Bond Funds and Credit Risk*

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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, funds exposed to flow-performance relationships are reluctant to refinance bonds of companies with poor cash flow prospects fearing future investor outflows as a result of potential default events. This lowers refinancing prices, enhancing incentives for strategic default by equityholders, engendering a positive association between bond funds' presence and credit risk. Empirically, we find that in firms with poor cash flow prospects, fund holding shares are associated with increased CDS spreads, more so when flows are more sensitive to fund performance. We use an instrumental variable approach and two quasi-experiments to address the endogeneity between fund holdings and credit spreads.

JEL classification: G23, G32

Keywords: Fund flows, credit risk, flow concerns, bond rollover, default-liquidity loop

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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, the open-end mutual funds' corporate bond holdings more than doubled from 8.4% to 18.8% between 1998 and 2017, whereas the combined share of pensions and insurance firms fell from 46.8% to 34.8% during the same period.

FIGURE 1 HERE

This shift in investor base implies a fundamental change in capital supply in corporate bond markets, as these open-end funds, unlike other institutional investors, face the risk of investor redemptions. Funds care about investor flows since they are compensated via flat assets under management fees, and thus reductions in future flow affect their payoffs directly; in other words, open-ended bond funds are *flow-motivated*. Investor flows, in turn, respond positively to fund performance generating so-called *flow-performance relationships*.[1] These two factors, when combined with the strategic default incentives of equityholders, can increase the credit risk of corporations. For example, a negative outlook for a company rolling over its debt may make bond funds reluctant to refinance, because a potential subsequent default event may impose higher penalties on funds. While financial losses from default affect all investors, open-end funds are additionally exposed to potential outflows, reducing their willingness to participate in refinancing, thus increasing rollover risk faced by corporations. Rollover risk fosters credit risk because failure to negotiate favorable rollover prices strengthens equityholders' default incentives, generating a feedback loop. In other words, the incentives of the *suppliers* of capital for corporate bonds may affect the nature of credit risk in the economy.

The literature has not yet examined how the changes in the composition of capital supply, as represented by the emergence of open-end funds, 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

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[1] There is a long list of papers documenting the positive flow-performance relationship, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), and Spiegel and Zhang (2013) among many others. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) show that the relationship is positive and concave for funds holding illiquid securities including corporate bonds.

term debt when faced with declining collateral values (e.g., Diamond, 1991; Titman, 1992; Gopalan, Song, and Yerramilli, 2014; and Chen, Xu, and Yang, 2020). 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; He and Milbradt 2014; Valenzuela, 2016; Chen, Cui, He, and Milbradt 2017; Choi, Hackbarth, and Zechner, 2018; 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 show theoretically that 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 illustrating the link between the presence of flow-motivated bondholders at refinancing and the strategic default choice of the firm's equityholders, using a simple three-date model with binary cash flows. At the interim date, a firm's existing debt matures and needs to be refinanced by bondholders. Any loss that accrues from refinancing can be borne by the firm's equityholders, who have deep pockets.[2] However, if the equilibrium refinancing price is too low, equityholders will refuse to bear the losses and strategically default on the existing debt. We then separately derive the equilibrium refinancing prices with flow-motivated bondholders ("funds") and standard profit-maximizers ("individuals"), respectively, and compare the two.

Prior to participating in refinancing, all bondholders receive a signal about the terminal cash flow, which can either be high or low. Bondholders differ in the precision of their information about the firm but are unsure about the quality of their information. What distinguishes funds from individuals is that, in addition to profit or losses from bond investment, funds derive additional utility from being perceived to be well-informed by their principals. This is a short-hand for flow motivations: since investors prefer to invest with well-informed funds, being viewed as being well-informed is likely to enhance future investor flows. Funds thus contemplate whether their action, i.e., whether to buy the bond at refinancing, would enhance or damage their posterior probability of their being viewed as being well informed.

[2] Thus, in our model, as in He and Xiong (2012), there are no costs associated with the issuance of equity, and default arises purely endogenously.

We first demonstrate that the equilibrium bond price with funds as bondholders carries a component that reflects their flow motivations; when refinancing the bond improves (hurts) posterior reputation (and thus future flows), the funds' equilibrium willingness to pay rises (falls). This leads bond refinancing prices to differ between whether a firm's refinancing bondholders are funds or individuals: in particular, refinancing prices are more sensitive to future firm prospects in the presence of open-ended funds.

From this set-up, we derive the following empirical implications. First, when future cash flow prospects are poor at the time of refinancing, default risk will be higher particularly for firms whose bonds are held primarily by bond funds. Funds are reluctant to refinance such firms because of the anticipated negative impacts of potential defaults on future fund flows. This lowers refinancing bond prices and in turn strengthens equityholders' strategic default incentives, leading to a positive association between bond funds' presence at refinancing and credit risk for such firms. A key implication of our model is that the flow motivations have an *asymmetric* effect. That is, while flow motivations could also lead funds to overbid at refinancing when the firm has strong cash flow prospects, under such circumstances, equityholders will not default in the first place, so the presence of funds will not have an impact on credit risk. Thus, the effect of flow-motivated bondholders will be asymmetric, clustered amongst firms with poor cash flow prospects. Second, as their degree of flow motivation becomes more severe, the presence of bond funds results in a deeper price discount, thus exacerbating the effect on default risk.

The empirical literature on bond funds suggests that there is concavity in the flow-performance relationship due to a first-mover advantage for withdrawing investors (Chen, Goldstein, Jiang, 2010; Goldstein, Jiang, and Ng, 2017). While the theoretical results discussed to date do not rely on concavity in the flow-performance relationship,[3] we use a simple extension of the baseline model to show that the relationship between the presence of flow-motivated bondholders and credit risk becomes more pronounced as the flow-

[3] The asymmetry in the credit-risk impact of flow-motivated bond funds in our baseline setting arises from a combined consequence of (i) funds being rewarded for making informed choices and (ii) the strategic default incentives of shareholders. Recent evidence suggest that mutual fund investors do reward funds for generating superior performance, specifically the capital asset pricing model (CAPM) alpha for the case of active equity mutual funds (e.g., Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016).

performance relationship itself becomes more concave, due to the increased downside risk to funds resulting from concavity.

We empirically explore this link between bond funds and credit risk using the data on the bond holdings of mutual funds and the credit default spread (CDS) spreads of bond issuers for the period between 2001 and 2015. For each firm at each month-end, we compute the share of its outstanding bonds held by active bond mutual funds whose bond holdings data exist in Morningstar, which we refer to fund holding share (FHS) of corporate bonds.[4] We use this measure to proxy for the presence of flow-motivated bondholders at a firm's bond refinancing, given the high degrees of persistence in bond investor base documented in the existing literature because of investment constraints and/or information acquisition costs (e.g., Zhu, 2021). We then examine whether FHS has a material impact on a firm's credit risk as reflected in CDS spreads, which we use as a cleaner measure of credit risk than bond spreads following He and Xiong (2012). However, given that FHS and a firm's credit risk are likely to be determined simultaneously, our analysis is susceptible to potential endogeneity problems. For example, mutual funds are known to invest in firms with higher credit spreads to "reach for yield" (Choi and Kronlund, 2018). To address this issue, we use the instrumental variable (IV) approach of Koijen and Yogo (2019) throughout our empirical analysis, which is motivated by the idea that an investment mandate of a mutual fund is pre-determined and should be exogenous to contemporaneous shocks to firms' credit risk. Our IV exploits variation in mutual funds' demand for corporate bonds, which is driven by the cross-sectional composition of mutual funds that include these bonds in their mandates. This strategy is intended to tease out the effect of exogenous changes in fund holdings on credit risk.

We begin with the analysis of the overall relationship between FHS and credit risk. Our two-stage least squares regression using the IV *à la* Koijen and Yogo (2019) indicates that a one-standard-deviation increase in FHS increases a firm's credit risk by around 22 to 28 bps, almost a fifth of the average CDS spread of our sample firms. Moreover, consistent with our first theoretical prediction, we document a strong asymmetry in the relationship: the positive relationship between fund holding share and CDS spread is only in evidence

[4] We focus on active funds' bond holdings because a default event serves as a signal of the manager's ability for active managers but not for benchmark-following passive managers.

among firms rated BBB or below, i.e., firms with poor cash flow prospects. In contrast, we do not find a significant relationship between fund holding share and CDS spread among firms rated A or above. Similarly, interacting fund holding share with the firm's one-year stock return reveals that the increased presence of bond funds has a more pronounced impact on a firm's credit risk for those with poor stock performance. We also find evidence of a strong association between FHS and the likelihood of actual default within the next five years among firms rated CCC or below.

To further correct for potential endogeneity, we follow Adelino, Cheong, Choi, and Oh (2021) by focusing on plausibly exogenous changes to FHS arising from Morningstar's overall star rating methodology for fund share classes that turn 5 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 to arrive at 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 to this largely mechanical change, leading to a significant increase in FHS among firms held in substantial quantities by upgraded five-year-old funds compared to those held by funds that are not upgraded at the five-year mark. Exploiting this exogeneous FHS change in an difference-in-difference setting, we show that the credit risk of the firms held by upgraded funds increases *pari passu* with the FHS, lending further support to a causal link between fund holding share and credit risk.

We perform a couple of additional tests of our model implications, which further help us address the endogeneity concern pertinent to fund holdings and credit risk. We focus first on the refinancing channel. Our model conceptualizes that the presence of bond funds *at refinancing* elevates a firm's level of credit risk because flow-motivated funds are less likely to rollover expiring bonds with poor cash flow prospects. If so, the effect of high fund holding share on credit spreads should be *stronger* when refinancing events are imminent. We thus interact fund holding share with a maturity dummy, which takes the value of 1 if a firm has a maturing bond within the next month, and our theoretical framework suggests a significantly positive coefficient for this interaction term. The results support our hypothesis. A one-standard-deviation increase in FHS increases the next-period five-year CDS premium by around 22 bps in the absence of a maturing bond, but the corresponding figure rises to 56 bps during the month when a firm faces a bond maturity, confirming the relevance of the refinancing channel in driving up the credit risk. Next, we also examine the differential effects of fund holdings on credit risk by focusing on times of market distress. We find that the positive effect of FHS on CDS spreads is much stronger when the default spread or VIX is high. These results, combined with those obtained from the refinancing analysis, further help us distinguish our channel from the potential reverse causality channel working through the risk-taking of mutual funds, e.g., reaching for yield. As is shown in previous studies (e.g., Choi and Kronlund, 2018), risk-taking incentives such as reaching for yield tend to be weaker, not stronger, during high risk periods, which stands in sharp contrast to our results from these conditional analyses.

We then test the second prediction of the model that the positive relationship between FHS and CDS premium strengthens for more flow-motivated funds. Our proxies for funds' exposure to outflow risk include past fund performance, fund flow volatility, management company size, and rear-load fees. We find that the holding share of funds with poor recent return or high flow volatility has a more significant positive impact on the next-period CDS spreads. Likewise, the holding share of funds belonging to large families with better intra-family liquidity provisions (Bhattacharya, Lee, and Pool, 2013; Agarwal and Zhao, 2019) or those with a high share of load fee classes—which inhibits investor flow response—has a less pronounced impact on a firm's subsequent CDS premium.

We utilize another quasi-experiment setting—the departure of Bill Gross from Pacific Investment Management Company (PIMCO) in September 2014—to isolate the impact of funds' flow concerns on credit risk in difference-in-differences regressions. The sudden departure of the "Bond King" from PIMCO, the largest management company in the U.S. bond fund market, was unthinkable at the time and unsettled PIMCO's investors. As many investors chose PIMCO funds solely because of the track record of Bill Gross, his unexpected departure substantially raised uncertainty in fund flows, which can thus be deemed a plausibly exogenous increase in PIMCO fund managers' flow concerns. We therefore compare firms held by PIMCO against all other sample firms or those held by Prudential or Vanguard, the next two largest management companies for U.S. bond funds, in a [-6, 6] month window around Bill Gross' departure. For firms with over 5% of PIMCO holding share prior to Bill Gross' departure, we find that their credit risk increases by 11 to 14 bps relative to control firms following his departure, with statistical significance at the 1% level. Further analyses indicate that there is no noticeable pre-trend, and that the increase in credit spread appears to be driven by the increased concerns regarding flow volatility rather than the immediate impact of PIMCO's fire sales to meet redemption demands. This quasi-natural experiment highlights the economic relevance and importance of funds' flow concerns in exacerbating the positive relationship between fund holdings and credit risk.

In the final part of the analysis, we examine how the concavity of the flow-performance relationship affects the relationship between FHS and CDS premium, thus testing our third model prediction. We find that the positive association between FHS and CDS premium largely emanates from funds with more pronounced degrees of flow-performance concavity, particularly when they hold firms with poor cash flow prospects. These results are in line with the predictions of our model and reveal important asymmetric responses along two separate dimensions; in addition to the *firm*'s cash flow prospects, the *funds*' flow-performance concavity also matters.

Related literature. We contribute to the literature in several ways. At the broadest level, we extend the literature on credit risk (e.g., Merton, 1974; Black and Cox, 1976; Leland, 1994; Longstaff and Schwartz, 1995; Duffee, 1999; Collin-Dufresne and Goldstein, 2001; Huang and Huang, 2012) that focuses on firm fundamentals and the "distance-to-default" in estimating a firm's credit risk.[5] This literature offers a rich discussion on how these demand-side characteristics and the developments of credit instruments interact with the incentives of debt- and equityholders in various contexts, both within and across firms (e.g., Das, Duffie, Kapadia, and Saita, 2007; Chen, Collin-Dufresne, and Goldstein, 2009; Chava and Purnanandam, 2010; Bolton and Oehmke; 2011; 2015; Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 2014; Bai, Collin-Dufresne, Goldstein, and Helwege, 2015; Colonnello, Efing, and Zucchi, 2019; Gamba and Saretto, 2020).[6] A strand of the literature on

[5] A related strand of the literature examines sovereign credit risk in a similar vein, e.g., Duffie, Pedersen, and Singleton (2003), Pan and Singleton (2008), Ang and Longstaff (2013), and Benzoni, Collin-Dufresne, Goldstein, and Helwege (2015).
[6] For more on credit default swaps, see Augustin, Subrahmanyam, Tang, and Wang (2014) for a survey.

debt rollover risk (e.g., Diamond, 1991; Titman, 1992; Gopalan, Song, and Yerramilli, 2014; Chen, Xu, and Yang, 2019) also focuses on demand-side characteristics. In contrast, following the 2008 financial crisis, another strand of the literature on rollover risk 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; He and Milbradt, 2014; and Chen, Cui, He, and Milbradt, 2017). In contrast to all of these papers, we highlight a novel *supply-side* factor, namely the flow motivations of a subset of bondholders, i.e., mutual funds. In short, *who* holds a firm's bonds may matter for its credit risk. We provide both theoretical and empirical evidence that the increased presence of flow-motivated bond funds in the corporate bond market could further exacerbate this channel of default-liquidity interaction, particularly among firms with poor credit quality.

Second, our study also contributes to the vast 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; Manconi, Massa, Yasuda, 2012; Hau and Lai, 2013). 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., Alexander, Cici, and Gibson, 2007; Chernenko and Sunderam, 2016; Schmidt, Timmermann, and Wermers, 2016, DiMaggio and Kacperzcyk, 2017; Zeng, 2017; Christoffersen, Keim, Musto, and Rzeźnik, 2018; Choi, Hoseinzade, Shin, and Tehranian, 2020; Chernenko and Sunderam, 2020; Jin, Kacperczyk, Kahraman, and Suntheim, 2021) and also exert financial and real effects on their stock holdings (Edmans, Goldstein, and Jiang, 2012; Khan, Kogan, and Serafeim, 2012, Gordon and Zhdanov, 2013; Derrien, Kecsks, and Thesmar, 2013; Dessaint, Foucault, Frésard, and Matray, 2019) 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. Model

2.1. Main Set-Up

To illustrate the potential effect of the presence of flow-motivated bond funds on corporate credit risk, we present a simple model of endogenous default and bond refinancing with dates $t = 1, 2$. Our model starts with a reduced-form, discrete-time version of continuous-time models of strategic default by equityholders (e.g., Leland and Toft, 1996; He and Xiong, 2012), and then extends it to introduce flow-motivated institutional bondholders, i.e., bond funds.

Suppose a firm generates terminal cash flow $V \in \{0, \ \bar{V}\}$ at $t = 2$ without any intermediate cash flow at $t = 1$. The firm is owned by equityholders with unlimited wealth but subject to limited liability. The firm has pre-existing debt in the form of a discount bond with face value 1 maturing at $t = 1$. The firm's maturing bond must be rolled over with a new discount bond with face value 1 maturing at $t = 2$. The firm's existing bondholders must decide whether to purchase this new bond, i.e., whether to refinance the firm, and how much to pay for it.[7] We denote by p the equilibrium price of the new bond.[8]

To repay the pre-existing bondholders, the shortfall $1-p$ is made up by the firm's existing equityholders; by assuming unlimited wealth, we posit—as in He and Xiong (2012)—that there is no constraint to the issuance of new equity at $t=1$ if the equityholders choose to bail out the bondholders. If the equityholders, on the other hand, decline to provide new equity, the firm defaults and all future cash flows are seized by the pre-existing bondholders. The discount rate is zero for simplicity, and all agents are risk neutral. Finally, suppose that $\bar{V}>1$ so that the equityholders will default at $t=2$ only if the terminal cash flow turns out to be 0.

Let us denote the public prior of V at $t=1$ with $\gamma_V=\Pr(V=\bar{V})$, which reflects the firm's future cash flow prospects. Then:

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

Proof. If the equityholders default at $t=1$, their payoff is 0 because of their limited liability. However, if the equityholders decide to bail out the pre-existing bondholders, their expected payoff is given by:

$$\underbrace{\gamma_V(\bar{V}-1)}_{\text{No default at } t=2}+\underbrace{(1-\gamma_V)\cdot 0}_{\text{Default at } t=2}-\underbrace{(1-p)}_{\text{Refinancing losses at } t=1} \tag{1}$$

[7] We implicitly assume that existing bondholders will participate in refinancing. In the corporate bond market, it is well documented to be the case that the holders of a firm's existing bonds repeatedly participate in the firm's new bond issuances, that is, the investor base of corporate bonds is highly persistent. This can be because either the issuer-underwriter-investor relationships are sticky, or the costs associated with information acquisition of firms' credit risk are high. Zhu (2021), for example, shows that a firm's existing bondholders are five times more likely to buy its newly-issued bond shares compared to those with no prior bond ownership because of informational advantage of investing in the same firms. DiMaggio, Kermani, and Song (2017), Hendershott, Li, Livdan, and Schürhoff (2020), Nikolova, Wang, and Wu (2020), and Nagler and Ottonello (2021) 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 also tend to be highly persistent.

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

Thus, equityholders will default strategically whenever (1) is less than or equal to 0, i.e., whenever $p \leq 1 - \gamma_V(\bar{V} - 1)$ as in the proposition. □

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

For expositional ease, we present our refinancing analysis in two separate parts. First, in section 2.2, we assume that (all) refinancing bondholders are flow-motivated bond funds. Then, in section 2.3, we shut down flow motivations, so that (all) refinancing bondholders may be interpreted as individuals or more patient institutions. Given this separation, we can also simplify the analysis by abstracting from refinancing *quantities*. In other words, we assume that the required refinancing quantity is small enough that the firm can successfully refinance by charging the willingness to pay of the most optimistic refinancer present. In the real world, both flow-motivated and patient refinancing bondholders will be present simultaneously, and the required refinancing quantity may affect the identity of the *marginal* refinancing bondholder. Our qualitative findings hold in such enriched settings, as discussion in section 2.6.

2.2. Flow-Motivated Bondholders

Suppose first that the population of bondholders 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

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

As in the "feedback effects" literature (see Bond, Edmans, and Goldstein, 2012 for a survey), we assume that equityholders have no access to this signal and learn from the bondholders' purchase decisions. To simplify the analysis, suppose that $\sigma_G = 1$ and $\sigma_B = 1/2$. In other words, good types observe the firm's terminal cash flow with certainty, while the signal of a bad type is no better than noise. However, 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. While this assumption—common in the signal jamming literature—simplifies the analysis, it is worth noting that Dasgupta and Prat (2008) show that incentives in this class of models are qualitatively unchanged even if agents know their types, as long as such self-knowledge is not perfect. Each fund's action is denoted a, with $a = 1$ if the fund chooses to buy the bond or $a = 0$ if not. We further assume that τ and V are independent of each other. We now state the fund's payoff at $t = 2$, given by:

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

The first term of (3) represents the fund's profits from bond investment if the manager decides to buy the bond. The second term represents the fund's additional gains from taking actions likely to be viewed by the principal as being indicative of good type. In other words, the principal evaluates the fund on the basis of her action and the eventual cash flow, and if the action and the cash flows are such that the principal's posterior probability of a fund being of the good type, i.e., the fund's "reputation," improves, the manager is rewarded in the form of additional flows, for example. This flow additionally compensates the fund, and κ then measures the fund's intensity of flow motivation.[9] Microfoundations for such payoff functions can be found in Dasgupta and Prat (2008).[10]

In reputational cheap-talk models, it is usually possible for both pooling and separating behavior to arise in equilibrium. In the former type of equilibrium, funds choose actions that are not contingent on their

[9] Bond funds face an increasing *concave* flow-performance relationship (e.g., Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017) rather than an increasing *convex* relationship faced by equity funds (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The theoretical mechanism arising from our model *only* relies on monotonicity in the flow-performance relationship, which arise *endogenously* in equilibrium (see below). However, as will be clear below, any concavity in the flow performance relationship, implying that bond funds face disproportionate flow penalties for performing poorly would strengthen our results.

[10] In a related study, Guerrieri and Kondor (2012) model asset price volatility arising from funds' flow motivations.

private signals, while in the latter their actions are informative about their signals. It is only in separating equilibria that funds are rewarded (or penalized) for making correct (or incorrect) choices on the equilibrium path, 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.[11] Then, upon assuming the payoff function as in (3), we derive the following proposition regarding the equilibrium price:

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:

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

Proof. See Appendix A. □

In this equilibrium, only funds with high signal ($s = \bar{V}$) participate in the refinancing 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 $t = 2$. However, in addition to this fundamental value, the second term represents the fund managers' additional willingness to pay arising from their flow motivations. Upon receiving a favorable signal, funds evaluate how their purchase decision is likely to affect their principals' posterior assessment of their type being good or bad 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 refinancing game, they have an additional reason to participate in the refinancing; the reverse holds if funds are less likely to be viewed as being of the good type.

[11] For the interested reader, we argue in the appendix 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.

The second term in (4) captures the expected reputation gain or loss – i.e., flow rewards or penalties – to high signal funds from participating in the refinancing vs. not doing so. Thus, the price in (4) extracts the high-signal funds' full willingness to pay. At the equilibrium price, therefore, high-signal funds are indifferent between refinancing or not. Given that high-signal funds are indifferent between refinancing or not at equilibrium prices, the less optimistic low-signal funds will clearly strictly prefer not to participate, thus completing the equilibrium argument.

In the above equilibrium, posterior reputation—and thus, implicitly, flow—is positively correlated with correct choices; funds can only improve their $t = 2$ reputation relative to the $t = 1$ prior by refinancing at $t = 1$ the bonds that subsequently do *not* default at $t = 2$ or by declining at $t = 1$ to refinance bonds of companies that do default at $t = 2$.

2.3. Bondholders without flow motivations

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

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 $p = \Pr(V = \bar{V} | s = \bar{V})$.

2.4. Comparison of equilibria with flow-motivated vs. standard bondholders

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 bondholders in Proposition 2 as p_f^*, and the price with standard bondholders in Proposition 3 as p^*. We show that:

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

Proof. See Appendix A. □

In other words, flow-motivated funds act as punitive buyers at refinancing in firms with relatively low prospects of generating successful cash flow. This is because, as γ_V gets progressively 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 participated" when $V = \bar{V}$, their flow-driven willingness to pay diminishes, progressively reducing p_f^* relative to p^*. The oppose is true as γ_V gets progressively large.

Moreover, a lower γ_V increases the refinancing price threshold at which equityholders call for strategic default at $t = 1$ because of their unwillingness to bail out existing bondholders in light of low and uncertain cash flow prospects. In this instance, the presence of flow-motivated funds at refinancing leads not only to lower refinancing prices but also potentially to an increase in the likelihood of strategic default and hence increased credit risk. We explore this connection next.

2.5. Asymmetric impact of flow motivations

We show that the presence of flow-motivated bondholders has an *asymmetric* effect. That is, these investors are willing to underpay (overpay) for low (high) cash-flow prospect firms, but such behavior affects default risk only for low cash-flow prospect firms.

We first check that potential bondholders' flow motivations are relevant from equityholders' perspective. In other words, we need to rule out a case where equityholders call for strategic default even in the absence of flow-motivated funds for all values of γ_V that satisfy $p_f^* < p^*$, for otherwise, the presence of flow-motivated bondholders has no bearing on equityholders' decision-making. One way to rule out such case is to determine the strategic default threshold for the case of standard profit-maximizers and ensure that the value of γ_V that corresponds to the case is lower than $\frac{1}{2}(1-\gamma_\tau)$. In this instance, for a non-empty range of γ_V, strategic default would not arise when standard profit-maximizers participate at the refinancing stage but does arise with flow-motivated participants. From Proposition 1, strategic default occurs whenever

$$p^* \equiv \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau} \leq 1-\gamma_V(\bar{V}-1). \tag{5}$$

The left hand side of (5) 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 (5) 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 $\bar{\gamma}_V(\bar{V}) < \frac{1}{2}(1-\gamma_\tau)$. Assuming this "infrequent strategic default" condition is satisfied, the presence of flow-motivated bondholders at the refinancing stage strictly increases the range of γ_V over which equityholders choose to default strategically. 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 strategic default if and only if bondholders are flow-motivated. Intuitively, the infrequent strategic default condition corresponds to a situation where equityholders are promised with an unlikely but large cash flow in case of success at $t=2$. Thus, equityholders have an incentive to roll over the existing debt and continue as long as the bond price is not set too low. If the standard profit-maximizers are willing to refinance at this price but not the flow-motivated bondholders, then strategic default occurs only when the latter group participate in the refinancing game.

It is clear that, under the infrequent strategic default condition, default never arises even with profit-motivated bondholders when $\gamma_V > \frac{1}{2}(1-\gamma_\tau) > \bar{\gamma}_V(\bar{V})$. For such high cash-flow prospects firms, the presence of flow-motivated bondholders makes no difference to strategic default incentives, even though they are willing to "overpay" at refinancing ($p_f^* > p^*$). Thus, the presence of flow-motivated bondholders has an *asymmetric* effect: it affects the default probability only for firms with *low* cash-flow prospects at refinancing.

Our analysis to date is illustrated in Figure 2, which plots the refinancing prices of flow-motivated and profit maximizing bondholders (the dark and light blue curves, respectively) and the strategic default threshold (the red straight line). The refinancing price set by flow-motivated bondholders is lower than that of standard profit-maximizing bondholders when γ_V is smaller than $\frac{1}{2}(1-\gamma_\tau)$. The equityholders choose interim strategic default in the region to the left of the intersection between the refinancing price and the strategic default threshold. Given that the refinancing price falls below the strategic default threshold for a wider range of γ_V whenever the market is populated with flow-motivated bondholders, the figure reveals that there exists a non-empty region of γ_V whereby strategic default occurs only when the bondholders have flow concerns.

FIGURE 2 HERE

2.6. Flow-motivated and non-flow motivated bondholders' simultaneous presence

In Sections 2.2–2.5, we qualitatively illustrated our core mechanism by separately considering flow-motivated and non-flow-motivated bondholders, which also enabled us to ignore the role of refinancing quantity. But, in reality, both types of bondholders are simultaneously present. We now briefly discuss how our analysis extends to such settings.

Imagine that the firm requires to refinance 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 $K_{NF} + K_F > K$. Thus, the analysis of Section 2.2 can be thought of as a special case in which $K_{NF} = 0$, while the analysis of section 2.3 can be viewed a special case in which $K_{NF} > K$.

Firms with poor cash flow prospects, i.e., those with $\gamma_V \leq \frac{1}{2}(1-\gamma_\tau)$, can charge p^* per refinanced bond to non-flow-motivated refinancers but only $p_f^* < p^*$to flow motivated bond funds. Thus, they will sell as much as possible to non-flow motivated refinancers. Hence, if $K_{NF} > K$, then such firms will sell only to non-flow-motivated bondholders, rendering non-flow-motivated bondholders marginal buyers. On the other hand, if $K_{NF} < K$, then these firms will first raise $K_{NF}p^*$ from non-flow-motivated bondholders 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 clearly decreasing in $K - K_{NF}$ since $p_f^* < p^*$.[12] In other words, the subsidy that equity holders must provide to prevent default *increases* in $K - K_{NF}$, i.e., in the measure of flow-motivated funds to whom they must sell at refinancing, increasing their incentives to default strategically.

2.7. Concave flow-performance relationships

In our model, learning about funds' ability endogenously generates reputational rewards and punishments, which proxy for an increasing flow-performance relationship. For simplicity, we have specified a single parameter κ in (3) to capture the impact of such reputational rewards and punishments on the fund. Such a simple characterization draws on prior microfoundations in the career concerns literature (e.g., Dasgupta and Prat, 2008). At an applied level, this single-parameter specification is tantamount to assuming a *linear* flow-performance relationship, whereby reputational rewards are treated symmetrically to reputational punishments. Despite the assumed *symmetry* of reputational rewards and punishments, our analysis shows that the impact on corporate behavior is *asymmetric*: the risk of reputational punishments when refinancing low cash-flow prospect firms incentivizes strategic default but the prospect of reputational rewards when refinancing high cash-flow prospect firms has no impact. Of course, if, for some extraneous reason, funds were to experience *asymmetrically* high disutility from reputational losses relative to utility from reputational gains, our endogenously asymmetric effect would be strengthened.

In this context, it is relevant that the empirical literature shows that the flow-performance relationship of bond funds to be 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: withdrawals by some investors may incentive

[12] This discussion assumes that it is possible to engage in differential pricing at refinancing. 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.

withdrawal by others, leading to a feedback loop and excess withdrawals (Chen, Goldstein, and Jiang, 2010). As noted above, such an effect would work in a complementary manner to our existing mechanism. While a full model combining fund-level flow concerns and investor-level complementarity is beyond the scope of this paper, we can approximate 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 incremental reputational rewards from refinancing are negative, i.e., the flow-premium is negative, the equilibrium refinancing price with flow motivated bond funds would decline more steeply in cash-flow prospects than in the baseline single-parameter case, leading to a *higher* incidence of strategic default. This case is illustrated in Figure 3.

FIGURE 3 HERE

Formally, this is equivalent to the analysis of Section 2.2 with a contingent κ as follows: [13]

$$\kappa = \begin{cases} \kappa_G & \text{if } \gamma_V > \dfrac{1}{2}(1-\gamma_\tau), \\ \kappa_L & \text{if } \gamma_V \leq \dfrac{1}{2}(1-\gamma_\tau). \end{cases}$$

Since concavity in the flow performance relationship is empirically most evident for funds with illiquid holdings, at an applied level, the discussion in this section suggests that our effect should be stronger when refinancing is undertaken by such funds.

2.8. Testable implications

The main testable implications of our model may be summarized as follows.

(i) (*Mutual funds' bond holdings and credit risk*) The presence of mutual funds at the time of refinancing increases credit risk particularly for firms with poor cash flow prospects.

(ii) (*Flow concerns and credit risk*) Funds with greater flow concerns will demonstrate more reluctance to refinance, thus strengthening the effect of fund presence on credit risk.

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

(iii) (*Flow-performance concavity and credit risk*) Funds with a more concave flow-performance relationship will exacerbate the effect of fund presence on credit risk.

Given that the presence of flow-motivated funds reduces the price of refinanced bonds for firms with relatively poor prospects, equityholders are less likely to absorb the losses from refinancing, opting to default instead. In this instance, their presence prior to refinancing will contribute toward firms' default risk. The effect of their presence, however, will be concentrated among poorly performing firms. For firms with strong cash flow prospects at refinancing, flow-motivated funds may overbid relative to standard profit-maximizing bondholders for bonds at refinancing. But, for these types of firms, equityholders are unlikely to call for strategic default in the first place, so the presence of flow motivated funds is unlikely to impact credit risk. Furthermore, we expect that, for funds with greater flow-related concerns (high κ), the effect of funds' bond holdings on credit risk would be stronger, because such funds will be even less willing to roll over expiring debt given poor cash flow prospects, leading to greater default risk. Finally, we expect our effect to arise even more strongly for funds with a concave flow-performance relationship, whereby an unfavorable credit event would lead to a disproportionately large outflow, thus exacerbating flow concerns.

These predictions illustrate how the presence of flow-motivated funds at future refinancing can affect the ex-ante risk of default. However, the exact presence of active funds at the time of bond refinancing is not directly observable.[14] Thus, at an empirical level, we need to identify variables that are potentially correlated with the presence of flow-motivated funds at refinancing. To this end, our main variable of interest is the holding share of a firm's outstanding bonds by active mutual funds, which we refer to as fund holding share (FHS); as Zhu (2021) notes, there is substantial persistence among a firm's corporate bond clientele, with existing bondholders five times more likely to provide financing to a firm's new bond issuance, particularly when information acquisition costs are high. As a measure of credit risk, we employ CDS spreads. CDS spreads are standardized across maturities and are less sensitive to non-credit-related pricing issues (i.e., the illiquidity

[14] We focus on active funds because a default event serves as an informative signal of managerial ability for active funds but not for passive funds, where the efficient replication of the benchmark index is the primary concern of the investors.

premium), allowing us a fair cross-sectional comparison of firms' credit risk. In the tests of our model predictions, we thus employ CDS spreads as the proxy for credit risk and FHS as the proxy for the flow-motivated funds' presence at refinancing.

3. Data and Variable Construction

In this section, we outline how our main variables of interest and controls are constructed using several 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.

3.1. Mutual fund data

Using the fund holdings data from Morningstar from 2001 through 2015, 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 Goldstein, Jiang, and Ng (2017) and Choi and Kronlund (2018);[15] a total of 1,128 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 (2011a; 2011b), we use the latest available holdings information within the past six months.[16] We obtain further information on each fund using the CRSP Mutual Funds databases. As an illiquidity measure of funds' corporate bond portfolios, we compute zero-trading-day (ZTD) ratios at monthly frequency using transactions recorded in the TRACE database. The advantage of using ZTDs is that the illiquidity of mutual fund portfolios can be measured

[15] 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.
[16] This carries an implicit assumption, that a fund that reports its holdings at quarterly frequency in March 2006, for example, does not change its holdings until the next reporting date, i.e., June 2006.

even when bond prices are unavailable, unlike other price-based measures. Then, by taking the holding-weighted average of each corporate bond's ZTD ratio using the latest holdings information, we arrive at a fund-level measure of holding illiquidity, updated every month.

3.2. CDS premium 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. 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.[17]

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.[18] 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 also consider an alternative version of FHS by dividing active fund holdings with the total amounts debt (including other forms of debt such as bank loans) and obtain consistent results.[19]

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

[17] 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."
[18] Bonds with Morningstar *sectype* code B, BF, or BI are classified as corporate bonds.
[19] Please see Table A.13 in the Appendix for more detail.

$$Flow_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{6}$$

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. For a detailed definition of each variable in our study, refer to Appendix C.

3.4. Summary statistics

Table 1 presents the summary statistics of our sample of 570 firms between Oct. 2001 and Oct. 2015, with firm-level fund holdings data constructed using 1,128 corporate and general fixed income funds. The average five-year CDS spread for our sample is around 130 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 110 bps and 330 bps, respectively. Our variable of interest, FHS, has the mean and median of 30.2% and 26.0%, respectively. We observe substantial cross-sectional variation in FHS, with the standard deviation exceeding 21% and the inter-quartile range of over 27%. We further report that, in line with the trend of sustained investor inflows into bond funds throughout our sample period,[20] average fund holding share in our sample increases over time (untabulated); FHS, for example, has increased from 21.7% in 2002 to 32.0% by 2013.

TABLE 1 HERE

3.5. Instrumental Variable

Identifying a causal relationship between FHS and CDS spreads suffers from a potential simultaneity problem. Although our model predicts that the presence of flow-motivated funds at refinancing should positively affect credit risk among poor cash flow prospect firms, we cannot rule out the possibility that unobservable factors drive both active funds' demand for corporate bonds and the credit risk of bond issuers. One such example would be the risk-taking behavior of institutional investors, also commonly referred to as "reaching for yield." For example, Becker and Ivashina (2015) find that insurance firms tilt their corporate bond

[20] Between 2009 and 2018, more than $2.2 trillion has moved into bond mutual funds, according to ICI Factbook (2019).

portfolio toward firms with higher CDS spreads within the same rating category to take advantage of regulatory arbitrage. Choi and Kronlund (2018) report prevalent risk-taking behavior among bond mutual funds during periods of low interest rates and volatilities. In such cases, a simple OLS specification is insufficient in delineating our model's predictions from these alternative stories.

To alleviate the potential endogeneity concern, we employ an IV approach in our main regression analyses. 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 latest total net assets over 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 possible investments that they have held in recent periods rarely changes over time. We refer to the equal-weighted holdings based 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 of each firm at each month-end 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 above all, credit rating constraints on what assets they can or cannot hold. In addition, high costs of acquiring firm-specific information further restricts an active fund's potential investment universe. Thus, our 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 in the same cross section. Since the investment universe of bond mutual funds is largely predetermined and the cross-sectional distribution of funds' total net assets is not related to the firms' current levels of 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 active 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 that determine the marginal pricers of these bonds. In most empirical analyses that follow, we thus present the second-stage results of two-stage least squares (2SLS) panel regressions.

4. Empirical Results

We test our main empirical predictions that FHS increases the credit risk of fund holdings particularly for poor cash prospect firms and that this effect of FHS on credit risk is stronger when funds' flow sensitivity is higher. We employ three distinct approaches to address potential endogeneity concerns. First, our regression results are based on the IV approach as described in the previous section. Second, we exploit a mechanical upgrade in the Morningstar star rating that is based on stale information, which provides an exogenous increase in FHS for upgraded funds. Third, we exploit a quasi-experiment setting in which funds' flow concerns are exogenously heightened, following the departure of Bill Gross from PIMCO.

4.1. Fund holdings and credit risk

We first examine the effect of FHS on CDS spreads. Our first testable prediction states that the presence of flow-motivated funds would have little impact on credit risks of firms with good cash flow prospects at refinancing, but it should have a significantly positive impact on the credit risks of those with poor cash flow prospects. Thus, on average, the overall relationship between FHS and CDS premium should be positive in the full sample. To test this prediction, we first run the following 2SLS regression of the following form:

$$FHS_{i,t} = \beta_0 + \beta_1 \cdot Counterfactual\ FHS_{i,t} + \beta \cdot Controls_{i,t} + \varepsilon_{i,t}, \quad \text{(first stage)} \tag{7}$$

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot \widehat{FHS}_{i,t} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}, \quad \text{(second stage)} \tag{8}$$

where $CDS\ Premium_{i,t}$ is the five-year CDS spread of firm i in month t. The control variables 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 variables, 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 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 the month fixed effect. We use standard errors robust to heteroscedasticity and two-way clustered by firm and month. Table 2 presents our results.

TABLE 2 HERE

In line with our model's predictions, we find a significantly positive association between fund holding share and the next-period CDS premium; in both columns, the coefficient on FHS is statistically significant at the 1% level. Moreover, first-stage Kleibergen-Paap F-statistics of over 90 in both instances strongly indicate that our instrument is highly relevant in explaining the actual FHS. In terms of economic magnitude, a one-standard-deviation increase in FHS of 21.36% is estimated to raise the next-month CDS premium by between 22 and 28 bps. Given that the unconditional average CDS premium of our sample is around 135 bps, the estimated increase corresponds to around 15 to 20% of average CDS spread, a sizeable figure.

We proceed to examine whether the positive relationship between FHS and CDS premium is indeed more pronounced among firms with poor cash flow prospects. To test this prediction, we consider two proxies of firms' cash flow prospects. First, we interact fund holding share with two mutually exclusive dummy variables, one for those rated A and above and another for those rated BBB or below.[21] Second, we interact FHS with rolling 1-year stock returns of bond issuers. We then run two separate 2SLS regressions with the respective second stage specification as follows:

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot \widehat{FHS_{\iota,t} \times I(A\ or\ above)_{\iota,t}} + \gamma_2 \cdot \widehat{FHS_{\iota,t} \times I(BBB\ or\ below)_{\iota,t}} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}, \quad (9)$$

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot \widehat{FHS_{\iota,t}} + \gamma_2 \cdot \widehat{FHS_{\iota,t} \times 1yr\ stock\ return_{\iota,t}}$$

[21] We split our credit rating subsample at the A-BBB boundary rather than the traditional IG-HY boundary because high yield firms constitute a relatively small percentage of our sample, as shown in Table 1.

$$+\gamma_3 \cdot 1yr\ stock\ return_{i,t} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}. \tag{10}$$

In both (9) and (10), FHS is interacted with either credit rating dummies or 1-year stock returns, creating more than one endogenous variable. Thus, in each instance, we interact the instrumental variable with credit rating dummies or stock returns in the identical manner in the first stage. Table 3 presents our results.

TABLE 3 HERE

As predicted by our model, Panel A reveals that the relationship between FHS and the next-period CDS spread is statistically significant *only* among firms with credit rating below BBB. For firms with A rating or above, we fail to observe a similarly statistically significant relationship between FHS and the next-period CDS spread, and the point estimates on FHS, if anything, are negative. The differences in these two interaction coefficients exhibit high statistical significance with F-statistics exceeding 20 in both instances. Thus, the effect of FHS on credit risk appears to increase monotonically as the firm's credit rating declines and is concentrated among those rated BBB or below. In terms of economic magnitude, a one-standard-deviation increase in FHS among firms rated BBB or below (22.92%) is associated with a 23-bp to 30-bp increase in the next-period CDS premium. Given that the average CDS spread of the firms rated BBB or below stands at 174 bps, the increase amounts to around 15% of the average spread.[22] The fact that we observe a statistically significant relationship between FHS and the next-period CDS spread among firms with poor credit ratings further highlights the importance of the changing *supply-side* landscape of the market for corporate bonds and the relevance of our theoretical framework.

In Panel B, we report panel regression results with the addition of the interaction term between FHS and 1-year stock return, which similarly turns out to be significantly negative at the 10% level in column (1) and 1% level in column (2). The estimated coefficients in column (2) with month fixed effect imply that, for a firm with its 1-year stock return at the third quartile of our sample, i.e., 30.2%, a one-standard-deviation increase in FHS increases the next-period CDS premium by around 17 bps. In contrast, for a firm with its latest 1-year

[22] In Table A.1 in the Appendix, we further find that the results in Table 2 and Table 3 Panel A are robust to the inclusion of lagged CDS spread.

stock return at the first quartile of -6.2%, the corresponding figure is almost 30 bps.[23] Taken together, Table 3 highlights that the effect of active mutual funds' holding share on the reference firm's credit risk is particularly prominent among those with poor fundamentals as our model suggests.

In addition to our analysis of CDS premia, in Table A.3 in the Internet Appendix, we present evidence of a strong association between FHS and the *ex post* likelihood of an actual default occurring within the next five years for firms with the poorest credit ratings of CCC or below, further suggesting that the effect of FHS on credit risk has a material impact on corporate default. Moreover, the strong association between bond holdings and CDS premia among poor cash flow prospect firms appears largely limited to active bond funds; when we examine the holding shares of insurance and pensions—two types of financial institutions that have traditionally been active in the corporate bond market—in Table A.4 in the Internet Appendix, they are mostly found to have a *negative* association with credit risk, if anything.

4.2. The introduction of five-year Morningstar star rating and credit risk

While our IV approach is designed to tease out causal relations between fund holdings and credit risk, it is desirable to also examine plausibly exogenous shocks to fund holdings. To this end, following Adelino, Cheong, Choi, and Oh (2021), we focus on the mechanism by which Morningstar assigns an overall star rating to funds when they turn five years old, which arguably creates an exogenous shock to such funds' flows. Morningstar constructs its overall star rating for each share class using three-, five-, and ten-year star ratings. For each time horizon, the star rating is calculated by ranking the share class's Morningstar risk-adjusted return (MRAR) among its category peers over the specified period, with the top 10% rated 5 stars, the next 22.5% 4 stars, and so on. For share classes aged between 36 months and 59 months, five- or ten-year rating cannot be constructed, so the overall rating consists entirely of the three-year star rating. 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 with weights of 40% and 60%, respectively, rounding

[23] In Table A.2, we consider shorter return horizons of one and six months, respectively, and re-estimate Table 2 Panels A and C. Results are qualitatively unchanged.

to the nearest integer to determine the overall rating. This means that, even though the three-year star rating remains unchanged when the fund turns five, the share class could still be upgraded or downgraded on the basis of the new five-year star rating. Importantly, any difference in risk-adjusted performance that leads to an upgrade or downgrade stems from how a share class performed between three and five years from the time of rating publication and is thus "stale" news, unlikely to be correlated with the fundamentals 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 (2021), Evans and Sun (2021) and Reuter and Zitzewitz (2021), investor flows may nevertheless respond.

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 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 is our control. Then, we examine flow responses to rating changes using difference-in-difference regressions over [-6: 6] months around the five-year mark. Column (1) of Table 4 shows that upgraded funds receive, on average, extra flows close to 0.5% per month, i.e., nearly 3% over the six-month window following the rating change relative to those that remain at their previous ratings, with the difference-in-difference term significant at the 5% level.

TABLE 4 HERE

We then examine whether an upgrade at the five-year mark leads to a material change in FHS as well as credit risk. Specifically, we first identify all funds with one of its share classes satisfying our treated or control criteria and focus on firms for which treated or control funds have a minimum collective holding weight of 2.5% or 5%. Our next step is to examine, in a difference-in-difference setting, whether firms with more than 2.5% or 5% of their shares held by treated funds experience an increase in FHS and credit risk relative to those that are held mainly by control funds. Columns (2) and (4) of Table 4 show that the FHS of firms that are held by treated funds increase by around 1.5% to 2.1% following rating changes at the five-year mark, with statistical significance at the 1% level, likely emanating from extra inflow of capital. Crucially, columns (3) and (5) further show that this increase in FHS is accompanied by a corresponding increase in CDS premium of around 15 to 20 bps, with the *t*-statistic close to or exceeding 4 in both the columns. The identification exercise in Table 4 thus confirms the main finding of our IV approach, namely a causal link between fund holding share and credit risk.

4.3. Is the rollover channel relevant?

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 refinancing. If so, it is reasonable to believe that the more imminent bond refinancing is, the more evident should be our effect. This is particularly likely when the current holders of its bonds are expected to participate in the upcoming issuance of new bonds, as is found to be the case in Zhu (2021). Thus, the presence of mutual funds will affect the credit risk of bond issuers especially when the issuers are facing refinancing risk.

To explore whether this is the case empirically, we construct the maturity dummy, which takes the value of 1 whenever the firm has a bond maturing within the next month according to the Mergent FISD database. We then re-estimate Table 2 with the interaction of FHS with this maturity dummy. This analysis is further intended to alleviate any remaining concerns over reverse causality in addition to our instrumental variable approach; to generate a significantly positive coefficient for the interaction term under this alternative story based on "reaching for yield," funds should have a heightened incentive to hold riskier firms right before refinancing events, which seems less plausible given that a refinancing failure of riskier, illiquid bonds could be particularly costly to these funds.[24] Table 5 presents our results.

TABLE 5 HERE

Table 5 reveals that the effect of FHS on CDS premium more than doubles during the month of a bond maturity. Our estimates in column (2) reveals that a one-standard-deviation increase in FHS increases the next-period five-year CDS spread by around 22 bps in normal times, but the corresponding figure rises to 56 bps during the month preceding a firm's bond maturity, which is over 40% of our sample average CDS spread. In both instances, the interaction term between FHS and the maturity dummy is significantly positive at the 5%

[24] 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 (He and Milbradt, 2014).

level. In addition to our analysis of the CDS premium, we examine offering yields (i.e., yields at issuance) in Table A.5 in the Internet Appendix; we find that a larger presence of bond funds is associated with lower refinancing yields among poor cash flow prospect firms, which is in line with our prediction and thus provides further support to the relevance of our channel. Put differently, the presence of flow-motivated active funds *just before* a refinancing event is perceived by the market as a potential contributing factor to a firm's credit risk, highlighting the relevance and importance of our model's rollover channel.

As an additional analysis on the relevance of our rollover channel, we examine the overall market conditions. Existing studies on "reaching for yield" find that funds' risk-taking incentives are particularly heightened during periods of low interest rate and relative market calm (Choi and Kronlund, 2018); potential costs of risk-taking are high during periods of market stress owing to the high illiquidity and high credit risk of the corporate bond market (e.g., Chen, Lesmond, and Wei, 2007). Thus, we examine whether the relationship between FHS and CDS spread, particularly around bond maturities, is affected by market conditions; this enables us to explore whether the observed patterns are in line with the existing studies on the "reaching for yield" behavior. To this end, we form two equal-sized subsamples on the basis of each of the following market proxies. First, we form subsamples using whether a given month's default spread, specifically the difference between Moody's seasoned Baa vs. Aaa corporate bond yields, is above or below the sample median. Second, we form subsamples in the identical manner using VIX. We then re-estimate our main regression in Table 2 and the maturity dummy interaction in Table 5 for each subsample. We further test the subsample difference in coefficients for the fund holding share terms by running a pooled regression of the entire sample with every independent variable and fixed effect term interacted with the high default spread or high VIX dummy. Table 6 presents our results.

TABLE 6 HERE

In Panel A, we report the subsample regression results for our main specification. We find that the coefficient on FHS is significantly positive at the 5% level in both subsamples. Furthermore, although the subsample coefficient differences are not statistically significant, the point estimates on FHS have larger magnitudes in high default spread and/or VIX periods. A more interesting result emerges in Panel B, when we consider the interaction of FHS with the maturity dummy. We find that the interaction term is significantly positive at the 5% level during periods of high default spread, but insignificant during low default spread periods; the subsample coefficient difference is also marginally significant at the 10% level. Put differently, the presence of flow-motivated active funds just before a firm's bond maturity has a more pronounced impact on its credit risk during periods of market stress as indicated by high default spread. The observed patterns are markedly different from those found in the previous studies on the "reaching for yield" phenomenon, with the effect of FHS on credit risk around bond maturities substantially *stronger* during periods of credit stress. While our model is silent on aggregate conditions, it seems natural that overall cash flow prospects at the firm level are likely to be lower during periods of stress, bringing our mechanism into play and thus consistent with our empirical findings in Table 6.[25]

4.4. Credit risk and fund flow concerns

We now turn our attention to the second testable implication: the positive relationship between flow-motivated funds' holdings and credit risk should be more pronounced when the funds exhibit higher degrees of flow concerns. Specifically, one corollary of Proposition 2 in our model is that, whenever the flow-motivated funds find it in their interest to under-bid for the bond at the refinancing stage, the extent of under-bidding will be more severe as the intensity of their flow-motivated concerns increases. We thus examine the circumstances under which fund managers' flow concerns are more likely to be pronounced. First, given the evidence of concave flow-performance relationship documented for funds investing in illiquid securities—including corporate bonds—arising as a result of payoff complementarity (e.g., Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017), we expect flow concerns, especially those related to outflows, to be more severe for poorly-performing, i.e., lower-ranked, funds. Second, flow concerns will naturally be greater among funds whose investor base is not stable. Third, flow-motivated concerns will likely be more pronounced for funds belonging to a small family, because larger families have various means at their disposal to provide

[25] In Table A.6 in the Appendix, we re-run the subsample regressions in Table 6 using the 3-month T-Bill rate or the term spread as the sorting variable instead. Though we do not find statistical significance for the subsample difference of coefficients, point estimates for FHS are always higher for the high short-term rate or term spread subsample.

liquidity to those experiencing temporary outflows. For example, Bhattacharya, Lee, and Pool (2013) find that large families use affiliated funds of mutual funds, which invest only in other funds within the same family, to act as providers of liquidity insurance to avoid costly liquidation of holdings, which will alleviate outflow concerns of funds.[26] If so, for funds belonging to large families, outflow-related concerns will likely be less severe. Finally, the presence of a prohibitively high load fee should dampen investor response and alleviate the fund managers' flow-related concerns.

To analyze whether there exist differential effects of fund holding share on credit risk for funds with different characteristics, we proceed as follows. At each month-end, we split our sample of active funds into high vs. low groups based on the sample median of following characteristics for each Lipper category that a fund belongs to at the same point in time: (i) latest 12-month fund return, (ii) latest 12-month fund flow volatility, (iii) management firm size, and (iv) the asset share of load fee classes within the fund. Similar to Spiegel and Zhang (2013), we compare a fund's characteristics against their Lipper category median because these are funds' natural peers; investors are likely to assess a fund's performance relative to other funds with similar investment mandate.[27] In Table 7, we then re-estimate column (2) of Table 2 using the high- and low-group fund holding shares instead.[28] In each instance, we further perform tests of coefficient equality between the two groups' holding shares and report the resulting F-statistics. Table 7 presents our results.

TABLE 7 HERE

Column (1) of Table 7 indicates that the holding shares of funds with relatively low 12-month return compared to their peers has a larger positive impact on the next-period CDS premium, as shown by the coefficient estimate on the low-return group's FHS (1.257), which is statistically significant at the 1% level and also economically larger than the coefficient estimate on the high-return dummy (0.769). This result is consistent with the concave flow-performance relationship in corporate bond funds with poor-performing managers

[26] Agarwal and Zhao (2019) further find that large families are more likely to apply for an interfund lending program in response to large temporary outflows, providing their affiliated funds with yet another means of liquidity management.
[27] In addition, a management firm's decision to charge a load fee differs substantially between funds with different investment mandates. For example, fund managers are thus more willing to charge load fees for high yield strategies given their high flow volatility; the average asset share of load fee classes for high yield bond funds is 37%, much higher than the corresponding figure for investment grade bond funds at under 15%. Within-Lipper-category comparison addresses these concerns.
[28] In each case, we separately construct the high- and low-group counterfactual holding shares to instrument for these two variables.

disproportionately punished with large outflows. Also in line with our model's predictions, column (2) clearly indicates that the holding share of high flow volatility funds has a substantially stronger impact on the CDS premium, with the coefficient difference between the high and low groups' holding shares significant at the 5% level. In fact, a one-standard-deviation increase in the holding share of active funds with relatively high flow volatility (of around 9.9%) increases the next-period CDS premium by 22 bps, compared to around 8 bps (16.0%×0.52) for the case of funds with relatively low flow volatility.

Column (3) further reveals that the holding share of funds belonging to smaller families appears to have a more pronounced effect on the CDS premium compared to that of large family funds. Whereas a one-standard-deviation increase in the holding share of active funds belonging to small families (11.5%) increases the next-period CDS spread by around 26 bps, the corresponding figure for a one-standard-deviation increase in the holding share of large family active funds (16.8%) is markedly smaller at around 9 bps. Once again, we find that the coefficient difference is significant at the 5% level. This may be due to large family funds' greater access to within-family liquidity as noted in Bhattacharya, Lee, and Pool (2013) or Agarwal and Zhao (2019). Finally, column (4) reveals that the holding share of funds with relatively low asset share of load fee classes have a significantly more pronounced impact on the next-period CDS premium, with the coefficient difference between the two groups' holding shares significant at the 1% level. This is not surprising given that the presence of a prohibitively high load fee may act as an impediment to the investors' flow response, partially alleviating the fund managers' flow-related concerns. Overall, results in Table 7 are in line with our model's predictions, with the degree of flow motivations (i.e., κ) exacerbating the relationship between FHS and credit risk.

As a further demonstration of the importance of active funds' flow concerns, we re-estimate the baseline regressions in Table 2 and credit rating interactions in Table 3 Panel A with passive fund holding share (PFHS) instead in Table A.7 in the Appendix. These passive funds hold similar assets to active funds, but are different in that, because of their benchmark-following nature, defaults and impairments do not act as a signal of manager quality. We find that the PFHS bears the opposite sign to the FHS, once again highlighting the importance of flow-related concerns.

4.5. Changes in the intensity of flow motivations: the departure of Bill Gross from PIMCO

Although the results in Table 7 show a strong positive relationship between FHS and CDS premium when bonds are held by funds with high degrees of flow concerns, it is worthwhile to further identify a setting where funds' flow motivations change as a result of exogenous shocks. To this end, we use the sudden departure of Bill Gross from PIMCO in September 2014 as such a setting. 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, with Morningstar stating in 2010 that "[no] other fund manager made more money for people than Bill Gross."[29] However, he surprisingly left PIMCO in September 2014 for Janus Capital and sued his former employer soon afterward, citing fierce in-fighting among PIMCO executives.

FIGURE 4 HERE

This sent a major shockwave to investors. Many of the PIMCO investors have chosen PIMCO funds based on the long track record of the sole manager—Bill Gross. However, uncertainty about how the new management team with much shorter history of a performance record would perform led to greater flow concerns to PIMCO funds. Even with a slight hint of underperformance and a lack of management skills, investors were ready to leave PIMCO.[30]

Above all, Bill Gross' departure created significant uncertainty about PIMCO amongst investors and raised the flow-performance sensitivity and flow volatility. As we show in Tables A.8 in the Appendix, PIMCO funds' flow-performance sensitivity has increased substantially after the departure of Bill Gross.[31] Thus, for PIMCO-held firms, his departure marks a substantial increase in flow concerns that is unrelated to the fundamentals of PIMCO holdings. We therefore 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

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[29] From "Announcing the Morningstar Fund Managers of the Decade (Jan. 12, 2010)" (available at: https://www.morningstar.com/articles/321713/announcing-the-morningstar-fund-managers-of-the-de)

[30] We confirm this to be the case for Janus Capital, Prudential, and Vanguard in Figure A.1 in the Appendix.

[31] In Table A.9 we show that firms whose corporate bonds were held by PIMCO experienced a sharp increase in the weighted average flow volatility of its active fund bondholders relative to their peers after his departure.

portfolio holding in August 2014, i.e., just before Bill Gross' departure, we identify all firms (i) held by PIMCO and (ii) those with PIMCO holding share greater than 5%. As controls, we either use (i) all other sample firms or (ii) those held by Prudential and Vanguard (Zhu, 2021).[32] Then, for the window of [-6, 6] months around the departure of Bill Gross, we run difference-in-difference regressions in the following manner:[33]

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot PIMCO\ dummy_{i,t} \times Post\ Bill\ Gross_{i,t} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}, \quad (11)$$

where the PIMCO dummy takes the value of one when a firm's corporate bond is held in nonzero quantities (or with holding share of over 5%) by PIMCO in August 2014, and post-Bill Gross departure dummy takes the value of one for all sample observations after the departure of Bill Gross. We use the identical set of controls as before, with firm and month fixed effects.[34] According to the predictions of our model, the interaction term between the PIMCO dummy and post-Bill Gross departure dummy should have a significantly positive sign, because the heightened flow concerns should exacerbate the relationship between fund holdings and credit risk. Table 8 presents our difference-in-difference regression results.

TABLE 8 HERE

Table 8 Panel A presents the results for all firms held by PIMCO prior to the departure of Bill Gross. We find that the difference in CDS spread between these PIMCO-held firms and other sample firms increases by 4 bps after the departure of Bill Gross, with the corresponding figure rising to 7 bps when we restrict the control firms to be Prudential- or Vanguard-held firms. In both instances, this difference-in-difference term is statistically significant at the 1% level. When we interact this with credit rating dummies as in Table 3 Panel A, we find this increase in CDS spread difference to be concentrated almost entirely around firms rated BBB or below. These results are consistent with the predictions of our model, whereby the heightened intensity of flow concerns exacerbates the relationship between fund holdings and credit risk primarily among poor cash flow prospect firms. When we consider firms with PIMCO holding share exceeding 5% in Panel B, we find even

[32] Whenever we consider firms with PIMCO holding share greater than 5%, we also compare these firms to those with Prudential and/or Vanguard holding share greater than 5%.
[33] We do not include the standalone PIMCO dummy or post-Bill Gross departure dummy because they are perfectly collinear with firm and month fixed effects, respectively.
[34] Our results are robust to a longer difference-in-difference window of [-12, 12] month, as shown in Table A.10 in the Appendix.

stronger results in terms of economic magnitude. Depending on the definition of control firms, we find that the CDS spread difference between our PIMCO-held and control firms increases by 11 to 14 bps following the departure of Bill Gross, with statistical significance at the 1% level in both instances. Once again, the effect is primarily concentrated around firms rated BBB or below.

FIGURE 5 HERE

We plot the average monthly CDS spread of firms with PIMCO holding share greater than 5% vs. the CDS spread of our two sets of control firms around our difference-in-difference window in Figure 5. In both panels, there is no noticeable trend in the difference between the CDS spreads of PIMCO-held versus control firms prior to Bill Gross departure. However, the plot reveals a sizeable increase in this difference after his departure, which remains significant and noticeable until the end of our difference-in-difference window in March 2015.

The persistent gap in CDS spreads that remain wide throughout the second half of our test window suggests that this pattern is driven by heightened flow concerns rather than the actual outflows that PIMCO experienced. To see this, flow patterns of PIMCO funds plotted in Figure 4 Panel A reveals that the immediate wave of investor outflows from PIMCO largely dissipated by January or February 2015, and yet the CDS spread gap between PIMCO-held vs. control firms persisted through the end of March 2015. In addition, as Figure 4 Panel C reveals, there is no significant pattern in overall FHS among PIMCO-held firms relative to Prudential- or Vanguard-held firms around the time of Bill Gross' departure, with other funds filling the void created by PIMCO's asset sales,[35] suggesting that the outflows experienced by PIMCO alone cannot account for the observed patterns in the CDS spread.

FIGURE 6 HERE

In contrast, as Figure 6 reveals, firms with PIMCO holding share greater than 5% prior to Bill Gross' departure witnessed a sharp increase in weighted average flow volatility of their active fund bondholders, which remained higher than Prudential- or Vanguard-held firms throughout the last half of our estimation window.[36]

[35] We confirm this to be the case for Janus Capital, Prudential, and Vanguard in Figure A.1 in the Appendix.
[36] As discussed earlier, Table A.9 in the Appendix confirms a similar pattern in a difference-in-difference regression setting.

This could be attributed to either PIMCO's own flow volatility increase and/or (on average) higher flow volatility of funds that increased their bond position in firms sold in large quantities by PIMCO. In any case, the observed patterns in average flow volatility of active funds around Bill Gross' departure are markedly more in line with the CDS spread patterns documented earlier. This difference-in-difference exercise thus reveals how active fund bondholders' heightened flow concerns translates into higher credit risk of firms, as the second testable implication of our model highlights.

4.6. Credit risk and concave flow-performance relationship

The final prediction of our theory states that the relationship between active 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 refinance. This concave flow-performance relationship is known to stem from the payoff complementarity that arises as a result of the open-end funds' liquidity mismatch (Chen, Goldstein, and Jiang 2010). As a result, flows become disproportionately more sensitive to bad performance. We examine the flow-performance concavity of our sample funds as follows. First, we run a rolling three-year regression of monthly fund flow on the interaction of lagged fund return and a negative fund return indicator. The coefficient on the interaction term then captures extra flow response to negative return relative to a positive return of the same magnitude. We refer to this as "concavity coefficient" and use this to divide our sample of active bond funds into high- and low-concavity subsamples using the sample median of their Lipper peers at each month-end as the cut-off. Then, as in Table 7, we separately calculate the holding share of each group. Using these two holding share measures, we re-estimate our main results and credit rating interactions in Table 2 and Table 3 Panel A. Furthermore, we examine the role of overall market illiquidity by separately examining high vs. low VIX sub-periods as in Table 6. Table 9 presents our results.

TABLE 9 HERE

Column (1) of Table 9 Panel A 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, both in terms of statistical and economic significance, though the coefficient difference test between the two groups yields an insignificant result. Furthermore, credit rating interaction results in column (2) strongly suggest that, once again, the strong association between FHS and credit risk among firms rated BBB or below is more pronounced for high-concavity funds, both in terms of statistical and economic significance. However, even among low-concavity funds, we find a significant relationship between FHS and credit risk for firms rated BBB or below, suggesting that our results are not driven by concavity alone. Thus, overall, our empirical analysis reveals an important asymmetric response in two dimensions; at the firm level, FHS is strongly associated with credit risk of firms with poor cash flow prospects, while at the fund level, the positive relationship between FHS and the next-period CDS spread is more noticeable among funds with greater flow-performance concavity.

Finally, in columns (3) to (5), we separately estimate our baseline regressions in Table 9 Panel A for VIX sub-periods. We find that, during periods of high VIX, only the high-concavity FHS retain statistical significance in the CDS spread regression, while low-concavity FHS turns insignificant. In terms of economic coefficient, the point estimate on high-concavity FHS (0.521) is more than double that of low-concavity FHS (0.254). In contrast, during periods of low VIX, point estimates on the two coefficients are virtually indistinguishable from each other (0.294 vs. 0.328), further suggesting the importance of concave flow-performance relationship during periods of high overall market illiquidity. Overall, the empirical results in Table 9 suggest that the positive relationship between fund holdings and credit risk becomes more pronounced as the funds' flow-performance relationship becomes more sensitive to bad performance.[37]

5. Conclusion

[37] In Tables A.11 and A.12 in the Internet Appendix, we examine whether the strong link between FHS and credit risk found among high-concavity funds emanates solely from the illiquidity of fund holdings. While Table A.11 reveals that the link between FHS and the next-period CDS spread is indeed stronger among funds with illiquid holdings, when we double-sort on concavity and holdings illiquidity in Table A.12, it appears that flow-performance concavity matters more for the relationship than illiquid holdings. For firms rated BBB or below, we find a strong link between FHS and CDS spread regardless of holdings illiquidity when we consider funds with high flow-performance concavity, but the coefficient on the high illiquidity, low concavity subsample loses significance, suggesting flow-performance concavity to be a more important driver of the fund holdings-credit risk relationship.

Through a simple illustrative model and a series of empirical analyses, 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 shows that the flow-based career concerns of bond funds reduce their willingness to pay for the bond at refinancing when a firm's cash flow prospects are poor, which in turn intensifies the equityholders' endogenous default incentives and worsens the firm's credit risk. The model further predicts that the positive relationship between bond funds and credit risk should strengthen as the funds' intensity of career concerns becomes stronger and/or the flow-performance relationship becomes more concave. We thus demonstrate that, in addition to firm fundamentals and other demand-side characteristics, *who* holds the bonds could become a non-trivial factor in determining a firm's credit risk.

Our empirical analyses support the model's predictions. Even after controlling for potential endogeneity issues by using an instrumental variable that exploits the funds' cross-sectional variations in total net assets and their investment universe, we find that a one-standard-deviation increase in the holding share of active bond funds increases a firm's next-period CDS premium by over 20 bps, particularly for firms rated BBB or below. We further confirm the 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. The economic relevance of fund holding share on credit risk increases substantially ahead of a firm's debt maturity, confirming the importance of the refinancing channel at work in the model, and our results are stronger in turbulent market periods, distinguishing our findings from "reaching for yield" by bond funds. This relationship becomes stronger in statistical and economic significance when the funds holding the firm's bonds are susceptible to flow fragility because of poor returns, high flow volatility, low TNA share of load fee classes, or small size of their fund families. We further address endogeneity concerns inherent in the relationship between fund holdings and credit risk by using Bill Gross' departure from PIMCO in 2014 as an exogenous shock to PIMCO funds' flow concerns, showing 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 theoretical and empirical results 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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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

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

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

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

which, upon substituting in the price, becomes

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

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 refinancing would fail. □

Proof of Proposition 4. First, note that:

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

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 $\gamma_V < \frac{1}{2}(1-\gamma_\tau)$. □

Appendix B. A Short Discussion on Refinancing 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 refinancing 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 refinancing, 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 refinancing 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 refinancing 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 refinancing price relative to that in Proposition 3.

Appendix C. Variable Descriptions

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

C.1. Fund bond holdings data

Fund holding share (Morningstar, CRSP Mutual Funds, TRACE, 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 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 an index 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 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.

C.2. CDS Premium 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. Controls

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

Historical stock return (CRSP): 1-, 6-, and 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.

Table 1. Summary Statistics

In this table, we report summary statistics on the sample of 570 firms with five-year CDS spread data available on Markit and non-missing coverage of at least one of its corporate bonds in the Morningstar fund holdings data. Our sample period is between October 2001 and October 2015, with the holdings data of 1,128 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. For a detailed description of how each variable is constructed, refer to Appendix C.

	Obs.	Mean	St. Dev.	P25	P50	P75
CDS premium characteristics						
CDS spread (bps)	45,667	134.72	191.45	39.37	71.84	146.25
of which:						
AAA to A	15,809	60.98	71.50	25.09	43.33	69.84
BBB	21,592	113.49	125.37	46.53	80.68	134.10
BB or below	8,266	331.19	318.59	119.60	234.51	417.87
Fund holding characteristics						
Fund holding share (all funds) (%)	45,667	38.21	22.27	22.06	36.17	52.54
Fund holding share (active funds only, FHS) (%)	45,667	30.18	21.36	14.26	26.02	41.74
Fund holding share (passive funds only) (%)	45,667	7.759	8.235	0.000	5.967	12.83
Other characteristics						
1-month stock return (%)	45,666	1.021	8.647	-3.526	1.060	5.426
6-month stock return (%)	45,667	6.514	23.45	-5.815	6.431	18.43
12-month stock return (%)	45,667	13.29	34.92	-6.239	12.14	30.23
Historical volatility (annualized %)	45,667	32.23	18.35	20.48	27.18	37.40
Historical skewness	45,667	0.0898	0.857	-0.243	0.0739	0.404
Historical kurtosis	45,667	4.518	6.930	1.110	2.207	4.688
Total assets ($ millions)	45,667	47,623.1	118,500.4	6,064	14,302	32,279
Leverage (%)	45,667	46.74	22.52	30.79	43.29	58.68
Return on equity (%)	45,667	5.416	12.99	2.638	5.185	8.113
Dividend payout per share ($\times 100$)	45,667	0.511	0.508	0.131	0.421	0.733
S&P 500 index return (%)	45,667	1.877	21.61	-11.27	-2.869	10.65
3-month T-Bill rate (%)	45,667	1.444	1.741	0.070	0.900	2.230
Term spread (%)	45,667	2.030	1.144	1.550	2.210	2.920
VIX	45,667	20.09	8.696	13.88	17.40	23.70

Table 2. Fund Holdings and Credit Risk

We report the second-stage results of two-stage least squares firm-month level panel regression of CDS premium (in bps) on fund holding share. As an instrument for fund holding share, we use the hypothetical holding share proposed by Koijen and Yogo (2019). At each month-end for each fund, we form an equal-weighted portfolio of all firms they ever held during the previous three-year period (referred to as the fund's "investment universe"). Then, for each fund, we aggregate the hypothetical "holding", i.e., total net assets divided by the number of firms in the investment universe, of all other active funds holding a firm's bond. We then aggregate this at the firm-month level and divide by the total amount of corporate bonds outstanding, which we use as instrument. In column (1), we include market-level controls without fixed effect, while in column (2), we include month fixed effect. Controls are 1-year realized volatility, skewness, and kurtosis, recovery rate, firm size, leverage, ROE, and dividend payout per share, and in the case of columns (1), 1-month S&P 500 return, 3-month T-Bill rate, term spread, and VIX. All controls are lagged by one month. 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 month 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)
Fund holding share (%)	1.310***	1.008***
	(3.51)	(2.81)
1-year stock return (%)	-0.904***	-1.188***
	(-7.45)	(-11.02)
Historical volatility (%)	5.112***	7.048***
	(9.51)	(13.74)
Historical skewness	1.197	5.400**
	(0.52)	(2.42)
Historical kurtosis	0.071	-0.965***
	(0.21)	(-3.07)
Recovery rate	-15.999***	-15.610***
	(-5.55)	(-5.32)
Log assets	-12.148***	-12.295***
	(-4.78)	(-4.81)
Leverage (%)	1.843***	1.705***
	(7.45)	(7.69)
ROE (%)	-0.837***	-0.607***
	(-3.26)	(-3.10)
Dividend payout per share	-19.841***	-3.557
($\times 100$)	(-2.75)	(-0.57)
1-month S&P 500 return (%)	0.605***	
	(3.70)	
3-month T-Bill rate (%)	-13.145***	
	(-3.99)	
Term spread (%)	-16.073***	
	(-3.00)	
VIX	-0.932	
	(-1.26)	
Month FE	NO	YES
Kleibergen-Paap F-statistic	100.88	96.30
No. of obs.	45,462	45,459

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

In this table, we re-estimate the two-stage least squares specification in Table 2, albeit with fund holding share either interacted with two mutually exclusive credit rating dummies (A or above vs. BBB or below) or 1-year stock return. In Panel A, we interact fund holding share with two indicator variables, namely a dummy for credit rating of A or above, and another with credit rating of BBB or below. In Panel B, we report the panel regression results with an interaction term between fund holding share and 1-year stock return. In the untabulated first stage, our instrumental variable, i.e., counterfactual fund holding share, is also interacted with credit rating dummies or 1-year stock return in the identical manner. In column (1), we include market-level controls without fixed effect, while in column (2), we include month 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 month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Credit rating interactions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
Fund holding share × I(A or above) (%)$^{(A)}$	-0.193	-0.239
	(-0.42)	(-0.53)
Fund holding share × I(BBB or below) (%)$^{(BBB)}$	1.310***	1.004***
	(3.53)	(2.80)
F-statistic: (A) = (BBB)	32.68***	20.60***
Controls	YES	YES
Month FE	NO	YES
No. of obs.	45,462	45,459

Panel B. Interaction with 1-year stock return

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
Fund holding share (%)	1.500***	1.276***
	(3.44)	(3.09)
Fund holding share × 1-year stock return (%)	-1.218*	-1.662***
	(-1.83)	(-2.67)
1-year stock return (%)	-0.448*	-0.553**
	(-1.82)	(-2.28)
Controls	YES	YES
Month FE	NO	YES
No. of obs.	45,462	45,459

Table 4. Difference-in-Difference Test: Morningstar Rating Change at the Five-Year Mark

In this table we estimate the effect of Morningstar star rating change when a fund's share class reaches the age of 5 years and Morningstar's star rating calculation methodology changes. We identify all events when a share class of a fund reaches the five-year mark and the star rating either goes up (our "upgraded" or treated sample) or remains the same (control). Then, for a window of [-6, 6] months around these five-year Morningstar rating change, we proceed as follows. First, at the share class-month level, we run the difference-in-difference regression of monthly fund flow. Then, using the holding information at the month-end prior to the five-year mark, we identify (i) all firms with treated or control fund holding share greater than 2.5%, or (ii) 5%. We then present the difference-in-difference regressions at the firm-month level for the fund holding share and the next-month five-year CDS spread with a full set of controls using firm and month fixed effects. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable				
	Monthly flow (%)	FHS (%)	CDS spread	FHS (%)	CDS spread
	(1)	(2)	(3)	(4)	(5)
	5-year classes	Holding share > 2.5%		Holding share > 5%	
Upgrade at 5-year dummy	-0.528***	-1.013**	-5.852*	-1.904***	-4.048
	(-2.71)	(-2.05)	(-1.75)	(-2.68)	(-0.95)
Post 5-year dummy	-0.245**	0.279	-10.703***	0.042	-18.083***
	(-2.04)	(0.73)	(-3.15)	(0.08)	(-4.12)
Upgrade at 5-year dummy × Post 5-year dummy	0.479**	1.534***	15.645***	2.106***	20.475***
	(2.20)	(2.84)	(3.73)	(2.91)	(4.13)
Controls	NO	YES	YES	YES	YES
Firm FE	NO	YES	YES	YES	YES
Month FE	NO	YES	YES	YES	YES
Adjusted R-squared	0.000	0.492	0.786	0.521	0.806
No. of obs.	48,637	18,413	18,413	12,327	12,327

Table 5. Fund Holding and Credit Risk around Bond Maturities

In this table we re-estimate Table 2, albeit with an interaction term between fund holding share and the maturity dummy. Maturity dummy takes the value of one if the firm has a maturing bond within the next month. Controls are identical to 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 month 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)
Fund holding share (%)	1.578***	0.973***
	(4.24)	(2.69)
Fund holding share × Maturity dummy	1.641**	1.483**
	(2.34)	(2.18)
Maturity dummy	-56.780**	-55.631**
	(-2.42)	(-2.35)
Controls	YES	YES
Month FE	NO	YES
No. of obs.	45,462	45,459

Table 6. Fund Holdings and Credit Risk: Do Market Conditions Matter?

In this table, we engage in subsample analysis by creating two equal-sized subsamples based on whether the (i) default spread, namely the difference between Moody's Seasoned Baa vs. Aaa corporate bond yields (constant maturity), or (ii) VIX is above or below the sample median. In Panel A, we re-estimate the baseline regressions in Table 2, whereas in Panel B, we re-estimate the maturity interaction in Table 5. Controls and fixed effect specification are identical to Table 2 column (2). In columns (3) and (6), we report the subsample coefficient difference test results. Specifically, we test the difference in coefficient estimates between the two subsamples by running a pooled regression with each variable interacted with the high credit spread or high VIX dummy, respectively, and report the corresponding *t*-statistics. *T*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All sample

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High default spread	Low default spread	Coeff. Diff. test (*t*-stat)	High VIX	Low VIX	Coeff. Diff. test (*t*-stat)
Fund holding share (%)	1.085**	0.846**	0.238	1.065**	0.894**	0.171
	(2.38)	(2.32)	(0.56)	(2.31)	(2.45)	(0.38)
Controls	YES	YES		YES	YES	
Month FE	YES	YES		YES	YES	
No. of obs.	25,368	20,091		25,174	20,285	

Panel B. Interaction with the maturity dummy

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High default spread	Low default spread	Coeff. Diff. test (*t*-stat)	High VIX	Low VIX	Coeff. Diff. test (*t*-stat)
Fund holding share (%)	1.036**	0.831**	0.205	1.027**	0.866**	0.161
	(2.27)	(2.24)	(0.48)	(2.23)	(2.34)	(0.36)
Fund holding share	2.367**	0.559	1.808*	1.997*	1.015*	0.982
× Maturity dummy	(2.19)	(1.01)	(1.79)	(1.75)	(1.90)	(0.89)
Maturity dummy	-90.048**	-19.509	-70.538**	-78.184*	-32.303**	-45.881
	(-2.33)	(-1.21)	(-2.04)	(-1.93)	(-2.04)	(-1.22)
Controls	YES	YES		YES	YES	
Month FE	YES	YES		YES	YES	
No. of obs.	25,368	20,091		25,174	20,285	

Table 7. Fund Characteristics, Fund Holdings, and Credit Risk

In this table, we re-run the two-stage least squares regressions in column (2) of Table 2, albeit separately for those with high vs. low (i) 12-month fund return, (ii) 12-month fund flow volatility, (iii) management firm size, and (iv) TNA-share of fund classes with a load fee. To divide the funds into high vs. low groups, we first calculate the median for each Lipper objective code at each month-end using the latest available fund-level data. We then check whether a fund's latest value is above or the median of its Lipper category at the same point in time. Controls are identical to Table 2 column (2) with month fixed effect. We further report F-statistic testing the hypothesis that the coefficients of high- and low-group bond 62oldings are equal. *T*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month 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	1-year fund return	1-year fund flow volatility	Management firm size	TNA-share of load fee classes
High-group holding share (%)$^{(H)}$	0.769*	2.238***	0.555	0.488
	(1.71)	(4.48)	(1.36)	(1.11)
Low-group holding share (%)$^{(L)}$	1.257***	0.522	2.233***	2.498***
	(3.00)	(1.15)	(3.63)	(4.78)
F-statistic: (H) = (L)	0.81	6.16**	5.59**	8.92***
Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of obs.	45,459	45,459	45,459	45,459

Table 8. Difference-in-Difference Test: Departure of Bill Gross

In this table we estimate the effect of Bill Gross' surprise departure from PIMCO in September 2014 on credit risk of firms held by PIMCO. For a window of [-6, 6] months around the departure of Bill Gross, we proceed as follows. Using the August 2014 portfolio holding, we identify (i) all firms held by PIMCO (Panel A) and (ii) all firms with PIMCO holding share greater than 5%. In each instance, we compare these firms against either (i) all sample firms or (ii) those held by Prudential or Vanguard (with the holding share exceeding 5% in Panel B). We present the difference-in-difference regression results with a full set of controls using firm and month fixed effects in columns (1) and (2). We then separately consider the firms rated A or above vs. BBB or below in columns (3) and (4). We further report F-statistic testing the hypothesis that the two coefficients are equal. *T*-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All firms held by PIMCO

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO dummy × Post-Bill Gross departure	4.214*** (3.16)	7.344*** (4.02)		
PIMCO dummy × *I*(A or above) × Post-Bill Gross departure(A)			-2.749 (-1.62)	1.769 (0.93)
PIMCO dummy × *I*(BBB or below) × Post-Bill Gross departure(BBB)			6.885*** (3.66)	9.499*** (4.14)
F-statistic: (A) = (BBB)			11.79***	8.30**
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Adjusted R-squared	0.958	0.926	0.958	0.926
No. of obs.	5,561	3,542	5,561	3,542

Panel B. Firms with PIMCO holding share greater than 5%

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO dummy × Post-Bill Gross departure	11.137*** (3.28)	13.663*** (3.35)		
PIMCO dummy × *I*(A or above) × Post-Bill Gross departure(A)			2.938 (0.90)	10.362* (2.07)
PIMCO dummy × *I*(BBB or below) × Post-Bill Gross departure(B)			12.508*** (3.33)	14.214*** (3.26)
F-statistic: (A) = (BBB)			5.38**	0.57
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Adjusted R-squared	0.958	0.919	0.958	0.919
No. of obs.	5,561	3,399	5,561	3,399

Table 9. Fund Holdings and Credit Risk: The Role of Concavity in the Flow-Performance Relationship

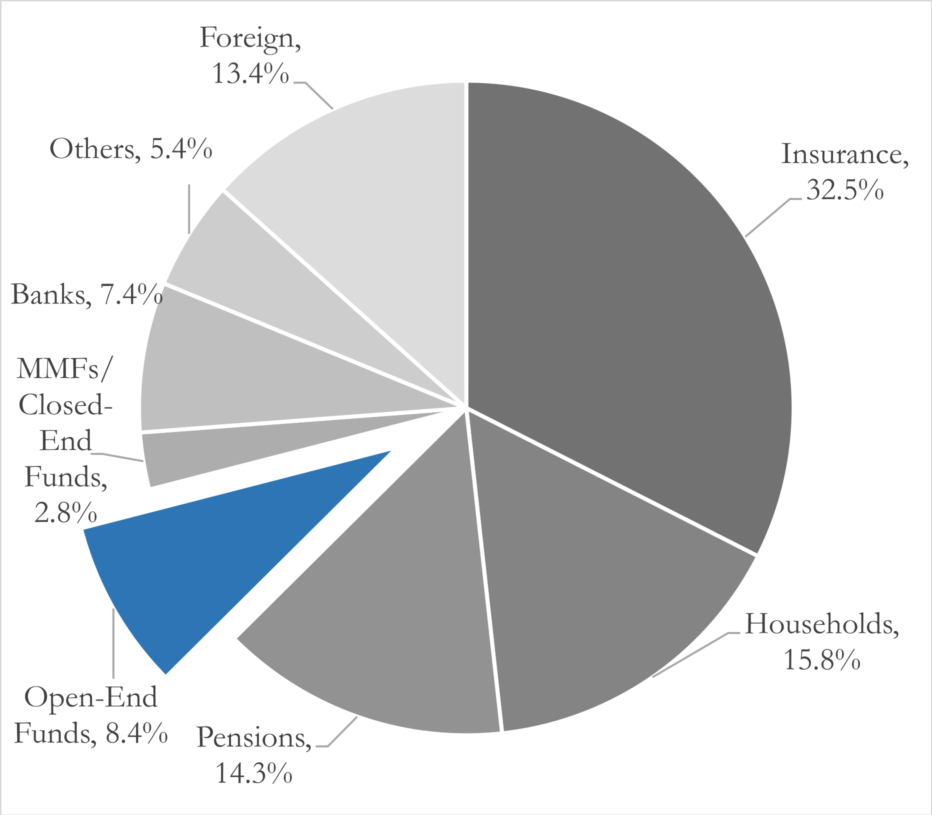
In this table, we split the fund holding share into "high-concavity" and "low-concavity" fund holding shares. At each month-end, for each share class, we run a three-year rolling regression of monthly flow on lagged return and the interaction of lagged return with a negative return dummy indicator. We define concavity as the rolling regression coefficient on this interaction term. We then aggregate this concavity at the share class level into fund level using the lagged TNA of each share class as the weight. Then, we split our sample funds in the Morningstar database into high- and low-concavity subsamples using the sample median of each Lipper objective code at the time as the cut-off. In column (1), we re-estimate the regressions analogous to Table 2 column (2). In column (2), we interact each bond holding measure with two mutually exclusive credit rating dummies (A or above vs. BBB or below), as in column (2) of Table 3 Panel A. Finally, in columns (3) to (5), we separate our sample into two sub-periods on the basis of VIX, as in Table 6 Panel A. In column (5), we report the subsample coefficient difference test results. Specifically, we test the difference in coefficient estimates between the two subsamples by running a pooled regression with each variable interacted with the high VIX dummy and report the corresponding *t*-statistics. Controls are identical to Table 2. *T*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month 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)				
	Full sample		VIX sub-period		
			High VIX	Low VIX	High – Low
	(1)	(2)	(3)	(4)	(5)
High concavity fund holding share (%)(H)	0.427***		0.521***	0.294**	0.226
	(2.96)		(2.64)	(2.12)	(1.10)
Low concavity fund holding share (%)(L)	0.296*		0.254	0.328**	-0.074
	(1.81)		(1.13)	(2.08)	(-0.34)
High concavity fund holding share × *I*(A or above)(HA)		-0.275			
		(-1.62)			
High concavity fund holding share × *I*(BBB or below)(HB)		0.541***			
		(3.78)			
Low concavity fund holding share × *I*(A or above)(LA)		-0.166			
		(-0.77)			
Low concavity fund holding share × *I*(BBB or below)(LB)		0.346**			
		(2.00)			
F-statistic: (H) = (L)	0.71		1.25	0.07	
F-statistic: (HA) = (HB)		22.15***			
F-statistic: (LA) = (LB)		5.16**			
Month FE	YES	YES	YES	YES	YES
No. of obs.	45,459	45,459	25,174	20,285	

Figure 1. Who Holds Corporate Bonds? 1998 vs. 2017

Figures are from the Federal Reserve's Flow of Funds (L.213).

Panel A. 1998 Year-End



Panel B. 2017 Year-End

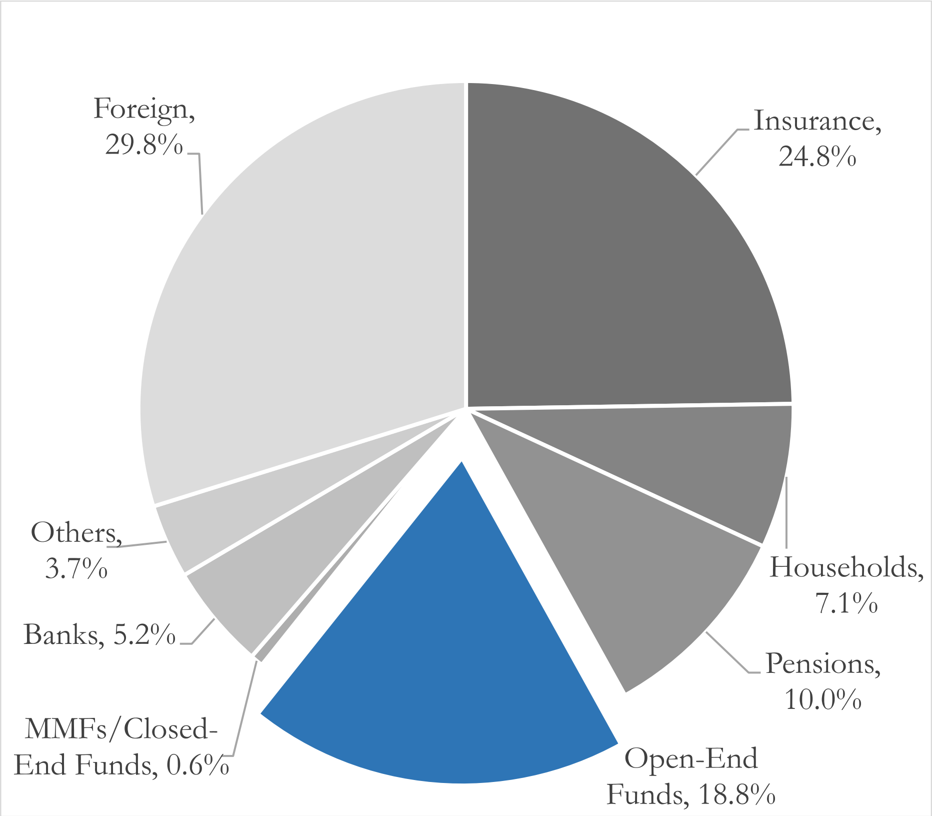


Figure 2. Bondholders With vs. Without Flow Concerns and Strategic Default

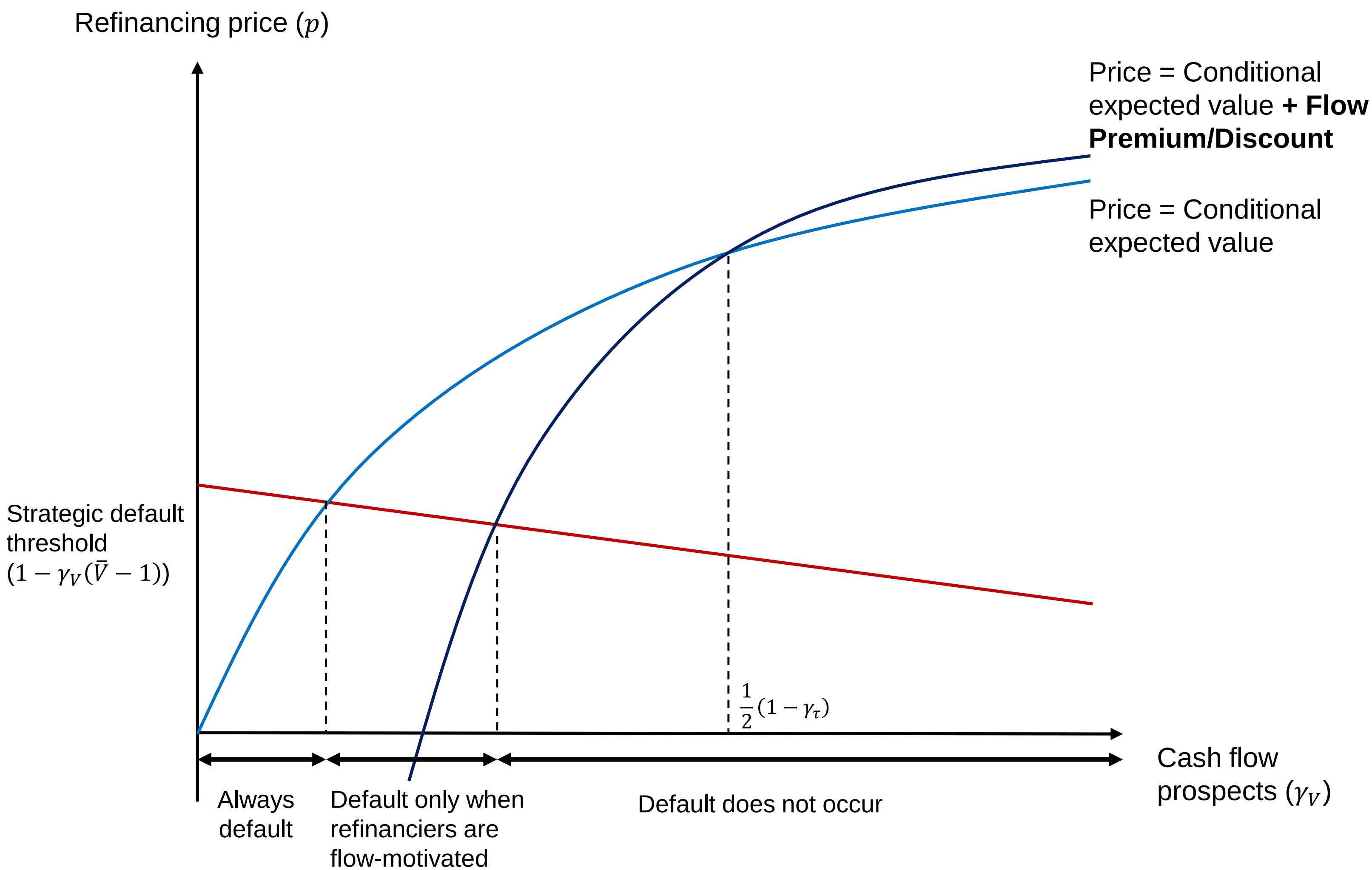


Figure 3. Flow-Motivated Bondholders, Concave Flow-Performance Relationship, and Strategic Default

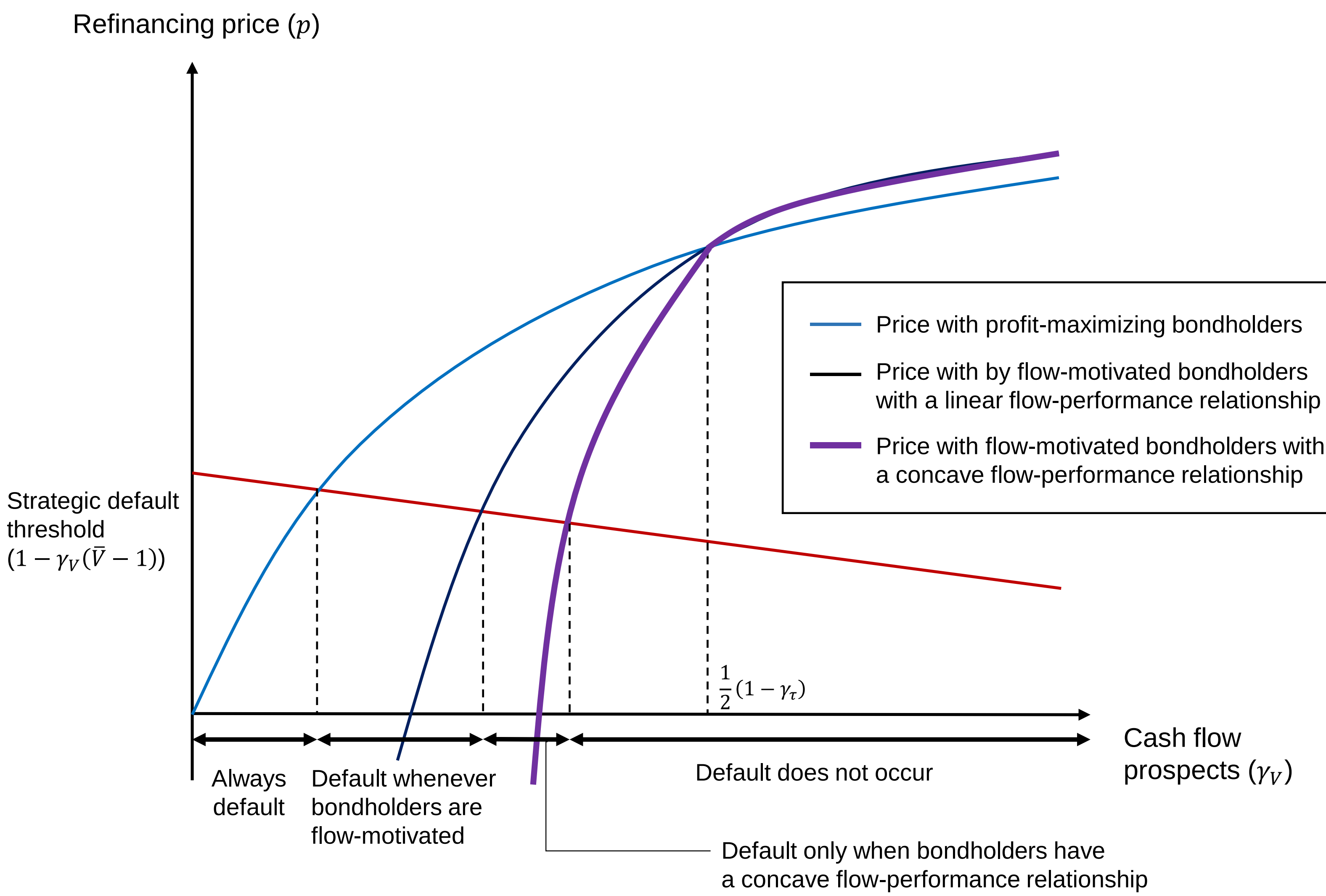
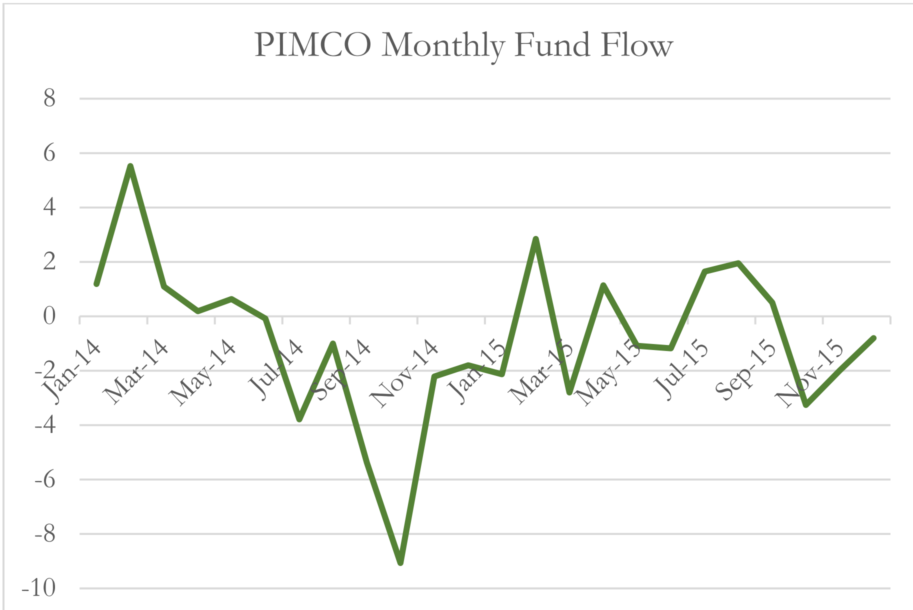


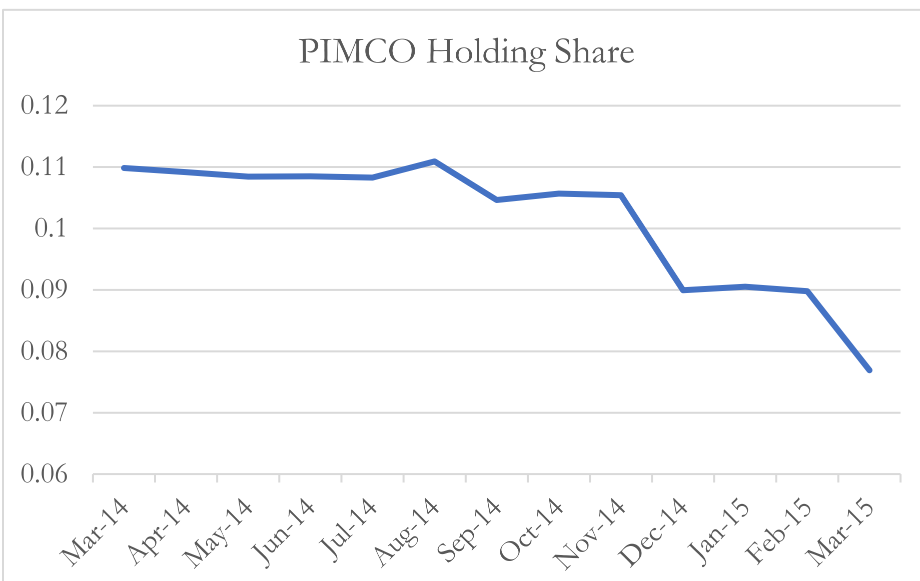
Figure 4. PIMCO Fund Flows and Holding Share Around the Departure of Bill Gross

In Panel A, we present the monthly fund flows of PIMCO around the departure of Bill Gross in September 2014. Then, for all firms held by PIMCO in their August 2014 holding, we track these firms' PIMCO holding share over our [-6, 6] months of difference-in-difference test window in Panel B. Finally, we track the overall fund holding share of all firms held by PIMCO vs. Prudential or Vanguard over the same test window in Panel C.

Panel A. PIMCO monthly fund flows



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



Panel C. Fund holding share of firms held by PIMCO vs. Prudential or Vanguard in August 2014

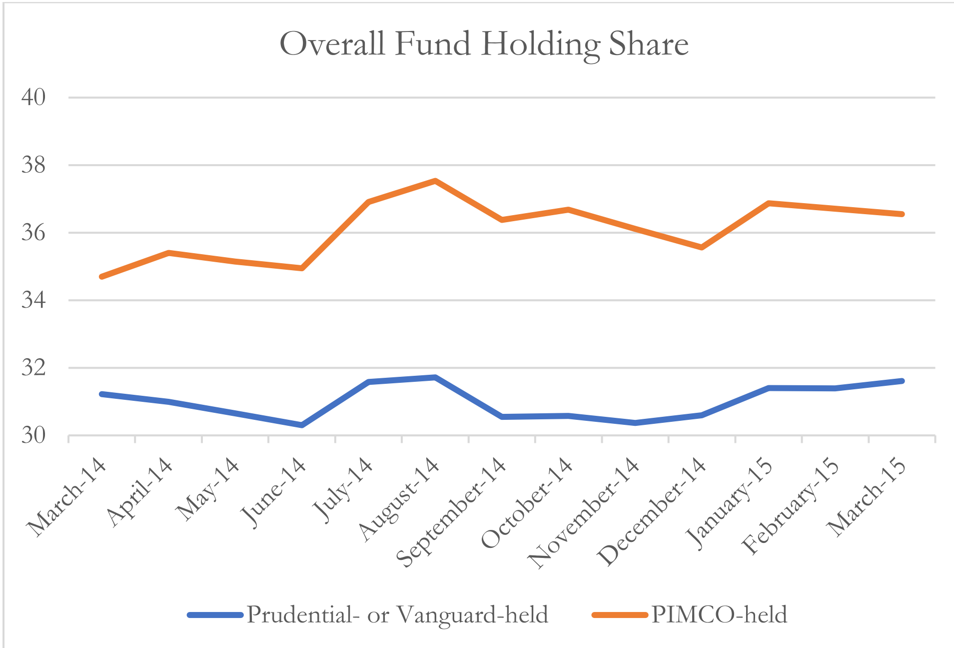
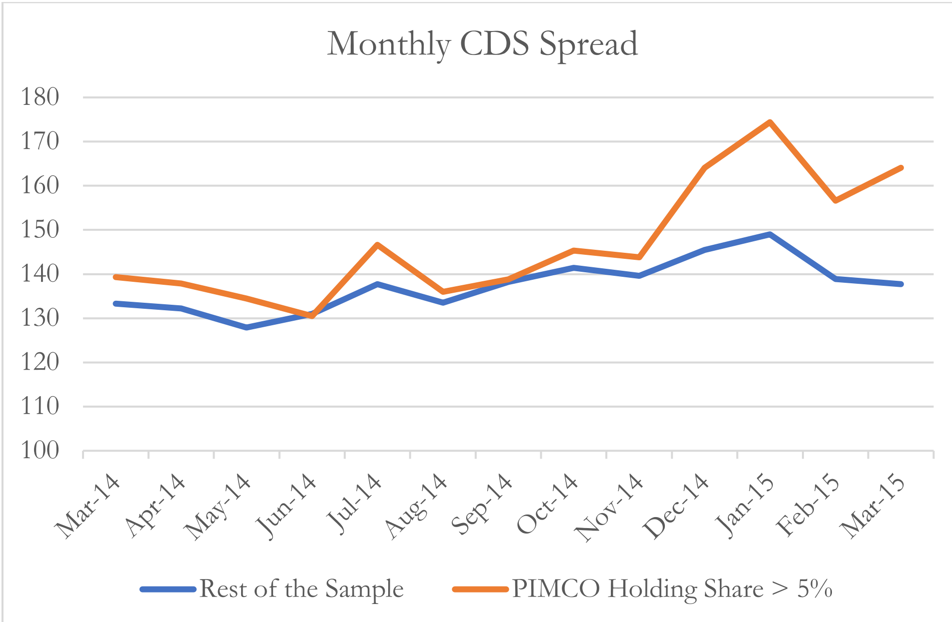


Figure 5. CDS Spreads of PIMCO and Control Firms around the Departure of Bill Gross

For all firms with PIMCO holding share greater than 5%, we track their monthly CDS spread over our [-6, 6] months of difference-in-difference test window. In Panel A, we compare their spreads against all other control firms, while we use firms with Prudential or Vanguard holding share greater than 5% as controls in Panel B.

Panel A. All sample firms



Panel B. Firms with Prudential or Vanguard holding share greater than 5% as controls

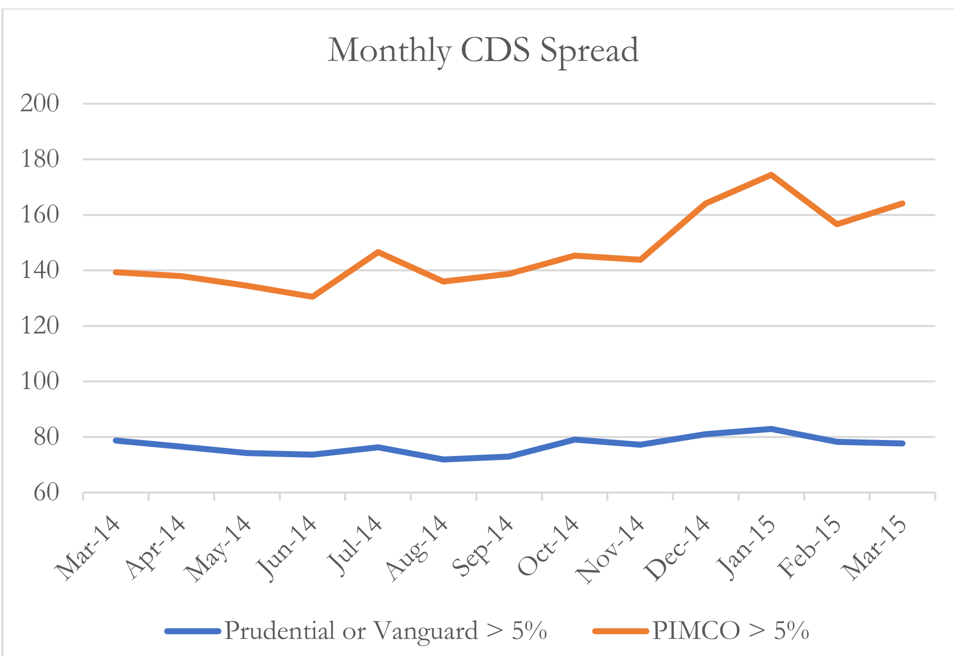
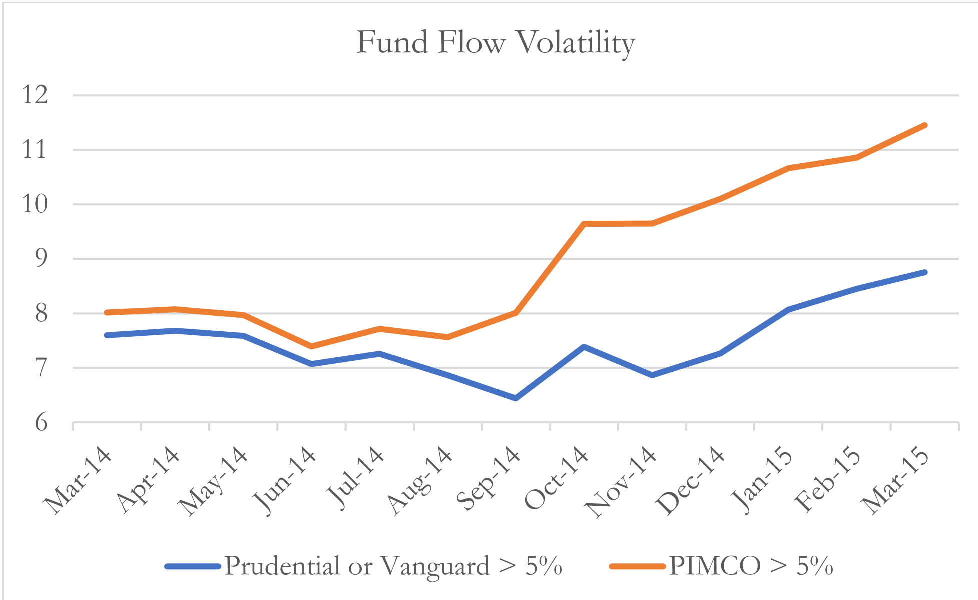


Figure 6. Fund Flow Volatility of PIMCO-Held Firms

For all firms with PIMCO holding share greater than 5% in their August 2014 holding, we track their active fund bondholders' weighted average 12-month fund flow volatility around our difference-in-difference analysis test window. As for the control group, we choose all firms with Prudential or Vanguard holding share greater than 5% in their August 2014 holding.



Internet Appendix to "Bond Funds and Credit Risk"

This Version: December 19, 2021

Table A.1. Robustness Check: Inclusion of Lagged CDS Spread

In this table we re-estimate the results reported in columns (3) and (4) of Table 2 and Table 3 Panel A, albeit with the lagged CDS spread as an additional control. All other controls 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 month 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 holding share (%)	0.161***	0.095**		
	(3.42)	(2.39)		
Fund holding share × *I*(A or above) (%)[(A)]			0.071	0.011
			(1.59)	(0.31)
Fund holding share × *I*(BBB or below) (%)[(BBB)]			0.162***	0.095**
			(3.43)	(2.40)
Lagged 5-year CDS spread (bps)	0.966***	0.955***	0.965***	0.955***
	(110.54)	(118.22)	(111.20)	(118.48)
F-statistic: (A) = (BBB)			9.22**	10.66***
Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of obs.	45,462	45,459	45,462	45,459

Table A.2. Robustness Check: Alternative Return Horizons

In this table we re-estimate the results in Table 2 Panel B using 1- and 6-month stock returns instead. Controls are identical to those in Table 2 Panel B, 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 month 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)
	1-month return		6-month return	
Fund holding share (%)	1.133***	0.946**	1.492***	1.186***
	(2.99)	(2.56)	(3.93)	(3.16)
Fund holding share × stock return measure (%)	-3.469*	-3.883**	-2.946***	-3.180***
	(-1.76)	(-2.14)	(-3.31)	(-3.66)
Stock return measure (%)	-1.005	-0.489	-0.860***	-0.514
	(-1.50)	(-0.80)	(-2.65)	(-1.63)
Controls	YES	YES	YES	YES
Month FE	NO	YES	NO	YES
No. of obs.	45,462	45,459	45,462	45,459

Table A.3. Fund Holdings and the Likelihood of Default

In this table we estimate the likelihood of a corporate default. Using the corporate default events as identified in Mergent FISD, we create an indicator variable that takes the value of one whenever a firm entering into default within the next five years at each month-end. Using this as the dependent variable, we interact fund holding share with the following mutually exclusive set of credit rating dummies: AAA or AA, A or BBB, BB or B, CCC or below, and run regressions analogous to column (2) of Table 3 Panel A. Column (1) presents OLS regression results, while 2SLS regression results using the Koijen-Yogo (2019) hypothetical holding share measure is presented in column (2). Our sample firms are all firms with corporate bonds identified in the Morningstar holdings, regardless of whether a quote for five-year CDS exists in the Markit database or not. Controls are identical to those in Tables 2 and 3, with the exception of recovery rate, 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 month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Corporate default within 5-years	
	(1)	(2)
	OLS	2SLS
Fund holding share ×	0.007	0.007
I(AAA or AA)	(0.16)	(0.10)
Fund holding share ×	-0.020	-0.051
I(A or BBB)	(-0.75)	(-1.54)
Fund holding share ×	0.002	-0.020
I(BB or B)	(0.09)	(-0.69)
Fund holding share ×	0.165***	0.234***
I(CCC or below)	(2.93)	(3.33)
Controls	YES	YES
Month FE	YES	YES
No. of obs.	110,435	110,422

Table A.4. Insurance and Pension Holding Share

In this table we re-estimate the 2SLS regressions in column (2) of Table 2 and Table 3 Panel A, albeit with insurance and pension holding shares instead. We use the Thomson Reuters eMaxx data to compute the insurance and pension holding shares in the identical manner to the fund holding share as outlined in Table 2. We further compute the hypothetical holding share measure of Koijen and Yogo (2019) in an analogous manner. In all instances, we include month 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 month 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	Insurance	Pension
Institutional holding share	-1.734***	-6.870***		
	(-6.30)	(-3.43)		
Institutional holding share × I(A or above) (%)$^{(A)}$			-1.955***	-8.607***
			(-7.15)	(-4.13)
Institutional holding share × I(BBB or below) (%)$^{(BBB)}$			-1.535***	-5.216*
			(-4.92)	(-1.90)
Kleibergen-Paap F-statistic	386.20	427.10	190.83	127.91
F-statistic: (A) = (BBB)			5.55**	1.59
Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of obs.	44,297	44,297	44,297	44,297

Table A.5. Fund Holdings and Offering Yield

In this table we re-estimate the 2SLS regressions in column (2) of Table 2 and Table 3 Panel A, albeit using the offering yield of a firm's new bond issuance as the dependent variable. Offering yield is defined as the offering-amount-weighted average offering yield of a firm's bonds issued during the month. We focus our attention on all firm-months with bond issuance in columns (1) and (3), while we focus on bond issuances occurring within six months of a bond's maturity in (2) and (4), which we refer to as "refinancing issues." In all instances, we include month fixed effect. Controls are identical to those in Table A.4, 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 month 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)	(3)	(4)
Issuances	All	Refinancing	All	Refinancing
Fund holding share (%)	1.485***	1.520**		
	(4.51)	(2.43)		
Fund holding share × *I*(A or above) (%) (A)			-2.207**	-2.156
			(-2.56)	(-1.58)
Fund holding share × *I*(BBB or below) (%) (BBB)			1.900***	2.090***
			(5.82)	(3.88)
F-statistic: (A) = (BBB)			23.23***	12.15***
Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of obs.	4,356	1,690	4,347	1,690

Table A.6. Fund Holdings and Credit Risk: Do Market Conditions Matter?

In this table, we re-estimate Table 6 by creating two equal-sized subsamples based on whether the (i) 3-month T-Bill rate or (ii) term spread, namely the difference between 10-year and 3-month Treasury rates, are above or below sample median. Controls are identical to Table 6. In columns (3) and (6), we report the subsample coefficient difference test results. Specifically, we test the difference in coefficient estimates between the two subsamples by running a pooled regression with each variable interacted with the high T-Bill or term spread dummy, respectively, and report the corresponding *t*-statistics. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All sample

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High T-Bill rate	Low T-Bill rate	Coeff. diff. test (*t*-stat)	High term spread	Low term spread	Coeff. diff. test (*t*-stat)
Fund holding share (%)	1.152***	1.067*	0.085	1.152**	0.810**	0.342
	(3.23)	(1.84)	(0.13)	(2.40)	(2.61)	(0.79)
Controls	YES	YES		YES	YES	
Month FE	YES	YES		YES	YES	
No. of obs.	22,697	22,762		26,360	19,099	

Panel B. Interaction with the maturity dummy

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High T-Bill rate	Low T-Bill rate	Coeff. diff. test (*t*-stat)	High term spread	Low term spread	Coeff. diff. test (*t*-stat)
Fund holding share (%)	1.082***	1.051*	0.030	1.115**	0.778**	0.337
	(3.05)	(1.80)	(0.05)	(2.31)	(2.49)	(0.78)
Fund holding share × Maturity dummy	2.610**	0.653	1.957	1.743	1.173**	0.570
	(2.39)	(0.80)	(1.54)	(1.64)	(2.32)	(0.54)
Maturity dummy	-80.331***	-27.477	-52.854	-67.858*	-40.534**	-27.324
	(-2.79)	(-0.85)	(-1.34)	(-1.87)	(-2.32)	(-0.82)
Controls	YES	YES		YES	YES	
Month FE	YES	YES		YES	YES	
No. of obs.	22,697	22,762		26,360	19,099	

Table A.7. Passive Fund Holdings and Credit Risk

We re-run and report the second-stage results of two-stage least squares firm-month level panel regressions in Table 2 and Table 3 Panel A using the passive fund holding share (PFHS) instead. The Koijen-Yogo (2019) instrument variable is constructed in the identical manner to Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month 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)
Passive fund holding share	-2.974***	-3.305***		
	(-3.79)	(-3.88)		
Passive fund holding share × *I*(A or above) (%)[(A)]			-3.033***	-3.074***
			(-3.36)	(-3.12)
Passive fund holding share × *I*(BBB or below) (%)[(BBB)]			-2.952***	-3.376***
			(-3.68)	(-3.95)
F-statistic: (A) = (BBB)			0.02	0.23
Controls	YES	YES	YES	YES
Month FE	NO	YES	NO	YES
No. of obs.	45,462	45,459	45,462	45,459

Table A.8. Difference-in-Difference Test: PIMCO's Flow-Performance Sensitivity

In this table we run the monthly regression of fund share class flow on the triple interaction between fund share class return, PIMCO dummy, and post-Bill Gross departure dummy. We run monthly flow regressions in a similar set-up to Choi, Kronlund, and Oh (2021) for the window of [-6, 6] month around the departure of Bill Gross for the sample of all corporate and general bond funds. Regressions are run at the fund share class-month level. Controls include lagged fund share class flow, fund share class size, management firm size, fund age, passive fund dummy, institutional share class dummy, turnover ratio, expense ratio, and load fund class dummy, with the variable definition identical to Choi, Kronlund, and Oh (2021). Returns and all fund characteristics are lagged by one month. We include Lipper-objective-by-month fixed effect. t-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund share class flow (%)
Fund share class return (%)	0.855 (1.63)
PIMCO dummy	-1.962*** (-4.61)
Fund share class return × PIMCO dummy	0.601 (0.71)
Fund share class return × Post Bill Gross departure	-0.302 (-0.54)
PIMCO dummy × Post Bill Gross departure	-3.640 (-1.56)
Fund share class return × PIMCO dummy × Post Bill Gross departure	**6.680**** **(2.87)**
Lagged fund flow	0.152*** (9.57)
Fund share class size	-0.158*** (-6.04)
Management firm size	0.063 (1.45)
Fund age	-0.125*** (-16.66)
Passive fund dummy	-0.671** (-2.51)
Turnover ratio	0.049 (0.69)
Expense ratio	-1.849*** (-8.66)
Institutional class dummy	0.120 (0.54)
Load class dummy	-0.358** (-2.44)
Lipper-objective-by-month FE	YES
Adjusted R-squared	0.068
No. of obs.	25,192

Table A.9. Difference-in-Difference Test: Change in the Fund Flow Volatility of PIMCO-Held Firms

In this table we re-estimate the difference-in-difference regressions in columns (2) and (4) of Table 8, albeit with the weighted average rolling 12-month annualized fund flow volatility of PIMCO-held vs. control group firms' active mutual fund bondholders as the dependent variable instead. We use Prudential- or Vanguard-held firms as controls. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by firm and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Fund flow volatility (%)			
	PIMCO vs. Prudential or Vanguard held firms			
	All PIMCO held firms		PIMCO holding share > 5%	
	(1)	(2)	(3)	(4)
PIMCO dummy × Post-Bill Gross departure	0.862*** (6.20)		1.893*** (10.62)	
PIMCO dummy × *I*(A or above) × Post-Bill Gross departure		-0.280 (-1.72)		1.939*** (8.47)
PIMCO dummy × *I*(BBB or below) × Post-Bill Gross departure		1.307*** (7.80)		1.885*** (10.19)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Adjusted R-squared	0.498	0.502	0.507	0.506
No. of obs.	3,536	3,536	3,395	3,395

Table A.10. Difference-in-Difference Test: Longer Test Window

In this table we re-estimate the difference-in-difference regressions in Table 8 for a longer test window of [-12, 12] months around the departure of Bill Gross. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All firms held by PIMCO

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO dummy × Post-Bill Gross departure	7.567***	11.637***		
	(3.24)	(3.62)		
PIMCO dummy × *I*(A or above) × Post-Bill Gross departure[(A)]			-4.377***	-0.080
			(-2.94)	(-0.04)
PIMCO dummy × *I*(BBB or below) × Post-Bill Gross departure[(BBB)]			12.146***	16.136***
			(3.58)	(3.87)
F-statistic: (A) = (BBB)			15.74***	16.59***
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Adjusted R-squared	0.918	0.859	0.918	0.859
No. of obs.	10,652	6,727	10,652	6,727

Panel B. Firms with PIMCO holding share greater than 5%

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO dummy × Post-Bill Gross departure	20.134***	22.477***		
	(3.73)	(3.68)		
PIMCO dummy × *I*(A or above) × Post-Bill Gross departure[(A)]			-0.343	3.781
			(-0.06)	(0.50)
PIMCO dummy × *I*(BBB or below) × Post-Bill Gross departure[(BBB)]			23.517***	25.557***
			(4.16)	(4.11)
F-statistic: (A) = (BBB)			19.30***	13.62***
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Adjusted R-squared	0.918	0.850	0.918	0.851
No. of obs.	10,652	6,452	10,652	6,452

Table A.11. Fund Holdings and Credit Risk: The Role of Holdings Illiquidity

In this table, we split the fund holding share into the "illiquid" and "liquid" fund holding share, namely those with high vs. low holding-level zero-trading-day (ZTD) ratios. At each month-end, we calculate the ZTD of individual bonds, i.e., the ratio of nontrading days, using the TRACE database. This then allows us to calculate the holding-weighted average ZTD of each active bond fund at each month-end. Due to the coverage of the TRACE database, our sample begins in September 2002. We then split our sample funds in the Morningstar database into high- and low-ZTD subsamples using the sample median at the time as the cut-off. In column (1), we re-estimate the regressions analogous to Table 2 column (2). In column (2), we interact each measure with two mutually exclusive credit rating dummies (A or above vs. BBB or below), as in column (2) of Table 3 Panel A. Finally, in columns (3) to (5), we separate our sample into two sub-periods on the basis of VIX, as in Table 6 Panel A. In column (5), we report the subsample coefficient difference test results. Specifically, we test the difference in coefficient estimates between the two subsamples by running a pooled regression with each variable interacted with the high VIX dummy and report the corresponding *t*-statistics. Controls are identical to Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month 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)				
	Full sample		VIX sub-period		
			High VIX	Low VIX	High – Low
	(1)	(2)	(3)	(4)	(5)
Illiquid fund holding share (%)[(H)]	0.780***		1.050***	0.405*	0.645***
	(3.55)		(3.88)	(1.91)	(2.65)
Liquid fund holding share (%)[(L)]	0.046		-0.118	0.318**	-0.437*
	(0.24)		(0.44)	(2.19)	(-1.82)
Illiquid fund holding share × *I*(A or above)[(HA)]		-0.241			
		(-0.84)			
Illiquid fund holding share × *I*(BBB or below)[(HB)]		0.848***			
		(3.50)			
Liquid fund holding share × *I*(A or above)[(LA)]		0.215			
		(0.74)			
Liquid fund holding share × *I*(BBB or below)[(LB)]		-0.035			
		(-0.16)			
F-statistic: (H) = (L)	4.85**		7.39***	0.09	
F-statistic: (HA) = (HB)		8.84***			
F-statistic: (LA) = (LB)		0.50			
Month FE	YES	YES	YES	YES	YES
No. of obs.	45,064	45,064	24,670	20,394	

Table A.12. Fund Holdings and Credit Risk: Illiquidity and Flow-Performance Concavity Double-Sort

In this table, we double-sort and split the fund holding share on the basis of holding-level illiquidity and the concavity in flow-performance sensitivity. At each month-end, we calculate concavity in the identical manner to Table 9. We further calculate the weighted-average ZTD of a fund's holdings to calculate the holding-level illiquidity. We double-sort and split our sample funds in the Morningstar database on the basis of (i) illiquidity and (ii) concavity, using the sample median of each Lipper objective code at the time as the cut-off, allowing us to compute four double-sorted fund holding share. In column (1), we re-estimate the regressions analogous to Table 2 column (2). In column (2), we interact each bond holding measure with two mutually exclusive credit rating dummies (A or above vs. BBB or below), as in column (2) of Table 3 Panel A. Controls are identical to Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month 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)	
	Full sample	
	(1)	(2)
High illiquidity, high concavity (%)	0.232 (1.54)	
High illiquidity, low concavity (%)	0.288 (1.34)	
Low illiquidity, high concavity (%)	0.880*** (4.52)	
Low illiquidity, low concavity (%)	0.173 (0.73)	
High illiquidity, high concavity × *I*(A or above)		-0.035 (-0.15)
High illiquidity, high concavity × *I*(BBB or below)		0.313** (2.09)
High illiquidity, low concavity × *I*(A or above)		-0.175 (-0.73)
High illiquidity, low concavity × *I*(BBB or below)		0.334 (1.47)
Low illiquidity, high concavity × *I*(A or above)		-0.132 (-0.41)
Low illiquidity, high concavity × *I*(BBB or below)		0.926*** (4.61)
Low illiquidity, low concavity × *I*(A or above)		-0.648** (-1.99)
Low illiquidity, low concavity × *I*(BBB or below)		0.282 (1.13)
Month FE	YES	YES
No. of obs.	45,459	45,459

Table A.13. Fund Holding and the Firm's Total Debt

In this table, we re-estimate the results in Table 2, Table 3 Panel A, Table 5, and Table 6 with the amount of active funds' bond holdings divided by a firm's total debt (*DLCQ* + *DLTTQ* in the latest Compustat quarterly data) rather than a firm's total amount of corporate bonds outstanding. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline regressions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
Fund holding share (%)	1.046***	0.680*
	(2.66)	(1.74)
Controls	YES	YES
Month FE	NO	YES
Kleibergen-Paap F-statistic	195.84	191.00
No. of obs.	45,454	45,451

Panel B. Credit rating interactions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
Fund holding share ×	-0.979*	-0.893
I(A or above) (%)$^{(A)}$	(-1.67)	(-1.62)
Fund holding share ×	1.122***	0.730*
I(BBB or below) (%)$^{(BBB)}$	(2.84)	(1.85)
F-statistic: (A) = (BBB)	19.46***	12.19***
Controls	YES	YES
Month FE	NO	YES
No. of obs.	45,454	45,451

Panel C. Maturity dummy interactions

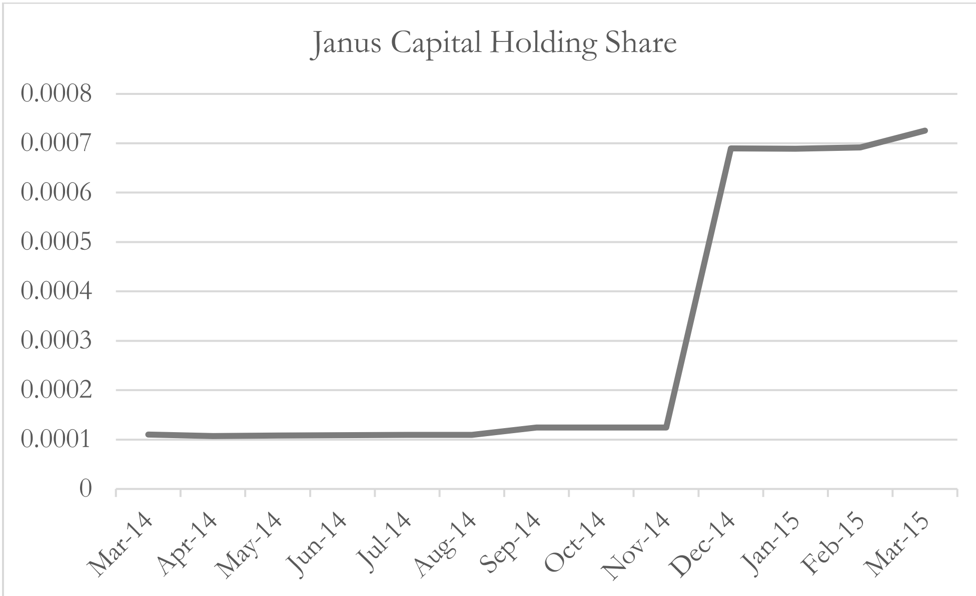
	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
Fund holding share (%)	1.475***	0.652*
	(3.89)	(1.66)
Fund holding share ×	1.141**	1.327**
Maturity dummy	(2.03)	(2.28)
Maturity dummy	-28.415**	-33.184**
	(-2.24)	(-2.45)
Controls	YES	YES
Month FE	NO	YES
No. of obs.	45,454	45,451

Panel D. Fund characteristics

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Fund characteristic of interest	1-year fund return	1-year fund flow volatility	Management firm size	TNA-share of load fee classes
High-group holding share (%)[(H)]	0.874 (1.45)	2.411*** (2.78)	-0.051 (-0.09)	-0.207 (-0.42)
Low-group holding share (%)[(L)]	0.418 (0.58)	-0.091 (-0.13)	2.294** (2.35)	3.479*** (4.07)
F-statistic: (1) = (2)	0.20	3.33*	3.05*	11.50***
Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of obs.	45,451	45,451	45,451	45,451

Figure A.1. More on Fund Holding Shares Around the Departure of Bill Gross
In Panel A, for all firms held by PIMCO in their August 2014 holding, we track these firms' Janus Capital holding share around our difference-in-difference analysis test window. In Panel B, we track the sum of Prudential- and Vanguard-holding shares for (i) all firms and for (ii) all firms held by PIMCO in their August 2014 holding.

Panel A. Janus Capital holding share



Panel B. Prudential and Vanguard holding shares