(preliminary and incomplete)

Monetary Policy and Corporate Bond Fund Fragility *

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Abstract

This paper examines the effects of monetary policy on the fragility of U.S. corporate bond mutual funds. We empirically show that, despite better funds' performance, loose monetary policy exacerbates the fragility of corporate bond funds, measured by the sensitivity of outflows to negative performance. We rationalize this phenomenon through a global game model with an endogenous liquidity risk premium. In the equilibrium, liquidity risk is compensated but strategic complementarity discount is not. In a relatively liquid market where complementarity discount is modest, the discounted fund return decreases faster when lowering the interest rate, incentivizing investors to run from the fund. Moreover, the model predicts that in a liquid (illiquid) market, the fund becomes more (less) fragile as monetary policy uncertainty increases. Our empirical analysis supports these predictions. The results highlight the unintended impacts of monetary policy on the asset management sector.

Keywords: monetary policy, corporate bond mutual funds, fund fragility, financial fragility, market liquidity

1 Introduction

Since the financial crisis of 2008, the Federal Reserve has been actively lowering federal fund rate (FFR) to boost the economy, reduce the unemployment rate, and make financial conditions more accommodative. The achievements are conspicuous. Ten years after the financial crisis, GDP of US has exceeded pre-crisis level and the stock market has quadrupled in value, and the unemployment rate is at an 18-year low. Nevertheless, we also see some side products of the expansionary monetary policy. According to SIFMA, outstanding US corporate bonds have increased from 5.4 trillion in 2008 to 8.5 trillion in 2017. Over the same period, the total asset under management in corporate bond mutual funds has gone up by three times, reaching 2 trillion at the end of 2017, see Figure 10. This dramatic growth brings corporate bond mutual funds to the center of the debate on its potential threat to the financial market stability due to the illiquidity feature of corporate bonds. The focus of this paper is to understand how monetary policy could affect financial market stability in the corporate bond mutual fund sector.

The fragility of open-end mutual funds originates from the first-mover advantage in investors' redemption decisions (see Chen, Goldstein, and Jiang 2010; Goldstein, Jiang, and Ng 2017). Specifically, when investors withdraw from a fund, they get net-asset-value (NAV) as of the day of redemption. To fulfill withdrawal requirements, the fund manager needs to liquidate corporate bonds, potentially at a significant discount when underlying corporate bonds are illiquid. The fire sale posts negative externality on the non-withdrawal investors in the fund, generating the first-mover advantage among fund investors. With such strategic complementarities, it is possible to observe large redemptions from mutual funds for non-fundamental reasons – fund fragility or fund fragility (see Chen, Goldstein, and Jiang 2010; Goldstein, Jiang, and Ng 2017). The risk of run-like dynamics could result in disruptions in the underlying asset markets and threaten the financial stability. Indeed, "taper tantrum" in 2013 and "selloff" of emerging market in 2014 confirmed that our worries were not uncalled-for. To reduce fund-run risk, US Securities and Exchange Commission (SEC) in 2016 proposed new guidelines for liquidity management and redemption practices in open-end mutual funds, aiming to improve the stability of mutual fund industry[1].

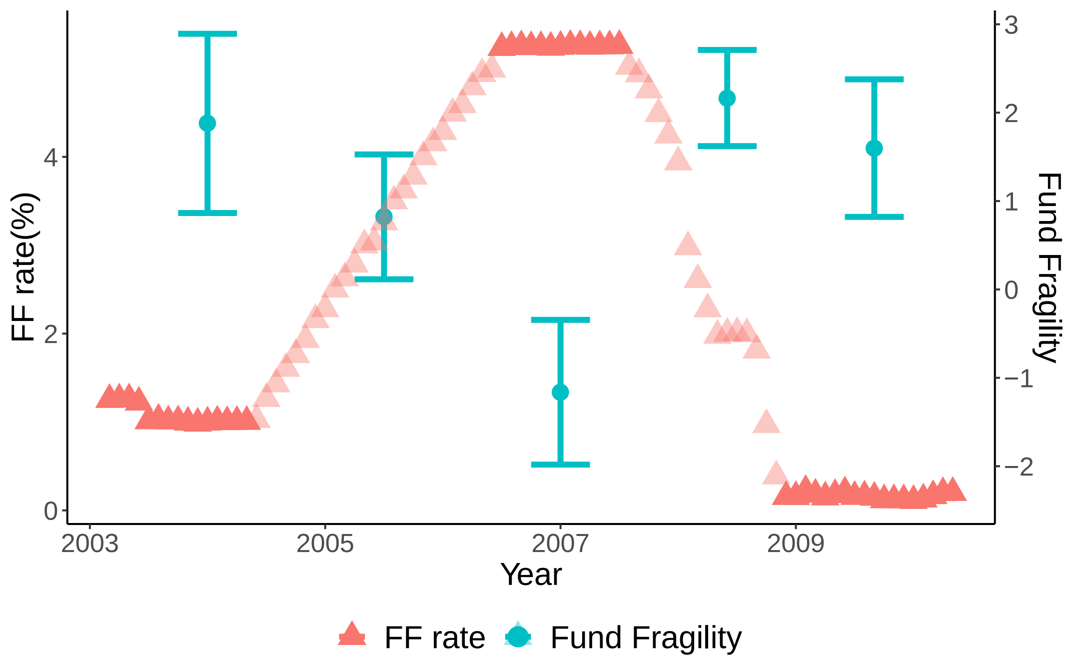

Figure 1: Federal Fund Rate and Corporate Bond Mutual Fund Fragility.

In this paper, we argue that the expansionary monetary policy can exacerbate the bond fund fragility even if we see substantial capital flows into the corporate bond fund sector. Therefore, policymakers should be more concerned about fund fragility when they lower federal fund rate, not when they raise federal fund rate. As motivation evidence, we plot federal fund rate (FF rate) and mutual fund fragility, measured as flow-performance sensitivity for negative performance, over 2003 to 2010 in Figure 1 [2]. It is evident that fund fragility and federal fund rate are negatively correlated. In two regions with low federal fund rates (in 2004 and 2009), outflow-to-poor-performance sensitivities are significantly higher than that in 2007 with higher federal fund rates. This suggests that

[1] See:https://www.sec.gov/news/pressrelease/2016-215.html

[2] We split the time interval into five periods according to different patterns of FF rate. Then, for each period, we run a regression of corporate bond fund flows on negative fund performance and plot the coefficient (flow-performance sensitivity) with its 95% confidence interval. Fund performance is measured as Alpha in Equation (9), the intercept from a regression of excess corporate bond fund returns on excess aggregate bond market and aggregate stock market returns. Negative performance corresponds to negative Alpha.

expansionary monetary policy exacerbates the corporate bond mutual fund fragility.

This argument sounds counter-intuitive at first sight. One may think that investors have little incentive to redeem from the fund and deposit in the bank in the expansionary monetary policy regime, leading to less of run risk. However, this partial equilibrium view ignores one key effect: fund return declines as more capital flows into corporate bond funds. This effect directly intensifies investors' incentives to coordinately withdraw from funds. So why the second effect dominates, whether there is another factor which can alter the relationship are unclear.

To answer these questions, we extend the fund-run model of Liu and Mello (2011) to incorporate an ex-ante asset allocation problem. In the beginning, investors need to decide how to allocate their endowed capital between a long-term asset (such as corporate bonds) managed by an (aggregate) mutual fund and a short-term note issued by the bank. The bank determines the future short-term rate, similar to the central bank in reality. This future short-term rate is unknown to investors ex-ante, but they will receive noisy signals about it. Upon receiving information, bond investors have choices to withdraw from the fund and invest in the bank. However, the long-term asset is illiquid. When fund manager liquidates the long-term asset at a discount to meet redemptions, the remained investors in the fund bear the cost of liquidation. This generates the first-mover advantage among bond investors, originating fund-run behaviors. In the model, we define the fragility of the fund as the likelihood that all investors coordinately withdraw for non-fundamental reasons.

Under this model, monetary policy (of the central bank) exerts impacts on investors' withdrawal decisions and the fragility of the fund. The model predicts that in a relatively liquid market, loose monetary policy exacerbates the fund fragility, while in a relatively illiquid market, tight monetary exacerbates the fund fragility. The intuition is as follows. Investors' run decisions depend on the tradeoff of complementarity discounted fund return and bank return. The higher complementarity discounted fund return compared to bank return is, the lower investors' incentive to run from the fund. Forecasting the potential fund run problem, fund investors ask for risk compensation, which is embedded in the fund return. However, complementarity discount, which measures liquidation distress of non-withdrawal investors, is not compensated in the fund return. Taken together, what non-withdrawal investors would get is complementarity discounted fund return. In a liquid market, complementarity discount is small and liquidity compensation dominates. As interest-rate increases, the discounted fund return increases faster than the bank return, lowering investors' running incentive and fund fragility. In an illiquid market, the opposite happens: complementarity discount controls over such that per unit increase in the bank return comes with less than one unit increase in discount fund return. Therefore, the higher $\bar{r}$, the higher incentives investors have to withdraw from the fund concerning strategic complementarity. In a short, the effect of short-term rate $\bar{r}$ on fund fragility depends on the market liquidity.

We further adopt the model to understand how the monetary policy uncertainty affects the fund fragility. In the past ten years, there has been a surge in monetary policy uncertainties, like presidential elections, Taper Tantrum, QE1, and QE2. Undoubtedly, these uncertainties have profound effects on the general economy and investors' behaviors. The monetary policy uncertainty is modeled as the volatility of future monetary policy. We show that the effects of monetary policy uncertainty on the fund fragility also depends on the market (asset) liquidity. Similar to previous intuition, when the market is liquid, the discounted fund return is higher than the bank return ex-ante. As monetary policy uncertainty increases, investors become less certain about whether the fund is superior than the bank in the future. As a consequence, the fund becomes less attractive, and investors have high incentives to coordinately withdraw from the fund, making the fund more fragile. On the contrary, when the market is illiquid, the story flips. In an illiquid market, the bank return is higher than the discounted fund return. When monetary policy uncertainty increases, the attractiveness of bank reduces since the chance that bank return is less than the fund return increases, leading to a less fragile fund industry.

As a transition to empirical analysis, we adopt outflow-to-poor-performance sensitivity as a measure of the fund fragility, following Goldstein, Jiang, and Ng (2017). Using corporate bond mutual fund data over January 1992 to December 2017, we provide supporting evidence for above model predictions. First, we present evidence that overall investors respond strongly to poor performance in low-federal fund rate regimes. In particular, compared to the high federal fund rate regime, a 1% decrease in performance is associated with 1% higher outflows in a low federal fund regime. The negative relationship between fund fragility and federal fund rate suggests that the market is relatively liquid across our sample period. We further show that this negative relationship is stronger in a liquid market but almost disappears in an illiquid market. Therefore, we conclude that monetary policy affects fund fragility differently under varied liquidity conditions. The more liquid market is, the lower federal fund rate exacerbates fund fragility.

Second, using monetary policy index (MPU) constructed by Husted, Rogers, and Sun (2017) and Baker, Bloom, and Davis (2016), we confirm that the outflow-to-poor-performance sensitivity is lower when MPU is higher in an illiquid market. In particular, when the market is illiquid, compared to periods with low MPU, a 1% decrease in performance is associated with 1.613% higher outflows in periods of high MPU. Then, we also have significant evidence that the outflow-to-poor-performance sensitivity is higher when MPU is higher in a liquid market.

Arguably, outflow-to-poor-performance sensitivity is not an ideal measure for the fund fragility, which aims to capture investors' coordinately withdrawals for non-fundamental reasons. It is likely that investors withdraw simultaneously because the fund has very bad performance. If corporate bond funds generally perform poorly in a low federal-fund rate regime, then it is not surprising to see more outflows in the same period due to the stronger flow-performance relation for bad performance. In this case, outflow-to-poor-performance sensitivity does not precisely measure the fund fragility, and our previous empirical findings are not credible. To rule out this concern, we compare fund performance in different federal fund rate regimes. The t-statistic shows that corporate bond funds perform significantly better when federal fund rate is lower. Therefore, the strong outflow-to-poor-performance sensitivity in a low-federal fund rate regime is not due to poor performance.

Literature review First, this paper closely links with theoretical work on fund fragility (fund fragility) of open-end mutual funds. In a similar spirit of the seminal work by Diamond and Dybvig

(1983) for bank runs, the strategic complementarities for fund fragility arise from fire-sale discounts for underlying assets. Chen, Goldstein, and Jiang (2010) and Liu and Mello (2011) are pioneers to formalize this idea in a theoretical work. Chen, Goldstein, and Jiang (2010) focuses on the relationship between asset illiquidity and fund fragility, while Liu and Mello (2011) studies the optimal liquidity management of funds to reduce cost from fund fragility. Recently, Zeng (2016) extends to a dynamic model to study how funds should build cash buffers knowing that cash rebuilding causes liquidation discount. Morris, Shim, and Shin (2017) asks when fund managers should hoard cash in anticipation of redemptions in the future. This paper closely follows this line of research that models fund fragility. However, we shift our focus from liquidity management to the effects of macro monetary policy. In their models, the performance of funds is exogenously given. Our model relaxes this restriction by allowing an endogenous fund performance.

The only other papers modeling monetary policy and asset management sector together are Morris and Shin (2017) and Feroli et al. (2014). Their mechanism to generate strategic complementarities is through short-term relative performance rankings among asset managers. Due to the strategic complementarities, the model engenders a jump in the yield of the risky bond. Moreover, this jump is higher when the asset management sector is more substantial. Similar to them, our model also generates a jump in fund return when all fund investors withdraw and the jump is more considerable when the amount of asset in the fund L is high. However, different from Morris and Shin (2017) in which that the size of asset management sector is exogenously given, the fund size in our model (L) is endogenously affected by monetary policy. So our model builds a direct bridge between monetary policy and the fund fragility.

Second, this paper contributes to the recent growing literature on the transmission of monetary policy to non-banking financial intermediaries. Liang and Nellie (2017) provides an excellent survey. They highlight the endogenous risk-taking channel under an expansionary monetary policy for non-banking financial intermediaries. For example, Adrian and Shin (2008) shows that an accommodative monetary policy increases intermediaries' incentives to take leverage. Di Maggio and Kacperczyk

(2016), Choi and Kronlund (2017) and Ivashina and Becker (2015) document risk-taking behaviors of money market funds, corporate bond funds, and insurance companies over zero interest rate periods, respectively. This paper emphasizes that even without risk-taking, the fire-sale externalities combined with compressed fund return are enough to create high financial fragilities under a looser monetary policy. Risk-taking behaviors will magnify this effect.

Third, this paper belongs to the literature of empirically testing fund fragility. Shin, Adrian, and Arturo (2018) identify the impacts of investors' redemptions on fire sale discount in corporate bond markets, suggesting the existence of negative externalities in bond markets. Similarly, Feroli et al. (2014) finds that fund outflows are positively correlated with declines in NAV, creating incentives for bond investors to fund simultaneously. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) firstly use outflow-to-poor-performance relationship as a proxy for strategic complementarities among fund investors. They find both equity mutual funds and corporate bond mutual funds tend to have greater sensitivity of outflows to bad performance when they have more illiquid assets. Using structural recursive vector autoregression (VAR), Banegas, Montes-Rojas, and Siga (2016) also find that bond fund flows instrumented by the unexpected monetary policy are closely related fund performance, indicating a first-mover advantage among investors. At more micro level, Schmidt, Timmermann, and Wermers (2016) use daily money market mutual fund flow data to examine fund run in money market mutual funds. Our paper further provides evidence on how monetary policy affects corporate bond fund fragility.

Lastly, we also contributes to the growing research on corporate bond funds, see Shin, Adrian, and Arturo (2018); Jiang, Li, and Wang (2017); Chen, Ferson, and Peters (2010); Morris, Shim, and Shin (2017), among others.

The remainder of the paper is organized as follows. Section 2 presents the model and testable hypotheses. Section 3 presents the empirical analysis and tests the model's predictions. Section 4 concludes.

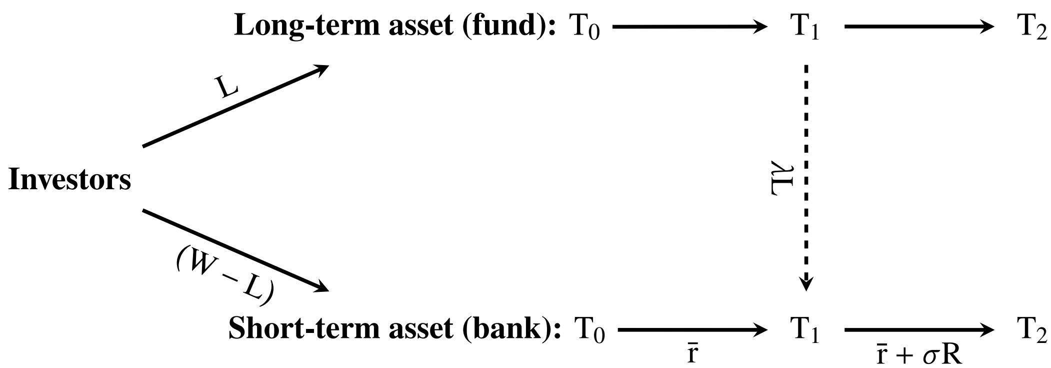

Figure 2: The time line for the four period model.

2 A Model of Asset Allocation and Fund Run

In this section, we hone our insights by a fund run model incorporating an ex-ante asset allocation problem between the fund and the bank and then examine how monetary policy affects investors' asset allocation decisions and withdraw decisions.

As our focus is on the monetary policy' impacts on the mutual fund industry, we consider an aggregate mutual fund which depends on investors for funding. We will first describe a general model, identify the equilibrium conditions, and then conduct a comparative statics analysis.

2.1 The Setup

The basic set-up is depicted in Figure 2. There are three dates: T_0, T_1 and T_2. All agents are risk-neutral. There is no discount factor.

Assets There are two types of assets in the market: the long-term asset and the short-term asset. The long-term asset is a corporate bond that pays only at the terminal date T_2. Its rate of return is determined after investors' asset allocation at T_0. Without loss of generality, we assume that the expectation of return from the fund is $r_L(L)$, which is a decreasing function on the investment volume

L (i.e., $r_L^{'}(L) < 0$). When the investment volume L for the bond is high, its price is high, and hence the rate of return is low. [3] Both L and $r_L(L)$ are endogenously determined in equilibrium. Investors have access to this asset only via the open-ended mutual fund (to be described below).

The short-term asset is a floating rate money market fund or bank account with perfectly elastically supply. For simplicity, we assume that the central bank exogenously sets the short-term interest rate. At T_0, the current one-period interest rate $\bar{r}$ is known, but there is an uncertainty of the interest rate ruling over the next time interval of T_1 to T_2. The interest rate is equal to $\bar{r} + \sigma R$, where R has a cumulative distribution function $F(\cdot)$ with zero mean and unit variance. Its density function is denoted as $f(\cdot)$. Parameter σ, also exogenously given, quantified the monetary policy uncertainty over T_1 and T_2. The higher σ is, the more uncertain investors are about the future floating rate. To distinguish, we call $r_L(L)$ fund return and $\bar{r}$ bank return.

Mutual fund The long-term asset is managed by the open-end mutual fund. The only duty of fund is to liquidate the long-term asset and repay investors at T_1 when it receives notice of withdrawing. When the liquidation occurs, due to illiquidity generated by price impacts or transaction cost, the fund cannot sell the asset at the NAV at time T_1. Instead, the asset is sold at an exogenous discount α of NAV, with $0 < \alpha < 1$.

As in Liu and Mello (2011), we could have considered that mutual fund needs to determine how much cash to hold to reduce liquidating the amount of the long-term asset. While this is a realistic assumption for the mutual fund, we decide to leave this liquidity management problem out for the following three reasons. First, we are interested in the monetary policy's impacts on the mutual fund industry, while the liquid management is at the individual fund level. Conceptually, a liquid mutual fund industry with high cash holdings can be captured by a relatively large discount price α. Second, liquidity management problem usually involves nonlinear payoff, see Morris, Shim, and Shin (2017) and cannot be solved in closed form. Third, adding additional complexity to the model blurs the

[3] The implicit assumption is that the firm's investment opportunity is limited and the supply of bond (or demand for loan) is inelastic. Alternatively, we can assume that the firm's demand for a loan is decreasing when the lending rate is higher, i.e., $L^{'}(r_L) < 0$.

focus of the paper while does not alter the qualitative results. Therefore, we decide to take it away.

Investors There is a continuum of risk-neutral investors with measure W, which are indexed by the interval $[0, W]$. Each investor has one unit of capital and only consumes once at the terminal date T_2. At time T_0, each investor can decide to allocate one unit capital either to the short-term asset managed by the bank or to the long-term asset managed by the fund. After T_0, measure L of investors invest in the mutual fund, and the remaining $W - L$ invests in the bank.

Right before T_1, each investors receive a signal about uncertain short-term rate R over T_1 and T_2. The information structure will be discussed more formally in section 2.2.1. Based on the signal, each investor decides whether to stay or withdraw from the fund. If withdrawing, he receives a fraction of the mutual fund's mark-to-market net asset value $(1 + \bar{r})$ and invests in the bank, obtaining uncertain gross bank return $1 + \bar{r} + \sigma R$ between T_1 and T_2. Non-withdrawal investors receive the expected return of bond $r_L(L)$ at T_2 after undertaking the liquidation cost.

The key advantage of being a fund investor is that mutual funds allow investors to redeem based on the last updated NAV such that they do not suffer any price impact or liquidation cost. This mechanism guarantees bond fund investors to benefit from their private information on short-term rate. For example, John is a bond fund investor. A few days before Federal Reserve Board's Open Market Committee (FOMC) meeting, John receives an information that the federal fund rate is going to raise. To seize this investment opportunity, he immediately notifies his fund manager, gets his investment back based on the that day's NAV, and wait until FOMC meeting to invest in treasure bills. In this way, if his information is correct, he can boost his wealth. However, if he directly holds bonds, then he has to sell bonds first. When many other investors also share similar information, bond price would decrease due to selling pressure, such that his private information is not as valuable as if hi invests in the bond fund. Therefore, bond fund investors have strong incentives to withdraw when they receive positive news on future short-term rate R.

Payoffs Suppose that the proportion of investors withdrawing from the fund is λ, where $0 \leq \lambda \leq 1$, then the payoff at T_2 of an investor who withdraws is [4]

$$\pi^W(\lambda) = \begin{cases} (1+\bar{r})(1+\bar{r}+\sigma R) & \text{if } 0 \leq \lambda L \leq \alpha L \\ \frac{\alpha L(1+\bar{r})}{\lambda L}(1+\bar{r}+\sigma R) & \text{if } \lambda L > \alpha L. \end{cases} \tag{1}$$

Since we assume that the mutual fund holds zeros cash, any early withdrawal requires liquidation of the long-term asset. When the total amount of withdrawal is less than the total liquidation value of the fund ($\lambda L \leq \alpha L$), the mutual fund is liquid. In this case, withdrawal investors get the mutual fund's market-to-market net asset value, $1+\bar{r}$ unit of capital), back, and they then deposit in the bank. When there are too many withdrawals, the fund needs to liquidate all the assets at T_1, in which case nothing is left for the remaining investors. The amount of capital each withdrawing investor gets is $\frac{\alpha L(1+\bar{r})}{\lambda L}$[5]. Withdrawal investors also deposit received capital in the bank.

The payoff at T_2 of an investor who stays in the mutual fund (does not withdraw at T_1) is

$$\pi^S(\lambda) = \begin{cases} \frac{L-\frac{\lambda L(1+\bar{r})}{\alpha(1+\bar{r})}}{(1-\lambda)L}(1+r_L(L)) & \text{if } 0 \leq \lambda L \leq \alpha L \\ 0 & \text{if } \lambda L > \alpha L. \end{cases} \tag{2}$$

When λL investors withdraw from the fund and the fund is still liquid, the number of the asset to be sold is $\frac{\lambda L(1+\bar{r})}{\alpha(1+\bar{r})}$. Then, the remaining share $(L - \frac{\lambda L(1+\bar{r})}{\alpha(1+\bar{r})})$ is equally distributed among $(1-\lambda)L$ investors who stay in the fund. So, the payoff of these investors is $\frac{L-\frac{\lambda L(1+\bar{R})}{\alpha(1+\bar{r})}}{(1-\lambda)L}(1+r_L(L))$, the first line in Equation (2). If the number of withdrawal investors exceeds the total liquidation value of the fund, the hedge fund is completely liquidated, and nothing is left after T_1. The payoff is summarized in Table 1.

[4] Our set-up is similar to the case of zero cash holding modeled in Liu and Mello (2011).

[5] As in Liu and Mello (2011), we assume a special downward-sloping demand curve for the mutual fund. The market can absorb a tiny amount of asset sale at a price of 1. After that, the price drops to constant α.

	$0 \leq \lambda L \leq \alpha L$ (liquid)	$\lambda L > \alpha L$(illiquid)
Withdraw (π^W)	$(1+\bar{r})(1+\bar{r}+\sigma R)$	$\frac{\alpha L(1+\bar{r})}{\lambda L}(1+\bar{r}+\sigma R)$
Stay (π^S)	$\frac{L-\frac{\lambda L(1+\bar{r})}{\alpha(1+\bar{r})}}{(1-\lambda)L}(1+r_L(L))$	0

Table 1: The payoff of investors in the mutual fund.

2.2 The Equilibrium

Investors have two decisions to make in the model: asset allocation decisions at T_0 and withdrawal decisions after receiving signals right before T_1. The aggregate allocation to the fund L determines the fund return $r_L(L)$, which then affects withdrawal decisions. Withdrawal decisions determine whether the fund stays liquid or nor, which, in turn, influence the ex-ante asset allocation decisions.

We solve the equilibrium by backward induction. In the first step, we solve the investors' optimal withdrawal decision right before T_1 given a total capital in the fund L (hence, the yield of the long-term asset $r_L(L)$). In the second step, we work out investors' optimal portfolio allocation problem at T_0 by taking into account the future fund run behavior.

2.2.1 Investors' Withdrawal Decisions right before T_1

We define the difference in payoffs between staying and withdrawing at T_1 as $\Delta\pi(\lambda) = \pi^W(\lambda) - \pi^S(\lambda)$. Figure 3 plots $\Delta\pi(\lambda)$. Figure 3 clearly shows that the higher proportion of redemption at T_1, the higher return investors who withdraw can get. The fire sale losses for the remaining investors when early investors withdraw is the source of coordination problem and the origin of fund run in the model.

With perfect information about R and λ, there could be multiple equilibria when $1 + r_L(L) > (1+\bar{r})(1+\bar{r}+\sigma R)$. If an investor expects all other investors to withdraw from the fund, it is optimal for him to withdraw as well to avoid zero payoffs (comparing the payoffs in the second column of Table 1). Everyone withdrawing and the mutual fund becoming illiquid is an equilibrium. On the other hand, if

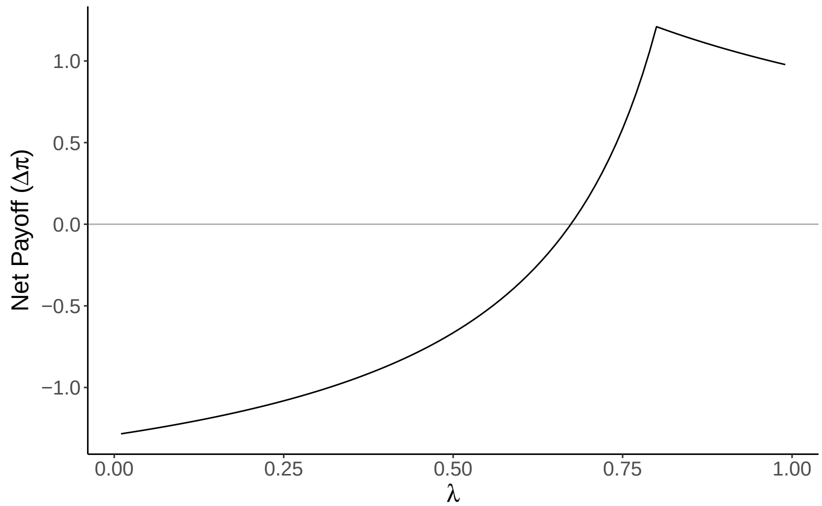

Figure 3: The difference between the payoff of staying and withdrawing, $\Delta\pi(\lambda)$**.** This figures plots the net payoff of staying and withdrawing for parameters: $\alpha = 0.8$, $R = 0$, $\bar{r} = 0.1$, $r_L = 1.5$.

an investor expects others to stay in the fund, it is rational to stay since $1 + r_L(L) > (1 + \bar{r})(1 + \bar{r} + \sigma R)$. No one withdrawing and the mutual fund staying liquid is an equilibrium. In summary, there exists sun-spot equilibria when $R \in (-\infty, \bar{R}]$, where $\bar{R} = \frac{1}{\sigma}\left(\frac{1+r_L(L)}{1+\bar{r}} - (1+\bar{r})\right)$. When $R \in (\bar{R}, \infty)$, withdrawing is a dominant strategy.

Global game To overcome the problem of multiplicity, we apply the technique developed in the literature of global game. Specifically, we assume investors in the fund, at T_1, receive noisy signals s_i about the uncertain part in the future floating return R, given by

$$s_i = R + \sigma_\varepsilon \varepsilon_i,$$

where $\sigma_\varepsilon > 0$ is a parameter that captures the size of noise, and ε_i is an idiosyncratic component which has a cumulative distribution $F_\varepsilon(\cdot)$. The noise terms $\{\varepsilon_i\}$ are independent across investors, and its density function $f_\varepsilon(\cdot)$ is assumed log-concave to guarantee the monotone likelihood ratio property (MLRP). In contrast, the market depth, α, and the rate of return function for the long-term asset, $r_L(L)$ are perfectly observed by everyone at T_1 and therefore common knowledge.

Since investors do not share the common knowledge about R, they could not coordinate perfectly.

Following Goldstein and Pauzner (2005) we can show that there is a unique symmetric equilibrium, in which there is a cutoff threshold R^* such that every investor withdraws from the fund if his signal is above the threshold and stays otherwise. This strategy can be characterized as:

$$\begin{cases} \text{Withdraw} & s_i > R^* \\ \text{Stay} & s_i \leq R^*. \end{cases}$$

The equilibrium switching point is determined by the fact that for the investor exactly at the switching point, the expected payoff from withdrawing has to equal to the expected payoff from staying. In other words, the expected net payoff $\Delta\pi(\lambda)$ given signal R^* is zeros:

$$\int_{\lambda} \Delta\pi(\lambda) f_{\lambda|R^*} d\lambda = 0 \tag{3}$$

The question left is what the distribution of λ is given R^*. Remind that λ is the proportion of investors withdrawing from the fund at T_1. Following Morris, Shin, and Yildiz (2016), we will prove that λ is uniformly distributed over $[0, 1]$ as $\sigma_\varepsilon \to 0$. This is so-called "Laplacian beliefs". When $\sigma_\varepsilon \to 0$, the fundamental uncertainty disappears, while the coordination uncertainty is at its maximum. Investors' withdrawal decisions are purely determined by their beliefs on other investors' behaviors. This highlights the fragility of the fund — the fund becomes illiquid purely due to the coordination problem instead of the fundamental. When $R > R^*$, each investor believes that other investors will withdraw, so it is optimal for him to withdraw as well. As a result, all investors withdraw and the fund becomes illiquid. When $R \leq R^*$, no investor thinks other investors will withdraw, so everyone stays and the fund is liquid. We then can conclude the entire proposition of investors withdrawing can be expressed as:

$$\lambda = \begin{cases} 0 & \text{if } R \leq R^* \\ 1 & \text{if } R > R^*. \end{cases}$$

Combining above result with the indifference condition for investors with signal R^* in Equation (3) yields

$$\underbrace{\int_0^{\alpha}\Big((1+\bar{r})(1+\bar{r}+\sigma R^*)-\frac{1-\lambda/\alpha}{1-\lambda}(1+r_L(L))\Big)d\lambda}_{\text{net payoff when the fund is liquid}}+\underbrace{\int_{\alpha}^{1}\frac{\alpha(1+\bar{r})}{\lambda}(1+\bar{r}+\sigma R^*)d\lambda}_{\text{net payoff when the fund is illiquid}}=0.$$

(4)

We summarize the equilibrium result in Proposition 1.

Proposition 1. *For $\sigma_\varepsilon \to 0$, there is a unique perfect Bayesian equilibrium for investors. In this equilibrium, for realization of $R > R^*$, all investors withdraw ($\lambda = 1$) and the fund becomes illiquid. For realization of $R \leq R^*$, all investors stay in the fund ($\lambda = 0$) and the fund is liquid. The threshold R^* is characterized by*

$$(5) \qquad (IC) \qquad R^* = \frac{1}{\sigma}\Bigg(\underbrace{\frac{1+r_L(L)}{g(\alpha)(1+\bar{r})}}_{\textit{discounted fund return}} - \underbrace{(1+\bar{r})}_{\textit{bank return}}\Bigg),$$

where $g(\alpha) = \frac{\alpha-\alpha\log\alpha}{\frac{1-\alpha}{\alpha}\log(1-\alpha)+1}$.

*The **fund fragility** is defined as the likelihood that the fund becomes illiquid due to the coordination withdrawing , i.e., $\mathbb{P}(R > R^*) = \bar{F}(R^*)$.*

Proof. See the Appendix C.1 □

Equation (5) highlights an important characteristic of the fund fragility — it is affected by the exogenous parameters $\bar{r}$, σ and α as well as the endogenous fund return $r(L)$. In this section, we take $r_L(L)$ as given, discuss the tradeoff investors face.

In general, the fund fragility depends on investors' discounted fund return if staying, $\frac{1+r_L(L)}{g(\alpha)(1+\bar{r})}$ and bank return if withdrawing, $1+\bar{r}$. Fund return is discounted by coordination multiplier $g(\alpha)$, which captures the liquidation distress undertaken by non-withdrawal investors. The more illiquid the market is, the higher coordination discount $g(\alpha)$ is. When the discounted fund return is higher than the bank return, staying in the fund is more attractive for investors than withdrawing, hence increasing R^* and lowering fund fragility, and vice versa.

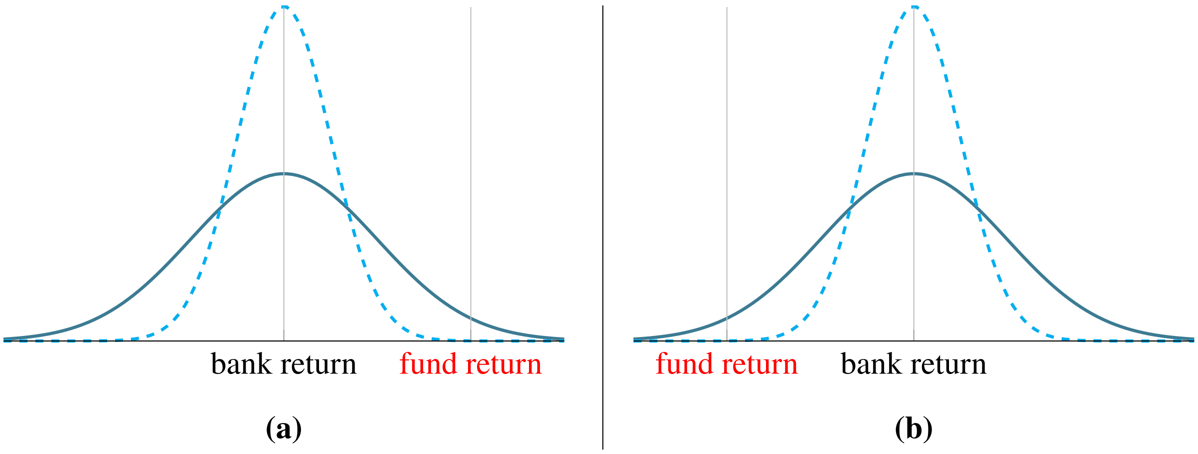

Figure 5: Illustration of the effect of σ.

Lemma 1. *Function $g(\alpha)$ has the following properties: 1) $\frac{\partial g(\alpha)}{\partial \alpha} < 0$; 2) $g(\alpha) - \alpha > 0$;3) $g(\alpha) \to 1$ as $\alpha \to 1$.*

With this general guideline in mind, it is easy to see how $\bar{r}$, σ, α and $r_L(L)$ determines the fund fragility. First, an increase in $\bar{r}$ or a decrease in $r_L(L)$ makes bank return more attractive, hence pushing up the fund fragility. Second, a decrease in α amplifies coordination discount and lowers the discounted fund return, hence boosting the fund fragility. Third, the effect of σ is a bit tricky: it relies on the relative values of the discounted fund return and the bank return. If the discount fund return is higher than the bank return, then an increase in σ results in higher fund fragility. The intuition is illustrated in panel (a) of Figure 5. Consider the case that the fund is more attractive than the bank ex-ante and the run probability is relatively low. As σ increases, investors become less certain about whether the discounted fund return will be higher than the bank return in the future. As a consequence, the fund becomes less attractive, and investors have high incentives to withdraw and invest in the bank. Therefore, the fund fragility increases as σ increases. However, if the discount fund return is less than the bank return, the story flips, as illustrated in panel (b) of Figure 5. When σ increases, the attractiveness of bank reduces since the chance that bank return is less than the discounted fund return increases. Therefore, investors' run incentives decrease as σ increases.

Lemma 2 summarizes above results:

Proposition 2. *Without internalizing asset allocation L and fund return $r_L(L)$, the fund is more fragile in:*

- ***a high interest rate regime**, i.e, $\left.\frac{\partial \bar{F}(R^*)}{\partial \bar{r}}\right|_{IC} > 0$;*
- ***an illiquid market** i.e, $\left.\frac{\partial \bar{F}(R^*)}{\partial \alpha}\right|_{IC} < 0$;*
- ***a high monetary policy uncertain market** when the discounted fund return is higher than the bank return, i,e, $\left.\frac{\partial \bar{F}(R^*)}{\partial \sigma}\right|_{fund>bank,IC} > 0$;*
- ***a low monetary policy uncertain market** when the discounted fund return is lower than the bank return, i,e, $\left.\frac{\partial \bar{F}(R^*)}{\partial \sigma}\right|_{yield<return,IC} > 0$.*

2.2.2 Investors' Portfolio Allocation Decisions at T_0

The second step in the backward induction is to derive investors' asset allocation decisions at T_0, each considering potential fund fragility in the following period. In the equilibrium, investors should be indifferent between investing in the fund or in the bank. In other words, the expected return of the fund is equal to the expected return of the bank. Given the equilibrium threshold R^* as defined by (5), the indifference condition for investors takes a simple form:

(6)
$$\underbrace{\int_{-\infty}^{R^*} (1 + r_L(L))dF(R)}_{\text{expected return when the fund is liquid}} + \underbrace{\int_{R^*}^{\infty} \alpha(1 + \bar{r})\Big(1 + \bar{r} + \sigma R\Big)dF(R)}_{\text{expected return when fund is illiquid}} = \underbrace{(1 + \bar{r}) \int_{-\infty}^{\infty} \Big(1 + \bar{r} + \sigma R\Big)dF(R)}_{\text{expected return of investing in bank at } T_0}$$

The expected return of the bank is the simple compounding interests over two periods. The expected return of the fund is composed of two parts. For the realization of R below R^*, all investors stay in the fund and get the fund return, $1 + r_L(L)$. For the realization of R above R^*, all investors in the fund withdraw and the fund becomes illiquid. Due to liquidation discount, each investor only gets α capital back. Each then invests α capital in the bank and gets bank return $1 + \bar{r} + R$ over the next period.

Equation (6) can be rearranged to be

$$(7) \quad (BC) \qquad \underbrace{1 + r_L(L) - (1+\bar{r})^2}_{\text{Excess return of the fund}} = \underbrace{\Big((1+\bar{r})^2 - \alpha(1+\bar{r})^2\Big)}_{\text{liquidity cost}} \times \underbrace{\frac{1 - F(R^*)}{F(R^*)}}_{\text{liquidity risk}} - \underbrace{\alpha(1+\bar{r})\sigma \frac{\int_{R^*}^{\infty} R dF(R)}{F(R^*)}}_{\text{option value of withdrawing}}$$

The left side of Equation (7) is the excess return of the fund over T_0 to T_2. The excess return is determined by two components, liquidity premium and option value of withdrawing. Liquidity premium compensates potential cost from fund fragility, which is captured by "liquidity cost" × "liquidity risk" in Equation (7). The term "liquidity cost" captures how much an investor gives up when he withdraws from the illiquid fund; the term "run risk" captures the likelihood of fund fragility. Even though investing in the fund exposes to potential fund fragility, fund investors benefit from holding an option to leave the fund when interest rate increases sharply over T_1 and T_2. This is reflected in "option value of withdrawal" in Equation (7). Summarily, the excess return of the fund increases when liquidity premium increases, but decreases when the option value of withdrawal increases.

Both liquidity premium and option value are closely related to fund fragility threshold R^*. When there is no run risk (i.e., $R^* \to \infty$), the excess return of the fund is zero, $1 + r_L(L) - (1+\bar{r})^2 = 0$. So the non-zero excess return of this model is entirely driven by potential fund fragility at T_1. Moreover, the excess return of the fund is higher when the market is more illiquid (α is lower). Two effects contribute to this result. First, illiquid market condition boosts "liquidity cost", leading to a higher excess return of the fund. Second, the option value of withdrawing drops in an illiquid market because withdrawal investors suffer from high liquidation cost and do not value this option that much.

Lemma 2. *Excess return of the fund is higher when market is illiquid, i.e.,* $\left.\frac{\partial r_L(L)}{\partial \alpha}\right|_{BC} < 0$.

Overall, the unique equilibrium of the economy is determined by investors' withdrawal decisions at T_1 and asset allocation decisions at T_0. We summarize the result in Proposition 3.

Lemma 3. *Equation* (5) *and* (7) *implicitly define the interim switching threshold* R^* *and the optimal allocation* L^* *in the economy.*

2.3 Implications and Predictions of the Model

This section studies how the equilibrium responds to exogenous changes in interest rate $\bar{r}$, momentary policy uncertainty σ, and market liquidity α. The goal is to characterize the fund flow, L^*, and fund fragility, $\bar{F}(R^*)$, in response to changes in monetary policies. Remind that the change of exogenous variables can directly affect R^* and L^* from investors' withdrawal decisions at T_1, and indirectly affect them from investors' asset allocation decisions at T_0. So it is not trivial to conclude how fund flow and fund fragility get affected in equilibrium.

2.3.1 Changes in Short-term Rate $\bar{r}$

First, we investigate the effects of changes in the short-term rate $\bar{r}$ holding other variables constant. In real-world, this short-term rate, usually federal fund rate, is determined by the central bank to influence general financial conditions, which could have profound impacts on the broad economy including employment, growth, and inflation. Due to its significant impact on the whole economy, it is unlikely that central bank would adjust federal fund rate purely for corporate bond funds with negative alpha. Therefore, we take the changes in $\bar{r}$ as an exogenous event in this paper.

When $\bar{r}$ is lowered, more capital flows into the fund and $r_L(L)$ shrinks. The reason is straightforward. A negative shock to $\bar{r}$ widens the gap between fund return and bond return, inducing new investors to the fund. Even though this change also shifts the fund fragility threshold R^* at T_1, this secondary order effect is dominated by the first order effect. Because investors stop investing in the fund whenever the potential rise in fund fragility hurt themselves. Therefore, a fall in $\bar{r}$ increases the allocation to the fund L^*. This leads to Lemma 3:

Proposition 3. *The flow to the fund is higher in a low-interest rate regime, (i.e,* $\frac{\partial L^*}{\partial \bar{r}} < 0$*).*

Proof. See the Appendix C.3. □

Now, we move to understand how the changes in $\bar{r}$ affect the fund run probability. From Equation (5), we know that threshold R^* is determined by the tradeoff of discounted fund return and bank return. Both terms are positively correlated with $\bar{r}$. So the overall effect depends on which effect dominates. The following proposition shows that the effect crucially relies on the liquidity level α.

Proposition 4. *The sign of effect of current short-term rate* $\bar{r}$ *on fund fragility (i.e.* $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}}$*) has the* ***opposite*** *sign of* $k(\alpha, R^*)$*, where*

$$k(\alpha, R^*) = \underbrace{\Big(1 - g(\alpha)\Big)F(R^*)}_{\text{Complementarity discount}} + \underbrace{(1-\alpha)\Big(1 - F(R^*)\Big)}_{\text{Liquidity compensation}}. \tag{8}$$

There exists and only exists one $\tilde{\alpha}$ *such that the fund fragility decreases with* $\bar{r}$ *for any* $\alpha \in [\tilde{\alpha}, 1]$*, and increases otherwise (i.e.* $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}} < 0$ *if* $\alpha \in (\tilde{\alpha}, 1]$ *and* $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}} > 0$*, otherwise), where* $\tilde{\alpha}$ *is the solution to* $k(\alpha, R^*) = 0$*. Moreover, the relationship* $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}}$ *decreases as* α *increases when* $\alpha \in [0, \bar{\alpha}]$*, where* $\left.\frac{\partial k(\alpha, R^*)}{\partial \alpha}\right|_{\bar{\alpha}} = 0$ *and* $\bar{\alpha} > \tilde{\alpha}$*.*

Proof. See the Appendix C.2. □

In a relatively liquid market, loose monetary policy exacerbates the fund fragility, while in a relatively illiquid market, tight monetary exacerbates the fund fragility. This is the key result of the paper[6]. The intuition is as follows. As stated in Equation (5), the threshold R^* depends on the tradeoff of discounted fund return and bank return at T_1. Forecasting the potential fund run problem, investors ask for compensation when the fund becomes illiquid, which is embedded in $1 + r_L(L)$. However, complementarity discount $g(\alpha)$, which measures liquidation distress of non-withdrawal investors, is

[6] The results are quite general. Only very general assumptions are required. First, the distribution of R is continuous and its mean is well defined. Second, the return can not be negative.

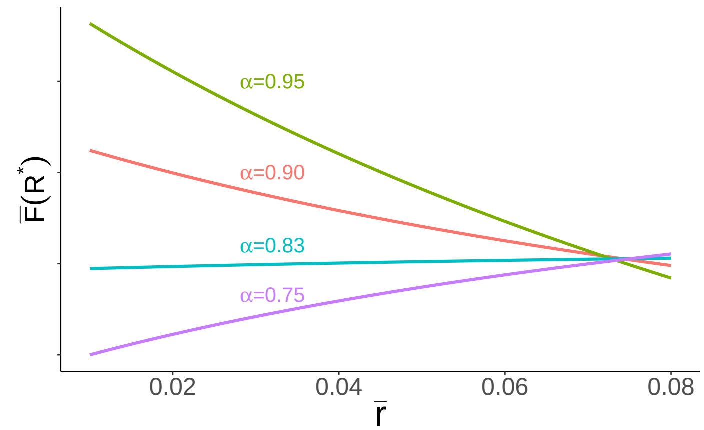

Figure 6: The relation between $\bar{r}$ and $\bar{F}(R^*)$. The effect of short-term rate $\bar{r}$ on fund fragility, $\bar{F}(R^*)$, under different liquidity levels α. Note that the levels of $\bar{F}(R^*)$ are adjusted to see clear trend.

not compensated by $1+r_L(L)$. These two terms show up in function $k(\alpha, R^*)$: when the fund is liquid, with probability $F(R^*)$, non-withdrawal investors suffer from complementarity discount $(1-g(\alpha))$; when the fund is illiquid, with probability $1-F(R^*)$, investors get liquidity risk compensation $(1-\alpha)$. In a liquid market, complementarity discount is small and liquidity compensation dominates. As $\bar{r}$ increases, the discounted fund return increases faster than the bank return, pushing up the threshold R^* and lowering run probability. In an illiquid market, the opposite happens: complementarity discount controls over such that per unit increase in the bank return comes with less than one unit increase in discount fund return. Therefore, the higher $\bar{r}$, the higher incentives investors have to withdraw from the fund concerning strategic complementarity. In a short, the effect of short-term rate $\bar{r}$ on fund fragility depends on the market liquidity.

Above results can be further generalized. It can be shown that in a large parameter set of α, the relationship, $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}}$, decreases as the market becomes more liquid, i.e., α increases. Figure 6 presents the relationship between fund fragility and $\bar{r}$ under different market liquidity α. This result shares the same intuition as before: the higher market liquidity, the lower complementarity discount such as liquidity compensation is "high" to attract more investors stay in the fund when short-term rate $\bar{r}$

increases.

In summary, when the short-term interest rate is adjusted down, we expect to see an inflow to the fund and a increase in strategic complementarities among bond investors (fund fragility) in a liquid market, otherwise in an illiquid market.

2.3.2 Changes in Monetary Policy Uncertainty σ

Next, we consider changes in monetary policy uncertainty σ, holding other parameters constant. In general, σ affects the allocation L through two channels. First, it has bifurcated effects on fund run threshold R^*, as described in Lemma 2. Second, it enhances the option value of running in Equation (7)[7]. So its overall effect on the allocation L is no-monotonic. In this section, we focus on how changes in σ influence fund fragility. The result is summarized in Lemma 4.

> **Proposition 5.** *The sign of effect of monetary policy uncertainty σ on fund fragility (i.e. $\frac{\partial \bar{F}(R^*)}{\partial \sigma}$) has the **same** sign of $k(\alpha, R^*)$ in Equation (8).*
>
> *There exists and only exists one $\tilde{\alpha}$ such that the fund fragility increase with σ for any $\alpha \in [\tilde{\alpha}, 1]$, and decreases otherwise (i.e. $\frac{\partial \bar{F}(R^*)}{\partial \sigma} > 0$ if $\alpha \in (\tilde{\alpha}, 1]$ and $\frac{\partial \bar{F}(R^*)}{\partial \sigma} < 0$, otherwise), where $\tilde{\alpha}$ is the solution to $k(\alpha, R^*) = 0$.*

Proof. See the Appendix C.2. □

This result shares a similar intuition as the result in Lemma 2. The difference is that in Proposition 5, the tradeoff between discounted fund return and bank return is linked to market liquid, as specified in Equation (8). In a liquid market, weak complementarity discount makes the fund more attractive. In this case, an increase in σ reduces the attractiveness of the fund because investors are less certain about whether the fund is superior than the bank in the future. This effect gives investors higher incentives to coordinately withdraw from the fund, making the fund more fragile. On the contrary, when the market is illiquid, the story flips. In an illiquid market, strong complementarity

[7] The effect is similar to call option. When underlying volatility increases, call option value increases.

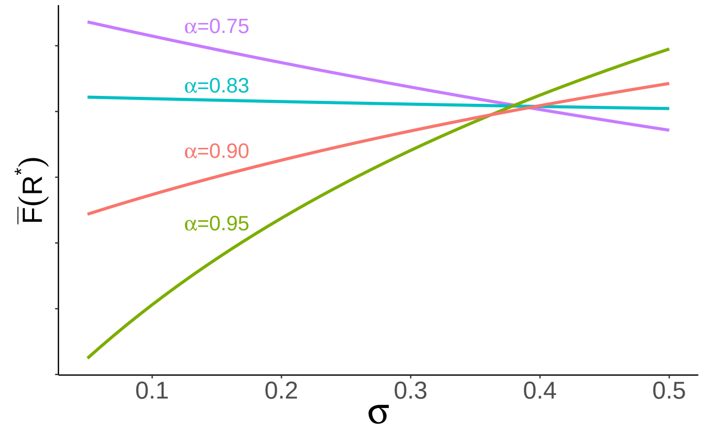

Figure 5: The relation between σ and $\bar{F}(R^*)$. The effect of monetary policy uncertainty σ on fund fragility, $\bar{F}(R^*)$, under different liquidity level α. Note that the levels of $\bar{F}(R^*)$ are adjusted to see clear trend.

discount dominates and discounted fund return is less than bank return. An increase in σ reduces the attractiveness of the bank since the chance that bank return is less than the fund return increases. This leads to a less fragile fund industry. This intuition can also be generalized to a continuous spectrum of α. Figure 7 presents the relationship between fund fragility and σ under different market liquidity α.

2.3.3 Changes in Liquidity α

Last, we revisit the effect of changes in market liquidity α with internalizing the asset allocation problem. Interestingly, in the general equilibrium, the fund fragility is not positively associated with market illiquidity. Instead, the relation could be U-shape under certain parameters. The intuition is as follows. When the market becomes more liquid, the fund attracts more inflows (high L), see Lemma 4. As a result, both $r_L(L)$ decreases and $g(\alpha)$ decreases, creating a non-monotonic relation between fund fragility and market liquidity in Equation (5).

Lemma 4. *The flow to the fund is higher in a liquid market, (i.e, $\frac{\partial L^*}{\partial \alpha} > 0$).*

Proof. See the Appendix C.3. □

2.3.4 Model Predictions: Summary

In summary, based on proposition 3 to 5, we offer the following testable predictions.

- H1: The flow to the fund is **higher** in a **low** interest rate regime;
- H2: The flow to the fund is **higher** in a **liquid** market.
- H3.1: The fund is **more fragile** in a **low** interest rate regime when the market is **liquid**;
- H3.2: The fund is **more fragile** in a **high** interest rate regime when the market is **illiquid**;
- H3.3: There is a **more positive** relationship between fund fragility and interest rate in a **more illiquid** market;
- H4.1: The fund is **more fragile** in a **low** monetary policy uncertain market when the market is **illiquid**;
- H4.2: The fund is **more fragile** in a **high** monetary policy uncertain market when the market is **liquid**;
- H4.3: There is a **more negative** relationship between fund fragility and interest rate in a **more illiquid** market.

3 Empirical Investigation

This section devotes to present empirical tests for the hypotheses developed in Section 2.3.4. This paper focuses on the corporate bond mutual funds because they exhibit a stronger flow-performance relation, see Goldstein, Jiang, and Ng (2017).

The empirical studies mainly focus on how monetary policies, specifically, the level of short-term rate and the monetary policy uncertainty, affect the flows and the fragility of the corporate bond funds, and how market liquidity plays a moderator role in these relationships.

3.1 Data

3.1.1 Sample Construction

We extract data on corporate bond funds from the Center for Research in Security Prices (CRSP). We consider sample periods from January 1992 to December 2017[8], since there are few corporate bond funds in the database prior to 1991. The dataset contains detailed monthly returns and monthly total net asset (TNA) values for each fund share, as well as its quarterly fund share characterizes, such as expense ratios, management fees. Following Goldstein, Jiang, and Ng (2017), we select corporate bond funds based on their objective code provided by CRSP [9]. We also exclude index corporate bond funds, exchange-traded funds, and exchange-traded notes. Our final sample contains 5157 unique fund share classes (1821 unique corporate bond funds). Note that as we use one year of data to estimate the performance of an individual bond fund, our raw sample starts from January 1991.

3.1.2 Measurements

In this section, we describe the construction of measurements used in the empirical study, mostly following Goldstein, Jiang, and Ng (2017).

Fund flow As a standard practice, the net fund flow of fund i at month t is calculated as

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

where $R_{i,t}$ is the return of fund i over month t, and $TNA_{i,t}$ is the total net asset value at the end of month t.

Fund fragility Based on the definition of fragility, one would like to measure it as the likelihood that investors withdraw capital because they believe that other investors are going to withdraw capital.

[8] We also run the analysis for the sample from January 2000 to December 2017. During this periods, there are balanced sample in th low- and high- federal fund rate regimes, where the low-federal fund rate regime is defined as the period when the federal funds rate is below the sample median as in Di Maggio and Kacperczyk (2016).

[9] We keep corporate bond funds if 1) its Lipper objective code in the set ('A', 'BBB','HY', 'SII', 'SID', 'IID'), or 2) its Strategic Insight Objective code in the set ('CGN','CHQ','CHY','CIM','CMQ','CPR','CSM'), or 3) its Wiesenberger objective code in the set ('CBD','CHY'), or 4) its CRSP objective code start with 'IC'.

However, in reality, it is almost impossible to observe investors' beliefs. As a compromise, we follow Goldstein, Jiang, and Ng (2017) to identify strategic complementarities by investigating whether investors respond to fundamentals stronger when complementarities are expected to be stronger. In other words, we study whether the strategic complementarities amplify the effect of fundamentals on outflows, hence creating financial fragility.

Specifically, we use performance as a proxy for fund's fundamental. Investors will withdraw from a fund if its past performance is poor. Then flow-performance sensitivity is our proxy for fund fragility. The performance of fund i at month t is measured as the past one year's alpha from the following time-series regression:

$$R^e_{i,\tau} = Alpha_{i,t-12\to t-1} + \beta_B R^e_{B,\tau} + \beta_M R^e_{M,\tau} + \varepsilon_{i,\tau}, \quad \tau \in (t-12, t-1) \tag{9}$$

where $R^e_{i,\tau}$, $R^e_{B,\tau}$ and $R^e_{M,\tau}$ are excess returns[10] over of the fund, the aggregate bond market and the aggregate stock market, respectively. Specifically, $R^e_{B,\tau}$ is approximated by the Vanguard total bond market index fund return and $R^e_{M,\tau}$ is approximated by CRSP value-weighted market return. The index return data is from Bloomberg and CRSP.

Short-term rate In reality, the US Federal Reserve directly set federal funds rate, which is the rate at which depository institutions (banks) lend reserve balances to other banks on an overnight basis. This rate directly has a bearing on short-term interest rates. In this paper, we directly adopt Federal fund rate, extracted from FRED[11] as a proxy for $\bar{r}$.

Monetary policy uncertainty Our main proxy for monetary policy uncertainty of US is the MPU index developed by Baker, Bloom, and Davis (2016). The MPU index is constructed monthly based on the number of news articles that contain the terms uncertain or uncertainty; and one or more of the federal reserve, the fed, money supply, etc[12]. They construct two variants of MPU index based on two different sets of newspapers: 1) hundreds of daily newspapers covered by Access World News

[10] The risk-free rate is approximated by 1-month London Interbank Offered Rate (LIBOR).
[11] https://fred.stlouisfed.org/series/FEDFUNDS
[12] See http://www.policyuncertainty.com/bbd_monetary.html for details

(denoted as "MPU 100"), and 2) a balanced panel of 10 major newspapers (denoted as "MPU 10"). Similarly, Husted, Rogers, and Sun (2017) construct an MPU index (denoted as "MPU HRS") by searching for keywords related to monetary policy uncertainty in the New York Times, Wall Street Journal and Washington Post. "MPU HRS" differs from previous two MPU indexes concerning scaling factors, newspaper coverage, and term sets. We plot three MPU indexes in Figure 11. Even though three-time series move differently, they all spike around near tight presidential elections, Taper Tantrum, QE1 and QE 2, the 9/11 attacks, and other significant changes for monetary policy.

Liquidity Since we only model the aggregate bond mutual fund industry in section 2, we focus on aggregate measures of liquidity. First, we use the index of corporate bond market illiquid index proposed by Dick-Nielsen, Feldhütter, and Lando (2012) (DFL). This index covers July 2002 to December 2017, which is slightly shorter than our sample. Notice that the DFL index shares 86% correlation coefficient with VIX index from the Chicago Board Options Exchange (CBOE). We adopt VIX index as our second measurement of market liquidity. VIX is confirmed in BAO, PAN, and Wang (2011) to positively correlate with the illiquidity of corporate bonds. Third, Brunnermeier and Pedersen (2009) argue that funding liquidity of financial institutions has positive effects on market liquidity. We use TED spread[13] (from St. Louis Fed) as the measure of funding liquidity, which further determines the liquidity of the bond markets.

3.1.3 Summary Statistics

Table A.1 presents the summary statistics for the funds in our sample from January 1992 to December 2017. To mitigate the influence of outliers and false data records in CRSP, we winsorize all the continuous variables of fund characteristics at the 1% and 99%[14]. The reported statistics are close to Table 1 in Goldstein, Jiang, and Ng (2017). Over the sample period, corporate bond funds have an inflow of 1.035% and a positive return of 0.395% per month on average. The average size of funds

[13] TED rate measures the difference between the three-month London Interbank Offered Rate and the three-month Treasury-bill interest rate.

[14] All results in this paper are robust when we winsorize data at 0.5% and 99.5% levels.

is \$47 million and the average age is 7.08 years. The funds hold around 2.9% cash in the portfolio on average, with a standard derivation of 10.7%. There are less than 25% of funds with negative cash holdings. Both mean and median of Alpha are negative, implying that the funds do not beat the market on average, even before the fees. The average regression loading on the aggregate bond market return, β_B, is 0.673, much higher than the average regression loading on the stock market return, β_M. It suggests that returns of bond mutual funds do not co-move with the returns of the stock market that much and the standard Capital Asset Pricing Model (CAPM) alone is not enough to approximate the wealth portfolio of bond investors.

3.2 Main Empirical Results

3.2.1 Fund Flow

In this section, we investigate whether investors move the capital to the bond mutual funds when Federal fund rate decreases or market becomes more liquid, as predicted in H1 and H2. Since flow L in the model mainly captures the aggregate flows to the bond mutual fund industry, we first run a time series regression of aggregated fund flows:

$$Flow_t \alpha + \beta_1 \Delta Key_t + \gamma_M Controls_t^M + \varepsilon_t, \tag{10}$$

where $Flow_t$ is the equally weighted fund flows across all the bond funds at month t, Key_t is the key variables: federal fund rate (FF) or market liquidity measures, VIX, TED and DFL. We adopt the change in the key measures to mitigate the bias induced by potential non-stationarity. To remove the effects of general bond market conditions on fund flows, we also include market controls ($Controls_t^M$), including changes in default spread (the yield difference between BBB- and AAA-rated corporate bonds), and changes in yield slope (the difference between 20-year and one-year Treasury yield). As additional controls, we include variables commonly employed in flow regressions: past flows, past returns, and the square of past returns. All are calculated as the equal-weighted averages across fund shares.

As a robustness check, we also conduct a panel regression analysis with fund and year fixed effects to study the time-series respond of fund flows to changes in federal rate and market illiquidity. The panel regression is specified as follows:

$$Flow_{i,t} = \alpha_t + \alpha_Y + \beta_1 \Delta Key_t + \gamma_M Controls_t^M + \gamma Controls_{i,t}^F + \varepsilon_{i,t}, \tag{11}$$

where fund level characteristics ($Controls_{i,t}^F$) include fund age, total net asset and expense ratio.

Table A.2 reports the results. Time series regressions and panel regressions give very similar results, regarding both magnitude and significances. We focus on interpreting statistics reported in column (1). First, the coefficients of changes in federal fund rate ΔFF_t are significantly negative in all specifications, meaning that a decrease in federal fund rate corresponds to contemptuous inflows to corporate bond funds. These results support H1, that is, capital flows into the bond fund in a low-federal fund rate regime. Moreover, the impact is economically sizable. On average, a one standard deviation decrease of monthly federal fund rate (around 0.166%) is associated with -0.01*-0.166*100% = 0.166% inflow to the corporate bond fund industry, roughly 2.5 billion USD if the total net asset is 1.5 trillion. Banegas, Montes-Rojas, and Siga (2016) also empirically examine the relationship between mutual fund flows and monetary policy. Using structural recursive vector autoregression (VAR), they find that an expansionary monetary policy is associated with persistent inflows to bond mutual funds, in line with our findings.

Second, consistent with H2, we find a negative relationship between market illiquidity, measured by VIX, TED, and DFL, and fund flows. When the market becomes more liquid, more capital flows into corporate bond funds. On average, a one standard deviation decrease of VIX (around 0.146%) is associated with -0.146*-0.008*100%= 0.117% inflow to the corporate bond fund industry, roughly 1.8 billion USD if the total net asset is 1.5 trillion.

Besides above tests, Table A.2 also shows that when yield slope becomes flatter, there are more inflows to corporate bond funds. Besides, the relationship between changes in monetary policy uncertainty and fund flows is weak. Indeed, the model does not have robust predictions on this relationship either.

Overall, we find supportive evidence for model predictions H1 and H2. There are more inflows to corporate bond funds when the federal fund rate is lower and the market is more liquid.

3.2.2 Fund Fragility

This section dedicates to examine model predictions on fund fragility. As discussed before, we use flow-performance sensitivity as a proxy for fund fragility. We first verify whether there is a strong relationship between flows and performance, especially for negative performance and outflows. Then we study how flow-performance sensitivity changes in different market conditions.

Flow-performance relation Following Goldstein, Jiang, and Ng (2017), we perform the following parametric regression that captures a potential non-linearity in the flow-performance relation:

$$\begin{aligned} Flow_{i,t} &= \alpha_t + \beta_1 Alpha_{i,t-12\to t-1} + \beta_2 \mathbb{1}(Alpha_{i,t-12\to t-1} < 0) \\ &\quad + \beta_3 Alpha_{i,t-12\to t-1} * \mathbb{1}(Alpha_{i,t-12\to t-1} < 0) + \gamma Controls^F_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{12}$$

where $Alpha_{i,t-12\to t-1}$ is estimated using equation (9) and $\mathbb{1}(Alpha_{i,t-12\to t-1} < 0)$ is an indicator variable equal to one if the fund achieves a negative alpha in the past year and zero otherwise. Fund characteristics are included as control variables in the regression. We include month fixed effect to control for inflows or outflows to the bond fund industry. To allow for an intertemporal dependence of flows at fund share level, we cluster standard errors by fund share class.

Column (1) in Table A.3 presents the result for all the corporate bond funds. Similar to Goldstein, Jiang, and Ng (2017), a significantly positive coefficient on $Alpha_{i,t-12\to t-1} * \mathbb{1}(Alpha_{i,t-1} < 0)$ indicates a concave flow-performance relation for corporate bond funds: the sensitivity of flows to bad performance is much higher than that of flows to good performance. Relatively, the sensitivity to bad performance is 4.6 times higher than that to good performance ($\frac{1.45+0.56}{0.56}$)[15].

To ensure the existence of strong flow-performance relations, we conduct subsample analysis.

[15] Our coefficients are larger than those reported in Table 2 of Goldstein, Jiang, and Ng (2017). The reasons is that we winsorize $Alpha_{i,t-12\to t-1}$ at 1% and 99% levels to remove influences from outliers.

We apply the same methodology for high and low federal fund rate regimes (months with federal fund rate more than and less than 1%), and for high and low monetary policy uncertain periods[16] (months with MPU_{10} above- and below- median over sample periods). Columns (2)-(5) in Table A.3 reports results on subsamples. It is quite clear that the higher sensitivity of outflows to under-performance than inflows to out-performance is remarkably robust across different federal fund rate regimes and different monetary policy uncertain periods. Moreover, the relative sensitivity for bad performance and good performance does not differ that much in different regimes.

Tests for fund fragility We conduct three-step analysis to test the impacts of monetary policy on fund fragility. In the first step, we investigate the overall effect, and in the second step, we look into how market liquidity moderates the relationship.

In the first step, we perform the following regression:

$$\begin{aligned} Flow_{i,t} &= \alpha + \beta_1 Alpha_{i,t-12\to t-1} + \beta_2 \mathbb{1}(Key_t) \\ &\quad + \beta_3 Alpha_{i,t-12\to t-1} * \mathbb{1}(Key_t) + \gamma Controls^F_{i,t} + \varepsilon_{i,t}, \quad \forall Alpha_{i,t-1\to t-12} < 0, \end{aligned} \tag{13}$$

where $Flow_{i,t}$ is flow of fund i in month t, $Alpha_{i,t-12\to t-1}$ measures the performance of fund i over past one year, $Control^F_{i,t}$ remains the same as before, $\mathbb{1}(\cdot)$ is an indication function and Key_t is the market conditions of interest. The coefficient β_3 is of interest, which measures the difference in flow-performance (fund fragility) under different regimes of variable Key_t. We consider three sets of variables for Key_t. Specifically, High FF rate equals to one if the corresponding federal fund rate is above sample median. High MPU_{HRS}, high MPU_{10}, and high MPU_{100} equal to one if the corresponding monetary policy uncertainty index is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. As we are interested in strategic complementarities for outflows, we only include samples with negative performance in the regression. To allow for an intertemporal dependence of flows at fund share level, we cluster standard errors by fund share class.

[16] The results are robust to the other two measures of monetary policy uncertainty, MPU_{HRS} and MPU_{100}.

In the second step, we run regression analysis of (13) in sub-sample of high- and low- market liquidity conditions to test for hypotheses H3.1, H3.2, H4.1, and H4.2. Lastly, we consider regression with a three-way interaction of liquidity included:

(14)

$$Flow_{i,t} = \alpha + \beta_4 Alpha_{i,t-12\to t-1} * Key_t * \mathbb{1}(\text{High Illiquidity}_t) + \gamma Controls^F_{i,t} + \varepsilon_{i,t}, \quad \forall Alpha_{i,t-1\to t-12} < 0.$$

In this regression, coefficient β_4 is of interest. This coefficient specifically quantifies whether the relationship between flow-performance sensitivity and our key variables (federal fund rate and monetary policy uncertainty) is different across the level of market liquidity. As predicted by hypothesis H3.3, we expect to see the a more positive relationship between fund fragility and federal fund rate in a more illiquid market. So when Key_t measures federal fund rate, β_4 should be positive. Similarly, based on hypothesis H4.3, we should observe a more negative relation between fund fragility and monetary policy uncertainty in a more illiquid market. This implies that β_4 should be negative when Key_t measures monetary policy uncertainty.

Results for federal fund rate Table A.4 presents test results of regression (14) for the overall effects. In column (1), we see a significant negative coefficient, of the interaction term of Alpha and $\mathbb{1}$(High FF rate), suggesting a higher sensitivity of investors' withdrawals to poor performance when federal fund rate is low. In particular, compared to the high federal fund rate regime, a 1% decrease in performance (Alpha) is associated with 1.0% higher outflows in a low federal fund regime. To further verify predictions H3.1 and H3.2, we extend the analysis on subsamples split according to high and low market liquidity. The results are presented in Table A.5. In all sub-samples, the interaction terms of performance and indication function of a low federal fund rate regime are significantly positive. In a nutshell, the fund industry becomes more fragile in the low federal fund rate regime. There results provide suggestive evidence for prediction H3.1, which indicates the market is relatively liquid across our sample period and complementarity discount is not the major concern for corporate bond investors.

Comparing the coefficients in the subsamples of liquid market and illiquid market, we see some evidence for hypothesis H3.3, for illiquidity proxy VIX and DFL, that the relationship between fund fragility and interest rate is more negative in a more liquid market. To formally test H3.3, we run regressions with three-way interactions and report results in Table A.6. As predicted by our model, the coefficient of three-way interaction are significantly positive, indicating that a more positive relationship between fund fragility and federal fund rate in a more illiquid market. We visualize these relationship in Figure 8. Three line in each figure plot the flow-performance relationship for federal fund rate at +/- 1 standard deviation around the average. In the left panel, we see clear derivations of fund fragility under different interest rate regimes: when federal fund rate is high, fund flow does not react to fund negative performance, while federal fund rate is low, fund flow follows performance strongly. This relationship corresponds to red- or green-curve in Figure 6. In the right panel, we see three line collapses together, revealing that monetary policy does not shape fund fragility in an illiquid market. This roughly corresponds to blue curve in Figure 6. Therefore, we conclude that monetary policy affects fund fragility differently under varied liquidity conditions. The more liquid market is, the lower federal fund rate exacerbates fund fragility.

Results for monetary policy uncertainty Columns (2)-(4) of Table A.4 aims to show the overall relationship between fund fragility and monetary policy uncertainty measured in three different ways. The coefficients on interaction terms of High MPU_{HRS} and MPU_{100} are significantly negative, while that of High MPU_{10} is insignificantly positive. It is hard to argue which of three better measures monetary policy uncertainty. So we can not conclude that there is a monotonic relation between fund fragility and monetary policy uncertainty.

From hypotheses H4.1 and H4.2, we know market liquidity can alter the relationship between fund fragility and monetary policy uncertainty. When the market is illiquidity, an increase in monetary policy uncertainty is associated with a decrease in fund fragile; while when the market is liquid, a positive relation between two should be observed.

To test above predictions, we run regressions on subsamples and report results in Table A.7.

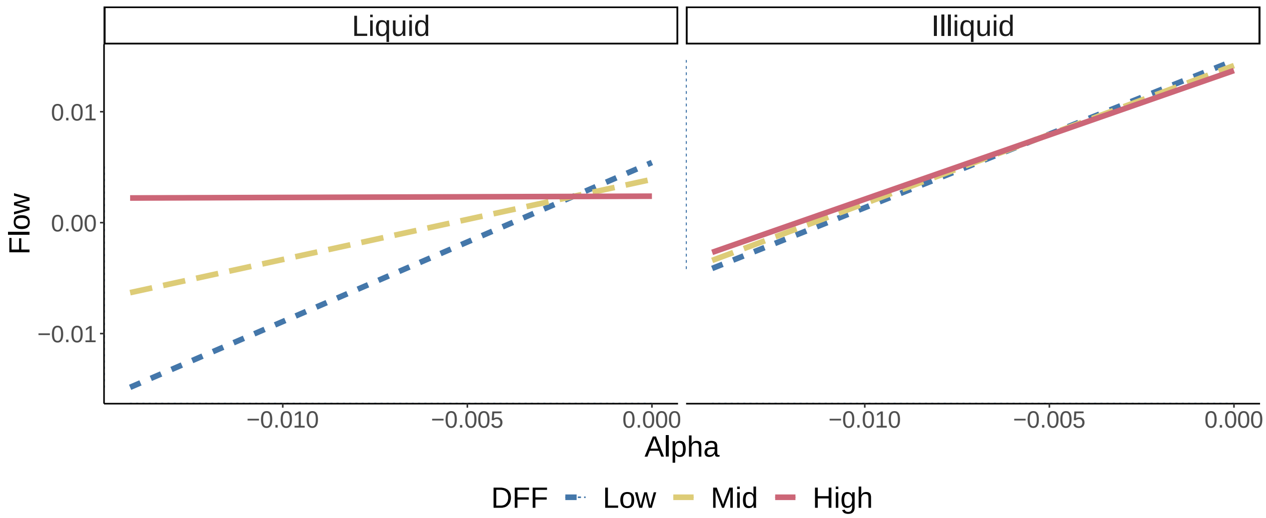

Figure 8: Visualization of regression result of column (1) in Table A.6.

Consistent with H4.1, the coefficients of interaction term are all negative when the market is illiquid, i.e., VIX is high, or TED is high, or DFL is high. Two of three negative coefficients are significant at 0.1% level. When MPU_{HRS} index is low, a 1% decrease in alpha results in 2.452% increases in outflows; while when MPU_{HRS} is high, a 1% decrease in alpha results in 0.839% (=2.452%-1.613%) increase in outflows. The results suggest that when the market is illiquid, the sensitivity of investors' withdrawals to poor performance is lower in periods in which monetary policy uncertainty is higher. In contrast, two out of three coefficients of interaction term are significantly positive in a liquid market, in line with the prediction from H4.2. One exception is in column (4), where TED measures market illiquidity. Even though this result is not consistent with hypothesis H4.2, but it is still in line with hypothesis H4.3. The coefficient of low TED case in column (4), -0.837, is much larger than the coefficient, -1.396, of high TED case in column (3).

The formal test of hypothesis H4.3 is presented in Table A.8. As predicted by our model, the coefficient of three-way interaction are significantly negative across different proxies for market liquidity, indicating that a more negative relationship between fund fragility and monetary policy in a more illiquid market. As before, we visualize these relationship in Figure 9. In the left panel of liquid

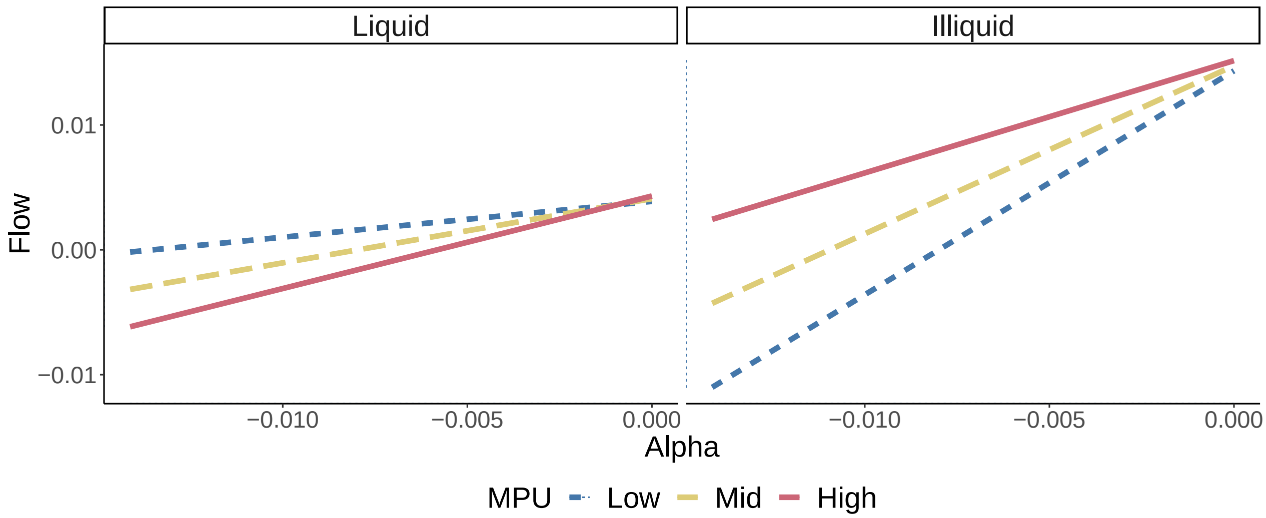

Figure 9: Visualization of regression result of column (1) in Table A.8.

market, the flow-performance sensitivity is higher when monetary policy uncertainty is higher than other cases, while in the right panel of illiquid market, we observe an opposite effect. Summarily, we can safely conclude that when the market is more liquid, the sensitivity of investors' withdrawals to poor performance is higher in periods in which monetary policy uncertainty is higher.

At last, we replicate tests of illiquidity in Goldstein, Jiang, and Ng (2017) in the last three columns of Table A.4. Our results are very similar to theirs: corporate bond funds have a higher outflow-to-poor-performance sensitivity in an illiquid market. Note that our model can not produce such monotonic prediction after considering the ex-an asset allocation problem[17]. The reason is that when the market becomes more liquid, more capital flows into the corporate bond funds[18], squeezing the fund return. This effect gives investors stronger incentives to withdraw, potentially creating fund fragility in liquid market as well. In the next section, we will point out one potential reason that we observe a monotonic relationship between market liquidity and fund fragility empirically.

Overall, we find supportive evidence for model predictions H3.1, H3.2, H3.3, H4.1, H4.2 and

[17] If only considering fund run problem at T_1, the model predicts that the fund becomes more fragile in an illiquid market (see Lemma 2), the same as Chen, Goldstein, and Jiang (2010).

[18] See model prediction H2 and empirical evidence in Table A.2

H4.3. Market liquidity plays an essential role for impacts of monetary policy on the strategic complementarities among fund investors Specifically, fund fragility gets exacerbated in a low federal fund rate regime, in a low monetary policy uncertain market when the market is illiquid, and in a high monetary policy uncertain market when the market is liquid. Table 2 summarizes both model and empirical results.

		Flow			Fragility		
		Partial	General	Empirical	Partial	General	Empirical
High interest rate	High liquidity	·	−	−	+	−	−
	Low liquidity	·	−	−	+	+	−
High monetary uncertainty	High liquid	·	·	·	+	+	+
	Low liquidity	·	·	·	−	−	−
High liquidity		·	+	+	−	+/−	−

Table 2: Results summary. This table presents summary results of both model predictions and empirical evidence. Columns "Partial" summarizes model results in Lemma 2, columns "General" summarizes model results in section 2.3, and columns"Empirical" summarizes empirical evidence reported in section 3.

3.2.3 Address Concerns

As mentioned in section 3.1.2, our proxy for fund fragility relies on investors' responses to funds' fundamental performance. This may not an ideal measure of fund fragility. It is possible that investors withdraw coincidentally because they all find out the poor fundamental of a fund, leading them to run. For example, if corporate bond funds generally perform poorly in a low federal fund regime, then it is not surprising to see more outflows in same periods due to the stronger flow-performance relation for poor performance. If this is the case, then outflow-to-poor-performance sensitivity does not precisely measure strategic complementarities and fund fragility. Instead, it merely indicates that bond investors react stronger to bad performance, as shown in Table A.3. Therefore, it is essential to rule out the concern of poor performance in high fund fragility cases.

In Table A.9, we summarize t-test results of funds' negative alphas in different market conditions.

First, we notice that alpha in a low federal fund rate regime (around -0.20%, on average, is significantly higher than that in a high regime (around -0.46%). This can potentially rule out the concern that the outflow-to-poor-performance sensitivity is stronger in a low federal fund rate regime because of poor performance in that regime. A same pattern can be found for monetary policy uncertainty. In an illiquid (a liquid) market, when monetary policy uncertainty is low, the outflow-to-poor-performance sensitivity is stronger (weaker) while the average performance is better (worse).

However, when the market is illiquid, funds' performance are significantly lower, compared to the case in a liquid market. When measuring market illiquidity using VIX index, the alpha is -0.40% in high VIX periods and -0.22% in low VIX periods. Based on the outflow-to-poor-performance sensitivity statistic given in Table A.3, we would already expect that the sensitivity is 1.45*0.18=0.261 unit higher in high VIX periods simply because of the negative performance. This effect can contribute to strong complementarity appeared in the coefficient of interaction term, 0.707, of Table A.4. Therefore, we do not find non-monotonic relationship between fund fragility and market liquidity as predicted in the model.

4 Conclusion

In this paper, we study how monetary policy could affect the fragility of corporate bond mutual funds. Opposite to common intuition, we argue that expansionary monetary policy can exacerbate the bond fund fragility even if we see substantial capital flows into corporate bond funds. We establish this result using a fund-run model with ex-ante portfolio allocation decisions for investors. The empirical analysis of corporate bond mutual funds over the January 1992 to December 2017 confirms the predictions of the model. A key takeaway from this paper is that when deciding monetary policy, policymakers need to consider its impacts on the fragility of the financial market.

Appendix

A Tables

	Mean	Std Dev	P5	P25	Median	P75	P95	N
Flow (%)	1.035	10.050	-7.440	-1.695	-0.189	1.734	11.949	489,226
Return (%)	0.395	1.339	-1.880	-0.163	0.382	1.061	2.462	489,226
Log(TNA)	3.850	2.444	-0.693	2.342	4.072	5.547	7.494	489,226
Log(Age)	1.958	0.822	0.509	1.374	2.023	2.580	3.183	488,839
Expense	1.030	0.485	0.380	0.660	0.910	1.400	1.900	455,341
Cash Holding (%)	2.907	10.688	-13.000	0.120	2.280	5.410	18.870	416,718
Rear Load	0.405	0.491	0.000	0.000	0.000	1.000	1.000	401,060
Institutional	0.373	0.484	0.000	0.000	0.000	1.000	1.000	435,955
Alpha (%)	-0.079	0.462	-0.752	-0.322	-0.081	0.076	0.750	489,226
β_B	0.673	0.466	-0.049	0.348	0.735	0.970	1.350	489,226
β_M	0.135	0.170	-0.025	0.013	0.064	0.221	0.500	489,226

Table A.1: Summary statistics of fund characteristics. This table presents the summary statistics for characteristics of all corporate bond funds in our sample from January 1992 to December 2017. Flow (%) is the percentage fund flow in a given month, Fund return (%) is the monthly net fund return in per cent, Log(TNA) is the natural log of total net assets (TNA), Log(Age) is the natural log of fund age in years since its inception in the CRSP database, Expense (%) is fund expense ratio in per cent, Cash Holdings is the proportion of fund assets held in cash in per cent, Alpha, β_B and β_M are coefficients from regression (9) for a fund in a given month. The unit of observations is share class-month. The sample includes 5236 unique fund share classes and 1846 unique funds. We exclude index corporate bond funds, exchange traded funds, and exchange traded notes from the CRSP mutual fund database.

	Dependent variable: $Flow_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel	TS	Panel	TS	Panel	TS
ΔFF_t	−0.010	−0.009	−0.010	−0.007	−0.010	−0.009
	-2.558^{**}	-2.795^{***}	-2.297^{**}	-1.982^{**}	-2.543^{**}	-2.346^{**}
ΔVIX_t	−0.008	−0.006				
	-2.590^{***}	-1.818^{*}				
ΔTED_t			−0.002	−0.007		
			−1.215	-2.666^{***}		
ΔDFL_t					−0.001	−0.002
					−1.330	-1.667^{*}
ΔMPU_t^{HRS}	0.001	0.001	0.0002	0.001	−0.0003	0.001
	1.041	1.669^{*}	0.294	1.380	−0.326	0.731
ΔYield (slope)$_t$	−0.007	−0.004	−0.007	−0.002	−0.009	−0.008
	-3.029^{***}	−1.613	-2.407^{**}	−0.930	-3.550^{***}	-3.132^{***}
ΔDefault spread$_t$	0.001	−0.006	−0.001	−0.004	0.001	−0.007
	0.200	−1.255	−0.122	−0.757	0.367	−1.449
Performance controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Characteristics	Yes		Yes		Yes	
Fund FE	Yes		Yes		Yes	
Observations	433,476	285	433,476	285	342,611	180
Adjusted R^2	0.087	0.584	0.087	0.589	0.092	0.631

Table A.2: Tests for fund flow. This table reports test results of H1 and H2 in section 2.3.4 from time-series regression (10) and panel regression (11) for corporate bond funds from January 1992 to December 2017. The dependent variable is $Flow_t$. The independent variables of interest are changes in federal fund rate ΔFF_t, changes in illiquidity measures ΔVIX_t, ΔTED_t, ΔDFL_t. To remove the effects of general bond market conditions on fund flows, we also control for changes in default spread (the yield difference between BBB- and AAA rated corporate bonds), and changes in yield slope (the difference between 20-year and one-year Treasury yield). Performance controls include past flows, past returns and square of past returns. Fund characteristics include Log(TNA), Log(Age), and expense ratios. All panel regressions include fund and year fixed effect to control for flows to individual fund due to specific reasons. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at month level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Dependent variable: $Flow_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
	All	Low FF rate	High FF rate	High MPU_{10}	Low MPU_{10}
$Alpha_{i,t-12\to t-1} * \mathbb{1}(Alpha_{i,t-1} < 0)$	1.449	2.036	0.790	2.041	1.137
	8.480***	8.945***	2.077**	7.324***	6.094***
$Alpha_{i,t-12\to t-1}$	0.557	0.542	0.890	0.424	0.609
	4.830***	4.484***	2.585***	2.090**	5.117***
$\mathbb{1}(Alpha_{i,t-1} < 0)$	−0.008	−0.007	−0.006	−0.006	−0.008
	−13.363***	−10.839***	−4.201***	−4.868***	−13.358***
$Flow_{t-1}$	0.144	0.155	0.115	0.165	0.138
	25.335***	22.140***	13.142***	17.460***	23.274***
Log(TNA)	0.001	0.001	0.0004	0.00004	0.001
	5.882***	5.559***	1.664*	0.211	6.654***
Log(Age)	−0.017	−0.017	−0.016	−0.017	−0.017
	−39.758***	−36.046***	−23.541***	−25.148***	−38.818***
Expense	−0.417	−0.487	−0.259	0.154	−0.612
	−7.013***	−6.612***	−2.954***	1.604	−10.059***
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	451,005	305,160	145,845	107,600	335,949
Adjusted R^2	0.060	0.063	0.053	0.069	0.057

Table A.3: Flow-performance relationship. This table represents flow-performance relations for corporate bond funds with negative alpha from January 1992 to December 2017. The dependent variable is $Flow_{i,t}$. $Alpha_{i,t-12\to t-1}$ is obtained from regression (9), which measures the performance of fund i over past one year. The independent variable of interest is the interaction of past performance and negative performance, $Alpha_{i,t-12\to t-1} * \mathbb{1}(Alpha_{i,t-1} < 0)$. Periods of federal fund rate below (above) sample median are classified as low (high) federal fund rate regime. Periods of monetary policy index (US) below (above) sample median are classified as low (high) MPU_{10} regime. Fund characteristics include Log(TNA), Log(Age), and expense ratios. All regressions include month fixed effect to control for inflows or outflows to the bond fund industry. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Dependent variable: $Flow_{i,t}$						
$Alpha_{i,t-12\to t-1} < 0$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Key	High FF rate	High MPU_{HRS}	High MPU_{10}	High MPU_{100}	High VIX	High TED	High DFL
$Alpha_{i,t-12\to t-1} * \mathbb{1}(Key)$	-0.996	−0.978	0.126	−0.638	0.707	0.720	0.814
	-5.395***	−7.044***	0.910	−4.744***	3.956***	4.429***	2.889***
$Alpha_{i,t-12\to t-1}$	1.281	1.258	0.772	1.166	0.511	0.287	0.766
	8.267***	10.338***	7.859***	9.990***	3.295***	2.236**	3.375***
$\mathbb{1}(Key)$	-0.003	−0.0002	0.008	0.003	0.010	0.003	0.008
	-3.814***	−0.257	10.663***	5.577***	14.220***	4.499***	9.368***
$Flow_{i,t-1}$	0.121	0.122	0.121	0.122	0.119	0.121	0.128
	17.847***	17.706***	17.732***	17.781***	17.689***	17.850***	15.659***
$R_{i,t-1}$	0.203	0.212	0.205	0.211	0.221	0.200	0.187
	10.715***	10.952***	10.606***	10.933***	11.344***	10.345***	8.003***
$R^2_{i,t-1}$	1.439	1.148	0.197	0.038	−0.172	0.943	0.363
	2.450**	1.849*	0.316	0.060	−0.274	1.525	0.488
Log(TNA)	0.001	0.0005	0.0005	0.0005	0.001	0.001	0.0005
	4.226***	3.619***	3.812***	3.906***	4.123***	4.249***	3.236***
Log(Age)	−0.016	−0.015	−0.016	−0.016	−0.015	−0.016	−0.014
	−34.411***	−34.036***	−34.323***	−34.303***	−34.630***	−34.770***	-27.279***
Expense	−0.381	−0.371	−0.360	−0.357	−0.359	−0.375	−0.650
	−6.031***	−5.780***	−5.619***	−5.565***	−5.699***	−5.914***	−8.568***
Constant	0.037	0.039	0.037	0.038	0.034	0.038	0.036
	29.100***	30.166***	29.777***	29.439***	26.742***	29.646***	23.987***
Observations	293,606	285,113	287,675	287,675	293,606	293,606	208,901
Adjusted R^2	0.037	0.037	0.038	0.038	0.038	0.037	0.038

Table A.4: Test for fund fragility. This table reports test for overall effects of monetary policy on fund fragility from panel regression (13) for corporate bond funds with negative alpha from January 1992 to December 2017. We only include data entries with negative performance as we are interested in strategic complementarities for outflows. The dependent variable is $Flow_{i,t}$. The independent variable of interest is the interaction of past performance and indicator function of market conditions, $Alpha_{i,t-12\to t-1} * \mathbb{1}(Key)$. Specifically, High FF rate equals to one if the corresponding federal fund rate is above the sample median. High MPU_{HRS}, high MPU_{10}, and high MPU_{100} equal to one if the corresponding monetary policy uncertainty index is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Fund characteristics include Log(TNA), Log(Age), and expense ratios. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

$Alpha_{i,t-12\to t-1} < 0$	Dependent variable: $Flow_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	High VIX	Low VIX	High TED	Low TED	High DFL	Low DFL
$Alpha_{i,t-12\to t-1} * \mathbb{1}(\text{High FF})$	−0.905	−1.214	−1.662	−1.071	−1.062	−3.050
	−4.098***	−2.889***	−5.754***	−4.055***	−3.654***	−5.838***
$Alpha_{i,t-12\to t-1}$	1.984	1.010	2.065	0.962	1.708	1.692
	10.869***	2.960***	7.680***	4.755***	7.779***	5.075***
$\mathbb{1}(\text{High FF})$	−0.002	−0.002	−0.009	0.001	−0.007	−0.006
	−1.542	−2.029**	−8.020***	0.827	−5.815***	−4.118***
$Flow_{t-1}$	0.125	0.108	0.130	0.110	0.161	0.092
	13.860***	13.023***	15.719***	11.725***	14.542***	9.726***
$R_{i,t-1}$	0.201	0.208	0.205	0.197	0.198	0.112
	9.426***	4.892***	9.957***	6.874***	8.302***	2.378**
$R^2_{i,t-1}$	−0.794	4.773	−0.569	3.291	−0.787	4.950
	−1.227	2.770***	−0.811	3.275***	−1.011	2.614***
Log(TNA)	0.0001	0.001	0.0004	0.001	0.0001	0.001
	0.606	4.620***	2.514**	3.882***	0.561	4.384***
Log(Age)	−0.016	−0.014	−0.016	−0.016	−0.013	−0.015
	−26.805***	−26.932***	−27.385***	−27.797***	−18.915***	−24.494***
Expense	0.077	−0.908	−0.247	−0.535	−0.387	−0.945
	0.924	−11.299***	−3.213***	−6.317***	−3.937***	−10.289***
Constant	0.042	0.034	0.037	0.040	0.034	0.034
	24.314***	19.416***	23.073***	22.096***	15.823***	15.967***
Observations	153,847	139,759	155,848	137,758	100,269	108,632
Adjusted R^2	0.039	0.036	0.040	0.035	0.047	0.031

Table A.5: Test H3.1 and H3.2 for fund fragility. This table reports test results for H3.1 and H3.2 in section 2.3.4 from panel regression (13) for corporate bond funds with negative alpha from January 1992 to December 2017. We only include data entries with negative performance as we are interested in strategic complementarities for outflows. The dependent variable is $Flow_{i,t}$. The independent variable of interest is the interaction of past performance and indicator function of high federal fund rate regime, $Alpha_{i,t-12\to t-1} * \mathbb{1}(HighFF)$, where High FF rate equals to one if the corresponding federal fund rate is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Fund characteristics include Log(TNA), Log(Age), and expense ratios. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Dependent variable: $Flow_{i,t}$		
$Alpha_{i,t-12\rightarrow t-1} < 0$	(1)	(2)	(3)
Key	High VIX	High TED	High DFL
$Alpha_{i,t-12\rightarrow t-1} * FF_t * \mathbb{1}(Key)$	0.281	0.031	0.392
	2.994***	0.265	2.930***
$Flow_{i,t-1}$	0.119	0.121	0.127
	17.697***	17.821***	15.659***
$R_{i,t-1}$	0.222	0.194	0.187
	11.590***	10.266***	8.100***
$R^2_{i,t-1}$	−0.075	0.872	0.186
	−0.127	1.481	0.255
Log(TNA)	0.001	0.001	0.0005
	4.114***	4.293***	3.421***
Log(Age)	−0.015	−0.016	−0.014
	−33.928***	−34.180***	−27.607***
Expense	−0.354	−0.375	−0.651
	−5.633***	−5.949***	−8.617***
Constant	0.036	0.038	0.037
	26.082***	27.913***	24.175***
Interaction terms	Yes	Yes	Yes
Observations	293,606	293,606	208,901
Adjusted R^2	0.038	0.037	0.039

Table A.6: Test for H3.3 for fund fragility. This table reports test results for H3.3 in section 2.3.4 from panel regression (13) for corporate bond funds with negative alpha from January 1992 to December 2017. We only include data entries with negative performance as we are interested in strategic complementarities for outflows. The dependent variable is $Flow_{i,t}$. The independent variable of interest is the interaction of past performance, federal fund rate and an indicator function of market liquidity condition, $Alpha_{i,t-12\rightarrow t-1} * FF_t * \mathbb{1}(Key)$. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Fund characteristics include Log(TNA), Log(Age), and expense ratios. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

$Alpha_{i,t-12\to t-1} < 0$	Dependent variable: $Flow_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	High VIX	Low VIX	High TED	Low TED	High DFL	Low DFL
$Alpha_{i,t-12\to t-1} * \mathbb{1}(\text{High } MPU_{HRS})$	−1.240	0.507	−1.396	−0.837	−0.336	1.176
	−7.133***	1.873*	−7.986***	−3.149***	−1.294	2.791***
$Alpha_{i,t-12\to t-1}$	2.152	−0.082	1.818	0.869	1.708	−0.047
	13.793***	−0.423	11.557***	3.863***	8.116***	−0.155
$\mathbb{1}(\text{High } MPU_{HRS})$	−0.0001	0.001	−0.004	0.003	−0.0003	0.003
	−0.155	1.742*	−4.004***	3.833***	−0.330	3.218***
$Flow_{i,t-1}$	0.125	0.110	0.131	0.112	0.161	0.093
	13.832***	12.913***	15.784***	11.490***	14.593***	9.438***
$R_{i,t-1}$	0.210	0.220	0.197	0.232	0.194	0.141
	9.732***	5.139***	9.406***	7.861***	7.986***	2.790***
$R^2_{i,t-1}$	−1.100	4.545	0.414	1.838	−0.027	3.435
	−1.643	2.476**	0.571	1.794*	−0.035	1.681*
Log(TNA)	0.0001	0.001	0.0003	0.001	0.0001	0.001
	0.567	4.147***	1.865*	3.299***	0.442	3.652***
Log(Age)	−0.016	−0.014	−0.015	−0.015	−0.013	−0.015
	−27.298***	−25.779***	−27.336***	−26.693***	−18.676***	−22.715***
Expense	0.062	−0.902	−0.237	−0.531	−0.378	−0.943
	0.763	−10.810***	−3.056***	−6.026***	−3.836***	−9.864***
Constant	0.044	0.034	0.042	0.037	0.040	0.036
	25.463***	20.012***	25.424***	21.020***	19.239***	19.120***
Observations	153,847	131,266	155,848	129,265	100,269	100,139
Adjusted R^2	0.040	0.036	0.040	0.035	0.047	0.030

Table A.7: Test H4.1 and H4.2 for fund fragility. This table reports test results of H4.1 and H4.2 in section 2.3.4 from panel regression (13) for corporate bond funds with negative alpha from January 1992 to December 2017. We only include data entries with negative performance as we are interested in strategic complementarities for outflows. The dependent variable is $Flow_{i,t}$. The independent variable of interest is the interaction of past performance and indicator function of high monetary policy uncertainty, $Alpha_{i,t-12\to t-1} * \mathbb{1}(\text{MPU } MPU_HRS)$. Specifically, high MPU_{HRS} equals to one if the corresponding monetary policy uncertainty index is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Fund characteristics include Log(TNA), Log(Age), and expense ratios. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Dependent variable: $Flow_{i,t}$		
$Alpha_{i,t-12\rightarrow t-1} < 0$	(1)	(2)	(3)
Key	High VIX	High TED	High DFL
$Alpha_{i,t-12\rightarrow t-1} * Log(MPU_{HRS}) * \mathbb{1}(Key)$	−1.473	−1.082	−0.766
	−4.728***	−3.840***	−1.770*
$Flow_{i,t-1}$	0.120	0.122	0.130
	17.498***	17.679***	15.498***
$R_{i,t-1}$	0.230	0.213	0.193
	11.836***	10.965***	8.209***
$R^2_{i,t-1}$	0.082	0.729	0.538
	0.131	1.182	0.724
Log(TNA)	0.0005	0.0005	0.0004
	3.579***	3.652***	2.775***
Log(Age)	−0.015	−0.015	−0.014
	−33.778***	−33.929***	−26.245***
Expense	−0.348	−0.364	−0.632
	−5.455***	−5.656***	−8.136***
Constant	0.031	0.017	0.019
	7.704***	4.695***	4.323***
Observations	285,113	285,113	200,408
Adjusted R^2	0.039	0.037	0.039

Table A.8: Test H4.3 for fund fragility. This table reports test results of H4.3 in section 2.3.4 from panel regression (13) for corporate bond funds with negative alpha from January 1992 to December 2017. We only include data entries with negative performance as we are interested in strategic complementarities for outflows. The dependent variable is $Flow_{i,t}$. The independent variable of interest is the interaction of past performance, monetary policy uncertainty and an indicator function of market liquidity condition, $Alpha_{i,t-12\rightarrow t-1} * Log(MPU_{HRS})\mathbb{1}(Key)$. Specifically, high MPU_{HRS} equals to one if the corresponding monetary policy uncertainty index is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Fund characteristics include Log(TNA), Log(Age), and expense ratios. Coefficients of regression are reported in the colored rows, and t-statistics are reported in the uncolored rows. Standard errors are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Condition	$Alpha_{i,t}$	t-stats	$Alpha_{i,t}$	t-stats
Low FF rate	-0.20%			
High FF rate	-0.46%			
Diff	0.26%	68.81***		
High VIX	-0.40%			
Low VIX	-0.22 %			
Diff	-0.18%	-58.14 ***		
High TED	-0.41%			
Low TED	-0.22%			
Diff	-0.19%	-68.91 ***		
High DFL	-0.30%			
Low DFL	-0.18%			
Diff	-0.12%	-47.90 ***		
	High VIX		Low VIX	
High MPU_{HRS}	-0.42%		-0.21%	
Low MPU_{HRS}	-0.38%		-0.25%	
Diff	-0.04%	-13.42***	0.04%	37.94***
High MPU_{10}	-0.45%		-0.26%	
Low MPU_{10}	-0.37%		-0.22%	
Diff	-0.08%	-35.25***	-0.04%	-21.40 ***
High MPU_{100}	-0.42%		-0.23%	
Low MPU_{100}	-0.36%		-0.22%	
Diff	-0.05%	-25.41***	-0.01%	-3.82***

Table A.9: The summary statistics for alphas in different market conditions. This table reports the averages of negative alphas in varied market conditions and t-test results of the differences. High MPU_{HRS}, high MPU_{10}, and high MPU_{100} equal to one if the corresponding monetary policy uncertainty index is above the sample median. High VIX, high TED and high DFL equal to one if the corresponding market illiquidity is above the sample median. All the variables are defined in section 3. Standard errors of t-test are clustered at fund share level. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

B Figures

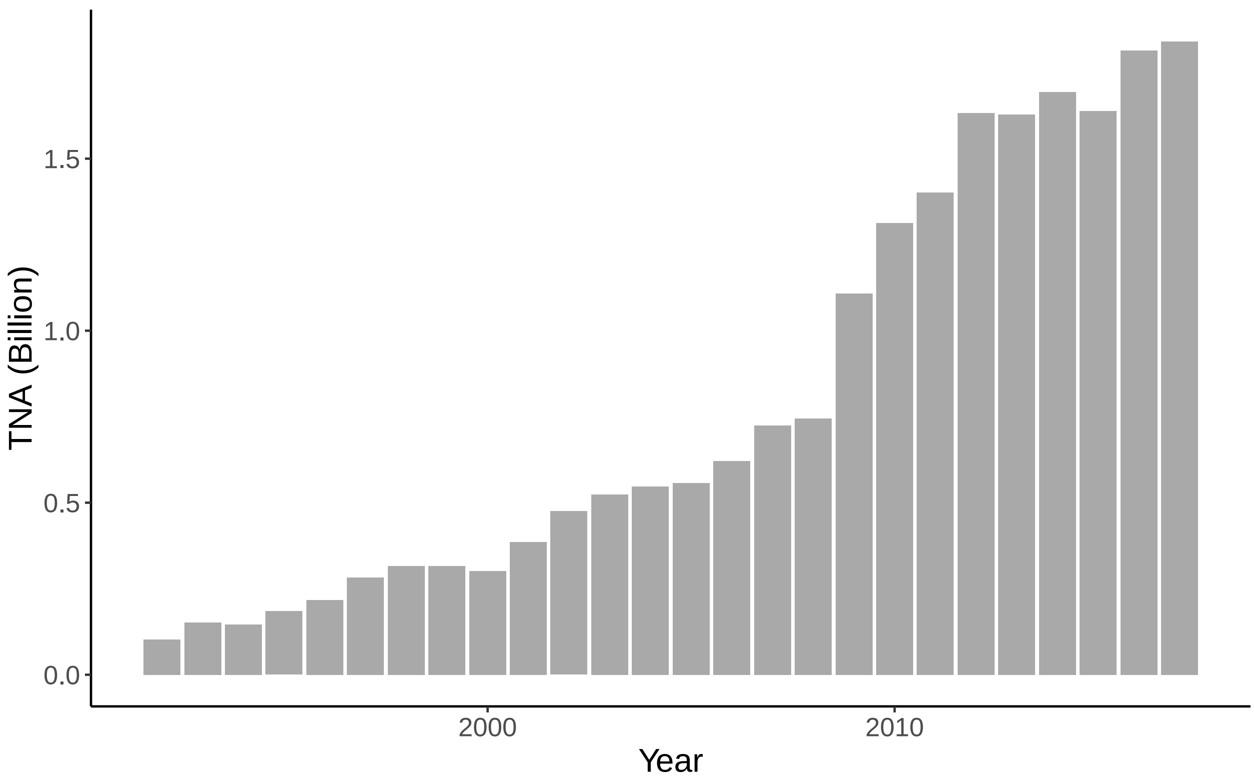

Figure 10: Total net asset of corporate bond funds. This figure shows total net assets (TNA) and dollar flows of managed corporate bond funds from January 1992 to December 2017. We exclude index corporate bond funds, exchange traded funds, and exchange traded notes from the CRSP mutual fund database.

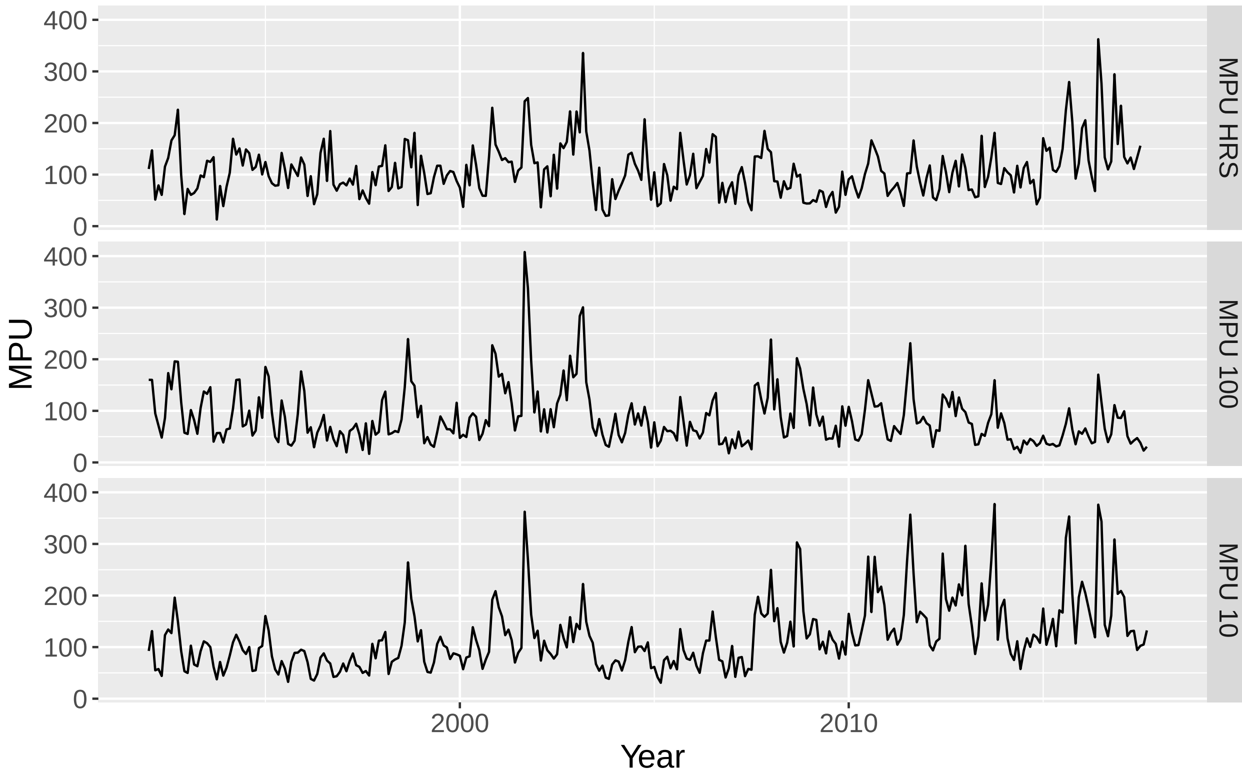

Figure 11: Monetary Policy Uncertainty Index. There figures plot monthly monetary policy uncertainty index constructed by Husted, Rogers, and Sun (2017) in panel 1 and Baker, Bloom, and Davis (2016) in panel 2 and panel 3. "MPU HRS" is constructed based on keywords related to monetary policy uncertainty in the New York Times, Wall Street Journal and Washington Post. Two series constructed by Baker, Bloom, and Davis (2016) use the same criteria to identify articles, but they differ in the set of newspapers covered. "MPU 100" draws on hundreds of U.S. newspapers covered by Access World News and "MPU 10" draws on a balanced panel of 10 major national and regional U.S. newspapers. See http://www.policyuncertainty.com/monetary.html for more details.

C Proofs

C.1 Proposition 1

Proof. This proof applied the standard global results in Goldstein and Pauzner (2005). The proof contains three steps. First, we proof there is a unique symmetric switching strategy, in which every investor withdraws when $s_i > R^*$ and stays when $s_i < R^*$. Second, we show λ given R^* is uniformly distributed. Last, we solve the equilibrium threshold R^*.

Step 1 The net payoff $\Delta\pi(\lambda, R)$ has the function form:

$$\Delta\pi(\lambda, R) = \begin{cases} \frac{1-\frac{\lambda}{\alpha}}{1-\lambda}(1 + r_L(L)) - (1 + \bar{r} + \sigma R) & 0 \leq \lambda \leq \alpha \\ -\frac{\alpha}{\lambda}(1 + \bar{r} + \sigma R) & \lambda > \alpha. \end{cases}$$

This net payoff function has the following properties:

1) $\Delta\pi(\lambda, R)$ is continuous and strictly decreasing in R for all λ (state monotonicity).
2) There is a unique R^* solving $\int_0^1 \Delta(\lambda, R)d\lambda = 0$ (Strict Laplacian State Monotonicity).
3) Payoff function is continuous (continuity).
4) $\Delta(\lambda, R)$ follows the single-crossing property: for each R, there exists a $\lambda^* \in (0, 1)$ such that $\Delta(\lambda, R) < 0$ for all $\lambda > \lambda^*$ and $\Delta(\lambda, R) > 0$ for all $\lambda < \lambda^*$.
5) There are upper and lower dominance regions (limit dominance).

The first four properties are straightforward. We discuss the validity of the fifth property in details. First, there exists a lower dominance region $R \in (-\infty, R^L)$, in which the dominant strategy for investors is to stay in the fund. To obtain this lower dominance region, we further assume that there is no discount in liquidation (i.e, $\alpha = 1$) when $R \in (-\infty, R^L)$. With this assumption, investors in fund do not bear any liquidation cost, so they do not have any incentive to run. This is because their updated beliefs of bank return is very low, compared to the expected return from the fund. Therefore, staying in the dominant strategy.

Second, there exists a upper dominance region $R \in (\frac{r_L(L)-\bar{r}}{\sigma}, \infty)$, in which the dominant strategy for investors is to withdraw from the fund. This happens when the expected return from the fund is less than the bank return even without early withdrawal and liquidation cost (i.e., $1 + r_L(L) < 1 + \bar{r} + \sigma R$). In other words, each investor should withdraw from the fund no matter his beliefs about behavior of other investors. Therefore, withdrawing is the dominant strategy.

Given all five properties of $\Delta(\lambda, \theta)$, Lemma 2.3 in **?** concludes that there is a unique equilibrium and it is in symmetric switching strategy around a critical value R^*.

Step 2 Conditional on observing a realized signal R^*, R has the following distribution

$$F_{R|s_i}(r|R^*) = \frac{\int_{-\infty}^{R^*} f(R) f_\varepsilon(\frac{R^*-R}{\sigma_\varepsilon}) dR}{\int_{-\infty}^{\infty} f(R) f_\varepsilon(\frac{R^*-R}{\sigma_\varepsilon}) dR}.$$

Given the switching strategy defined in Proposition 1, the proportion of investors withdrawing equals to λ:

$$\lambda = Pr(s_i > R^*|R^{'}) = Pr(R^{'} + \sigma_\varepsilon \varepsilon > R^*|R^{'}) = 1 - F_\varepsilon(\frac{R^* - R^{'}}{\sigma_\varepsilon})$$
$$\Rightarrow \quad R^{'} = R^* - \sigma_\varepsilon F_\varepsilon^{-1}(1-\lambda)$$

We denote $G(\cdot|R^*)$ as the cumulative density function for λ given R^*. It can be derived by equaling the probability that a fraction less than λ and the probability that R is less than the $R^{'}$ defined above:

$$\begin{aligned}
G(\lambda|R^*) &= F_{R|s_i}\left(R^* - \sigma_\varepsilon F_\varepsilon^{-1}(1-\lambda)\middle|R^*\right) \\
&= \frac{\int_{-\infty}^{R^*-\sigma_\varepsilon F_\varepsilon^{-1}(1-\lambda)} f(R) f_\varepsilon(\frac{R^*-R}{\sigma_\varepsilon}) dR}{\int_{-\infty}^{\infty} f(R) f_\varepsilon(\frac{R^*-R}{\sigma_\varepsilon}) dR} \\
&= \frac{\int_{F_\varepsilon^{-1}(1-\lambda)}^{\infty} f(R^* - \sigma_\varepsilon z) f_\varepsilon(z) dz}{\int_{-\infty}^{\infty} f(R^* - \sigma_\varepsilon z) f_\varepsilon(z) dz} \qquad z = \frac{R^* - R}{\sigma_\varepsilon} \\
\lim_{\sigma_\varepsilon \to 0} G(\lambda|R^*) &= \frac{\int_{F_\varepsilon^{-1}(1-\lambda)}^{\infty} f(R^*) f_\varepsilon(z) dz}{\int_{-\infty}^{\infty} f(R^*) f_\varepsilon(z) dz} \\
&= 1 - F_\varepsilon\left(F_\varepsilon^{-1}(1-\lambda)\right) \\
&= \lambda
\end{aligned}$$

Therefore, the proportion of investors withdrawing λ given switching threshold R^* is uniformly distributed over [0,1], that is, $f_{\lambda|R^*} = 1$.

Step 3 In the equilibrium, the marginal investor receiving signal R^* is indifference between investing in the fund and the bank, that is, $\int_\lambda \Delta\pi(\lambda) f_{\lambda|R^*} d\lambda = 0$. With above results, this equation can be written as

$$\underbrace{\int_0^\alpha \left((1+\bar{r})(1+\bar{r}+\sigma R^*) - \frac{1-\lambda/\alpha}{1-\lambda}(1+r_L(L))\right) d\lambda}_{\text{net payoff when the fund is liquid}} + \underbrace{\int_\alpha^1 \frac{\alpha(1+\bar{r})}{\lambda}(1+\bar{r}+\sigma R^*) d\lambda}_{\text{net payoff when the fund is illiquid}} = 0$$
$$\Longrightarrow \quad (1+\bar{r}+\sigma R^*) = \frac{1+r_L(L)}{1+\bar{r}} \frac{\frac{1-\alpha}{\alpha}\log(1-\alpha)+1}{\alpha - \alpha\log\alpha}.$$

Rearrange above equation gives the expression (5).

$\square$

C.2 Lemma 4

Proof. We first analyze the relationship between R^* and $\bar{r}$, then the results for the fund run probability $\bar{F}(R^*) = 1 - F(R^*)$ is straightforward.

We replace $(1 + r_L(L))$ in Equation (5) by Equation (7), yielding $h(R^*; \bar{r}, \alpha, \sigma) = 0$, where

(C.1)

$$h(R^*; \bar{r}, \alpha, \sigma) = \frac{1+\bar{r}}{\sigma}\Bigg(\Big(1 - g(\alpha)\Big)F(R^*) + (1-\alpha)\Big(1 - F(R^*)\Big)\Bigg) - \alpha \int_{R^*}^{\infty} RdF(R) - g(\alpha)R^*F(R^*).$$

We compute the effect of $\bar{r}$, σ, α on R^* by using the implicit function theorem as follows:

$$\frac{\partial R^*}{\partial \bar{r}} = -\frac{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \bar{r}}}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}; \qquad \frac{\partial R^*}{\partial \sigma} = -\frac{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \sigma}}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}; \qquad \frac{\partial R^*}{\partial \alpha} = -\frac{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \alpha}}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}.$$

The denominator $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}$ is given by

$$\begin{aligned}
\frac{\partial h(R^*; \bar{r}, \alpha, \sigma)}{\partial R^*} &= \frac{1+\bar{r}}{\sigma}\Big(\alpha - g(\alpha)\Big)f(R^*) + \Big(\alpha - g(\alpha)\Big)R^*f(R^*) - g(\alpha)F(R^*) \\
&= \Big(\frac{1+\bar{r}}{\sigma} + R^*\Big)\Big(\alpha - g(\alpha)\Big)f(R^*) - g(\alpha)F(R^*) \\
&= \frac{1}{\sigma}\frac{1 + r_L(L)}{g(\alpha)(1+\bar{r})}\Big(\alpha - g(\alpha)\Big)f(R^*) - g(\alpha)F(R^*) < 0,
\end{aligned}$$

since $\alpha - g(\alpha) < 0$. Thus, the sign of $\frac{\partial R^*}{\partial \bar{r}}$, $\frac{\partial R^*}{\partial \sigma}$, and $\frac{\partial R^*}{\partial \alpha}$ are the same sign of $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \bar{r}}$, $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \sigma}$ and $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \alpha}$, respectively.

The numerator terms are given by

$$\begin{aligned}
\frac{\partial h(R^*; \bar{r}, \alpha, \sigma)}{\partial \bar{r}} &= \frac{1}{\sigma}\Bigg(\underbrace{\Big(1 - g(\alpha)\Big)F(R^*)}_{\text{Complementarity discount}} + \underbrace{(1-\alpha)\Big(1 - F(R^*)\Big)}_{\text{Liquidity compensation}}\Bigg) \\
\frac{\partial h(R^*; \bar{r}, \alpha, \sigma)}{\partial \sigma} &= -\frac{1+\bar{r}}{\sigma^2}\Bigg(\underbrace{\Big(1 - g(\alpha)\Big)F(R^*)}_{\text{Complementarity discount}} + \underbrace{(1-\alpha)\Big(1 - F(R^*)\Big)}_{\text{Liquidity compensation}}\Bigg) \\
\frac{\partial h(R^*; \bar{r}, \alpha, \sigma)}{\partial \alpha} &= -\frac{1+\bar{r}}{\sigma}\Big(g'(\alpha)F(R^*) + \Big(1 - F(R^*)\Big)\Big) - \int_{R^*}^{\infty} RdF(R) - g'(\alpha)R^*F(R^*) \\
&= -g'(\alpha)F(R^*)(R^* + \frac{1+\bar{r}}{\sigma}) - \Bigg(\frac{1+\bar{r}}{\sigma}\Big(1 - F(R^*)\Big) + \int_{R^*}^{\infty} RdF(R)\Bigg)
\end{aligned}$$

Clearly, the sign of $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \bar{r}}$ and $\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial \sigma}$ depends on the sign of function $k(\alpha, R^*)$:

$$k(\alpha, R^*) = \Big(1 - g(\alpha)\Big)F(R^*) + (1-\alpha)\Big(1 - F(R^*)\Big).$$

Then we prove that there exists and only exists an $\tilde{\alpha}$ such that $k(\tilde{\alpha}, \tilde{R}^*) = 0$ and $k(\alpha, R^*) < 0 \; \forall \; \alpha \in [0, \tilde{\alpha})$ and $k(\alpha, R^*) > 0$, otherwise. First, under the restriction that $1 + r_L(L) > 0$, the threshold R^* is bounded below, i.e., $R^* > -\frac{1+\bar{r}}{\sigma}$ and $F(R^*) > 0$. Since $\lim_{\alpha\to 0} g(\alpha) \to \infty$, we have

$$\lim_{\alpha\to 0} k(\alpha, R^*) = \lim_{\alpha\to 0}(1-\alpha) + (\alpha - g(\alpha))F(R^*) \to -\infty.$$

Notice that $h(R^*; \bar{r}, \alpha, \sigma) = 0$, so $k(\alpha, R^*)$ can also be written as

$$\begin{aligned} k(\alpha, R^*) &= \frac{\sigma}{1+\bar{r}}\Big(\alpha \int_{R^*}^{\infty} RdF(R) + g(\alpha)R^*F(R^*)\Big) \\ &= \frac{\sigma}{1+\bar{r}}\Bigg(\alpha\Big(\int_{R^*}^{\infty} RdF(R) + R^*F(R^*)\Big) + \Big(g(\alpha) - \alpha\Big)R^*F(R^*)\Bigg), \end{aligned}$$

As $\lim_{\alpha\to 1} g(\alpha) - \alpha = 0$, we have

$$\lim_{\alpha\to 1} k(\alpha, R^*) = \frac{\sigma}{1+\bar{r}}\Big(\int_{R^*}^{\infty} RdF(R) + R^*F(R^*)\Big) > 0,$$

The inequality arises as 1) $\int_{R^*}^{\infty} RdF(R) + R^*F(R^*)$ is a increasing function in R^*; 2) $\lim_{R^*\to -\infty} \int_{R^*}^{\infty} RdF(R) + R^*F(R^*) = 0$ and 3) R^* is bounded by $-\frac{1+\bar{r}}{\sigma}$.

Therefore, there exists at least one $\tilde{\alpha}$ such that $k(\alpha, R^*) = 0$. Next, we analyze the derivative of $k(\alpha, R^*)$.

$$\begin{aligned} \frac{\partial k(\alpha, R^*)}{\partial \alpha} &= (\alpha - g(\alpha))f(R^*)\frac{\partial R^*}{\partial \alpha} - \Big(g^{'}(\alpha)F(R^*) + (1 - F(R^*))\Big) \\ &= \frac{\Big(g^{'}(\alpha)F(R^*) + 1 - F(R^*)\Big)g(\alpha)F(R^*) + (\alpha - g(\alpha))f(R^*)\Big(\int_{R^*}^{\infty} RdF(R) - R^*(1 - F(R^*))\Big)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}} \\ &= \frac{\Big(\frac{k(\alpha,R^*)}{F(R^*)(1-\alpha)} + \Big(g^{'}(\alpha) - \frac{1-g(\alpha)}{1-\alpha}\Big)\Big) + (\alpha - g(\alpha))\frac{f(R^*)}{g(\alpha)F^2(R^*)}\Big(\int_{R^*}^{\infty} RdF(R) - R^*(1 - F(R^*))\Big)}{g(\alpha)F^2(R^*)\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}. \end{aligned}$$

The term $\int_{R^*}^{\infty} RdF(R) - R^*(1 - F(R^*))$ is a decreasing function in R^* and $\lim_{R^*\to\infty} \int_{R^*}^{\infty} RdF(R) - R^*(1 - F(R^*)) = 0$, so the term is always positive. Therefore, we have both the denominator and the second term of numerator are negative, and the sign of $\frac{\partial k(\alpha,R^*)}{\partial \alpha}$ is determined by the first term in numerator $\frac{k(\alpha,R^*)}{F(R^*)(1-\alpha)} + g^{'}(\alpha) - \frac{1-g(\alpha)}{1-\alpha}$. Only if this term is positive and big enough, we have $\frac{\partial k(\alpha,R^*)}{\partial \alpha} < 0$.

We use proof by contradiction to prove there is only one $\tilde{a}$ such that $k(\tilde{\alpha}, R^*) = 0$. As $\lim_{\alpha\to 0} k(\alpha, R^*) = -\infty$, $\lim_{\alpha\to 1} k(\alpha, R^*) > 0$ and $k(\alpha, R^*)$ is a continuous function, there must be odd number of solutions to $k(\alpha, R^*) = 0$. Suppose that there are 3 solutions $\tilde{\alpha}_1 < \tilde{\alpha}_2 < \tilde{\alpha}_3$, such that $\frac{\partial k(\alpha,R^*)}{\partial \alpha}\Big|_{\tilde{\alpha}_1} > 0$, $\frac{\partial k(\alpha,R^*)}{\partial \alpha}\Big|_{\tilde{\alpha}_2} < 0$, and $\frac{\partial k(\alpha,R^*)}{\partial \alpha}\Big|_{\tilde{\alpha}_3} > 0$. This implies that at $\tilde{\alpha}_2$, function $z(\alpha) = g^{'}(\alpha) - \frac{1-g(\alpha)}{1-\alpha}$ is positive. Since $z(\alpha)$ is an increasing function in α, it is impossible to find an $\tilde{\alpha}_3$ such that $\tilde{\alpha}_3 > \tilde{\alpha}_2$ and $\frac{\partial k(\alpha,R^*)}{\partial \alpha}\Big|_{\tilde{\alpha}_3} > 0$. Therefore, there exists and only exists an $\tilde{\alpha}$ such that $k(\alpha, R^*) > 0 \; \forall \; \alpha \in [\tilde{\alpha}, 1]$ and $k(\alpha, R^*) < 0$, otherwise.

In summary, $\frac{\partial R^*}{\partial \bar{r}} > 0$, $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}} < 0$ when $\alpha \in [\tilde{\alpha}, 1]$, and $\frac{\partial R^*}{\partial \bar{r}} < 0$, $\frac{\partial \bar{F}(R^*)}{\partial \bar{r}} > 0$ otherwise. Similarly, $\frac{\partial R^*}{\partial \sigma} < 0$, $\frac{\partial \bar{F}(R^*)}{\partial \sigma} > 0$ when $\alpha \in [\tilde{\alpha}, 1]$, and $\frac{\partial R^*}{\partial \sigma} > 0$, $\frac{\partial \bar{F}(R^*)}{\partial \sigma} < 0$ otherwise. □

C.3 Lemma 4

Proof. We can rearrange equation (5) as

$$1 + r_L(L^*) = (1 + \bar{r} + \sigma R^*) g(\alpha)(1 + \bar{r})$$

Then taking derivative on both sides with respect to $\bar{r}$, σ and α yielding

$$\begin{aligned} r^{'}(L^*)\frac{\partial L^*}{\partial \bar{r}} &= g(\alpha)(1+\bar{r})\Big(\sigma \frac{\partial R^*}{\partial \bar{r}} + 1\Big) + g(\alpha)(1 + \bar{r} + \sigma R^*), \\ r^{'}(L^*)\frac{\partial L^*}{\partial \sigma} &= g(\alpha)(1+\bar{r})\Big(\sigma \frac{\partial R^*}{\partial \sigma} + R^*\Big), \\ r^{'}(L^*)\frac{\partial L^*}{\partial \alpha} &= g(\alpha)(1+\bar{r})\sigma \frac{\partial R^*}{\partial \alpha} + (1+\bar{r})(1+\bar{r}+\sigma R^*) g^{'}(\alpha). \end{aligned}$$

Then we plug in results in Proof C.2 to verify the sign of $\frac{\partial L^*}{\partial \bar{r}}$, $\frac{\partial L^*}{\partial \sigma}$ and $\frac{\partial L^*}{\partial \alpha}$.

First, we show the term $\sigma\frac{\partial R^*}{\partial \bar{r}} + 1 > 0$, then $\frac{\partial L^*}{\partial \bar{r}} < 0$.

$$\begin{aligned} \sigma \frac{\partial R^*}{\partial \bar{r}} + 1 &= \frac{-\Big(1-g(\alpha)\Big)F(R^*) - (1-\alpha)\Big(1 - F(R^*)\Big) + \Big(\frac{1+\bar{r}}{\sigma} + R^*\Big)\Big(\alpha - g(\alpha)\Big) f(R^*) - g(\alpha)F(R^*)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}} \\ &= \frac{-F(R^*) - (1-\alpha)\Big(1 - F(R^*)\Big) + \Big(\frac{1+\bar{r}}{\sigma} + R^*\Big)\Big(\alpha - g(\alpha)\Big) f(R^*)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}} > 0. \end{aligned}$$

Second, we can not determine the sign of $\sigma\frac{\partial R^*}{\partial \sigma} + R^*$, so the effect of monetary policy uncertainty on fund flow is uncertain.

$$\sigma \frac{\partial R^*}{\partial \sigma} + R^* = \frac{\frac{1+\bar{r}}{\sigma}\left(\Big(1 - g(\alpha)\Big)F(R^*) + (1-\alpha)\Big(1 - F(R^*)\Big)\right) + R^*\left(\frac{1+\bar{r}}{\sigma} + R^*\right)\Big(\alpha - g(\alpha)\Big)f(R^*) - R^* g(\alpha)F(R^*)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}$$

$$= \frac{R^*\left(\frac{1+\bar{r}}{\sigma} + R^*\right)\Big(\alpha - g(\alpha)\Big)f(R^*) + \alpha \int_{R^*}^{\infty} R dF(R)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}}$$

Since R^* could be positive, the sign of the last term is uncertain.

Third, we show that the term $g(\alpha)\sigma\frac{\partial R^*}{\partial \alpha} + (1 + \bar{r} + \sigma R^*)g'(\alpha) < 0$, then $\frac{\partial L^*}{\partial \alpha} > 0$.

$$g(\alpha)\sigma\frac{\partial R^*}{\partial \alpha} + (1 + \bar{r} + \sigma R^*)g'(\alpha) = \frac{g(\alpha)(1+\bar{r})\Big(1 - F(R^*)\Big) + g(\alpha)\sigma \int_{R^*}^{\infty} R dF(R) + \Big(1 + \bar{r} + \sigma R^*\Big)g'(\alpha)\left(\frac{1+\bar{r}}{\sigma} + R^*\right)\Big(\alpha - g(\alpha)\Big)f(R^*)}{\frac{\partial h(R^*;\bar{r},\alpha,\sigma)}{\partial R^*}} < 0.$$

$\square$

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