 1,000 to 400 due to early retirement, funds' holdings of that bond also decline by 60%$(= 1 - 400/1000)$.
[17] If a bond's amount outstanding declines from 1,000 to 400 due to early retirement *and* a rollover issuance occurs around the time, the fund buys 600 of the rollover issuance, i.e., the amount required to maintain its original position absent the retirement.

A discerning reader may wonder whether our assumptions regarding how funds respond to (1) bond retirements and (2) rollover issuances constitute the most representative benchmark for passive trading. If our passive trading benchmark is representative, it should capture the most common outcomes at retirements and rollovers; in other words, our measure of *active* trading should center strongly around 0 in quarters with retirements and rollovers. In Figure A.1 in the Internet Appendix, we present a set of histograms to confirm that active fund trading is indeed tightly centered and peaks heavily around 0 in firm-quarters with bond retirements or rollover issuances. It is also worth noting that, compared to the full sample, we find more dispersion in active fund trading in firm-quarters with bond rollovers, suggesting that funds take more active decisions around rollovers.

Using this measure of active fund trading, we examine whether funds' active portfolio adjustments are concentrated around rollover events, focusing on major downgrades that either push issuers into the high yield (HY) grade (IG-to-HY downgrades) or into a lower broad rating class within the HY segment (BB-to-B and B-to-CCC downgrades).[18] For [0, 4] quarters following a downgrade, we first compute average active fund trading separately for firm-quarters with and without rollover issuances. The results are reported in Table 4 Panel A1.

TABLE 4 HERE

Table 4 Panel A1 reveals a stark contrast in active fund trading between rollover and non-rollover quarters. In non-rollover quarters (column 2), average active trading is close to zero with little statistical significance. In contrast, when there is a rollover issuance (column 1), funds on average reduce their positions in the firm by 5.1 percentage points relative to the benchmark case, with a *t*-statistic in excess of 4 in absolute magnitude. Thus, following credit rating downgrades, funds appear to unwind their positions mostly around rollovers. We find similar patterns when we restrict our attention to IG-to-HY and BB-to-B downgrades in columns (3) through (6).

In Panel A2, we further examine active trading around rollover events using regressions. Specifically, we regress active fund trading on the rollover issuance indicator, which equals one if a firm has at least one

[18] We focus on these rating downgrade events as the FHS-CDS relationship is significantly positive for firms rated BBB or below, as reported earlier in Table 3 column (2).

rollover issuance in a given quarter. Column (1) reveals that, relative to quarters without a rollover issuance, funds reduce their positions in these firms with weaker fundamentals by an extra 8.74 percentage points when the firm engages in a rollover issuance, with statistical significance at the 1% level. When we separately consider each type of downgrade events in columns (2) through (4), we find a consistent pattern across all three types, with statistical significance at the 1% or 5% level in all instances.

In Panel B of Table 4, we examine the role of secondary market liquidity in funds' active trading around rollovers. In particular, we interact the rollover issuance indicator with the following bond liquidity measures: (i) log trading volume and (ii) a *traded price exists* indicator, which takes the value of one if the bond has a recorded trade in TRACE in the last trading day of the quarter.[19] The results in Panel B indicate that the interaction of rollover issuance and each of the two proxies for bond liquidity is positive and significant at the 1% level. Interestingly, in column (2), the statistical test (see *F-statistic:* $A + B = 0$) indicates that, when a firm's corporate bonds all have traded prices on the last trading day of the quarter, the difference in coefficients between the quarters with and without a rollover issuance is statistically insignificant. This is consistent with the idea that, when a firm's corporate bonds are sufficiently liquid, funds can flexibly adjust their positions following downgrades without needing to wait for a bond rollover, whereas when their bond holdings are illiquid in the secondary market, funds rely more on bond rollovers to adjust their positions in portfolio firms.[20] We note that, for the vast majority of firms, this equality of coefficients is unlikely to hold, and rollovers would thus play a significant role in active fund trading decisions on firms with declining fundamentals; only 4.1% of our sample firms that experience credit rating downgrades have all their corporate bonds liquid enough to report traded prices on the last trading day of the quarter.

A natural question is whether this association reflects funds' reluctance to roll over firms with weaker cash flow prospects or, instead, the greater illiquidity of such firms' bonds. As He and Milbradt (2014) observe,

[19] We aggregate these bond-level measures into firm-level liquidity measures by taking the par-weighted-average. The results are also robust to using trade existence in the last five trading days of the quarter.

[20] We find this pattern to hold more generally, not just around downgrade events. Table A.3 in the Internet Appendix reveals that funds' active trading is much larger in absolute terms when a firm has a rollover issuance in a given quarter. The interaction of the rollover issuance indicator and bond liquidity variables is significantly negative, suggesting that the difference in active trading between quarters with and without rollover issuance widens when a firm's bonds are illiquid in the secondary market.

the two are difficult to separate because default and liquidity risk are mutually reinforcing. Consistent with this, we find that poor secondary-market liquidity amplifies the FHS–CDS relation only among weak cash flow prospect firms (Table A.4 in the Internet Appendix), leaving the rollover channel central.

Firm-level proxies for rollover risk. According to the predictions of our model, a positive relationship between FHS and CDS spreads exists because the presence of flow-motivated funds lowers bond prices at rollover. It is reasonable, therefore, to expect this relationship to be more prominent among firms with greater rollover risk.[21] To explore this possibility, we examine several proxies for rollover risk. First, when a firm faces an imminent bond rollover, its rollover risk would likely be greater. Accordingly, we construct the near-maturity indicator variable, which takes the value of one whenever the firm has a bond maturing within the next three months. Second, when a firm's corporate bonds have shorter average maturities, the firm is likely to be more exposed to rollover risk as it must roll over its bonds more frequently. To capture this effect, we construct the weighted-average time-to-maturity of its corporate bonds, with each bond's par amount outstanding as the weight, as the second proxy for rollover risk. Third, when a firm has a "maturity tower", i.e., a concentrated maturity of its outstanding debt, it is more likely to face heightened rollover risk. We measure this maturity-tower effect using the maturity HHI measure following Choi, Hackbarth, and Zechner (2018), based on data from the S&P Capital IQ database. We then re-estimate the baseline OLS regression with the interaction of FHS with each of the proxy for rollover risk. Table 5 presents our results.

TABLE 5 HERE

Table 5 column (1) reveals that the relationship between FHS and CDS spread strengthens significantly around bond maturities. Whereas the standalone FHS loses significance altogether, the point estimate on the interaction term in column (1) implies that a one-standard-deviation increase in FHS increases the CDS spread by $6.517 \times (0.390 + 2.859) = 21$ bps when a firm nears the maturity of one of its bonds, with statistical significance at the 5% level. Columns (2) and (3) reveal the regression results for the interaction of FHS with

[21] Jankowitsch, Nagler, and Subrahmanyam (2014), for example, find that riskier and more illiquid bonds recover substantially less after a default event, with poor post-default liquidity in the secondary market.

the average bond time-to-maturity, both for the full sample as well as for firms with data coverage in the S&P Capital IQ database. In both instances, we find the interaction term to be significantly negative, with statistical significance at the 1% level in column (3), suggesting that the relationship between FHS and CDS spread becomes more prominent for firms with shorter average bond time-to-maturity. Column (4) presents the regression result for the interaction of FHS with debt maturity HHI measure of Choi, Hackbarth, and Zechner (2018). In line with our expectations, we find the interaction term to be positive with significance at the 5% level, suggesting that the presence of mutual funds is associated with more pronounced increases in credit risk for firms with concentrated debt maturities. When we interact the FHS with both the time-to-maturity as well as maturity HHI in column (5), these findings remain robust with interaction terms remaining significant at the 5% and 10% levels, respectively. Our analyses of different proxies for rollover risk indicate that the positive relationship between FHS and CDS spread intensifies when a firm is exposed to higher degrees of rollover risk, providing further support to the relevance of our rollover channel.[22]

4.3. Fund holdings and credit risk: Quasi-natural experiment 1

While our baseline OLS regressions are useful in documenting the statistical relationship, we employ a quasi-natural experiment that generates exogeneous shocks to fund flows and, in turn, FHS, that enables us to identify a causal relationship between FHS and CDS spreads. Following Adelino, Cheong, Choi, and Oh (2026), we focus on the mechanism by which Morningstar assigns overall star ratings to funds when they turn five years old. The Morningstar overall star rating for each share class is based on its three-, five-, and ten-year star ratings. For each of these time horizons, the star rating is calculated by ranking the funds' risk-adjusted performance within the Morningstar category over the specified period. For share classes aged between 36 and 59 months, the overall rating is solely based on the three-year star rating, as five- or ten-year ratings cannot be calculated.

When a share class turns five, however, a new five-year star rating is introduced. To calculate the overall rating, Morningstar now takes a weighted average of the three- and five-year star ratings, rounding the average

[22] In addition to our analysis of the CDS spread, we also examine offering yields (i.e., yields at issuance) in Table A.5 in the Appendix; we find that a larger presence of bond funds is associated with higher issuance yields, in line with our prediction.

to the nearest integer to determine the overall rating. This sudden introduction of a five-year rating means that, even if the three-year rating remains unchanged when the fund turns five, the share class could still be upgraded or downgraded based on the new five-year star rating. Importantly, any difference in risk-adjusted performance that leads to an upgrade or downgrade solely stems from how a share class performed between three years prior and five years prior, unlikely to be correlated with the credit risk of current holdings. Yet, if investors focus on the overall star rating, as is found to be the case in Ben-David, Li, Rossi, and Song (2022), Evans and Sun (2021) and Reuter and Zitzewitz (2021), investor flows may nevertheless respond.

To obtain exogeneous shocks to FHS, we thus employ the upgrades of Morningstar overall ratings when funds turn five years old. As shown by Adelino, Cheong, Choi, and Oh (2026), rating upgrades at the five-year mark generate exogenous inflows to the upgraded funds.[23] While these funds do not necessarily have to expand investments in the existing holdings dollar-for-dollar, it is documented that funds tend to do so (Lou, 2012; Choi, Hoseinzade, Shin, and Tehranian, 2020), as these additional flows are informationless. Expanding existing holdings is likely the best response to mechanical rating-driven inflows, which we later confirm to be the case. This in turn increases the FHS of the portfolio firms of upgraded funds.

The increase in FHS can potentially have two distinct effects. The first is the immediate price effect of the buying pressure, which must be controlled for. The second is the channel relevant to our prediction: the increased presence of flow-motivated bondholders resulting in greater credit risk. Our focus on CDS spreads is partly designed to isolate the latter effect, as CDS spreads are less prone to price pressure. In order to further disentangle these two effects, we also examine the CDS-bond basis, namely the difference between the spread on a cash bond and a par-equivalent CDS spread. A positive price impact on the physical bond combined with a deterioration in the firms' credit risk should manifest as a temporary widening of the CDS-bond basis.

Rating upgrades at the five-year mark and investor flows. In Table 6, we first check whether flows respond to a rating change at the five-year mark, despite the mechanical nature of such changes as discussed above. We

[23] We focus on upgrades, following Adelino, Cheong, Choi, and Oh (2026), who demonstrate that investors respond asymmetrically to Morningstar rating updates, with a stronger reaction to upgrades than to downgrades. We thus follow their approach to obtain a stronger shock to fund flows.

identify all share classes that reach the age of five whose overall star ratings are either upgraded or remain at their previous levels. The former group forms our treated group, while the latter serves as our control. Then, we examine flow responses to rating changes using difference-in-difference regressions over [-12, 12] months around the five-year mark. Column (1) of Table 6 Panel A shows that upgraded funds receive, on average, extra flows exceeding 0.53% per month, i.e., nearly 6.3% over the 12-month window following the rating change, relative to those that remain at their previous ratings. The difference-in-difference term (*Upgrade at 5-year* × *Post 5-year*) is significant at the 1% level.

TABLE 6 HERE

Investor flows and FHS. We then examine the extent to which FHS increases due to the rating upgrades at the five-year mark, using difference-in-difference regressions. The results provided in column (2) of Table 6 Panel A show a significant increase in FHS. The coefficient estimate on *Upgrade at 5-year* × *Post 5-year* suggests the FHS of firms that are held by treated funds increases by around 0.7% relative to those held by control peer funds, following the rating upgrades at the five-year mark, with statistical significance at the 1% level.

This increase in FHS is driven by the expansion of holdings in existing firms in the funds' portfolios when they receive inflows after the upgrades. In Panel B of Table 6, we provide supporting evidence based on funds' trading activity. Specifically, we examine how five-year-old funds allocate flows between firms already existing in their portfolios versus newly added firms, by separately regressing funds' holdings changes in existing firms and newly added firms on fund flows after rating upgrades. We find that over 83% of fund flows in upgrade quarters are allocated to existing portfolio firms, while only around 9% of flows to newly added firms. These results clearly indicate that extra inflows from mechanical rating upgrades are primarily used to expand positions in existing portfolio firms.

FHS and CDS spread. Our next step is to examine whether this material change in FHS is accompanied by a corresponding increase in credit risk. Column (3) of Table 6 Panel A reveals that firms held by upgraded funds do indeed experience an increase in CDS spread of approximately 11 bps compared to those held by control funds, with a *t*-statistic close to 3. A similar increase in the CDS spread for firms held by upgraded funds relative to control-held firms is graphically illustrated in Figure 3, which shows a noticeable rise in the CDS spread following funds' rating upgrade at the 5-year mark. This increase in the CDS spread remains elevated by around 10 to 14 bps at the end of the 12-month difference-in-difference window.

FIGURE 3 HERE

In Table 6 Panel C, we further interact the difference-in-difference terms with the HY indicator to examine whether the increase in CDS spread is more pronounced among firms with weaker cash flow prospects. As predicted by the model, we find that the increase in CDS spread is largely concentrated among HY firms, with a *t*-statistic of 4.4 for the triple interaction term. The identification exercise therefore strongly suggests a causal relationship between FHS and credit risk.

Price impact vs. credit risk. As discussed earlier, the increase in FHS following a mechanical rating upgrade can have two distinct effects. In addition to the increase in credit risk, buying pressure from the expansion of holdings in existing portfolio firms can create a direct price impact, which must be controlled for. To examine whether a price impact exists, we examine differences in the yield spreads of corporate bonds held by upgraded and control funds around the five-year mark. To ensure a direct comparison of similar bonds, we match each bond held by an upgraded fund to the nearest-neighbor bond held by a control fund within the same credit rating. Specifically, at each month-end, we identify a matched control bond with the same credit rating as the treated bond, using time to maturity, log amount outstanding, callable indicator, and putable indicator as matching variables, while imposing a caliper length restriction to identify close matches. The yield spread is defined as the difference between the month-end bond yield and the five-year Treasury yield. To ensure consistency with the analysis based on five-year CDS spreads, we focus on bonds with time to maturity between three and seven years.

FIGURE 4 HERE

Figure 4 Panel A shows that inflows into the upgraded funds bring about a notable decline in yield spread after the five-year mark. In the first six months following the Morningstar rating upgrade, we find that the average yield spreads of bonds held by upgraded funds fall by approximately 14 bps relative to their matched control peer bonds. We then observe a sizable reversal over the next six months, with the average yield spreads turning positive by the 12-month period. These results suggest that inflows into funds receiving a Morningstar rating upgrade create temporary price impacts, which are subsequently reversed as the buying pressure subsides.

To separate the effect of the increased credit risk from buying-pressure-induced price impact, we proceed to examine the CDS-bond basis. The fact that the yield spreads and CDS spreads initially move in opposite directions at the five-year mark suggests that the CDS-bond basis should indeed widen. In Figure 4 Panel B, we plot the CDS-bond basis, calculated as the difference between the five-year CDS spread and the par-equivalent bond credit spread, using the identical set of upgraded-held and matched control bonds.[24] The figure confirms that the CDS-bond basis widens, reaching its peak in the first six months after the five-year mark, and subsequently narrows back toward zero over the following six months. These results confirm that the credit risk component of bonds held by upgraded funds increases, distinct from the bond price impact created by investor inflows into these funds.

Active mutual funds vs. other institutional investors. Our analysis emphasizes the role of active mutual funds, which are subject to outflows, in increasing corporate credit risk. However, other institutional investors with more stable funding structures, such as insurance companies and pension funds, are also significant players in the bond market. Recent studies emphasize the potentially stabilizing role of such investors in bond markets (Chodorow-Reich, Ghent, and Haddad, 2021; Coppola, 2025).[25] Similarly, the presence of passive mutual funds is unlikely to worsen the credit risk of their portfolio firms, as they generally follow mechanical portfolio rules and do not exhibit unwillingness to hold defaultable bonds, unlike active mutual funds. If so, a question arises: is the observed effect on credit risk driven by the increased presence of active mutual funds or the decreased presence of other institutional investors? A potential alternative explanation for our results is that the increased

[24] CDS-bond basis is computed using the J.P. Morgan par-equivalent spread methodology as employed in Bai and Collin-Dufresne (2019) and Choi, Shachar, and Shin (2019), with Libor swap rates as the risk-free rate. Due to the phase-out of the Libor contracts at the end of 2021, the yield spread and CDS-bond basis figures consider a shorter sample period ending in December 2021.
[25] In line with these findings, Table A.6 in the appendix reveals that the presence of stable institutional investors, i.e., insurances, pensions, and passive funds, is negatively associated with CDS spread, particularly among HY firms.

credit risk of portfolio bonds stems from a decrease in the holding share of those other investors, due to bond ownership transferring from them to active funds.

To test this alternative story, we investigate how the holding shares of insurance companies, pension funds, and passive funds change when our sample funds receive Morningstar rating upgrades at the five-year mark. Insurer and pension fund holdings are constructed using the LSEG eMaxx data. Table 6 Panel D reports the difference-in-differences regression results of holding shares of these other institutions around the introduction of five-year Morningstar rating, similar to the setting of Panel A. While the coefficient on the interaction term for insurance and pensions holding share is -0.47, suggesting that they do absorb some of the purchase pressure of treated funds, the interaction term is not statistically significant. The statistical and economic significance of passive fund holding share is also noticeably weaker. Thus, the CDS spread increases that occur with fund flow and holding share increases appear unlikely to be driven primarily by decreases in holding shares of insurers, pension funds, or passive mutual funds.

Do funds channel flows to purchase riskier new firms? Our analysis in Table 6 Panel B indicates that five-year-old funds direct flows predominantly toward firms already held in their portfolios. We further examine whether funds direct the remaining flows substantially toward riskier *new* firms, thereby testing the possibility that investor flow responses to Morningstar rating upgrades mechanically generate a positive FHS-CDS spread relationship. To rule out this possibility, we repeat the analysis in Table 6 Panel B but split new firms into high vs. low subsamples on the basis of their corporate bonds' (i) within-rating-and-maturity RFY, i.e., whether the bond has a higher yield than its rating-and-maturity peers,[26] or (ii) time-to-maturity. In each case, we use the holding-weighted-average of the relevant variable measured in the quarter preceding the five-year mark to divide firms into high and low subsamples. Table A.7 in the Internet Appendix shows no statistically significant difference between the coefficients for the high and low subgroups, suggesting that new firms are not disproportionately riskier compared with what funds held prior to the upgrades.

[26] Following Choi and Kronlund (2018), we calculate within-rating-and-maturity RFY as the difference between a bond's yield and the amount-weighted average yield of its rating-and-maturity bucket, using month-end yields reported in LSEG Datastream.

A related possibility is that, upon receiving favorable inflows, these funds may purchase bonds of new firms that have recently received a bad signal about the fundamentals. These are likely to be firms that other institutional investors wish to sell, and investor inflows may merely enable upgraded five-year-old funds to provide "the other side of the trade." To examine whether this is the case, we compare the portfolio shares of downgraded firms (from IG to HY) or portfolio-level past 12-month stock returns between existing firms and newly-added firms in their portfolios. As shown in Table A.8, we find no statistically significant difference in either the share of such "fallen angel" firms or recent stock returns, suggesting that new firms do not mainly consist of firms with unfavorable fundamental signals. If anything, the coefficient on the proportion of IG-to-HY downgrade is lower and that on the 12-month stock return is higher for new firms, indicating that they may be slightly on the safer side.

Given that new firms do not consist of riskier firms or exhibit poor fundamental signals, it is not surprising if we find no significant change in within-rating-and-maturity RFY at the portfolio level for our DiD sample of five-year-old funds. Consistent with this interpretation, the DiD interaction term in Table A.9 of the Internet Appendix is small and bears little statistical or economic significance.

What drives upgraded funds' purchases in new firms? These results raise a natural question: If RFY or maturity does not explain upgraded funds' purchases in new firms, what other factors drive their purchase decisions? We consider two such factors. First, due to information asymmetry, funds are more likely to direct flows toward firms that they have interacted with before—that is, fund managers are more likely to purchase firms whose bonds they have purchased previously in either the primary or secondary markets, even if they do not currently hold them. This information-asymmetry channel may be further reinforced by issuer-underwriter-fund relationships in corporate bond markets. Second, fund managers are more likely to purchase firms whose corporate bonds can be acquired more easily because of high secondary market liquidity.

To explore this issue in more detail, we conduct a regression analysis of funds' purchase decisions in new firms to examine the roles of market liquidity and prior purchase experience. We begin by defining a set of bonds that are not currently held in the portfolios of upgraded funds but could plausibly be purchased by them. Specifically, for each upgraded fund, we construct a potential investment universe based on the 5th and 95th percentiles of ratings and maturities of its existing holdings. We then build a fund-firm-quarter sample that includes all firms outside upgraded funds' existing portfolio that have at least one eligible bond in the universe. This sample thus include all fund-firm-quarters in which a purchase could potentially occur. The dependent variable is the fund's percentage purchase share in a given firm. For explanatory variables, we consider an indicator variable that equals one if the fund has purchased the firm's corporate bond in the past 12 quarters, along with log bond trading volume, average bond time-to-maturity, within-rating-and-maturity RFY, and the firm's 12-month stock return. Table A.10 in the Internet Appendix indicates that prior purchase experience and secondary market liquidity both bear a strong positive association with funds' purchase shares, consistent with our expectations. In contrast, time to maturity, RFY, or recent stock returns remain statistically insignificant, echoing our earlier findings.

4.4. Fund holdings and credit risk: Can "reaching for yield" explain the observed patterns?

Our analysis in Section 4.3 is designed to establish a causal relationship between fund holdings of corporate bonds and credit risk. Nevertheless, it is still possible to ask whether the observed empirical patterns can instead be explained by bond funds' RFY behavior. A positive relationship between FHS and CDS spreads may arise if bond funds hold riskier bonds to reach for yield. To address this concern, we construct a fund-level RFY measure by taking a holding-weighted average of bond-level within-rating-and-maturity RFY across each fund's portfolio. In addition to computing average RFY for the full sample of funds, we examine subsamples based on (i) high vs. low default spread or (ii) high vs. low VIX subperiods. For comparison, we also calculate RFY for insurance companies and pension funds whose holdings are available from LSEG eMaxx. Table 7 Panel A presents average RFY for these samples.

TABLE 7 HERE

Column (1) of Panel A1 shows that bond funds in our sample, on average, do not engage in RFY, with the average within-rating-and-maturity RFY standing at −4.3 bps. This pattern holds across both IG and HY funds, with corresponding RFY estimates of −2.5 and −7.6 bps, respectively. When we condition on overall market conditions, we find that bond funds, particularly those with HY mandates, tilt their portfolios toward safer bonds during periods of market stress. For example, the average RFY for HY funds is −13.8 bps during periods of high default spreads, compared with −2.0 bps during low default spread periods, with their difference statistically significant at the 1% level. Thus, when funds hold riskier and more illiquid HY securities and the corporate bond market is under stress, they appear to restrain themselves from RFY. The observed RFY estimates are closely in line with those reported in previous studies on bond funds' RFY (Choi and Kronlund, 2018).

In contrast, Panel A2 shows the opposite pattern for insurance companies and pension funds. For these investors, the baseline RFY is 6.6 bps. Moreover, their RFY tendencies appear to intensify during periods of market stress: the average RFY is 8.3 bps high default spread periods, compared with 5.2 bps during low default spread periods, with the difference statistically significant at the 1% level. This behavior is consistent with the relatively stable funding bases of insurance companies and pension funds, which make flow and liquidity concerns less acute than for open-end mutual funds. For example, insurers and pension funds can acquire higher-yielding corporate bonds and classify them as held to maturity. Thus, mutual funds do not appear to hold riskier portfolios than insurance companies and pension funds; if anything, the opposite is true, particularly during periods of market stress.

As Table 7 Panel A shows, funds' risk-taking incentives are moderated during periods of market distress, as the potential costs of risk-taking rise owing to higher illiquidity and credit risk of the corporate bond market. Thus, we examine whether the relationship between FHS and CDS spreads also weakens during periods of market distress. This analysis allows us to further assess whether the observed FHS-CDS patterns are consistent with the RFY behavior documented above. To this end, we interact FHS with an indicator variable that equals one when a given month's (i) default spread—specifically the difference between Moody's Baa and Aaa corporate bond yields—or (ii) VIX is above or below the sample median. We further interact FHS with mutually exclusive IG and HY indicators as well as with the high default-spread or high VIX indicators.

In Table 7 Panel B columns (1) and (2), we find that the interactions of FHS with the high default spread or high VIX indicators enter positively, and in the latter case is statistical significant at the 5% level. This result indicates that the relationship between FHS and CDS spreads strengthens when the market is volatile and under stress. Crucially, this stronger relationship during periods of market stress is observed only among HY firms. While the coefficient on the triple interaction between FHS, the IG indicator, and the market-stress indicator is not statistically significant, the corresponding triple interaction for HY firms is positive and statistical significance at the 5% (column 3) or 1% (column 4) levels. These patterns are the polar opposite of the RFY behavior of mutual funds, with the effect of FHS on credit risk substantially *stronger* during periods of market stress, which in turn casts further doubt on the relative plausibility of the alternative story.

At a broad level our model helps unify findings in the RFY literature and those in this paper. At its core, our model microfounds excessive caution by open-end funds towards assets weak prospects, arising from their fear of outflow. The model suggests that funds' willingness to pay for bonds of firms with poor cash flow prospects is *lower* than that of non-flow-motivated investors, which translates into a higher risk of default, generating the core of our empirical analysis. However, the model also shows that their relative willingness to pay is *higher* than non-flow motivated investors for bonds of firms with *strong* cash flow prospects. This latter effect would suggest that, all else equal, bond funds would prefer to hold *safer* assets on average. This is exactly what the RFY literature documents and we confirm in our Table 7. Yet, suppose these *ex ante* safe firms, after being bought by funds, end up suffering from deteriorating fundamentals but their corporate bonds cannot be sold easily prior to rollover due to secondary market illiquidity. They now face funds with an excessive reluctance to roll over, which generates the credit risk effect that we document. In other words, our model provides a lens through which the baseline facts documented by Choi and Kronlund (2018) and in our paper can be conceptually linked together.

4.5. Fund holdings and credit risk: Instrumental variable regressions

As an additional way to tackle any potential endogeneity, we consider an IV approach akin to Koijen and Yogo (2019) in our baseline OLS regressions. In particular, we instrument FHS using hypothetical fund holding share based on the investment universe of mutual funds, following the approach of Koijen and Yogo (2019). For each fund at each month-end, we construct a hypothetical portfolio that equally divides the fund's total net assets over all issuers within its investment universe, which is measured as a set of all issuers whose bonds have been held by the fund at least once within the last three years. This measurement of the investment universe is also based on Koijen and Yogo (2019) who argue that institutional investors typically limit portfolio holdings to a relatively small set of investments and that the set of investments that they have held rarely changes over time. We refer to the equal-weighted holdings based on a fund's investment universe as its hypothetical holdings. To construct the IV for FHS for firm k at month t, we aggregate the hypothetical holdings of all funds and divide them by the total amounts of bonds outstanding for firm k. We use this IV for FHS in two-stage least square (2SLS) regressions.

The idea behind this instrument is that bond mutual funds have stable and predetermined investment universes reflecting investment mandates specified in their prospectuses, often with industry, size, maturity, and credit rating constraints on what assets they hold. In addition, high costs of acquiring firm-specific information further restricts a fund's potential investment universe. Thus, this IV exploits variation in bond funds' demand that arises mainly from their investment universes; that is, when a bond is included in the investment universe of many funds, the bond is likely to have a high fund holding share than other bonds. Since the investment universe of bond mutual funds is largely predetermined and the hypothetical holdings allocate a fund's total net assets equally, regardless of individual firms' credit risk, we may reasonably expect this investment-universe-based demand for a firm's bonds to be largely exogenous. This in turn allows us to exploit plausibly exogenous variations in funds' demand for corporate bonds to alleviate the simultaneity and reverse causality issues. It is worth noting that, in its reliance on fund-level capital allocation, this instrument is quite close to the spirit of the model, in which there are exogenous supply effects from investors that determine the marginal prices of these bonds.

TABLE 8 HERE

In Table 8, we present the second-stage results of two-stage least squares (2SLS) regressions. The results reveal that this IV approach once again confirms the baseline OLS findings, namely a strong positive relationship between FHS and CDS spread among weak cash flow prospect firms, with the coefficient on FHS significant at the 5% level in column (1) and the interaction of the FHS with the HY indicator significantly positive at the 1% level in column (2).

5. Further Results: Flow Concerns, Flow-Performance Concavity, and Robustness

In this section, we test our two secondary predictions. We show via baseline regressions that the association between FHS and credit risk is enhanced when funds' flow concerns are heightened (Section 5.1) and then utilize a quasi-natural increase in flow concerns for firms held by PIMCO following the departure of Bill Gross in September 2014 to establish causality (Section 5.2). We further examine the effect of the concavity of the flow-performance relationship (Section 5.3) and provide further robustness checks on our findings (Section 5.4).

5.1. Flow concerns and credit risk: Baseline OLS analysis

We now examine whether the positive relationship between flow-motivated funds' holdings and credit risk is more pronounced when funds exhibit higher degrees of flow concerns. To begin with, we examine broad circumstances in which fund managers' flow concerns are more pronounced. First, the presence of a high load fee should dampen investor response and alleviate the fund's flow concerns. Second, flow concerns would likely be more pronounced for funds belonging to a small family, because larger families have various means at their disposal to provide liquidity to those experiencing temporary outflows (Bhattacharya, Lee, and Pool, 2013; Agarwal and Zhao, 2019).

To analyze whether there exist differential effects of FHS on credit risk for funds with these different characteristics, we proceed as follows. At each month-end, we split our sample of funds into high versus low groups based on the sample median of following variables within each Lipper category: (i) the asset share of load fee classes within the fund, and (iii) management firm size. In Table 9, we then re-estimate column (2) of Table 2 using these low- and high-group FHS. Table 9 presents our results.

TABLE 9 HERE

Column (1) of Table 9 indicates that the holding shares of funds with relatively low TNA share of load fee classes has a larger positive impact on the CDS spread, as shown by the coefficient estimate on the low-return group's FHS (5.820), which is statistically significant at the 1% level. The coefficient difference between the low- and high-group FHS is also significant at the 1% level. Column (2) further reveals that the holding share of funds belonging to smaller families similarly has a significantly more pronounced impact on the next-period CDS spread, with the coefficient difference between low- and high-group FHS once again statistically significant at the 1% level.

When we interact the low- and high-group FHS with the IG and HY indicators in columns (3) and (4), we find that, across both IG and HY firms, the coefficients on the holding shares of funds with low load fee class share and small management firm size are substantially larger, with the coefficient difference between the low- and high-group FHS retaining statistical significance in all but one instance. All these findings are in line with our model's prediction that the degree of flow concerns exacerbates the relationship between FHS and credit risk, particularly for firms with poor cash flow prospects.

5.2. Flow concerns and credit risk: Quasi-natural experiment 2

To establish causality with respect to the effect of funds' heightened flow concerns, we consider a second quasi-natural experiment. We exploit a setting where flow concerns change as a result of exogenous shocks: the sudden departure of Bill Gross from PIMCO (e.g., Zhu, 2021). Bill Gross was one of the co-founders of PIMCO and managed its famous Total Return Fund. Dubbed the "Bond King" by popular media, he was one of the most influential investors in the bond market. However, he surprisingly left PIMCO in September 2014 for Janus Capital, citing fierce in-fighting among PIMCO executives. The sudden departure of Gross shocked investors, as PIMCO without Bill Gross was almost unthinkable.

The departure of Bill Gross had two distinct effects on PIMCO funds. First, these funds experienced substantial outflows immediately following his departure. As we document later on, PIMCO active bond funds experienced outflows amounting to over 10% of their AUMs in the first month, potentially generating a sizable negative price impact. Second, and more relevant to our testable implication, uncertainty about the future performance of the new management team increased flow concerns for PIMCO funds, as many investors had chosen PIMCO based on the long, reliable track record of Bill Gross. Importantly, this increase in flow concerns following Bill Gross's departure was not directly related to the fundamentals of PIMCO holdings.

It is therefore important to tease out the effect of increased flow concerns from that of the outflow-driven price impact. One important empirical pattern that helps us disentangle the two effects, as we show later, is the fact that PIMCO flows begin to stabilize after the first six months while the increased flow concerns remain strong for much longer, making it possible to separate the two stories.

Bill Gross's departure and the CDS spread of PIMCO-held firms. We first use the departure of Bill Gross in a difference-in-difference setting to uncover the effect of increased flow concerns on credit risk. Specifically, using the latest available portfolio holding in August 2014, i.e., just before Bill Gross' departure, we identify treated firms as all firms with at least 0.5% of its holdings held by PIMCO. To identify control firms, we use propensity score matching. We identify either one or two closest neighbor control firms with the same credit rating in August 2014, with log assets, leverage, ROE, and dividend payout per share as matching variables. We further consider various caliper length restrictions to rule out potential bad matches and check the robustness of our matching procedure. Then, for the window of [-12, 12] months around the departure of Bill Gross, we run a set of difference-in-difference regressions by interacting the PIMCO indicator, which takes the value of one for PIMCO-held firms and zero for matched control firms, with the post-Bill Gross departure indicator. According to the predictions of our model, the interaction term between the PIMCO indicator and post-Bill Gross departure indicator should have a positive sign due to the elevated flow concerns of firms held by PIMCO in the aftermath of Bill Gross's departure.

TABLE 10 HERE

Table 10 Panel A presents the results. Regardless of the matching procedure, we find that PIMCO-held firms experience a substantial increase in CDS spread relative to their matched control peers following the departure of Bill Gross. The economic magnitude is also sizable: we find that the CDS spread increases by between 27 and 35 bps depending on the matching specification used, with statistical significance at the 1%

level in all instances. When we interact the difference-in-difference terms with the mutually exclusive IG and HY indicator variables in Panel B, we find both the statistical and economic significance to be substantially stronger among HY firms, though the increase in CDS spreads is observed for both IG and HY firms.

Figure 5 graphically illustrates the increase in CDS spread of PIMCO-held firms relative to matched controls, with little evidence of pre-trend prior to the departure of Bill Gross and the CDS spread responding immediately afterward, remaining at a substantially elevated level even at the end of our difference-in-difference window, which is important in distinguishing the relative plausibility of the price impact vs. flow concern stories.

FIGURE 5 HERE

Outflows vs. flow concerns. As discussed earlier, in addition to heightened flow concerns, the departure of Bill Gross brought about investor exodus from PIMCO. In October 2014, for example, PIMCO active bond funds experienced outflows amounting to over 10% of their AUMs, as is revealed in Figure 6 Panel A. PIMCO-held firms experienced a notable ensuing fall in their holding share by PIMCO following the departure of Bill Gross, with the PIMCO holding share falling from close to 2% in the month leading up to Bill Gross's departure to around 1.4% after the first six months. It is therefore worth examining whether the increase in CDS spread is brought about by the immediate impact of investor outflows from PIMCO or heightened flow concerns.

FIGURE 6 HERE

Even though the investor outflows from PIMCO funds are noticeable in the first six months following the departure, Figure 6 Panel A also reveals that the flows stabilize in the next six months of our 12-month test window. As a result, PIMCO holding share also begins to stabilize in the second half of the window, as is evident in Figure 6 Panel B. Importantly, Figure 6 Panel C reveals that, after a sharp decline in the FHS of PIMCO-held firms relative to their matched control peers over the immediate three to four months following Gross's departure, the FHS recovers fully during the first half of the test window, as other funds begin to replace the previously PIMCO-held positions. The difference-in-difference regressions also fail to detect a statistically significant change in FHS of PIMCO-held firms relative to matched control firms, as is shown in columns (1) through (3) of Table 10 Panel C. Thus, it is unlikely that the elevated CDS spreads, plotted in

Figure 5, that persist until the end of the 12-months window are driven by the selling pressure by PIMCO funds, as the FHS has fully recovered during the first half of the window. These results suggest that potential fire sales of bonds held by PIMCO funds cannot account for the observed patterns in the CDS spread.

In contrast, when we compare the average flow volatility of funds holding PIMCO-held firms and their control peers, Figure 7 reveals a noticeable increase in flow volatility among PIMCO-held firms, which remains substantially elevated until the end of the 12-month window. This is confirmed in a regression setting, with a significantly positive difference-in-difference term regardless of the matching specification when we consider the average flow volatility as the dependent variable in columns (4) through (6) of Table 10 Panel C. Thus, the observed patterns for the CDS spread are consistent with heightened flow *concerns* rather than the *realized* outflows from PIMCO.

FIGURE 7 HERE

5.3. Is the concavity in the flow-performance relationship relevant?

The final prediction of our theory states that the relationship between fund holdings and credit risk should be more pronounced when mutual fund bondholders face a concave flow-performance relationship, because the fear of a large outflow following poor recent performance heightens the manager's downside flow concerns, further depressing her willingness to invest in bonds. This concave flow-performance relationship is known to stem from the payoff complementarity that arises from open-end funds' liquidity mismatch (Chen, Goldstein, and Jiang 2010). As a result, flows become disproportionately more sensitive to bad performance. We examine how flow-performance concavity affects the effect of FHS on credit risk as follows. First, we estimate flow-performance concavity using a rolling three-year regression of monthly fund flow on the interaction of lagged fund return and the negative fund return indicator. The coefficient on the interaction term then captures the extra flow response to a negative return relative to a positive return of the same magnitude. We use this coefficient to group our sample funds into high- and low-concavity funds based on the sample median of their Lipper peers at each month-end. Then, as in Table 9, we separately calculate the holding share of each group and re-estimate our main results. Table 11 presents our results.

TABLE 11 HERE

Column (1) of Table 11 reports the baseline regression results with high- and low-concavity FHS. We find that the positive relationship between FHS and the next-period CDS spread is more pronounced among high-concavity funds, though the coefficient difference test between the two groups yields an insignificant result. In fact, even among low-concavity funds, we find a significant relationship between FHS and credit risk, indicating that our results are not driven by concavity alone. IG and HY credit rating interaction results in column (2) also suggest that, once again, the strong association between FHS and credit risk among firms rated BBB or below is at its most significant when high-concavity funds hold a HY firm. The results in Table 11 suggest that, while our results do not rely on the existence of a concave flow-performance relationship, it does strengthen the relationship between fund holdings and CDS spread, as predicted by our illustrative model.

5.4. Robustness checks

We engage in a number of robustness checks to further strengthen our findings. First, given that our FHS measure scales fund holdings with the amount of corporate bonds outstanding, the measure does not take into account of corporate loans and other debt instruments. As a robustness check, we consider an alternative measure of FHS, which scales fund holdings with the firm's total amount of debt outstanding as reported in Compustat. The results in columns (1) and (2) of Table A.11 indicate that the positive association between FHS and the CDS spread, particularly for firms with poor cash flow prospects (i.e., HY-rated firms), is fully robust to this alternative measure of FHS.

Second, instead of the level of CDS spread, we consider monthly change in the CDS spread as a dependent variable, using fund holdings scaled by either the amount of bonds outstanding or the total amount of debt as the main measure of interest. The results in Table A.11 columns (3) through (6) reveal that our baseline OLS result, namely the positive association between FHS and the next-month CDS spread for weak cash flow prospect firms, is fully consistent with these specification changes, regardless of whether fund holdings are scaled by the amount of corporate bonds outstanding or the total debt outstanding.

Third, we re-estimate the difference-in-difference regressions using the Morningstar rating upgrades around the five-year mark as in Table 6 but focusing only on a subset of funds whose three-year Morningstar star rating (i.e., the overall star rating under the old methodology) remains unchanged. For this smaller set of funds, the upgrade in the overall star rating is purely attributable to the rating methodology change based on stale information, as they would not have been upgraded in the absence of a methodological change, thereby strengthening the causal link between fund holdings and credit risk even further. In Table A.12 in the Appendix, we reveal that all results are fully consistent with similar statistical and economic magnitudes.

Finally, we revisit our instrumental variables regressions presented in Section 4.5 to examine the role of flow concerns by forming subsamples on the basis of the share of load fee classes and the fund family TNA and separately calculate the high- and low-group FHS as in Table 9, which we then use in a 2SLS setting.[27] The results in Table A.13 fully confirm the OLS findings in Table 9, with the coefficient on the holding share of funds with low shares of load fee classes or belonging to smaller families significantly larger than that of the high-group counterparts, particularly among HY-rated firms.

6. Conclusion

We show that firms with a large share of their corporate bonds held by bond mutual funds subsequently experience an increase in credit risk. Our model illustrates how the flow concerns of bond funds reduce their willingness to pay for bonds of firms with weak cash flow prospects, which in turn intensifies the equityholders' default incentives and worsens the firm's credit risk. Additionally, the model predicts that the positive relationship between bond funds and credit risk strengthens as funds' flow concerns intensify and if the flow-performance relationship becomes more concave. Overall, our conceptual framework suggests that, in addition to firm fundamentals and market characteristics, *who* holds the bonds is a relevant factor in determining a firm's credit risk.

[27] To instrument for the two holding shares, we separately calculate the hypothetical holding share for high- and low-group in each instance, creating two separate instruments for two potentially endogenous FHS variables. When we interact the FHS variables with the mutually exclusive IG and HY indicators, the two instruments are also interacted with these rating indicators.

Our empirical analyses support the model's main predictions. We find that a one-standard-deviation increase in the holding share of active bond funds is associated with an increase in a firm's next-period CDS spread by around 13 bps, particularly for firms rated BBB or below. We provide further micro-level evidence supporting the relevance of our rollover channel: funds make most of their active trading decisions around bond rollovers and the relevance of fund holdings on credit risk increases for firms with higher rollover risk. We confirm a causal relationship using a mechanical change in Morningstar's rating methodology for funds turning five years old, with a quasi-exogenous inflow into upgraded five-year-old funds resulting in increased fund holdings and subsequent credit risk. Our results are stronger in turbulent market periods, which is the polar opposite of the "reaching for yield" behavior exhibited by bond funds, further alleviating reverse causality concerns. We also find evidence supporting the model's additional predictions. Using Bill Gross' departure from PIMCO in 2014 as an exogenous shock to PIMCO funds' flow concerns, we reveal that heightened flow concerns can have a material impact on the credit risk of firms that these funds hold. Finally, we show that the relationship between fund holdings and credit risk becomes stronger when funds holding the bonds exhibit high degrees of flow-performance concavity.

Our findings are highly relevant in the context of the changing landscape of the market for corporate bonds. The bond holdings of bond funds in the corporate bond market have more than doubled in the previous two decades, and they are the only group of U.S. domestic institutional investors with a growing presence in the market, filling the gap created by the declining share of more traditional investors. Our results indicate that this could be a cause for concern from the issuers' perspective. The fragility of these funds' flow base and the resulting flow concerns of fund managers could prove an obstacle to a firm's bond rollover and exacerbate its credit risk, particularly during times of credit stress and market uncertainty. If so, our results further suggest that better monitoring of a firm's existing bond investor base should form an integral part of future regulatory approaches to ensure financial stability of the market for corporate debt financing.

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Table 1. Summary Statistics

In this table, we report summary statistics on the sample of 926 firms with five-year CDS spread data available on Markit and non-missing coverage of at least one of its corporate bonds (defined as those with the Mergent FISD bond type "CDEB") in the Morningstar fund holdings data. Our sample period is between January 2002 and December 2022, with the holdings data of 1,405 corporate and general fixed income funds. The observations are at the firm-month level. All firm-level continuous variables are winsorized at the 1% and 99% levels, and we report the summary statistics computed using winsorized values. We further provide details on the portfolio characteristics at the fund-month level, with bond and equity fund holdings from Morningstar. For a detailed description of how each variable is constructed, refer to Appendix C.

	Obs.	Mean	St. Dev.	P25	P50	P75
CDS premium						
All firms	104,781	169.82	251.82	45.11	85.20	180.17
AAA to A	28,800	59.89	77.50	26.24	43.15	68.58
BBB	49,128	113.94	120.78	50.03	83.77	133.30
BB or below	26,853	389.94	383.65	151.58	273.03	465.42
Fund holding share (FHS)						
All funds (%)	104,781	7.625	6.495	2.824	5.964	10.84
Active funds only (%)	104,781	6.446	6.517	1.798	4.148	9.146
Other characteristics						
12-month stock return (%)	104,781	13.37	38.67	-7.634	11.22	30.09
Historical volatility (annualized %)	104,781	33.49	19.87	20.57	27.70	39.36
Historical skewness	104,781	0.072	0.962	-0.310	0.036	0.397
Historical kurtosis	104,781	8.041	7.952	4.162	5.417	8.459
Total assets ($ millions)	104,781	46,037.7	101,872.8	5,798.0	14,240.0	35,018.0
Leverage (%)	104,781	51.12	25.32	33.57	48.36	63.52
Return on equity (%)	104,781	3.302	14.10	1.323	3.207	5.504
Dividend payout per share	104,781	0.262	0.286	0.030	0.185	0.390
Fund portfolio characteristics						
No. of public firms held in the portfolio						
Bond mutual funds	147,470	72.81	67.09	30	57	93
Equity mutual funds	380,094	163.40	328.78	41	69	128

Table 2. Fund Holdings and Credit Risk

We report the OLS regression results of firm-month level panel regression of CDS premium (in bps) on fund holding share (FHS) of active funds. In column (1), we include market-wide control variables without fixed effects, while in column (2), we include credit-rating-by-time fixed effects. Controls are 1-year return, realized volatility, skewness, and kurtosis, recovery rate, firm size, leverage, ROE, and dividend payout per share, and in the case of column (1), 1-month S&P 500 return, 3-month T-Bill rate, term spread, and VIX. All controls are lagged by one month. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS	4.575***	1.980***
	(7.65)	(3.82)
1-year stock return	-1.119***	-1.023***
	(-10.84)	(-12.36)
Historical volatility	5.491***	5.785***
	(12.42)	(15.69)
Historical skewness	8.261***	5.506***
	(4.04)	(3.18)
Historical kurtosis	-0.615**	-0.825***
	(-2.08)	(-3.46)
Recovery rate	-27.103***	-18.822***
	(-10.65)	(-8.29)
Log assets	-13.509***	-0.510
	(-5.73)	(-0.23)
Leverage	1.899***	1.180***
	(9.09)	(7.46)
ROE	-0.475***	-0.153
	(-2.72)	(-1.19)
Dividend payout per share	-44.200***	8.666
	(-3.97)	(1.04)
1-month S&P 500 return	-6.305***	
	(-5.21)	
3-month T-Bill rate	-7.177*	
	(-1.94)	
Term spread (%)	-2.194	
	(-0.36)	
VIX	-2.656***	
	(-3.68)	
Credit-rating-by-time FE	NO	YES
Adjusted R-squared	0.561	0.677
No. of obs.	104,781	104,754

Table 3. Fund Holdings, Cash Flow Prospects, and Credit Risk

In this table, we estimate the OLS regressions of CDS spreads as in Table 2, albeit with fund holding share (FHS) either interacted with mutually exclusive credit rating indicators or past 1-year stock return. In column (1), we interact FHS with two indicator variables, namely an indicator variable for firms rated IG and another indicator variable for HY. In column (2), we separate the IG indicator into two components, namely A or above vs. BBB indicators, and run regressions using the three credit-rating-based indicators. In column C, we interact FHS with the past 1-year stock return. We also report F-statistics from the hypothesis testing that the coefficient estimates on various interaction terms are equal. Control variables are identical to those in Table 2, whose coefficient estimates are omitted for brevity, and we include credit-rating-by-time fixed effects in all specifications. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)		
	(1)	(2)	(3)
FHS × IG (IG)	1.338***		
	(2.91)		
FHS × A or above (A)		0.157	
		(0.19)	
FHS × BBB (BBB)		1.550***	
		(3.11)	
FHS × HY (HY)	2.498***	2.498***	
	(3.11)	(3.11)	
FHS × 1-year stock return			-2.123***
			(-2.98)
FHS			2.323***
			(4.13)
F-statistic: (IG) = (HY)	1.82		
F-statistic: (A) = (HY)		4.49**	
Controls	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES
Adjusted R-squared	0.677	0.677	0.678
No. of obs.	104,754	104,754	104,754

Table 4. Rating Downgrades, Rollover Issuances, and Fund Trading

In Panel A1 of this table, we first present the average active fund trading separately for firm-quarters with vs. without rollover issuances over [0, 4] quarters following a firm's credit rating downgrade. When a firm has multiple credit ratings, we use the pecking order of S&P, Moody's, and Fitch in the order of availability. We focus on all major downgrades (IG-to-HY, BB-to-B, and B-to-CCC downgrades) as well as separately for each downgrade type. To calculate active fund trading at the fund-firm-quarter level, we first define a passive trading benchmark as follows. First, at each quarter, we calculate flow-induced trading by assuming that fund proportionally allocates its quarterly flows to all bonds that it holds and sum across all bonds issued by firm j. Second, when fund i holds firm j's bond k that is retired either in part or in whole in quarter q due to early calls, tender offers, or upon reaching its maturity, we reduce fund i's position in bond k proportionally. For example, if a firm calls back 60% of a bond's outstanding amount early, and the fund held 1,000 in par amount prior to the early call, its bond holdings amount is reduced pro rata to 400. Summing this across all retiring bonds for firm j in a given quarter yields the amount of fund position reduction arising from bond retirement. Third, when firm j engages in a rollover issuance (namely an issuance occurring within the same quarter or a quarter preceding a bond retirement), we assume that fund i purchases the amount equal to the retirement amount, which enables the fund to return to its original holding position in firm j. For example, in the aforementioned example, if there is a rollover issuance around the time of early call, we assume that the fund buys back the retired amount, i.e., 600, to return to its original position of 1,000. We define active fund trading as the absolute difference between actual fund trading in firm j and the passive trading benchmark, divided by the previous quarter-end fund position in firm j, expressed in percentage terms. In Panel A2, we then run a set of OLS regressions of active fund trading on rollover issuance indicator and a set of fixed effects. Rollover issuance indicator takes the value of one if the firm undertakes at least one rollover issuance during the quarter and zero otherwise. In Panel B, we then pool together all major HY downgrade events and run the interaction of the rollover issuance indicator with bond liquidity variables. For bond liquidity variables, we consider (i) log trading volume, namely the natural log of bond trading volume during the last month of the quarter as reported in TRACE, and (ii) "*traded price exists*" indicator, which takes the value of one when the bond has at least one trade reported in TRACE during the last trading day of the quarter. We only consider institutional trades exceeding $100,000, and due to the availability of the TRACE database, the sample begins from the first quarter of 2005. To calculate firm-level measure of bond liquidity, we weighted-average the bond-level liquidity variables with the par amount outstanding in a given quarter. We exclude financial (SIC 6000-6999) and utilities firms (SIC 4900-4999) from the sample due to their frequent rollover issuances. We include firm and Lipper-objective-by-time fixed effects in all instances, and *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by Lipper objective and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Rollover issuances following rating downgrades

A1. Average active fund trading: Firm-quarters with vs. without rollover issuances

	Active fund trading (%)							
	All downgrades		IG-HY downgrades		BB-B downgrades		B-CCC downgrades	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rollover	Yes	No	Yes	No	Yes	No	Yes	No
	-5.102***	0.076	-2.711*	-0.460	-7.488***	0.940	-2.655	-1.343
	(-4.35)	(0.12)	(-1.71)	(-0.62)	(-4.22)	(1.44)	(-1.13)	(-1.38)
No. of obs.	26,767	137,567	12,270	49,792	11,817	65,788	7,028	33,931

A2. OLS regressions

	Dependent variable: Active fund trading (%)			
	(1)	(2)	(3)	(4)
	All downgrades	IG-HY downgrades	BB-B downgrades	B-CCC downgrades
Rollover issuance	-8.738***	-6.279**	-13.427***	-6.125***
	(-5.76)	(-2.61)	(-7.62)	(-3.59)
Firm FE	YES	YES	YES	YES
Lipper-objective-by-time FE	YES	YES	YES	YES
Adjusted R-squared	0.032	0.037	0.042	0.050
No. of obs.	164,323	62,044	77,559	40,885

Panel B. Interactions with bond liquidity variables

	Dependent variable: Active fund trading (%)	
	(1)	(2)
[0, 4] quarters around	All major HY downgrades	
Rollover issuance (A)	-64.060***	-14.682***
	(-4.84)	(-7.78)
Log trading volume	-1.048***	
	(-5.36)	
Rollover issuance × Log trading volume	3.242***	
	(4.23)	
Traded price exists		-0.739
		(-0.56)
Rollover issuance × Traded price exists (B)		16.334***
		(4.84)
F-statistic: (A) + (B) = 0		0.31
Firm FE	YES	YES
Lipper-objective-by-time FE	YES	YES
Adjusted R-squared	0.034	0.033
No. of obs.	151,527	151,527

Table 5. Fund Holdings, Rollover Risk, and Credit Risk

In this table we present the estimation results of the OLS regressions of CDS spreads. In column (1), we interact fund holding share (FHS) with a near-maturity indicator that takes the value of one when a firm has a bond maturing within the next 3 months. In columns (2) and (3), we interact FHS with weighted average time-to-maturity (TTM) of a firm's corporate bonds. In column (2), we consider the full sample, while in column (3), we restrict the sample to those that have reliable corporate debt structure data in the S&P Capital IQ Capital Structure database following the data cleaning procedure as outlined in Choi, Hackbarth, and Zechner (2018). In column (4), we interact FHS with a variable denoting a firm's debt maturity concentration, *Maturity HHI*. Maturity HHI is calculated in the analogous manner to Choi, Hackbarth, and Zechner (2018, CHZ 2018 hereafter). Herfindahl-Hirschman Index (HHI) is calculated using each maturity bucket's amount outstanding as a proportion of total corporate debt, and we define maturity bucket for each integer year (< 1 years, 1-2 years, 2-3 years, etc.). Finally, in column (5), we interact FHS with both the bond time-to-maturity and the maturity HHI. We include firm and credit-rating-by-time fixed effects in all specifications. Control variables are identical to those in Table 2, whose coefficient estimates we do not report. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)				
	(1)	(2)	(3)	(4)	(5)
Sample	Full sample		Capital IQ Capital Structure coverage		
FHS (%)	0.390	1.610	2.664**	-0.991	1.345
	(0.65)	(1.25)	(2.40)	(-1.08)	(0.98)
Near-maturity	10.862				
	(1.51)				
FHS (%) × Near-maturity	2.859***				
	(2.69)				
Bond TTM		0.395	0.412		0.237
		(0.68)	(0.87)		(0.49)
FHS (%) × Bond TTM		-0.236*	-0.327***		-0.295**
		(-1.67)	(-2.75)		(-2.47)
Maturity HHI				-20.372	-16.284
				(-1.12)	(-0.91)
FHS (%) × Maturity HHI				4.219**	3.432*
				(2.18)	(1.77)
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES	YES
Adjusted R-squared	0.770	0.775	0.762	0.761	0.762
No. of obs.	104,623	101,430	66,147	66,147	66,147

Table 6. Difference-in-Difference Test: Morningstar Rating Change at the Five-Year Mark

In Panel A of this table we estimate the effect of Morningstar star rating changes on fund flow, FHS, and CDS spreads when a fund reaches the age of 5 years. We first identify all events when a share class of a fund reaches the five-year old mark and its star rating either goes up (our treated share classes) or remains the same (the control share classes). In column (1), we run the share class-level difference-in-difference regression of fund flows for a window of [-12, 12] months around these events. The indicator variable, *Upgrade at 5-year*, takes the value of one for the treated share classes and zero otherwise. The indicator variable, *Post 5-year*, takes the value of one for the window of [0, 12] months after the event. In columns (2) and (3), we run the firm-level difference-in-difference regressions of next-month FHS and CDS spreads around the same event windows and using firms with treated or control fund holding share greater than 0.5%. The firm-level indicator variable, *Upgrade at 5-year*, takes the value of one if the firm is held by treated funds in the month prior to the event. The indicator variable, *Post 5-year*, is defined as in column (1). In column (3), we also include the controls as in Table 2. Panel B presents the regression results of mutual fund position changes on fund flows for our sample of 5-year-old funds. We compute position changes separately for (i) all corporate bonds issued by existing firms held at quarter $t-1$ (i.e., quarter preceding the upgrade), (ii) all corporate bonds issued by new firms not held prior to the upgrade, and (iii) cash. Mutual fund position change between quarters t and $t+q$ is defined as: $(AmtOut_{j,t+q} - AmtOut_{j,t-1})/TotAmtOut_{j,t-1}$, where $AmtOut_{j,t+q}$ is the par amount of corporate bonds (existing or new) or cash held by the fund at quarter $t+q$, and $TotAmtOut_{j,t+q}$, is the total par amount of bonds held by the fund at quarter $t+q$. For corporate bonds issued by new firms, $AmtOut_{j,t-1}$ is therefore 0. To avoid extreme position changes, we only include bonds with prices between $50 and $200. We regress this measure on fund flow over the same time horizon. Regressions are conducted at the fund-quarter level. In Panel C, we run triple-difference-in-difference regressions of either the next-month FHS or CDS spreads on *Upgrade at 5-year*, *Post 5-year*, and *HY* indicator variables. Finally, in Panel D, we run difference-in-difference regressions with the next-month holding share of (i) insurance & pensions and (ii) passive funds as the dependent variable instead. Due to data coverage, the insurance and pension holding share ends in December 2021. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fund flow, FHS, and CDS spread

	Dependent variable		
	(1)	(2)	(3)
	Monthly flow	FHS	CDS spread
Upgrade at 5-year		-0.297	4.919
		(-1.57)	(1.46)
Post 5-year	-0.320*	0.595***	2.873
	(-1.87)	(3.12)	(1.05)
Upgrade at 5-year × Post 5-year	0.528***	0.730***	10.976***
	(2.94)	(2.73)	(2.80)
Controls	NO	NO	YES
Share class FE	YES	NO	NO
Time FE	YES	NO	NO
Firm FE	NO	NO	YES
Credit-rating-by-time FE	NO	YES	YES
Adjusted R-squared	0.093	0.386	0.819
No. of obs.	101,858	35,217	35,056

Panel B. Bond funds' position changes

	Dependent variable: Fund position change in/between					
	Quarter t			Quarters t and $t+1$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Corporate bonds		Cash	Corporate bonds		Cash
	Existing firms	New firms		Existing firms	New firms	
Flow	0.834***	0.091***	0.114***	0.777***	0.114***	0.101***
	(5.04)	(3.18)	(5.84)	(7.33)	(3.95)	(3.33)
Lipper-objective-by-time FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.336	0.456	0.101	0.282	0.482	0.009
No. of obs.	641	641	641	641	641	641

Panel C. FHS and CDS spread: IG vs. HY

	Dependent variable	
	FHS	CDS spread
	(1)	(2)
Upgrade at 5-year	-0.143	14.402***
	(-0.64)	(5.27)
Post 5-year	0.920***	3.101
	(4.39)	(1.43)
Upgrade at 5-year × Post 5-year	-0.027	-4.216
	(-0.08)	(-1.46)
Upgrade at 5-year × HY	-0.370	-23.768***
	(-0.93)	(-3.33)
Post 5-year × HY	-0.660**	-0.113
	(-2.18)	(-0.03)
Upgrade at 5-year × Post 5-year × HY	1.597***	36.057***
	(3.31)	(4.40)
Controls	NO	YES
Firm FE	NO	YES
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.387	0.819
No. of obs.	35,217	35,056

Panel D. Insurance, pensions, and passive fund holding share

	Dependent variable	
	Insurance & pension holding share (%)	Passive fund holding share (%)
	(1)	(2)
Upgrade at 5-year	0.651*	-0.020
	(1.69)	(-1.08)
Post 5-year	-0.793***	0.041*
	(-2.78)	(1.77)
Upgrade at 5-year × Post 5-year	-0.470	0.009
	(-1.00)	(0.32)
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.378	0.790
No. of obs.	33,418	35,217

Table 7. Bond Funds' Reaching for Yield and Overall Market Conditions

In Panel A1 of this table we present the average within-rating-and-maturity reaching for yield (RFY) estimates of active bond funds in our sample. We first obtain the month-end yield of our sample of corporate bonds (with bond type "CDEB" in the Mergent FISD database) from Datastream. We exclude convertible bonds, bonds with maturity less than one year, and bonds with month-end traded price below $5 or above $1,000. When a firm has multiple credit ratings, we use the pecking order of S&P, Moody's, and Fitch in the order of availability. Then, for each rating (AAA, AA+, AA, AA- etc.) and maturity group (1-3 years, 3-5 years, 5-7 years, 7-10 years, and in excess of 10 years), we calculate the weighted-average monthly yield using each bond's amount outstanding as the weight. Then, for all corporate bonds held by each active fund at each quarter-end, we calculate within-rating-and-maturity RFY as the difference between the yield and the average yield of the rating-maturity group to which the bond belongs. We then calculate a fund-level weighted-average RFY with each bond holding's par value held as the weight. We report the average RFY coefficient for (i) all active funds as well as separately for (ii) IG and HY mandate funds. We define HY mandate funds to be those with Lipper objective codes "HY", "GB", "FLX", "MSI", "SFI", "SHY", and "ARB". Column (1) presents the full sample estimates. In columns (2) through (4), we present the subsample results for high vs. low default spread subperiods as well as the difference test between the two coefficients. In columns (5) through (7), we do so for high vs. low VIX subperiods. Then, in Panel A2, we repeat the analysis for insurance and pensions whose holdings information are available in the eMaxx database. Regressions are conducted at the investor-quarter level in both panels. Finally, in Panel B, we present the estimation results of the OLS regressions of CDS spreads on the interaction of FHS and an indicator variable that captures overall market conditions. In columns (1) and (3), we consider periods of high default spread, while in columns (2) and (4), we consider periods of high VIX. In columns (1) and (2), we interact the FHS with the high default spread or VIX indicator, while in columns (3) and (4), we interact the FHS with the mutually exclusive IG and HY indicators before interacting with the high default spread or VIX indicator. We include the credit-rating-by-time fixed effect in all specifications. The control variables are the same as in the baseline regression in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time (in Panel A) or two-way clustered by firm and time (in Panel B) are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Within-rating-and-maturity RFY of institutional investors

A1. Mutual funds

	Within-rating-and-maturity RFY (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full sample	Default spread subperiods			VIX subperiods		
		High	Low	High – Low	High	Low	High – Low
All funds	-0.043***	-0.067***	-0.020**	-0.047**	-0.062***	-0.025***	-0.037*
	(-4.50)	(-3.93)	(-2.51)	(-2.49)	(-3.63)	(-2.87)	(-1.96)
No. of obs.	45,457	21,541	23,916	45,457	21,600	23,857	45,457
IG mandate funds	-0.025***	-0.029**	-0.021***	-0.008	-0.031***	-0.018***	-0.013
	(-4.28)	(-2.68)	(-4.12)	(-0.70)	(-2.93)	(-3.63)	(-1.11)
No. of obs.	29,319	13,940	15,379	29,319	13,952	15,367	29,319
HY mandate funds	-0.076***	-0.138***	-0.020	-0.118***	-0.119***	-0.037**	-0.082*
	(-3.55)	(-3.63)	(-1.11)	(-2.82)	(-3.00)	(-2.06)	(-1.90)
No. of obs.	16,138	7,601	8,537	16,138	7,648	8,490	16,138

A2. Insurance and pensions

	Within-rating-and-maturity RFY (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full sample	Default spread subperiods			VIX subperiods		
		High	Low	High – Low	High	Low	High – Low
Insurance & pensions	0.066***	0.083***	0.052***	0.031***	0.069***	0.064***	0.006
	(11.45)	(7.49)	(12.79)	(2.66)	(6.29)	(11.82)	(0.47)
No. of obs.	30,091	13,963	16,128	30,091	13,739	16,352	30,091

Panel B. FHS, CDS spread, and overall market conditions

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Variable of interest	Default spread	VIX	Default spread	VIX
FHS	1.481***	1.292**		
	(2.73)	(2.37)		
FHS × High variable of interest	1.027	1.502**		
	(1.32)	(2.17)		
FHS × IG			1.699***	1.402***
			(3.33)	(2.91)
FHS × IG × High variable of interest			-0.673	-0.132
			(-1.25)	(-0.25)
FHS × HY			1.325*	1.209
			(1.66)	(1.49)
FHS × HY × High variable of interest			2.682**	3.135***
			(2.01)	(2.70)
Controls	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES
Adjusted R-squared	0.677	0.677	0.678	0.678
No. of obs.	104,754	104,754	104,754	104,754

Table 8. Instrumental Variable Regressions

In this table, we present the second-stage results of two-stage least squares firm-month level panel regression of CDS spread (in bps) on fund holding share (FHS). To construct an instrumental variable for a firm, we aggregate the hypothetical holdings of funds and divide them by the total amounts of bonds outstanding for the firm. The hypothetical holdings are calculated as the equal-weighted holdings that equally divide a fund's total net assets over its investment universe, defined as all firms that the fund has invested at least once within the past 36 months (excluding the latest month-end). Using this instrument, we re-estimate the baseline relationship between FHS and CDS spread in column (2) of Table 2 as well as the interaction of the FHS with the mutually exclusive IG and HY indicator variable as in Table 3 column (1). The control variables are the same as those in Table 2. We include time fixed effect in all specifications. We further report the Kleibergen-Paap F-statistic for the weak instrument test. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS	1.766**	
	(2.11)	
FHS × IG		-2.227**
		(-2.42)
FHS × HY		4.558***
		(4.94)
Controls	YES	YES
Time FE	YES	YES
Kleibergen-Paap F-statistic	366.1	196.2
No. of obs.	100,004	100,004

Table 9. Flow Concerns, Fund Holdings, and Credit Risk

In this table, we report the estimation results of the OLS regressions of CDS spreads, using fund holding share (FHS) constructed separately for high- and low-group funds based on the percentage of share classes with a load fee (columns 1 and 3) and management firm size (columns 2 and 4). We sort funds at each month end into above-median (high) and below-median (low) groups within each Lipper objective code. In columns (1) and (2), we run baseline regressions with the FHS of the two groups, while we interact these FHS measures with the mutually exclusive IG and HY indicators in columns (3) and (4). We also report F-statistics testing the hypotheses that various coefficients of high- and low-group FHS are equal. We include credit-rating-by-time fixed effect in all specifications. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Fund characteristic of interest	% of load fee classes	Management firm size	% of load fee classes	Management firm size
High-group FHS$^{(H)}$	1.145**	1.201**		
	(2.03)	(2.30)		
Low-group FHS$^{(L)}$	5.820***	6.502***		
	(3.86)	(3.54)		
High-group FHS × IG $^{(HIG)}$			0.863*	0.365
			(1.73)	(0.68)
Low-group FHS × IG $^{(LIG)}$			5.171***	6.952***
			(4.46)	(3.75)
High-group FHS × HY $^{(HHY)}$			1.427	1.779**
			(1.49)	(2.36)
Low-group FHS × HY $^{(LHY)}$			5.956***	6.506**
			(2.84)	(2.36)
F-statistic: (H) = (L)	7.55***	7.35***		
F-statistic: (HIG) = (LIG)			9.76***	10.02***
F-statistic: (HHY) = (LHY)			3.16*	2.78*
Controls	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES
Adjusted R-squared	0.678	0.678	0.678	0.678
No. of obs.	104,754	104,754	104,754	104,754

Table 10. Difference-in-Difference Test: Departure of Bill Gross

In this table we estimate the effect of Bill Gross's departure from PIMCO in September 2014 on credit risk of firms held by PIMCO, using difference-in-difference regressions. The treated firms are all firms held by PIMCO with a minimum holding weight of 0.5% at the end of August 2014. We engage in either one-to-two (in columns 1 through 4) or one-to-one nearest neighbor matching (without replacement, column 5) to find the closest non-PIMCO-held control firms. We exact match on credit rating and use log assets, leverage, ROE, and dividend payout per share as matching variables. In columns (1) through (3), we further impose caliper length restrictions to rule out potential bad matches. We employ an event window of [-12, 12] months around the departure of Bill Gross. The indicator variable, *Post-Bill Gross departure*, takes the value of one for the window of [0, 12] months after the departure. The indicator variable for the treated firms, *PIMCO*, takes the value of one for the treated firms and zero for matched control firms. In Panel A, we consider the standard interaction between PIMCO and post-Bill Gross departure indicators, while we further interact them with mutually exclusive IG and HY indicators in Panel B. Finally, in Panel C, we consider FHS and average flow volatility, defined as the 12-month holding-weighted-average flow volatility of all active fund bondholders, as dependent variables instead, for the cases of columns (1), (4), and (5) in Panels A and B. We include firm and credit-rating-by-time fixed effects in Panels A and B and credit-rating-by-time fixed effect in Panel C. Standalone indicators for the difference-in-difference regressions in Panels A and B are subsumed by the inclusion of fixed effects. The control variables are the same as those in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline regressions

	Dependent variable: 5-year CDS spread (bps)				
Nearest neighbors	One-to-two				One-to-one
	(1)	(2)	(3)	(4)	(5)
Caliper length restriction	≤ 0.02	≤ 0.03	≤ 0.05	None	None
PIMCO × Post-Bill Gross departure	28.872***	34.738***	34.164***	28.165***	26.928***
	(6.58)	(10.68)	(10.75)	(7.12)	(6.33)
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES	YES
Adjusted R-squared	0.826	0.841	0.841	0.908	0.906
No. of obs.	2,843	2,996	3,082	3,635	3,549

Panel B. IG vs. HY firms

	Dependent variable: 5-year CDS spread (bps)				
Nearest neighbors	One-to-two				One-to-one
	(1)	(2)	(3)	(4)	(5)
Caliper length restriction	≤ 0.02	≤ 0.03	≤ 0.05	None	None
PIMCO × Post-Bill Gross departure	15.716***	15.729***	15.553***	14.000***	12.772***
× IG	(3.46)	(3.51)	(3.50)	(3.93)	(3.33)
PIMCO × Post-Bill Gross departure	51.122***	61.949***	58.886***	45.770***	40.816***
× HY	(4.65)	(7.22)	(7.18)	(5.88)	(5.83)
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES	YES
Adjusted R-squared	0.827	0.842	0.843	0.908	0.906
No. of obs.	2,843	2,996	3,082	3,635	3,549

Panel C. FHS and flow volatility

	Dependent variable					
	FHS			Average flow volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
Nearest neighbors	One-to-two		One-to-one	One-to-two		One-to-one
Caliper length restriction	≤ 0.02	None	None	≤ 0.02	None	None
PIMCO	2.279***	3.000***	2.486***	0.059	-0.324**	-0.212***
	(23.79)	(99.52)	(70.96)	(0.49)	(-2.45)	(-3.19)
PIMCO ×	0.099	-0.092	-0.033	0.574***	0.808***	0.717***
Post-Bill Gross departure	(0.64)	(-0.75)	(-0.19)	(3.44)	(4.09)	(4.31)
Credit-rating-by-time FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.365	0.375	0.334	0.022	0.022	0.038
No. of obs.	2,813	3,605	3,533	2,755	3,537	3,448

Table 11. Fund Holdings and Credit Risk: The Role of Concavity in the Flow-Performance Relationship

In this table, we estimate the OLS regressions of CDS spreads, using fund holding share (FHS) constructed separately for high-concavity and low-concavity funds. To sort funds into high- and low-concavity fund, we first estimate concavity in flow-performance sensitivity by running a 12-month rolling regression of monthly flow on lagged return and the interaction of lagged return with a negative return indicator variable. The coefficient estimate on this interaction term is concavity in flow-performance sensitivity for the share class, which we aggregate to obtain fund-level concavity. We then sort funds into high- and low-concavity based on the sample median within each Lipper objective code. In column (1), we use FHS constructed separately from high and low concavity funds. In column (2), we interact FHS with two mutually exclusive credit rating indicators (IG vs. HY). Control variables are identical to those in Table 2. We include credit-rating-by-time fixed effect in all instances. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
High concavity FHS (H)	2.179***	
	(3.78)	
Low concavity FHS (L)	1.673**	
	(2.44)	
High concavity FHS × IG (HIG)		1.019*
		(1.71)
High concavity FHS × HY (HHY)		3.000***
		(3.28)
Low concavity FHS × IG (LIG)		1.825***
		(3.18)
Low concavity FHS × HY (LHY)		1.622
		(1.60)
F-statistic: (H) = (L)	0.42	
F-statistic: (HIG) = (HHY)		3.28*
F-statistic: (LIG) = (LHY)		0.04
Controls	YES	YES
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.677	0.677
No. of obs.	104,754	104,754

Figure 1. Who Holds U.S. Corporate Bonds?
Figures are from the Federal Reserve's Flow of Funds (L.213).

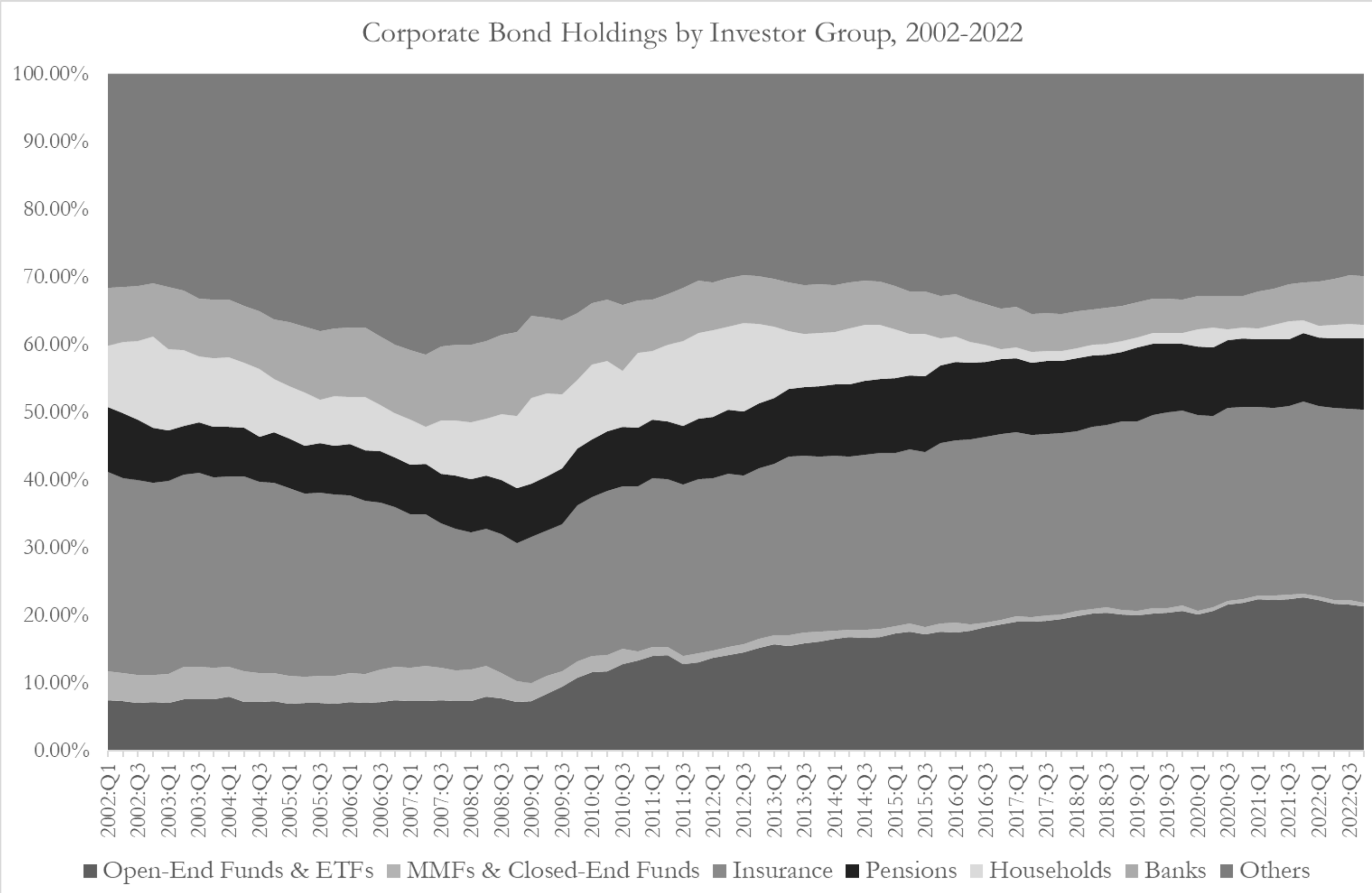


Figure 2. Bondholders With vs. Without Flow Concerns and Strategic Default

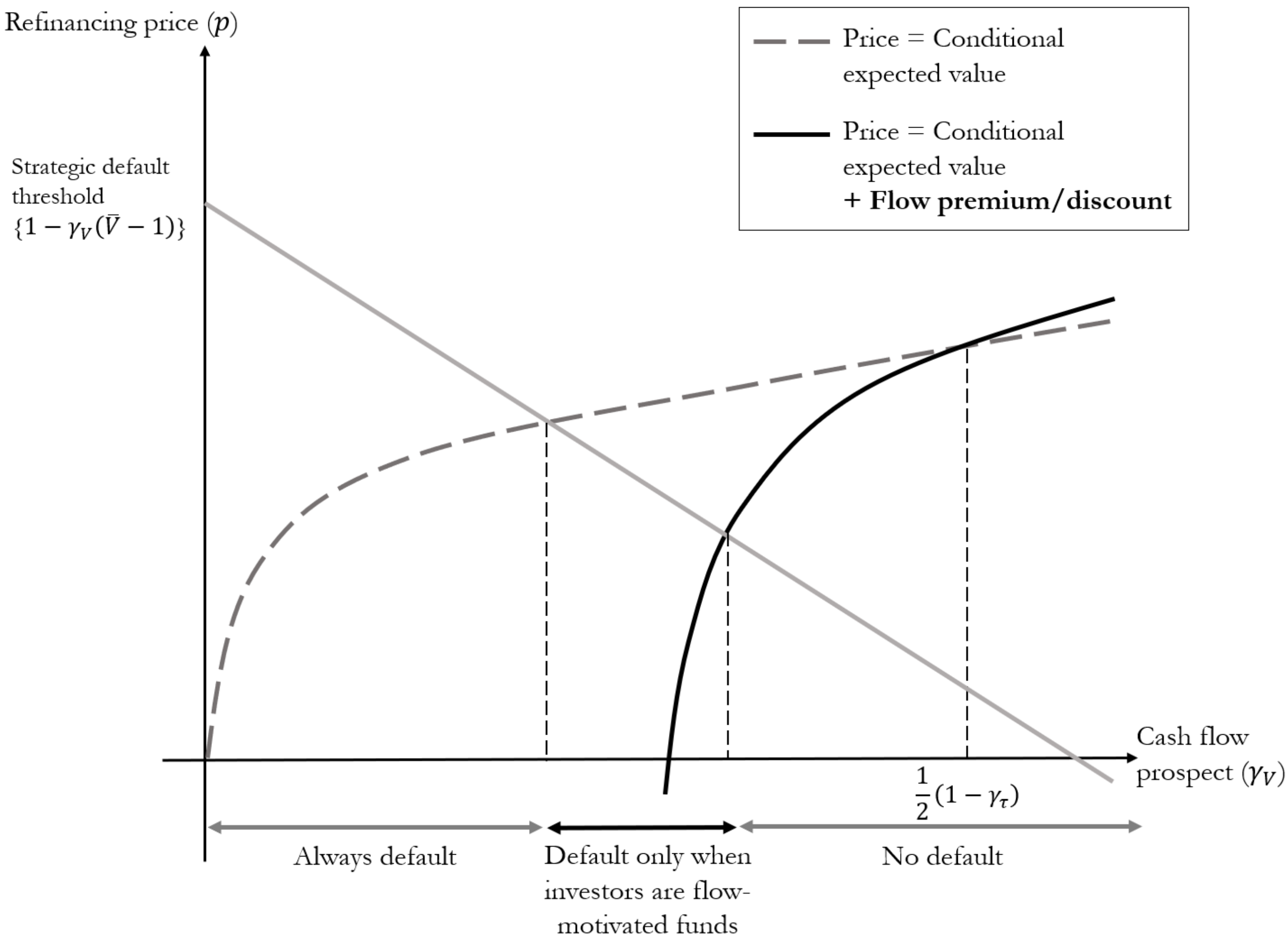


Figure 3. CDS Spreads of Firms Held by Upgraded and Control Funds Around the Five-Year Mark

For all firms held by treated and control funds reaching the 5-year mark with a minimum holding share of 0.5% in the month prior to the Morningstar rating upgrade, we plot the difference in their CDS spreads from 3 months before to 12 months after the month of the rating upgrade at the 5-year mark. Dashed lines denote the 90% confidence interval.

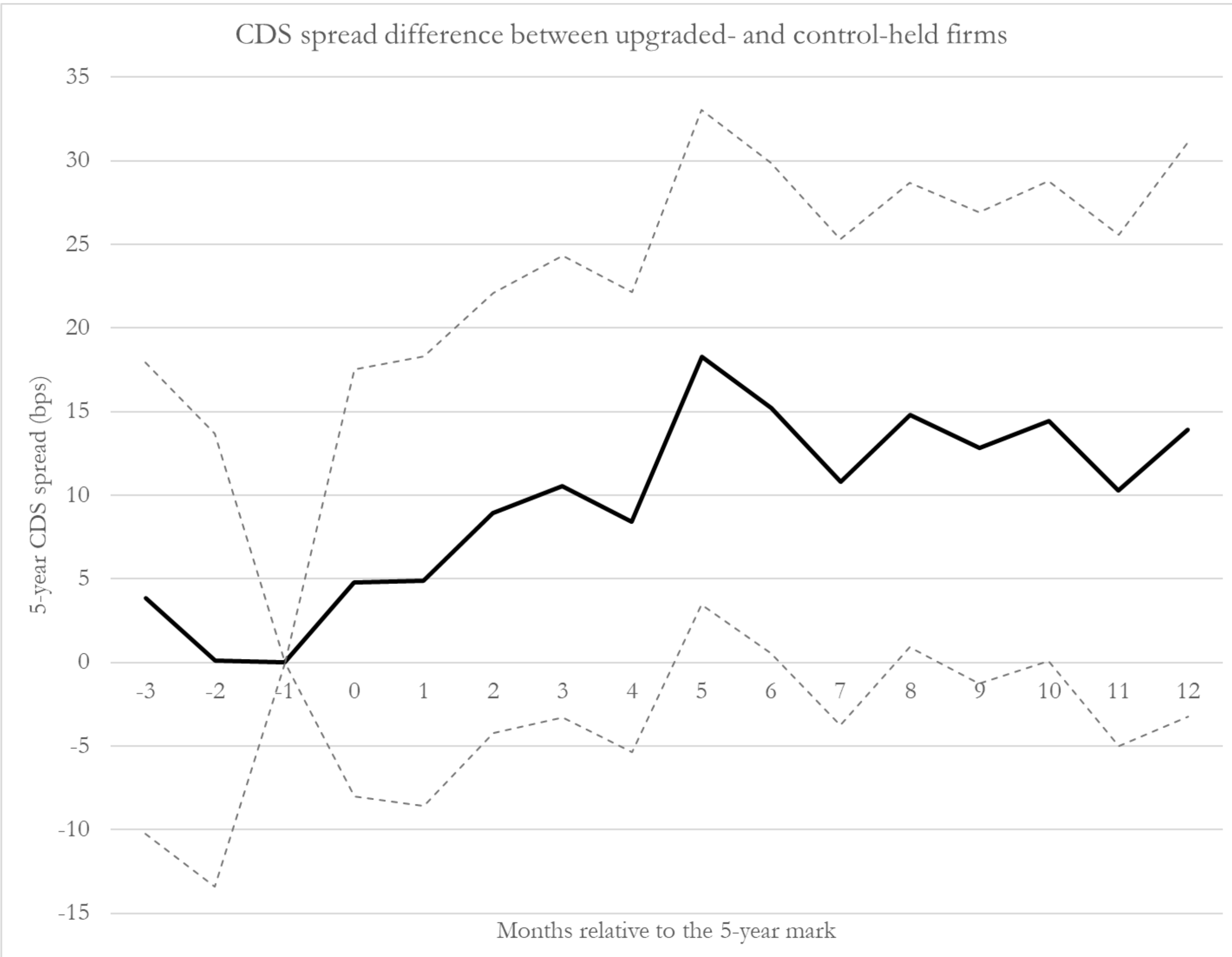
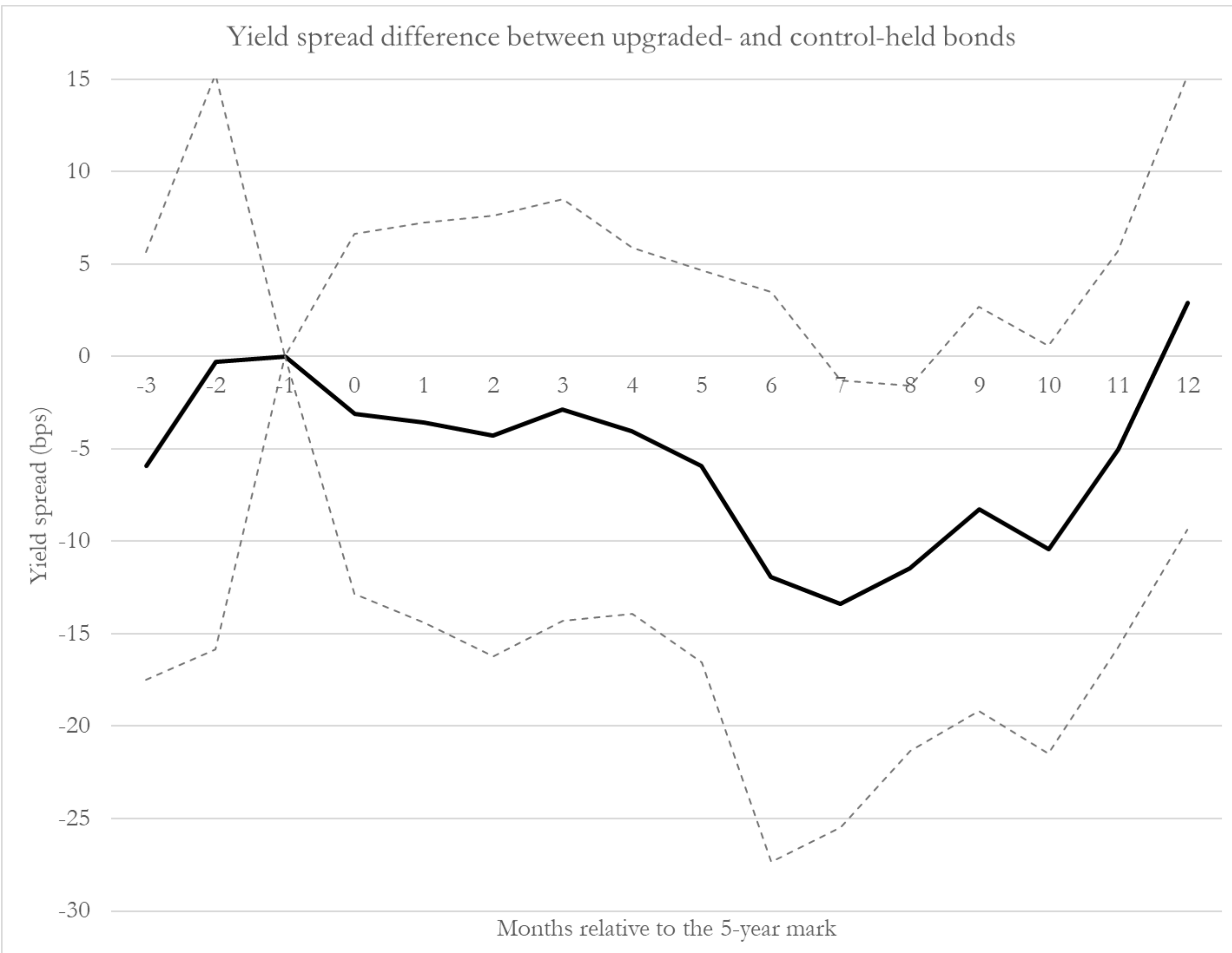


Figure 4. Yield Spreads and CDS-Bond Basis Around the Morningstar Upgrades at the Five-Year Mark

For all corporate bonds held by upgraded and matched control funds reaching the 5-year mark in the month prior to the Morningstar rating upgrade, we plot the monthly averages of differences in their yield spreads and CDS-bond basis from 3 months before to 12 months after the month of the rating upgrade. We consider all senior corporate bonds with Mergent FISD bond type "CDEB" and the time to maturity between three and seven years, while excluding convertible bonds. For each bond held by an upgraded fund, we identify the nearest neighbor bond held by a control fund (i.e., those without a Morningstar star rating change at the five-year mark) that is closest in bond characteristics. We impose exact matching on credit rating and month, with the time to maturity, log amount outstanding, callable indicator, and putable indicator as matching variables for one-to-one matching with a caliper length restriction at 0.03 to rule out bad matches. Yield spread is defined as the difference between the month-end yield of the corporate bond as reported in Datastream and the five-year Treasury yield as reported in FRED. CDS-bond basis is calculated as the difference between the 5-year CDS spread and the par-equivalent bond credit spread, using the J.P. Morgan par-equivalent spread methodology as in Bai and Collin-Dufresne (2019) and Choi, Shachar, and Shin (2019), with the month-end bond price data from Datastream and Libor swap rates as the risk-free rate. Due to the phase-out of the Libor contracts at the end of 2021, our sample period ends in December 2021. Dashed lines in both panels denote the 90% confidence interval.

Panel A. Yield spread



Panel B. CDS-bond basis

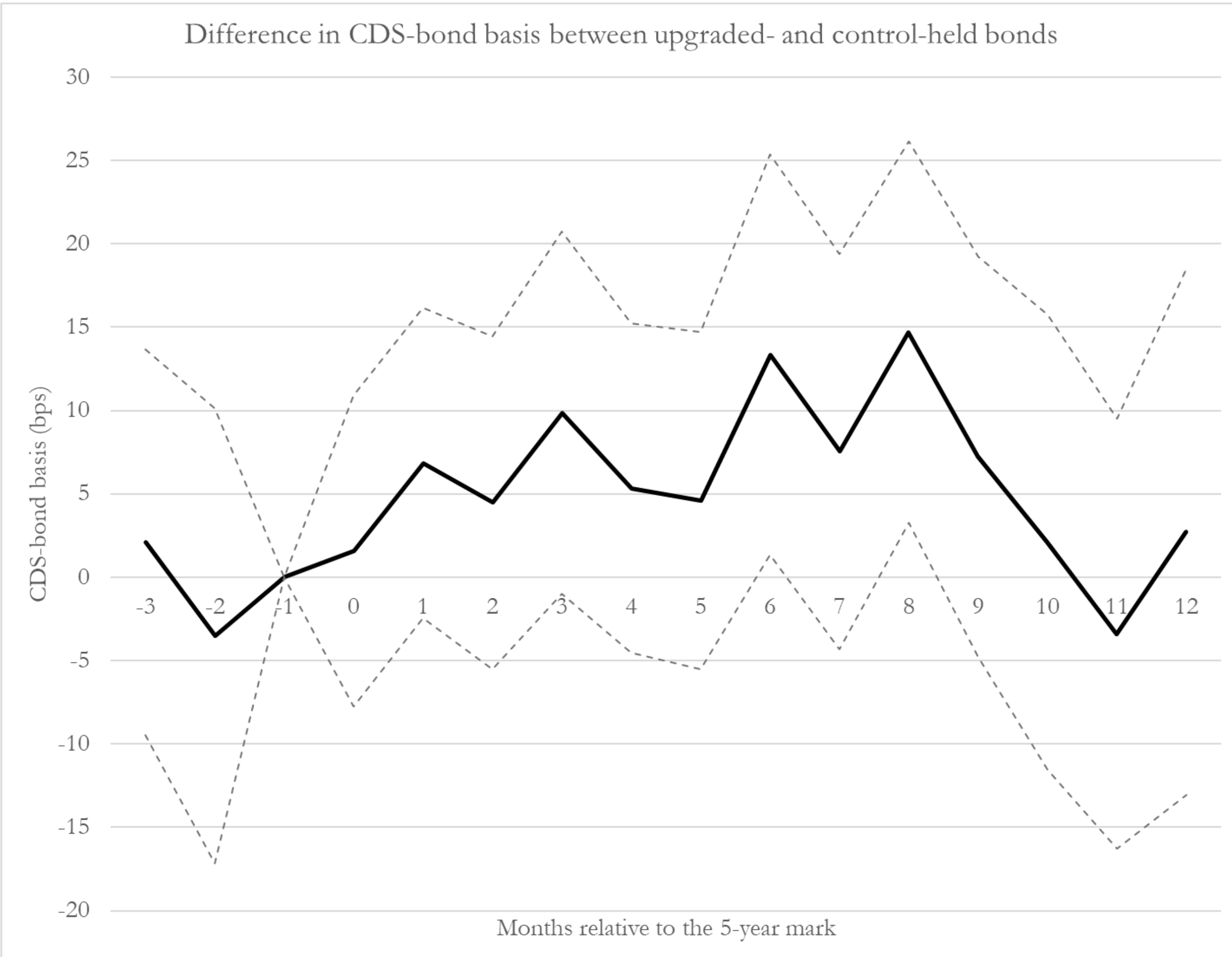


Figure 5. CDS Spreads of Firms Held by PIMCO around the Departure of Bill Gross

For all firms with held by PIMCO with a minimum holding share of 0.5% in August 2014, we plot the difference in their monthly CDS spread in comparison with control-held firms from 3 months before to 12 months following the departure of Bill Gross. Control firms are identified using one-to-two nearest neighbor matching with caliper length restriction set at 0.02 to exclude bad matches, with exact matching on credit rating while using firm financials (log assets, leverage, ROE, and dividend payout per share) as matching variables. Dashed lines denote the 90% confidence interval.

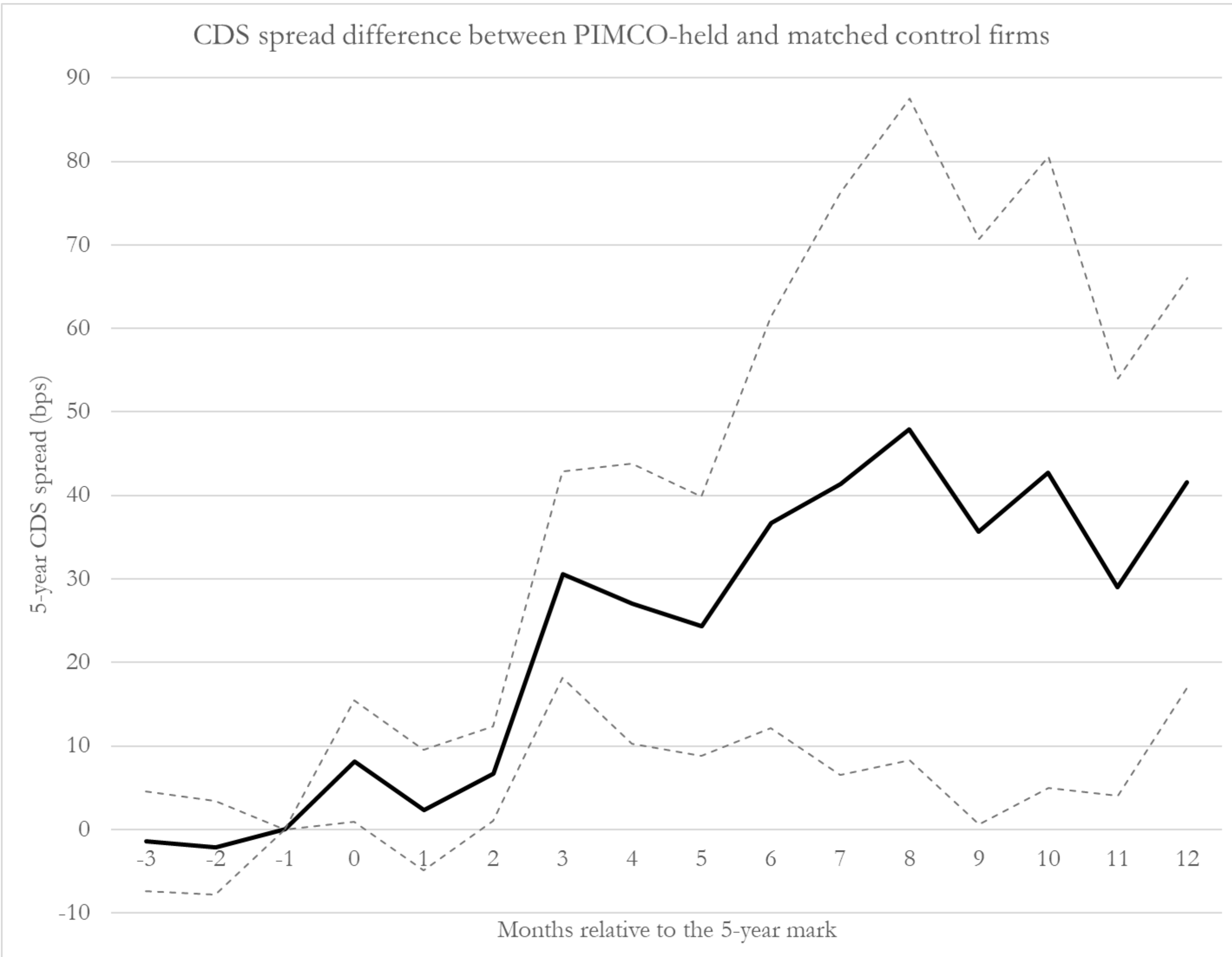
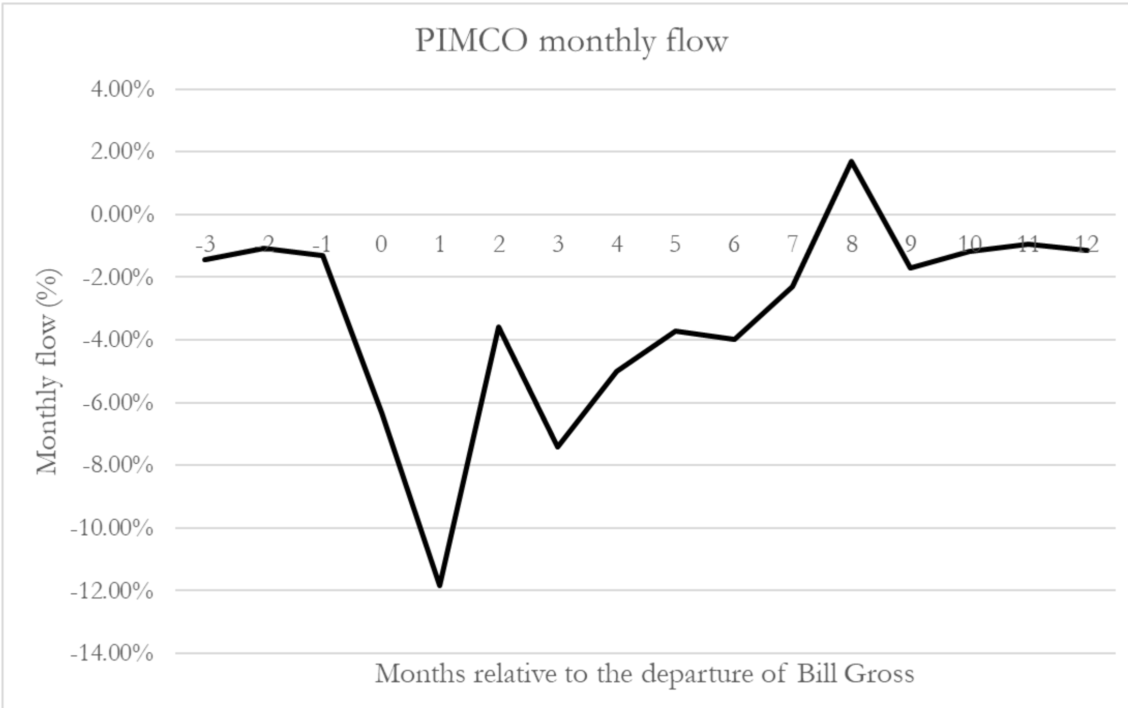


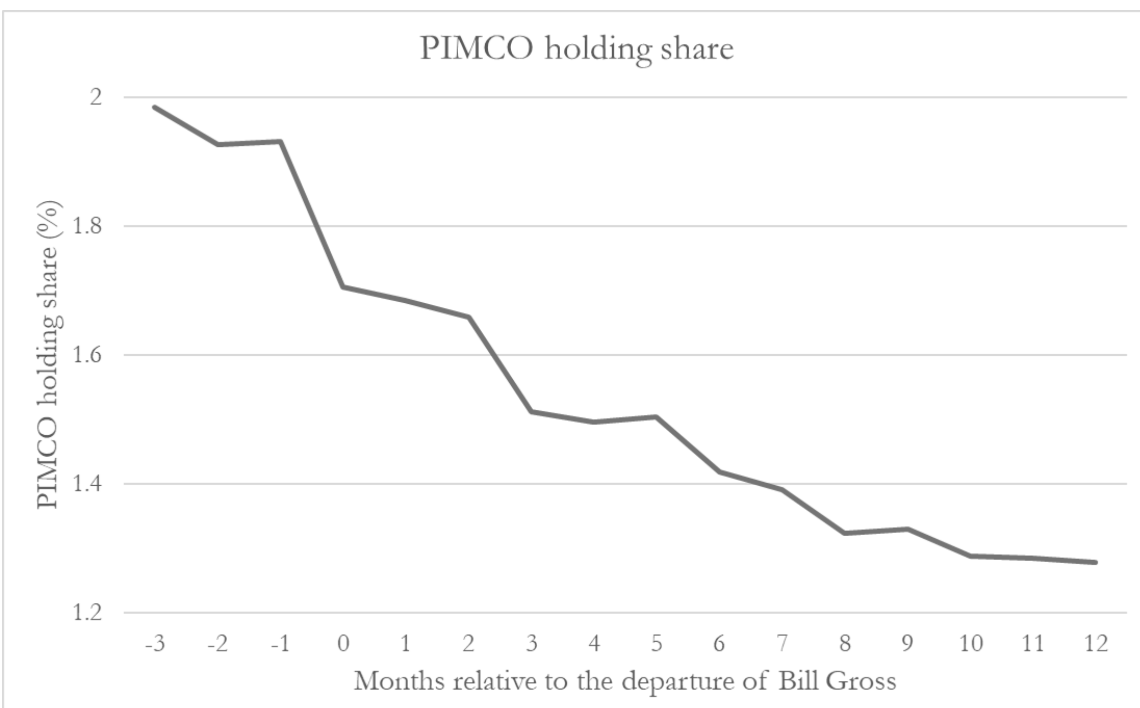
Figure 6. PIMCO Fund Flows and Holding Share Around the Departure of Bill Gross

In Panel A, we plot the monthly fund flows of PIMCO active bond funds from 3 months before to 12 months after the departure of Bill Gross. In Panel B, for all firms held by PIMCO at the month-end prior to the departure of Bill Gross, with a minimum holding share of 0.5%, we plot the time series patterns of these firms' PIMCO holding share over the same window. Finally, in Panel C, we run difference-in-difference regressions of PIMCO- and control-held firms' overall fund holding share, with control firms identified through one-to-two nearest neighbor matching as described in Figure 5. Dashed lines in Panel C denote the 90% confidence interval.

Panel A. PIMCO monthly fund flows



Panel B. PIMCO holding share of firms held by PIMCO in August 2014



Panel C. FHS of PIMCO-held vs. matched control firms

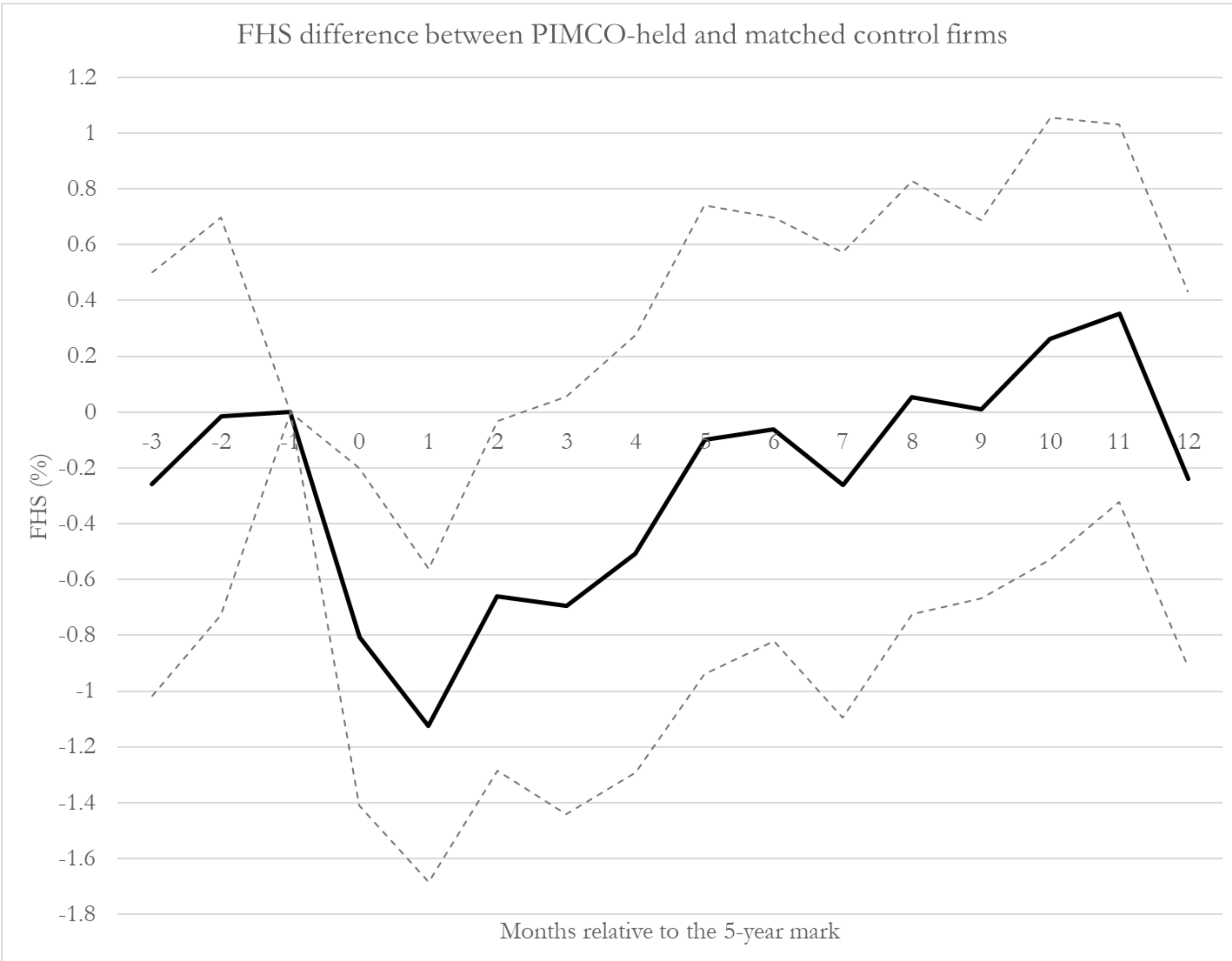
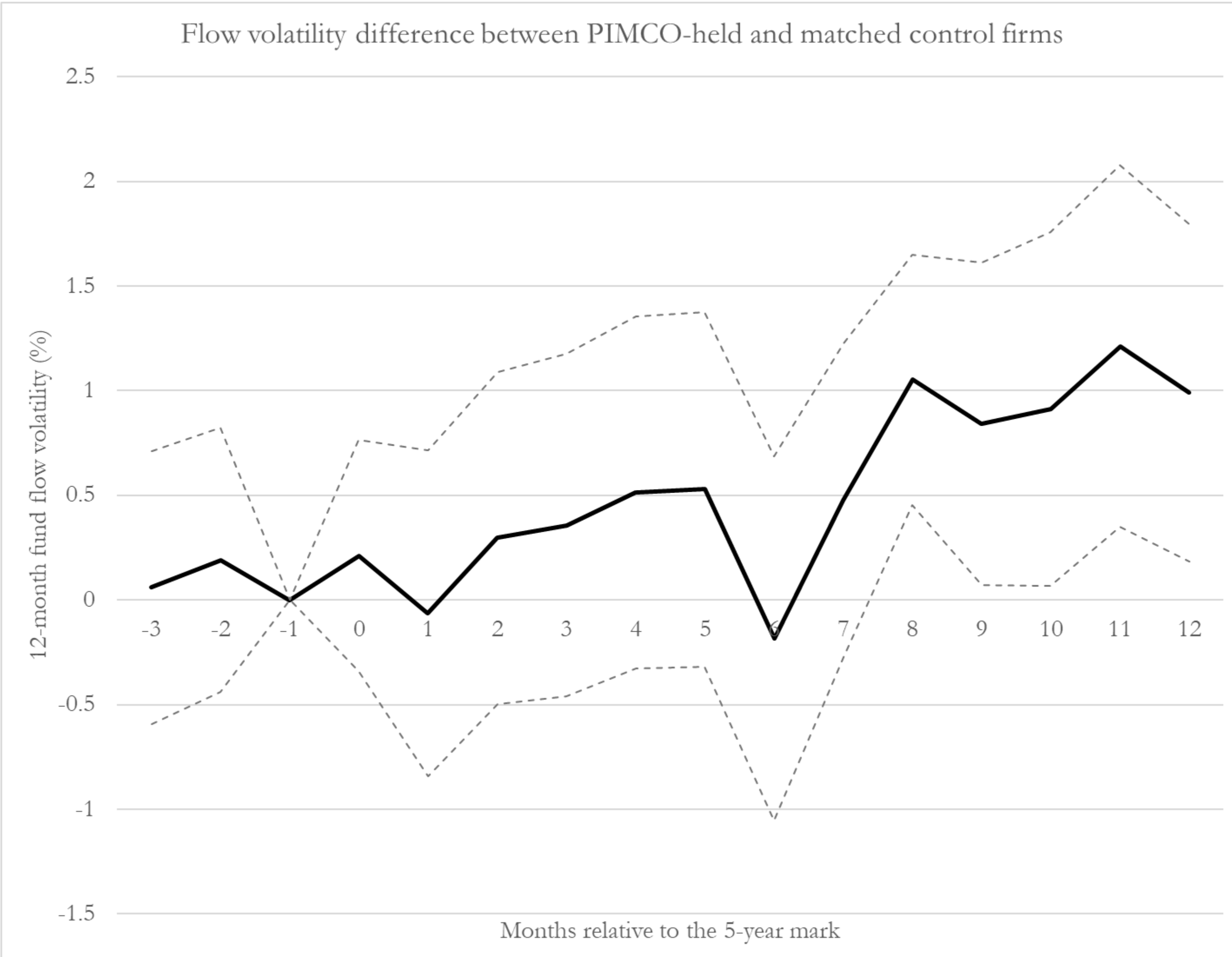


Figure 7. Fund Flow Volatility of PIMCO-Held Firms

In this figure, we obtain the difference in firm-level average fund flow volatility between PIMCO- and control-held firms by running difference-in-difference, with control firms identified through one-to-two nearest neighbor matching as described in Figure 5. The firm-level flow volatility is calculated as the holding-weighted-average 12-month annualized flow volatility of all funds holding the PIMCO- and control-held firms. Dashed lines denote the 90% confidence interval.



Internet Appendix to:

"Bond Funds and Credit Risk"

This version: July 12, 2026

Appendix A. Proofs

Proof of Proposition 2. Suppose that the firm sets the price of the bond as in (4). We then verify in steps that an equilibrium exists as outlined in the proposition.

Without loss of generality, consider a fund with $s = \bar{V}$. If the fund chooses to buy the bond, i.e., $a = 1$, its expected payoff is

$$\underbrace{\Pr(V = \bar{V}|s = \bar{V}) \cdot 1}_{\text{No default at } t=2} + \underbrace{\Pr(V = 0|s = \bar{V}) \cdot 0}_{\text{Default at } t=2} - p + \kappa E(\Pr(\tau = G|a = 1, V)|s = \bar{V}). \quad \text{(A.1)}$$

Substituting the price as stated in (4) yields this quantity to be $\kappa E(\Pr(\tau = G|a = 0, V)|s = \bar{V})$. Thus, upon receiving a high signal, the fund is indifferent between buying and not buying the bond; this represents the high signal funds' full willingness to pay for the bond. Thus, an equilibrium with $a = 1$ can be sustained.

Now consider a fund with $s = 0$. If the fund chooses $a = 1$, its expected payoff is

$$\underbrace{\Pr(V = \bar{V}|s = 0) \cdot 1}_{\text{No default at } t=2} + \underbrace{\Pr(V = 0|s = 0) \cdot 0}_{\text{Default at } t=2} - p + \kappa E(\Pr(\tau = G|a = 1, V)|s = 0), \quad \text{(A.2)}$$

which, upon substituting in the price, becomes

$$\Pr(V = \bar{V}|s = 0) - \Pr(V = \bar{V}|s = \bar{V}) + \kappa\{E(\Pr(\tau = G|a = 0, V)|s = \bar{V}) +$$
$$E(\Pr(\tau = G|a = 1, V)|s = 0) - E(\Pr(\tau = G|a = 1, V)|s = \bar{V})\}. \quad \text{(A.3)}$$

Now, let $\sigma \equiv \gamma_\tau \sigma_G + (1 - \gamma_\tau)\sigma_B$ be the average precision of the fund. Knowing that $\sigma_G = 1$ and $\sigma_B = 1/2$, this quantity becomes $\sigma = \gamma_\tau + \frac{1}{2}(1 - \gamma_\tau) = \frac{1}{2}(1 + \gamma_\tau)$.

In this instance, we have the following:

$$\Pr(V=\bar{V}|s=\bar{V})=\frac{\gamma_V\sigma}{\gamma_V\sigma+(1-\gamma_V)(1-\sigma)}=\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}, \tag{A.4}$$

$$\Pr(V=\bar{V}|s=0)=\frac{\gamma_V(1-\sigma)}{\gamma_V(1-\sigma)+(1-\gamma_V)\sigma}=\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}. \tag{A.5}$$

As long as the signal is informative, i.e.,. $\gamma_\tau>0$, we have $\Pr(V=\bar{V}|s=\bar{V})>\Pr(V=\bar{V}|s=0)$. Under the equilibrium strategies, a fund chooses $a=1$ if and only if $s=\bar{V}$. Then, due to the symmetric nature of the set-up, we have:

$$\Pr(\tau=G|a=1,V=\bar{V})=\Pr(\tau=G|a=0,V=0)=\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.6}$$

$$\Pr(\tau=G|a=0,V=\bar{V})=\Pr(\tau=G|a=1,V=0)=0. \tag{A.7}$$

If so, we have the following set of quantities:

$$E(\Pr(\tau=G|a=1,V)|s=\bar{V})=\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.8}$$

$$E(\Pr(\tau=G|a=0,V)|s=\bar{V})=\left(1-\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}\right)\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.9}$$

$$E(\Pr(\tau=G|a=1,V)|s=0)=\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.10}$$

$$E(\Pr(\tau=G|a=0,V)|s=0)=\left(1-\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}\right)\frac{2\gamma_\tau}{1+\gamma_\tau}. \tag{A.11}$$

A simple inspection reveals $E(\Pr(\tau=G|a=1,V)|s=0)-E(\Pr(\tau=G|a=1,V)|s=\bar{V})<0$, because $\Pr(V=\bar{V}|s=0)<\Pr(V=\bar{V}|s=\bar{V})$. This, along with the fact that $\Pr(V=\bar{V}|s=0)<\Pr(V=\bar{V}|s=\bar{V})$, ensures (A.3) is strictly less than $\kappa E(\Pr(\tau=G|a=0,V)|s=\bar{V})$.

We still need to compute the fund's payoff from choosing $a=0$ when $s=0$. This quantity is simply given by $\kappa E(\Pr(\tau=G|a=0,V)|s=0)$. However, from (A.9) and (A.11), it immediately follows that

$$E(\Pr(\tau=G|a=0,V)|s=0)>E(\Pr(\tau=G|a=0,V)|s=\bar{V}),$$

because $\Pr(V = 0|s = 0) > \Pr(V = 0|s = \bar{V})$. This, along with our earlier result regarding the low signal fund's payoff, ensures that any fund with $s = 0$ will be strictly better off choosing $a = 0$.

The results so far indicate that, if the price is set as in (4), neither the high nor the low signal funds will have any incentive to deviate from the strategy outlined in the proposition. However, we still need to check the optimal strategy of the equityholders. Given that there is excess supply of potential bondholders, the firm does not need to lower the bond's issuance price to attract the funds with low signal, i.e., $s = 0$. Then, knowing that the bond will be held only by those with $s = \bar{V}$, the firm will charge up to their full willingness to pay, which, from our earlier part of the proof, is given by (4). Implicit in our proof is the argument that, if the firm were to charge a higher off-equilibrium price, the principals of the funds will not change their inferences conditional on the funds' actions. If so, $s = \bar{V}$ funds would not pay a price higher than their full willingness to pay, i.e., (4), and rollover would fail. □

Proof of Proposition 4. First, note that:

$$p_f^* - p^* = \kappa\{E(\Pr(\tau = G|a = 1, V)|s = \bar{V}) - E(\Pr(\tau = G|a = 0, V)|s = \bar{V})\}. \tag{A.12}$$

Using (A.8) and (A.9), this quantity will be negative if and only if

$$\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau} < 1 - \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau},$$

which, upon rearranging, reduces to $\gamma_V < \frac{1}{2}(1-\gamma_\tau)$. □

Proof of Proposition 5.

Part i: From Proposition 1, endogenous default occurs whenever

$$p^* \equiv \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau} \leq 1 - \gamma_V(\bar{V} - 1). \tag{A.13}$$

The left hand side of (A.13) is increasing in γ_V for all $\gamma_\tau \in (0,1)$, with the derivative of $\frac{1-\gamma_\tau^2}{(1-\gamma_\tau+2\gamma_V\gamma_\tau)^2}$, while the right hand side, for all $\bar{V} > 1$, is decreasing in γ_V. Thus, it is easy to see that (A.13) will be satisfied as long as γ_V is less than or equal to some threshold $\bar{\gamma}_V(\bar{V})$ that is decreasing in $\bar{V}$. If so, for sufficiently large $\bar{V}$, it can always be guaranteed that $\bar{\gamma}_V(\bar{V}) < \frac{1}{2}(1-\gamma_\tau)$. At $\bar{\gamma}_V(\bar{V})$, equity holders would be exactly indifferent between strategically defaulting or not with profit-motivated bondholders, whereas with flow-motivated bondholders, they would strictly prefer to default. By continuity, for a positive-measure region to the immediate right of $\bar{\gamma}_V(\bar{V})$, there would be no default if and only if bondholders are flow-motivated.

Part ii: For $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, default never arises with profit-motivated bondholders because $\frac{1}{2}(1-\gamma_\tau) > \bar{\gamma}_V(\bar{V})$, and thus $\gamma_V > \bar{\gamma}_V(\bar{V})$. Default also never arises with flow motivated bondholders because $p_f^* - p^* > 0$ for $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$. □

Appendix B. Rollover under Pooling Equilibria

As discussed above, pooling equilibria are less natural in our context given that they do not generate a positive flow-performance relationship on the equilibrium path. That said, flow-motivated funds' reluctance to pay at rollover for firms with weak prospects survives qualitatively unchanged in pooling equilibria with reasonable off-equilibrium beliefs. To see this, consider the only possible pooling equilibrium with rollover, in which flow-motivated bondholders with signals $s = 0$ and $s = \bar{V}$ *both* buy (i.e., $a = 1$). Suppose the off-equilibrium choice of $a = 0$ is associated with the receipt of signal $s = 0$. This would indeed be the on-equilibrium inference if there was an infinitesimal measure of funds that refinanced "naively," i.e., bought if and only if they received the high signal. If so, these off-equilibrium beliefs are natural and robust.

It is easy to see, by analogy to Proposition 2, that the optimal pricing set by firms at rollover in such an equilibrium would be as follows:

$$p = \Pr(V = \bar{V} | s = 0) + \kappa\{\gamma_\tau - E(\Pr(\tau = G | s = 0, V) | s = 0)\}. \tag{B.1}$$

The second term of (B.1) represents the difference between the posterior reputation obtained by buying, which corresponds to the prior as no learning occurs in a pooling equilibrium, and the off-equilibrium reputation associated with not buying (under the off-equilibrium beliefs specified earlier). At such prices the fund manager with signal $s = 0$ would be indifferent between buying and not, while the fund manager with signal $s = \bar{V}$ would strictly prefer to buy.

It is clear that, for sufficiently low values of γ_V, we have:

$$p = \Pr(V = \bar{V} | s = 0) + \kappa\{\gamma_\tau - E(\Pr(\tau = G | s = 0, V) | s = 0)\} < \Pr(V = \bar{V} | s = 0), \tag{B.2}$$

because when the firm's prospects are sufficiently poor, the likely way to enhance reputation for a fund is to indicate via their action that they received $s = 0$. Thus, once again, poor corporate prospects will lead to lowered willingness to pay and result in a lower rollover price. This is further reinforced in a pooling equilibrium by the fact that $\Pr(V = \bar{V} | s = 0) < \Pr(V = \bar{V} | s = \bar{V})$, further lowering the rollover price relative to that in Proposition 3.

Appendix C. Variable Descriptions

In this appendix, we describe in detail how each variable used in our main empirical analysis is constructed. Data source is denoted in parentheses.

C.1. Fund-level data

Fund holding share (Morningstar, CRSP Mutual Funds, and Mergent FISD): For each bond at every month-end, we calculate the amount of bonds held by funds with the first two digits of CRSP objective codes "IC" or CRSP objective code "I," using each fund's latest available monthly or quarterly holdings data. We also compute the amount of bonds held by funds satisfying various characteristics, such as whether the previous 12-month return, rolling 12-month return volatility, or rolling 12-month flow volatility is above or below the sample median at the same point in time. For each fund, we further calculate the percentage of total assets held in institutional classes or classes with a load fee, with the latter defined as rear load fee applicable at the holding period of one month or minimum front load fee. We determine whether a fund is a passive fund using the index fund flag in the CRSP Mutual Funds database, complemented with the name-based index fund identification of Berk and van Binsbergen (2015), and separately compute the amount of bonds held by active (i.e., non-passive) funds. We do so for every bond with Morningstar *sectype* code B, BF, or BI. We further obtain the latest amount outstanding of each bond from Mergent FISD. We then sum fund holdings and amount outstanding of all bonds issued by a firm satisfying the criteria above and divide the former with the latter to arrive at a fund-month level fund holding share of corporate bonds.

Active fund trading (Morningstar, Mergent FISD): To calculate active fund trading at the fund-firm-quarter level, we first define a passive trading benchmark as follows. First, at each quarter, we calculate flow-induced trading by assuming that fund proportionally allocates its quarterly flows to all bonds that it holds and sum across all bonds issued by firm j. Second, when fund i holds firm j's bond k that is retired either in part or in whole in quarter q due to early calls, tender offers, or upon reaching its maturity, we reduce fund i's position in bond k proportionally. For example, if a firm calls back 60% of a bond's outstanding amount early, and the fund held 1,000 in par amount prior to the early call, its bond holdings amount is reduced *pro rata* to 400. Summing this across all retiring bonds for firm j in a given quarter yields the amount of fund position reduction arising from bond retirement. Third, when firm j engages in a rollover issuance (namely an issuance occurring within the same quarter or a quarter preceding a bond retirement), we assume that fund i purchases the amount equal to the retirement amount, which enables the fund to return to its original holding position in firm j. For example, in the aforementioned example, if there is a rollover issuance around the time of early call, we assume that the fund buys back the retired amount, i.e., 600, to return to its original position of 1,000. We define active fund trading as the absolute difference between actual fund trading in firm j and the passive trading benchmark, divided by the previous quarter-end fund position in firm j, expressed in percentage terms.

Fund position change between quarters t and $t+q$ (Morningstar): Fund position change is defined as $(AmtOut_{j,t+q} - AmtOut_{j,t-1})/TotAmtOut_{j,t-1}$, where $AmtOut_{j,t+q}$ is the par amount of corporate bonds (existing or new) or cash held by the fund at quarter $t+q$, and $TotAmtOut_{j,t+q}$, is the total par amount of bonds held by the fund at quarter $t+q$. For corporate bonds issued by new firms, $AmtOut_{j,t-1}$ is therefore 0. To avoid extreme position changes, we only include bonds with prices between \$50 and \$200.

Fund flow (CRSP Mutual Funds): Using fund returns and total net assets from the CRSP Mutual Funds databases, we calculate the flow of fund i at month t:

$$Flow_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{C.1}$$

where $TNA_{i,t}$ and $r_{i,t}$ are fund i's total net assets (TNAs) and monthly return at t, respectively. Share class level data are aggregated at the fund level using the CRSP identifier *crsp_cl_grp* with TNAs at the previous month-end as the weight.

C.2. CDS Spread Data

Five-year CDS spread (Markit): Month-end CDS spread on five-year senior unsecured obligation contracts issued in U.S. dollars with modified restructuring clause until April 2009 and no restructuring clause thereafter.

C.3. Firm-level variables

Average credit rating and recovery rate (Markit): These are as reported in the Markit database.

Historical stock return (CRSP): 12-month stock returns computed using the CRSP database.

Historical return volatility, skewness, and kurtosis (CRSP): Rolling 12-month standard deviation, skewness, and kurtosis of daily stock returns using the CRSP database.

S&P 500 return (Compustat): Latest monthly return of the S&P 500 index.

VIX (Chicago Board of Exchange): Month-end VIX as reported by the Chicago Board of Exchange.

3-month T-Bill and term spread (FRED): 3-month T-Bill rate and the difference between the 10-year Treasury bond and 3-month T-Bill, respectively.

Log assets (Compustat): Log of total assets (*ATQ*) as reported in Compustat.

Leverage ratio (Compustat): The sum of current and long-term debt (*DLCQ* + *DLTTQ*), divided by the sum of current and long-term debt plus total stockholder equity (*DLCQ* + *DLTTQ* + *SEQQ*).

Return on equity (Compustat): Total income before extraordinary items (*IBQ*) divided by total stockholder equity (*SEQQ*).

Dividend payout per share (Compustat): Dividend payout per share (*DVPSPQ*) as reported in Compustat.

Rollover issuance indicator (Mergent FISD): An indicator variable that takes the value of one if a firm issues a corporate bond in the same quarter as or during the quarter preceding the retirement (arising from early calls, tender offers, or bond reaching its maturity) of one of its existing corporate bonds.

Log trading volume (Mergent FISD, TRACE): The natural log of corporate bond trading volume during the last month of the quarter as reported in TRACE. We only consider institutional trades exceeding $100,000. To calculate firm-level measure, we weighted-average the bond-level log trading volume with the par amount outstanding as the weight in a given quarter.

Traded price exists indicator (Mergent FISD, TRACE): An indicator variable that takes the value of one when a corporate bond has at least one trade reported in TRACE during the last trading day of the quarter. We only consider institutional trades exceeding \$100,000. To calculate firm-level measure, we weighted-average the bond-level indicator with the par amount outstanding as the weight in a given quarter.

Near-maturity indicator (Mergent FISD): An indicator variable that takes the value of one when a firm has a corporate bond maturing within the next three months.

Bond time-to-maturity (TTM) (Mergent FISD): Weighted-average time-to-maturity of a firm's corporate bonds, expressed in years, with the par amount outstanding as the weight.

Debt Maturity HHI (S&P Capital IQ Capital Structure): This measure is calculated in the analogous manner to Choi, Hackbarth, and Zechner (2018). Herfindahl-Hirschman Index (HHI) is calculated using each maturity bucket's amount outstanding as a proportion of total corporate debt, and we define maturity bucket for each integer year (< 1 years, 1-2 years, 2-3 years, etc.).

Within-rating-and-maturity reaching for yield (RFY) (Datastream, Mergent FISD, Morningstar): To calculate the RFY measure, we first obtain the month-end yield of our sample of corporate bonds (with bond type "CDEB" in the Mergent FISD database) from Datastream. We exclude convertible bonds, bonds with maturity less than one year, and bonds with month-end traded price below \$5 or above \$1,000. When a firm has multiple credit ratings, we use the pecking order of S&P, Moody's, and Fitch in the order of availability. Then, for each rating (AAA, AA+, AA, AA- etc.) and maturity group (1-3 years, 3-5 years, 5-7 years, 7-10 years, and in excess of 10 years), we calculate the weighted-average monthly yield using each bond's amount outstanding as the weight. Then, for all corporate bonds held by an active fund at each quarter-end, we calculate within-rating-and-maturity RFY as the difference between the yield and the average yield of the rating-maturity group to which the bond belongs. We then calculate a fund-level weighted-average RFY with each bond holding's par value held as the weight.

Appendix D. Internet Appendix Tables

Table A.1. Fund-underwriter-issuer relationship

For the sample of corporate bond issuances in the Mergent FISD database (defined as those with bond type "CDEB", "CMTN", or "CMTZ"), we check the relationship between funds, underwriters, and issuers. First, we check the issuer-underwriter relationship by examining whether the issuer has used one or more of the lead underwriters in at least one of its previous issues within the past one or three years. Second, we check the fund-underwriter relationship by examining whether funds that purchase a new bond in the primary market (defined as an entry in the Morningstar holdings within the first 90 days of the offering date) have bought another bond underwritten by one of the lead underwriters within the past one or three years.

	Previous relationship in the primary market	No previous relationship in the primary market
Issuer-underwriter within:		
Past one year	87.2%	12.8%
Past three years	91.0%	9.0%
Fund-underwriter within:		
Past one year	95.9%	4.1%
Past three years	97.0%	3.0%

Table A.2. Robustness Check: Alternative Return Horizons

In this table we estimate the OLS regressions of CDS spreads on the interaction between fund holding share (FHS) and stock returns as in Table 3 column (3) but using past 1-, 3-, and 6-month stock returns instead. Controls are identical to those in Table 2 column (2), whose coefficient estimates we do not report. We include credit-rating-by-time fixed effect in all specifications. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread		
	(1)	(2)	(3)
Return horizon	1-month	3-month	6-month
FHS (%)	1.788***	1.932***	2.125***
	(3.37)	(3.61)	(3.91)
Stock return measure	-1.034***	-1.145***	-1.064***
	(-5.48)	(-7.65)	(-8.13)
FHS × stock return measure	-7.999***	-5.503***	-4.163***
	(-4.57)	(-4.13)	(-3.80)
Controls	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES
Adjusted R-squared	0.666	0.671	0.676
No. of obs.	104,784	104,784	104,784

Table A.3. Rollover Issuances and Active Fund Trading

In this table, we present the estimation results of OLS regressions of active fund trading (in absolute terms) on (i) the rollover issuance indicator and (ii) the interaction of the rollover issuance indicator with bond liquidity variables. Active fund trading for each fund-firm-quarter is calculated in a manner analogous to Table 5, and we take its absolute value. Rollover issuance indicator takes the value of one if the firm undertakes at least one rollover issuance during the quarter and zero otherwise. For bond liquidity variables, we consider (i) log trading volume, namely the natural log of bond trading volume during the last month of the quarter as reported in TRACE, and (ii) "*traded price exists*" indicator, which takes the value of one when the bond has at least one trade reported in TRACE during the last trading day of the quarter. We only consider institutional trades exceeding $100,000, and due to the availability of the TRACE database, the sample begins from the first quarter of 2005. To calculate firm-level measure of bond liquidity, we weighted-average the bond-level liquidity variables with the par amount outstanding in a given quarter as the weight. We exclude financial (SIC 6000-6999) and utilities firms (SIC 4900-4999) from the sample due to their frequent rollover issuances. In column (1), we run regressions with the rollover issuance indicator for the full sample, while in column (2), we exclude fund-firm-quarters with new issuances and re-estimate column (1). Then in columns (3) and (4), we interact the rollover issuance indicator with bond liquidity variables. We include firm and Lipper-objective-by-time fixed effects in all instances, and *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by Lipper objective and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: (Absolute) active fund trading (%)			
	Full sample	Excl. new issuances	Full sample	
	(1)	(2)	(3)	(4)
Rollover issuance	15.589***	17.003***	45.841***	18.800***
	(22.54)	(24.20)	(11.67)	(18.62)
New issuance				
Log trading volume			0.509***	
			(3.60)	
Rollover issuance × Log trading volume			-1.786***	
			(-7.90)	
Traded price exists				-0.213
				(-0.52)
Rollover issuance × Traded price exists				-6.977***
				(-3.23)
Firm FE	YES	YES	YES	YES
Lipper-objective-by-time FE	YES	YES	YES	YES
Adjusted R-squared	0.036	0.042	0.038	0.037
No. of obs.	2,204,992	2,055,196	1,901,678	1,901,678

Table A.4. Cash Flow Prospect, Bond Liquidity, and Credit Risk

In columns (1) and (2) of this table, we estimate the OLS regressions of CDS spreads on the interaction of fund holding share (FHS) and the "*traded price exists*" indicator, which takes the value of one when the bond has at least one trade reported in TRACE during the last trading day of the month, separately for IG and HY firms. Bond-level measure of liquidity is averaged at the firm level using the par amount outstanding as the weight at each month-end. Then, in column (3) of this table, we run a triple interaction of FHS, HY indicator, and the "*traded price exists*" indicator for the full sample of firms. In all instances, we include credit-rating-by-time fixed effect. Controls are identical to those in Table 2, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)		
	(1)	(2)	(3)
Firm sample	IG only	HY only	All firms
FHS	2.427***	2.420**	1.539***
	(4.31)	(2.55)	(2.76)
Traded price exists	5.055	85.669**	-9.909
	(0.82)	(2.29)	(-1.43)
FHS × Traded price exists	-0.603	-5.159**	-0.711
	(-0.64)	(-2.06)	(-0.70)
FHS × HY			1.805*
			(1.69)
HY × Traded price exists			132.665***
			(3.28)
FHS × HY × Traded price exists			-4.877*
			(-1.75)
Controls	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES
Adjusted R-squared	0.408	0.631	0.686
No. of obs.	66,980	22,601	89,581

Table A.5. Fund Holdings and Offering Yield

In this table we present the results of OLS regressions of the next-month offering yield of a firm's new bond issuance on fund holding share (FHS) as well as its interaction with credit rating indicators. Offering yield is defined as the offering-amount-weighted-average offering yield of a firm's corporate bonds (with the Mergent bond type "CDEB") issued during the month. Column (1) presents the baseline regression in Table 2 column (2), while column (2) presents the regression results with FHS interacted with IG and HY credit rating indicators. We include credit-rating-by-time fixed effect. Controls are identical to Table 2, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Offering yield (bps)	
	(1)	(2)
FHS	2.913***	
	(4.07)	
FHS × IG		2.957***
		(3.48)
FHS × HY		2.706**
		(2.26)
Controls	YES	YES
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.691	0.691
No. of obs.	4,028	4,028

Table A.6. Insurance Company, Pension Fund, and Passive Fund Holding Share

In this table we estimate the OLS regressions of CDS spreads on institutional holding share, but using the insurance company, pension fund, passive fund holding shares as the main variable of interest instead. We use the Morningstar holdings data to calculate the passive fund holding share, while we use Thomson Reuters eMaxx data to compute the insurance and pension holding share in the identical manner to the fund holding share as outlined in Table 2. Due to the coverage of the eMaxx data, the sample for the insurance and pension holding share finishes in December 2021. Columns (1) and (3) present the results for the baseline regressions as in Table 2, while in columns (2) and (4), we interact each group's holding share with the credit rating indicators as in Table 3 column (1). In all instances, we include credit-rating-by-time fixed effect. Controls are identical to those in Table 2, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Institution of interest:	Insurance & pension		Passive fund	
Institutional holding share	-0.880***		-10.912***	
	(-6.16)		(-3.68)	
Institutional holding share × IG (IG)		-0.081		-9.674***
		(-0.53)		(-3.21)
Institutional holding share × HY (HY)		-3.499***		-21.700**
		(-7.83)		(-2.12)
F-statistic: (IG) = (HY)		48.91***		1.34
Controls	YES	YES	YES	YES
Credit-rating-by-time FE	YES	YES	YES	YES
Adjusted R-squared	0.684	0.689	0.676	0.676
No. of obs.	101,949	101,949	104,754	104,754

Table A.7. Reaching for Yield, Time to Maturity, and Fund Position Changes Around the Five-Year Mark

This table presents the regression results of mutual fund position changes in corporate bonds issued by new firms on fund flows for our sample of 5-year-old funds as in Table 6 Panel B, but separately for (i) high vs. low within-rating-and-maturity RFY and (ii) long vs. short time-to-maturity bonds. We further test the statistical significance of coefficient differences. We define new firms as firms not held by a fund at the end of the quarter preceding the upgrade of the fund, i.e., quarter $t-1$. We define the weighted-average (i) within-rating-and-maturity RFY and (ii) time-to-maturity of the fund's corporate bond holdings at quarter $t-1$ as the cut-off for the high vs. low subsamples. Mutual fund position change between quarters t and $t+q$ is defined as: $(AmtOut_{j,t+q} - AmtOut_{j,t-1})/TotAmtOut_{j,t-1}$, where $AmtOut_{j,t+q}$ is the par amount of corporate bonds (existing or new) or cash held by the fund at quarter $t+q$, and $TotAmtOut_{j,t+q}$, is the total par amount of bonds held by the fund at quarter $t+q$. For corporate bonds issued by new firms, $AmtOut_{j,t-1}$ is therefore 0. To avoid extreme position changes, we only include bonds with prices between \$50 and \$200. We regress this measure on fund flow over the same time horizon. Regressions are conducted at the fund-quarter level. To calculate within-rating-and-maturity RFY, we first obtain the month-end yields of corporate bonds (with bond type "CDEB" in the Mergent FISD database) from Datastream. We exclude convertible bonds, bonds with maturity less than one year, and bonds with month-end traded prices below \$5 or above \$1,000. When a firm has multiple credit ratings, we use the pecking order of S&P, Moody's, and Fitch in the order of availability. Then, for each rating (AAA, AA+, AA, AA- etc.) and maturity group (1-3 years, 3-5 years, 5-7 years, 7-10 years, and in excess of 10 years), we calculate weighted-average monthly yields using each bond's amount outstanding as the weight. Then, for all corporate bonds held by each active fund at each quarter-end, we calculate within-rating-and-maturity RFY as the difference between the yield of a bond and the average yield of the rating-maturity group that the bond belongs to. Due to the availability of yield information as well as multiple screens used in RFY calculations, the numbers for the subsamples are smaller and do not necessarily add up to total fund position changes in new firms reported in columns (2) or (5) of Table 6 Panel B. We report the RFY subsample results in Panel A and time-to-maturity results in Panel B. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. High vs. low within-rating-and-maturity RFY

	Dependent variable: Fund position change in/between					
	Quarter t			Quarters t and $t+1$		
	(1)	(2)	(3)	(4)	(5)	(6)
	New firms		High-low difference	New firms		High-low difference
	High RFY	Low RFY		High RFY	High RFY	
Flow	0.013	0.014***	-0.001	0.015**	0.012**	0.004
	(1.78)	(3.15)	(-0.18)	(2.75)	(2.95)	(1.09)
Lipper-objective-by-time FE	YES	YES		YES	YES	
Adjusted R-squared	0.137	0.140		0.219	0.341	
No. of obs.	641	641		641	641	

Panel B. Long vs. short time-to-maturity (TTM)

	Dependent variable: Fund position change in/between					
	Quarter t			Quarters t and $t+1$		
	(1)	(2)	(3)	(4)	(5)	(6)
	New firms		Long-short difference	New firms		Long-short difference
	Long TTM	Short TTM		Long TTM	Short TTM	
Flow	0.032*	0.054***	-0.022	0.047**	0.056***	-0.010
	(2.18)	(3.64)	(-1.09)	(2.74)	(4.80)	(-0.57)
Lipper-objective-by-time FE	YES	YES		YES	YES	
Adjusted R-squared	0.183	0.215		0.330	0.307	
No. of obs.	641	641		641	641	

Table A.8. Characteristics of Firms Newly Purchased Around the Five-Year Mark

In this table, we compare the characteristics of firms whose corporate bonds are newly purchased by our sample of 5-year-old funds against those that they hold prior to the five-year mark. For each 5-year-old fund separately at the five-year mark quarter and the ensuing quarter (quarters t and $t+1$), we calculate the holding-weighted-average (i) likelihood of IG-to-HY downgrade and (ii) 12-month stock return, separately for existing firms (held at the quarter preceding the five-year mark, i.e., quarter $t-1$) and new firms (purchased either in quarter t or $t+1$). In each instance, we also compute and test the statistical significance of the coefficient difference between the existing and new firms. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	IG-to-HY downgrade			12-month stock return		
	(1)	(2)	(3)	(4)	(5)	(6)
	Existing firms	New firms	Difference	Existing firms	New firms	Difference
	0.056***	0.022***	0.034	0.122***	0.134***	-0.011
	(2.67)	(9.63)	(1.63)	(4.08)	(4.18)	(-1.41)
No. of obs.	1,512	1,512		1,512	1,512	

Table A.9. Fund Reaching-for-Yield Around the Morningstar Rating Change at the Five-Year Mark

In this table we estimate the effect of Morningstar star rating changes on average fund-level within-rating-and-maturity reaching-for-yield (RFY) when a fund reaches the age of 5 years. We first identify all events when a share class of a fund reaches the five-year old mark and its star rating either goes up (treated) or remains the same (control) over a [-4, 4] quarter-window around the five-year mark. The indicator variable, *Upgrade at 5-year*, takes the value of one if a fund has at least one share class is upgraded, and zero if a fund has no upgraded share class but has at least one control share class. If a fund has more than one share class reaching the five-year mark within any given five-year window, we take the first instance. The indicator variable, *Post 5-year*, takes the value of one for the window of [0, 4] quarters after the event. Fund-level within-rating-and-maturity RFY is calculated for each active fund at each quarter-end in the analogous manner to Table A.7 or Table 7. We consider (i) all funds as well as separately for (ii) IG mandate funds vs. (iii) HY mandate funds. We define HY mandate funds to be those with Lipper objective codes "HY", "GB", "FLX", "MSI", "SFI", "SHY", and "ARB". Regressions are conducted at the fund-quarter level. We include fund and Lipper-objective-by-time fixed effects in specifications. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Within-rating-and-maturity RFY (%)		
	(1)	(2)	(3)
	All funds	IG funds	HY funds
Upgrade at 5-year	0.085	0.038	0.136
	(1.14)	(0.58)	(0.90)
Post 5-year	-0.003	0.010	-0.030
	(-0.20)	(0.60)	(-0.67)
Upgrade at 5-year × Post 5-year	0.014	-0.004	0.048
	(0.36)	(-0.14)	(0.52)
Fund FE	YES	YES	YES
Lipper-obj.-by-time FE	YES	YES	YES
Adjusted R-squared	0.360	0.346	0.362
No. of obs.	6,120	4,000	2,117

Table A.10. Drivers of New Purchase Decisions by Upgraded Funds at the Five-Year Mark

In this table, we examine the drivers behind the upgraded funds' decision to purchase a new firm at the five-year mark. Our dependent variable is the purchase share, namely the quarter-on-quarter par purchase amount of a firm's corporate bonds as a percentage of the par value of all corporate bonds held by a fund in a given quarter. Our unit of observation is thus at a fund-firm-quarter level. We focus on all funds that are upgraded at the 5-year mark (quarter t) and examine their purchase decisions in quarters t and $t+1$. For each fund-quarter, we first identify all firms not held by the fund quarter $t-1$ in that either issues or has at least one outstanding bond that meets the fund's investment universe in a given quarter. We define investment universe along the following two dimensions: credit ratings and time to maturity. We group credit ratings as follows: AA or above, A, BBB, BB, B, and CCC or below. For the time-to-maturity, we group them as: ≤ 3 years, 3-5 years, 5-7 years, 7-10 years, and > 10 years. For each fund-quarter, we define investment universe as the 5th and 95th percentiles of the par value of its corporate bonds in terms of the rating bucket and the maturity bucket. This enables us to identify all new fund-firm pairs that could have potentially been formed in a given quarter. For all firms in which a fund does not decide to invest our dependent variable, the purchase share, thus equals zero. For explanatory variables, we first consider the fund's previous investment in the firm. First, we form dummy variables that indicate (i) the fund has previously purchased at least one of the firm's newly-issued bond (defined as a new entry in fund holdings within the first 91 days of the bond's offering date) within the past 12 quarters, i.e., quarters $[t-12, t-1]$, or (ii) the fund has purchased a firm's bond within the past 12 quarters, either in the new issuance or post-issuance secondary market. We also consider the firm-level weighted-average (i) log bond trading volume, (ii) bond time-to-maturity, and (iii) within-rating-and-maturity reaching for yield (RFY), with the par amount of each corporate bond as the weight. We further include the firm's 12-month stock return. In column (1), we consider the fund's previous purchase experience in the firm in the newly-issued market, while we consider both newly-issued and post-issuance experience in column (2). We include firm and fund-by-time fixed effects in all instances. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by fund and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Purchase share (%)	
	(1)	(2)
	All funds	All funds
Previous purchase in newly-issued bonds	0.163***	
	(5.57)	
Previous purchase (in any bond)		0.173***
		(9.22)
Log bond trading volume	0.012***	0.012***
	(3.07)	(2.99)
Bond time-to-maturity	0.002	0.002
	(1.12)	(1.19)
Within-rating-and-maturity RFY	-0.286	-0.301
	(-0.61)	(-0.65)
12-month stock return	0.006	0.007
	(0.40)	(0.47)
Firm FE	YES	YES
Fund-by-time FE	YES	YES
Adjusted R-squared	0.011	0.012
No. of obs.	171,068	171,068

Table A.11. Robustness Check: Alternative Specifications

In this table we estimate alternative specifications for the baseline regression in Table 2 column (2) and the IG-HY split regression in Table 3 column (1). In columns (1) and (2), we divide the bond holdings of active funds with total debt, namely the sum of the latest current and long-term debt (*DLCQ* and *DLTTQ*) as reported in Compustat quarterly data. Then, in columns (3) through (6), we consider the next-month change in the 5-year CDS spread as the dependent variable instead, first using the FHS (in columns 3 and 4) and the bond holdings scaled by the total firm debt (in columns 5 and 6) as the main variable of interest, respectively. In odd-numbered columns, we estimate the baseline relationship between either the level or the change in the next-month 5-year CDS spread and the fund holding measure, while in even-numbered columns, we interact the fund holding measure with the mutually exclusive IG and HY indicator variables. The control variables are the same as in the baseline regression in Table 2. All controls are lagged by one month. We include time fixed effect in all specifications. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable					
	5-year CDS spread		Change in 5-year CDS spread			
	(1)	(2)	(3)	(4)	(5)	(6)
Fund holding scaled by:	Total firm debt		Total bonds outstanding		Total firm debt	
Fund holding measure	2.375***		0.105		0.172***	
	(4.49)		(1.50)		(2.67)	
Fund holding measure × IG		-3.180***		-0.080		-0.140*
		(-4.26)		(-1.37)		(-1.75)
Fund holding measure × HY		3.397***		0.178**		0.229***
		(5.41)		(2.13)		(3.35)
Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.601	0.606	0.096	0.097	0.095	0.095
No. of obs.	106,675	106,675	104,781	104,781	106,675	106,675

Table A.12. Morningstar 5-Year Difference-in-Difference Test: Holding the 3-Year Rating Fixed

In this table we estimate the effect of Morningstar star rating changes on fund holding share (FHS) and CDS spreads when a fund reaches the age of 5 years as in Table 6 but imposing that the 3-year rating (i.e., the old methodology for star rating) remains unchanged at the 5-year mark. In Panel A column (1), we run the share class-level difference-in-difference regression of fund flows for a window of [-12, 12] months around these events. The indicator variable, *Upgrade at 5-year*, takes the value of one for the treated and zero otherwise. The indicator variable, *Post 5-year*, takes the value of one for the window of [0, 12] months after the event. In columns (2) and (3), we run the firm-level difference-in-difference regressions of next-month FHS and CDS spreads around the same event windows and using firms with treated or control fund holding share greater than 0.5%. The firm-level indicator variable, *Upgrade at 5-year*, takes the value of one if the firm is held by treated funds in the month prior to the event. The indicator variable, *Post 5-year*, is defined as in column (1). In column (3), we also include the controls as in Table 2. In Panel B, we then run triple-difference-in-difference regressions of either the next-month FHS or CDS spreads on *Upgrade at 5-year*, *Post 5-year*, and *HY* indicator variables. Finally, in Panel C, we run difference-in-difference regressions with the next-month holding share of (i) insurance & pensions and (ii) passive funds as the dependent variable instead. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. FHS and CDS spread

	Dependent variable		
	(1)	(2)	(3)
	Monthly flow	FHS	CDS spread
Upgrade at 5-year		-0.158	2.134
		(-0.66)	(0.59)
Post 5-year	-0.336*	0.610***	3.263
	(-1.96)	(2.88)	(1.14)
Upgrade at 5-year × Post 5-year	0.574***	0.649**	12.160***
	(2.91)	(1.98)	(2.95)
Controls	NO	NO	YES
Share class FE	YES	NO	NO
Time FE	YES	NO	NO
Firm FE	NO	NO	YES
Credit-rating-by-time FE	NO	YES	YES
Adjusted R-squared	0.094	0.392	0.819
No. of obs.	89,085	33,419	33,265

Panel B. FHS and CDS spread: IG vs. HY

	Dependent variable	
	FHS	CDS spread
	(1)	(2)
Upgrade at 5-year	0.121	18.025***
	(0.44)	(5.83)
Post 5-year	0.967***	4.560**
	(4.17)	(1.98)
Upgrade at 5-year × Post 5-year	-0.215	-5.854*
	(-0.56)	(-1.83)
Upgrade at 5-year × HY	-0.664	-38.726***
	(-1.44)	(-5.53)
Post 5-year × HY	-0.706**	-3.039
	(-2.16)	(-0.67)
Upgrade at 5-year × Post 5-year × HY	1.841***	43.917***
	(3.42)	(5.45)
Controls	NO	YES
Firm FE	NO	YES
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.393	0.819
No. of obs.	33,419	33,265

Panel C. Insurance, pensions, and passive fund holding share

	Dependent variable	
	Insurance & pension holding share (%)	Passive fund holding share (%)
	(1)	(2)
Upgrade at 5-year	0.117	-0.018
	(0.28)	(-0.89)
Post 5-year	-0.829**	0.059**
	(-2.53)	(2.43)
Upgrade at 5-year × Post 5-year	-0.114	0.003
	(-0.22)	(0.11)
Credit-rating-by-time FE	YES	YES
Adjusted R-squared	0.380	0.794
No. of obs.	31,640	33,419

Table A.13. Instrumental Variable Regressions: Flow Concerns and Credit Risk

In this table, we present the second-stage results of two-stage least squares firm-month level panel regression of CDS spread (in bps) on fund holding share (FHS), albeit separately for holding shares of funds with high vs. low flow concerns as in Table 9. To construct an instrumental variable for a firm, we aggregate the hypothetical holdings of funds (separately for each flow concern group) and divide them by the total amounts of bonds outstanding for the firm. The hypothetical holdings are calculated as the equal-weighted holdings that equally divide a fund's total net assets over its investment universe, defined as all firms that the fund has invested at least once within the past 36 months (excluding the latest month-end). The control variables are the same as those in Table 2. We include time fixed effect in all specifications. We further report the Kleibergen-Paap F-statistic for the weak instrument test. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Fund characteristic of interest	% of load fee classes	Management firm size	% of load fee classes	Management firm size
High-group FHS$^{(H)}$	-5.734***	-3.545**		
	(-2.61)	(-2.03)		
Low-group FHS$^{(L)}$	30.578***	16.374***		
	(6.33)	(2.68)		
High-group FHS × IG $^{(HIG)}$			-9.416***	-7.176***
			(-4.08)	(-3.73)
Low-group FHS × IG $^{(LIG)}$			19.505***	-1.635
			(4.03)	(-0.26)
High-group FHS × HY $^{(HHY)}$			3.217	1.260
			(1.48)	(0.61)
Low-group FHS × HY $^{(LHY)}$			23.270***	42.696***
			(4.77)	(3.69)
F-statistic: (H) = (L)	32.09***	10.06***		
F-statistic: (HIG) = (LIG)			20.83***	0.72
F-statistic: (HHY) = (LHY)			10.35***	11.40***
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Kleibergen-Paap F-statistic	73.69	98.17	53.40	20.27
No. of obs.	99,786	99,786	99,786	99,786

Figure A.1. Histogram Distribution of Active Fund Trading

In this figure, we plot the histograms of our active fund trading measure for (i) firm-quarters with partial or full bond retirements, (ii) firm-quarters with rollover retirements, and (iii) the full sample.

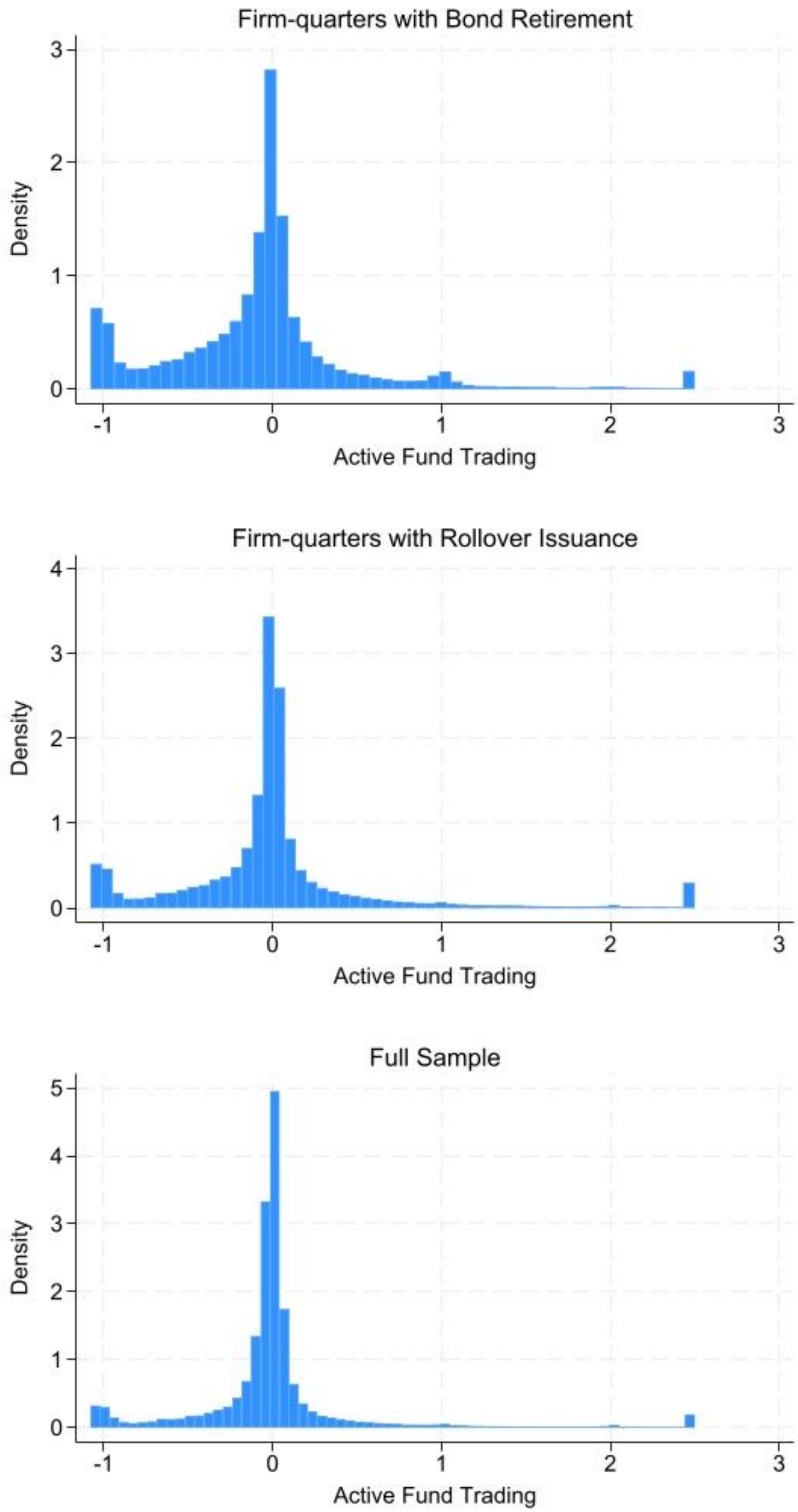
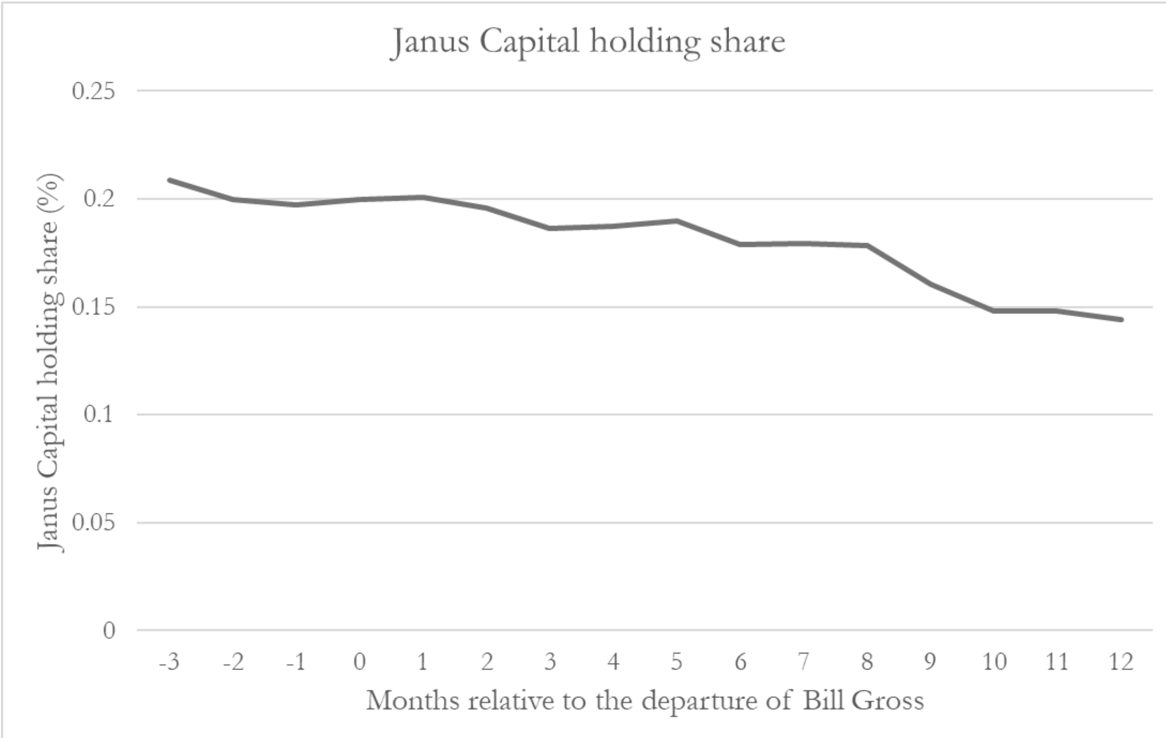


Figure A.2. Janus Capital Holding Shares Around the Departure of Bill Gross

For all firms held by PIMCO with a minimum holding share of 0.5% in August 2014, we plot these firms' Janus Capital holding share between 3 months before and 12 months after the departure of Bill Gross.



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