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Monetary Policy, Investor Flows, and Loan Fund Fragility

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Abstract

We show that monetary policy shocks have a positive effect on flows in bank-loan mutual funds. This relationship, however, is asymmetric: positive shocks cause small inflows, whereas negative shocks cause large outflows. Further, the effect of monetary policy shocks is stronger when short-term rates are higher. Finally, we document that large outflows from loan funds lead to significant declines in loan-level prices in the secondary leveraged loan market. Our results identify a novel channel of monetary policy transmission that not only affects a critical segment of the credit sector, but also has the potential to impact financial stability.

Key words: mutual funds, monetary policy, leverage lending

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1 Introduction

The way monetary policy affects economic activity through banks and their role as lenders is well understood. The last decades, however, have seen the rapid growth of nonbank financial institutions as key suppliers of credit. Due to their institutional differences, monetary policy will likely affect nonbanks differently from the way it affects banks. In this paper, we study the effect of monetary policy on investor flows in bank loan funds and their subsequent impact on leveraged loan prices, uncovering a new transmission channel of monetary policy to credit markets operating via nonbanks, with potentially important economic and financial stability implications.

Loan funds are open-end debt mutual funds that mainly invest in leveraged loans. We focus on these funds because they have grown significantly over the last 25 years. As Figure 1 shows, their total net assets (TNA) grew by 400% from 2000 to 2023, roughly the same growth rate as high-yield bond funds—another type of debt fund with comparable risk profile. Loan funds are now the largest holders of leveraged loans after collateralized loan obligations (CLOs), becoming an essential lender for a key segment of the credit market (Blackrock, 2019).[1] As a result, significant outflows from loan funds can have material effects on the leveraged lending market.[2]

The effects of monetary policy on financial intermediaries often depend on the institutional characteristics of these firms. This is true for banks (e.g., through the role of deposit franchise, through regulation), and it is also likely to be true for nonbanks.

[1]Leveraged loans account for a sizable share of lending to nonfinancial corporations, amounting to about 50% of total commercial loans, and are typically used to finance important economic activity, such as mergers and acquisitions, leveraged buyouts, business recapitalization, and business expansions.

[2]Anecdotal evidence from the Covid crisis supports this concern: the $14 billion outflow that loan funds experienced in March 2020 was sufficient to generate a severe dislocation in the leveraged loan market (S&P Global, 2020).

Hence, to understand how monetary policy affects loan funds, we build a conceptual framework that hinges on the institutional features of these funds and, in particular, of their holdings—leveraged loans.

Our starting observation is that unanticipated monetary policy rate hikes should positively affect loan funds' performance and therefore investor flows. The reason is that leveraged loans are floating-rate securities with coupons tied to a reference short-term rate. Moreover, their rates reset frequently, on a recurrent basis, normally between 30 and 90 days. This creates an *interest rate channel* of monetary policy (Hypothesis 1): positive monetary policy shocks (tightening) should increase the income stream of loan funds, leading to inflows from investors reaching for income; conversely, negative shocks (easing) should lead to outflows.

We then exploit another institutional feature of leveraged loans: the possibility of renegotiation. When their economic prospects improve, borrowers have an incentive to renegotiate their loans and demand better terms, including lower spreads; in contrast, when economic conditions deteriorate, borrowers have no incentive to renegotiate and instead benefit from the "more favorable" terms of their existing loans. This feature is important for the link between monetary policy and loan funds because positive (negative) policy shocks are typically associated with improving (deteriorating) economic conditions. As a result, positive monetary policy shocks should be associated with an increase in loan renegotiations, which would imply lower spreads and therefore lower income for loan funds.

Consistent with these insights, we show that leveraged loan borrowers are indeed more likely to refinance their loans following positive monetary policy shocks. Further, they are more likely to obtain cuts on their loan rates when they refinance following positive monetary policy shocks.

These observations suggest that for loan fund investors, the potential benefits of a positive monetary policy shock through the interest rate channel described above should be dampened by the compression in loan spreads caused by the renegotiation channel; in contrast, this dampening should not be present when shocks are negative. As a result, the effect of monetary policy on loan fund flows is likely *asymmetric* (Hypothesis 2): the impact of negative shocks (outflows) should be larger in magnitude than the impact of positive shocks (inflows).

We capitalize on yet another feature of leveraged loan contracts – the presence of interest rate floors – to help identify the effect of monetary policy on loan funds. Floor clauses state that the loan rate does not reset when the reference rate is below a certain threshold. This institutional feature, introduced after the Global Financial Crisis (GFC) to guarantee lenders with a minimum return while rates were at or near the zero lower bound (ZLB), suggests that the interest rate channel should be *nonlinear in the level of short-term rates* (Hypothesis 3): the effect of monetary policy on loan fund flows should be stronger when short-term rates are away from the ZLB.

Our empirical analysis, using a monthly panel of loan funds from 2000 to 2023, covering multiple tightening and easing cycles, corroborates these three hypotheses. First, positive monetary policy shocks lead to loan-fund inflows, whereas negative shocks lead to outflows, with an average monthly effect across positive and negative shocks of 0.34 percentage points (pp) of fund TNA per one-unit change in our measure of monetary policy shocks. Second, as we expect, investor reaction to monetary policy shocks is asymmetric: only moderate inflows in response to positive shocks (0.17 pp) and significant outflows in response to negative ones (0.5 pp); the latter effect is economically important, representing 11% of the inter-quartile range of monthly flows in our sample. Finally, we confirm that investors' response is nonlinear in the level of short-term rates: the impact of monetary policy shocks on loan-fund flows is small and insignificant at the ZLB, whereas it is large and significant above the ZLB.

These findings may be confounded by factors affecting debt mutual funds in general and unrelated to the unique institutional features of loan funds' holdings. In particular, the response of loan-fund flows to monetary policy may simply reflect the effect of monetary policy on investors' risk appetite and, therefore, their choice between debt and equity investments. Monetary policy easing, in fact, leads to "risk on" changes in financial markets, including higher stock returns, lower stock-market volatility, and tighter equity premia (Bernanke and Kuttner, 2005; Bauer, Bernanke, and Milstein, 2023). In particular, low policy rates incentivize investors to shift from debt to high-dividend equity funds (Daniel, Garlappi, and Xiao, 2021); moreover, the risk-taking channel of monetary policy also affects investor flows within the debt-fund category, depending on the risk profiles of fund portfolios.

To control for these possible confounding factors and strengthen our identification, we repeat our analysis comparing the flows in loan funds with the flows in high-yield bond funds. While loan funds and high-yield bond funds should be affected by the risk-taking channel of monetary policy in a similar way because they both invest in debt instruments and have similar risk profiles, our hypotheses only hold for loan funds because they are based on specific institutional features of leveraged loans. By using high-yield bond funds as a control group, we can control for time-varying factors common to both fund types and obtain identification from the differential response of loan-fund flows. To control for the effect of monetary policy on bond-fund flows through its effect on bond valuation due to changes in the discount rate, we additionally control for portfolio duration and its interaction with our measure of monetary policy.

The empirical analysis using this tighter identification strategy corroborates all of our findings. Moreover, the results are robust to a battery of additional checks (e.g., including portfolio credit rating-by-time fixed effects, using daily data, controlling for other monetary policy measures), enhancing the confidence in our conceptual framework.

While the first part of our framework focuses on the link between monetary policy and loan-fund flows, the second part focuses on a particular effect of these flows. Specifically, we conjecture that outflows from loan funds should have a negative impact on the prices of the loans held by these funds, whereas inflows should have no price effect (Hypothesis 4). This conjecture is based on two observations: (i) leveraged loans are highly illiquid; (ii) loan funds have to sell part of their loan portfolios to meet large redemptions, whereas they have several options to accommodate subscriptions, at least in the short run.

In our empirical analysis, we test this hypothesis by matching a panel of loan-level daily data on secondary-market prices with a panel of security-level data on loan-fund portfolios. We find that a one-percentage-point outflow from loan funds leads the prices of the loans held by these funds before the outflow to decline by 1.9 pp over 20 days (approximately a month). This effect is economically important, as the standard deviation of 20-day price changes in our sample is 2.7 pp; in contrast, as we conjecture, loan-fund inflows have no significant price impact. These results are qualitatively and quantitatively consistent with the effects of bond-fund flows on bond prices observed in the literature (Falato *et al.*, 2021).

In sum, we show that negative monetary policy shocks cause significant outflows from loan funds (whereas positive shocks have little or no effect), and that loan-fund outflows lead to significant declines in leveraged loans' secondary-market prices (whereas inflows have no effect). These results suggest a novel channel of monetary policy transmission to the leveraged-lending market operating via nonbanks, with potential economic and financial stability implications.

Our paper contributes to the emerging but still small literature on monetary policy and nonbank financial institutions. Stein (2012) argues that monetary policy is a sufficient tool to ensure financial stability when regulated banks are the only financial intermediaries, but it becomes insufficient in more complex systems where intermediation is also provided by nonbank entities. Consistent with this view, Feroli *et al.* (2014) point at a destabilizing role of monetary policy on bond funds: forward guidance could lead to an acceleration of outflows around interest rate hikes, especially after prolonged periods near the ZLB, as it happened during the "taper tantrum" of 2013; see also Stein (2014) and Banegas *et al.* (2016). Our results identify a distinct relationship between monetary policy and mutual funds, showing that loan funds are subject to significant outflows in response to *expansionary* surprises, whereas countervailing effects emerge during tightening periods.

Our paper also contributes to the literature on mutual fund flows and asset prices, and especially fire sales. Coval and Stafford (2007) show that flow-induced selling and buying pressures in equity funds have an impact on stock prices. Falato *et al.* (2021) show that fire sales induced by redemptions in bond funds have a negative impact on bond prices. We contribute to this literature by showing that outflows from loan funds have a similar impact on leveraged loans.

Finally, our paper contributes to the growing literature documenting that debt mutual funds engage in significant liquidity transformation (Ma *et al.*, 2022a and 2022b). In addition to showing that loan-fund outflows cause significant drops in loan-level market prices, in appendix, we also show that loan funds' flow-performance relation is highly concave. Consistent with Chen *et al.* (2010) and Goldstein *et al.* (2017), this evidence suggests that loan funds are exposed to the risk of self-fulfilling runs caused by the mismatch between illiquid assets and liquid (i.e., daily redeemable) liabilities. Moreover, we show that their flow-performance relation is more concave during periods of negative monetary policy shocks, suggesting that loan funds' exposure to self-fulfilling runs is greater exactly when they are more exposed to aggregate outflows.

The rest of the paper is organized as follows. Section 2 describes our conceptual framework and hypotheses. Section 3 describes the data. Section 4 tests the hypotheses on the effects of monetary policy on loan funds' flows. Section 5 investigates the link between loan-fund outflows and individual loan prices. Section 6 concludes.

2 Conceptual Framework and Hypotheses

In this section, we present a conceptual framework to understand how monetary policy affects loan fund flows and, in turn, how these flows affect leveraged loan secondary-market prices. Based on this framework, we develop four testable hypotheses.

To build our conceptual framework, we focus on the institutional characteristics of loan funds and the features of their main portfolio holdings, leveraged loans. The idea is that monetary policy affects the performance of loan funds through its effect on the income stream of leveraged loans; this then translates into an effect on fund flows because investors respond to fund performance. In turn, negative fund flows have a significant impact on the secondary-market prices of the loans held by the funds through a fire sale mechanism typical of mutual funds holding illiquid assets.

2.1 Floating rates and the interest rate channel of monetary policy

A key institutional feature of leveraged loans is that they are floating-rate securities. The loan rate is equal to a reference rate that adjusts on a recurrent basis plus a spread that reflects the creditworthiness of the borrower. The reference rate is tied to a money-market rate (in our sample, mainly the three-month LIBOR) and resets every 30 to 90 days, reflecting changing conditions in short-term rates.

By changing the reference rate, monetary policy shocks affect the income stream of leveraged loans. Of course, monetary policy shocks also affect debt valuations by changing discount rates. Leveraged loan valuations, however, are not materially affected by discount rate changes. The reason is that, because their rates reset frequently, leveraged loans have very short duration. Based on these observations, positive (negative) monetary policy shocks should improve (depress) loan funds' performance by increasing (decreasing) the income stream of their holdings, without significantly affecting their valuations. Consistent with this intuition, in Appendix A, we show that positive monetary policy shocks have a positive effect on loan funds' returns.

Given that investors in open-end mutual funds tend to chase fund performance, we then also expect monetary policy shocks to affect investor flows in these funds.[3] Indeed, in line with existing evidence on other mutual fund categories, in Appendix B, we show that loan fund flows positively respond to past fund performance.

With leveraged loan rates resetting when benchmark rates change, investors should flow into loan funds following positive monetary policy surprises and flow out of them following negative ones. We refer to this effect as the *interest rate channel* of monetary policy on loan fund flows.

Hypothesis 1: Unanticipated monetary policy rate hikes (cuts) cause inflows in (outflows from) loan funds through an interest rate channel linked to the floating-rate feature of leveraged loans.

2.2 Loan renegotiation and the asymmetric effects of monetary policy shocks

In addition to affecting short-term rates, monetary policy is also associated with changes in economic conditions. Specifically, rate hikes tend to signal improving macroeconomic conditions, whereas rate cuts tend to signal deteriorating conditions.[4]

This relation between monetary policy and economic conditions is relevant for

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[3]There is wide literature documenting that investor flows positively respond to fund performance for other mutual fund categories. See Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998) for equity mutual funds; Goldstein*et al.* (2017) for bond funds; Christoffersen and Musto (2002), Kacperczyk and Schnabl (2013), and La Spada (2018) for money market funds.

[4]This relationship can exist either because monetary policy shocks convey new information on economic conditions, leading the public to update its beliefs about the economic outlook (the information effect of monetary policy of Nakamura and Steinsson, 2018), or because changing economic conditions cause changes in monetary policy. Although our evidence on the effect of monetary policy on loan renegotiation in Appendix C suggests the former interpretation — because it is based on policy surprises, we cannot fully rule out the latter. For our purposes, however, this distinction is not material because our **Hypothesis 2** below is valid under either interpretation.

leveraged loans because loans can be renegotiated. When economic prospects improve, borrowers have an incentive to renegotiate the terms of their outstanding loans and ask for lower spreads; in contrast, when economic conditions deteriorate, borrowers have no incentive to renegotiate and instead benefit from the "more favorable" terms of their existing loans.[5] As a result, we expect rate hikes to be associated with an increase in loan refinancing and with a compression of loan spreads. Indeed, in Appendix C, we provide evidence consistent with this intuition. Using data on corporate loans between 2000 and 2023, we show that following positive monetary policy shocks: (i) leveraged loan refinancing is more likely, and (ii) conditional on refinancing, borrowers are more likely to obtain a reduction in their loan spreads.

By reducing the spreads on leveraged loans, the rise in renegotiation following positive monetary policy shocks reduces loan funds' income stream, counteracting the increase in income stream due to the surge in reference rates; that is, the interest rate channel of rate hikes on loan fund flows is dampened by an increase in loan renegotiation. As a result, we expect the relation between monetary policy and loan-fund flows to be asymmetric between positive and negative policy surprises.

Hypothesis 2: The effect of unanticipated monetary policy rate cuts on loan-fund flows (outflows) is stronger in magnitude than that of unanticipated rate hikes (inflows) because the interest rate channel of rate hikes is dampened by an increase in loan renegotiation.

[5]For instance, in 2017, a year characterized by improving macroeconomic conditions, about 70 percent of loan issuance by banks reflected refinancing and repricing of pre-existing loans (Morningstar, 2020).

2.3 Rate floors and the nonlinearity of the interest rate channel

The way monetary policy affects loan fund flows depends on another unique characteristic of leveraged loans: the presence of rate floors. When this happens, the loan rate is equal to the credit spread plus the greater between the reference rate and a predetermined floor. These clauses were introduced around 2010 to protect loan holders from prolonged periods of extremely low interest rates (Roberts and Schwert, 2022).

The presence of rate floors introduces a *non-linearity* in the effect of monetary policy on loan fund flows. Specifically, we expect the interest rate channel to be weaker when short-term rates are at the zero lower bound (ZLB) because reference rates are likely below the floors during those periods.

Hypothesis 3: The effect of the interest rate channel of monetary policy on loan fund flows is smaller in magnitude when short-term rates are at the ZLB due to the presence of rate floors in leveraged loans.

2.4 Leveraged loan illiquidity and the price impact of loan fund outflows

Two features of leveraged loans make these securities highly illiquid. First, leveraged loans are highly bespoke contracts, characterized by a complex covenant structure and limited information disclosure to market participants. A 2011 report by Standard and Poor's highlighted a rise in loan-price volatility in the secondary market, supporting anecdotal evidence that syndicate participants trade on private information. More to the point, Massoud *et al.* (2011), Ivashina and Sun (2011), and Bushman *et al.* (2011) show that investors use the private information they obtain while participating in the syndicated loan market to trade in other markets.

Second, the procedure used to trade leveraged loans is very complex. The purchase and sale of a loan—or of the interests in a loan—are structured as "assignments," in which the buyer becomes the new lender (or one of the new lenders) on record. This process requires the agreement of all parties involved, including the borrower and the other agents (LSTA, 2019). As a result, the settlement period associated with a loan trade can be fairly long, averaging about 10-12 days (Blackrock, 2019). Both their informational complexity and lengthy trading and settlement process make leveraged loans highly illiquid, as documented by Santos and Shao (2023) and Elkamhi and Nozawa (2022).

The illiquidity of loan funds' holdings creates a link between fund outflows and the secondary-market prices of the loans held by these funds. The reason is that mutual funds may be forced to sell their assets to meet investor redemptions, especially when redemptions are large.[6] If the assets are illiquid, outflow-induced sales will depress their market prices. In contrast, inflows should not affect the market prices of the loans held by the funds because the funds can (i) temporarily place the new capital in cash-like products and wait until they find the right investment opportunity and (ii) purchase assets other than what they currently hold. This potential asymmetric effect of loan fund flows on leveraged loan prices is consistent with the results of Falato *et al.* (2021), who show that fire sales induced by redemptions in bond funds have a negative impact on bond prices, but the effect of fund subscriptions is negligible.

[6]Even if funds use their cash buffers to meet redemptions on the same day, they will then need to sell their assets on the following days to replenish their cash buffers and prevent future runs (Zeng, 2017).

Hypothesis 4: Outflows from loan funds depress the secondary-market prices of the loans held by these funds, whereas inflows have no price impact on their loans.

Altogether, our four hypotheses suggest a channel of monetary policy transmission to the secondary market pricing of leveraged loans through the loan fund industry.

3 Data

3.1 Loan funds

Loan funds are mutual funds, mostly open ended, with an investment mandate to hold a portfolio of leveraged loans.[7] Their TNA doubled in size from 2000 to 2007 and shot up after 2010 to reach a peak of $144 bn in April 2014, an almost ten-fold increase since 2000 (see Figure 1). This dramatic growth was largely attributed to the floating-rate feature of these funds' portfolio holdings, combined with investors' expectation of rising rates (Banegas and Goldenring, 2019, Morningstar, 2020). Since the 2010s, loan funds have been the second largest source of funding in the leveraged loan market (Blackrock, 2019, Morningstar, 2024).

Our main source of loan fund data is Morningstar. For each share class, we obtain monthly data on its dollar net flows, TNA, net returns, and expense ratios.[8] These data allow us to construct a monthly panel of 302 loan-fund share classes (74 funds) from

[7]There is no exact definition of what constitutes a leveraged loan. Broadly speaking, leveraged loans are term loans (as opposed to credit lines) that carry a significant amount of risk of default (Kim *et al.*, 2018). Some market participants identify leveraged loans off the borrower's leverage; others use the loan's (or borrower's) rating; others rely on the purpose of the loan (i.e., loans for buyouts, acquisitions, or capital distributions); and yet others use the spread at origination.

[8]A share class is a type of mutual fund share. A mutual fund can offer its investors different share classes; each class within the fund invests in the same portfolio of securities but has different shareholder services, distribution arrangements, fees, expenses, or minimum initial investment requirements.

2000 to 2023[9] For a subset of share classes, we also have daily data on TNA, flows, and returns, which we use in robustness checks; the coverage of these daily data, however, is sparser, with just 84% of the reporting share classes available in the monthly sample. In terms of fund portfolios, we have monthly data on duration, composition (share of loans, bonds, stocks, and cash), average credit rating, and the share of unrated securities.

To clean the data and control for possible incubation and termination effects, we drop observations for the first two months and final month of a share class's lifespan. Following the literature, to mitigate the effect of outliers, we trim flows and returns at the first and ninety-ninth percentiles of their distributions.[10] While our analysis focuses on the absolute effects of monetary policy on loan funds, our robustness checks estimate these effects relative to those on high-yield bond funds. Data on high-yield bond funds are also from Morningstar and are cleaned in the same way as the loan fund data.

Table 1 shows basic summary statistics for both loan and high-yield bond funds over the sample period. Share classes in the two fund types are similar in most characteristics (despite loan funds having slightly lower net returns on average). Loan funds and high-yield bond funds have similar cash and equity holdings, average credit rating, and share of unrated securities. As expected, loan funds hold more loans (70% of their portfolios), and high-yield bond funds hold more bonds (86%). Similarly, since leveraged loans have floating rates, loan funds have shorter portfolio duration (0.5 years versus 3.6 years for high-yield bond funds).

In the last part of the paper, we study the impact of fund flows on the secondary-

[9] We choose January 2000 as our starting date because Morningstar data is not comprehensive before that year.

[10] We trim flows and returns in each month to prevent our sample from being biased towards a specific time period.

market prices of the individual loans held by loan funds. To identify these loans, we use the SEC N-PORT filings. These regulatory data, which all mutual funds are required to file quarterly, have security-level information on fund holdings at the end of the fund's fiscal quarter. We merge these data with the Morningstar data at the fund level. The merged dataset starts in 2019Q4, the first quarter for which N-PORT filings are available on the SEC website. Finally, we merge this dataset with loan-level data from the Loan Syndication and Trading Association (LSTA) to get daily information on loan prices (see next).

3.2 Leveraged loans

Leveraged lending has grown at an average yearly rate of more than 12% since the early 2000s, more than twice as fast as the market for high-yield corporate bonds. In 2024Q2, leveraged lending was estimated at about $1.4 trillion, roughly equal to 50% of total bank lending to non-financial corporations. While banks used to be the almost exclusive source of credit supply for leveraged loans, non-bank lenders have increasingly gained market share. Banks' market share was 70% the 1990s and is currently about 10% (IMF, Global Financial Stability Report, 2019); the largest funding sources in this market are now CLOs and loan funds (Paligorova and Santos, 2018).[11]

We rely on data from the LSTA to get daily information on the secondary-market prices of individual loans. The LSTA provides daily information on each loan that is available to be traded on the market, including the bid and ask prices, and the number of dealers (i.e., the number of quotes), going back to 1998; our data end in 2022Q4. A loan's

[11] It is worth noting that CLOs in turn depend extensively on banks and insurance companies, the two main investors in their bonds (Fringuellotti and Santos, 2021).

bid-ask prices are the average prices reported to the LSTA by all the trading desks at institutions that make the market for the loan; prices are quoted as a percentage of par. We merge these data with our loan-level data on loan fund holdings (see Appendix E for details). We are able to merge 31% of the loans held by loan funds from 2019Q4 through 2022Q4 with LSTA data, accounting for about 18% of the leveraged loans in the LSTA dataset. There are roughly 2.35 million loan-days in the final sample we estimate on.

Finally, we use Dealscan data to investigate the effect of monetary policy shocks on loan refinancing. Dealscan is dominated by syndicated loans and goes back to the 1980s. We use it starting in 2000 to match the sample period of our loan-fund analysis. Dealscan reports for each loan, at the time of its origination, the amount, maturity, purpose, type, spread, and borrower name. It also contains information on the amendments to the loan throughout its life. We build on this information to identify instances when a loan is refinanced (see Appendix C for details).

3.3 Measuring monetary policy surprises

To identify the causal effect of monetary policy on fund flows, it is important to use unanticipated monetary policy changes that affect these funds' income stream. We rely on Swanson (2021) forward guidance shocks. Using 30-minute asset-price responses to FOMC announcements, Swanson (2021) estimates a three-dimensional factor model with structural restrictions to separately identify shocks to the federal funds rate, forward guidance, and Large Scale Asset Purchases (LSAP), for all announcements from 1991.[12]

We use Swanson (2021) forward guidance shocks for two reasons. First, by con-

[12]While Swanson (2021) only estimates the shocks up to 2019, the author has very generously provided us with the additional shocks throughout 2023.

struction, they capture surprises on the path of short-term rates.[13] Since leveraged loans are priced off the 3-month LIBOR or similar reference rates, forward-guidance shocks should have a material and direct impact on loan funds' income stream; in Appendix A, we confirm that this is indeed the case. Second, Swanson (2021) forward guidance shocks exhibit significant variation throughout our sample; see Figure 1 in Swanson (2021).

Although federal funds shocks could also capture surprises in reference rates, Swanson (2021) shows that these shocks exhibit very little variation for most of our sample. This is because (i) the federal funds rate does not materially change at the ZLB (November 2008-December 2015 and March 2020-March 2022), and (ii) most FOMC changes in the target rate in our sample were highly anticipated by market participants.[14] In other words, the information content of the federal funds rate is small in our sample.

As for the LSAP shocks, they do not capture changes in reference rates by construction. The reason is that, by their own nature, LSAPs are intended to affect long-term rates through the purchases of long-term treasuries and MBSs; they are not meant to affect the short end of the yield curve.

For these reasons, in our empirical analysis, we focus on the impact of forward guidance shocks ("FG Shock") on fund flows. We also show, however, that our results are robust to controlling for the concomitant effects of the other two factors. Because our main data on fund flows are monthly, we convert Swanson (2021) surprises, which are measured around each FOMC announcement, to monthly frequency. For each month,

[13]Swanson (2021): "forward guidance [is defined] to be the component of FOMC announcements that conveys information about the future path of short-term interest rates above and beyond changes in the target federal funds rate itself."

[14]Swanson (2021): "Throughout the 2009–15 ZLB period, the funds rate was close to zero and barely changed, even in response to FOMC announcements;" and "the federal funds rate factor remains very small even after 2015, as the FOMC raised rates gradually and very predictably (similar to the period from 2003–07)."

our monetary policy shock is equal to Swanson (2021) surprise if a FOMC meeting occurred during that month and equal to zero if there were no meetings (and therefore no surprises) in that month. In robustness checks, we use daily fund-flow data and Swanson (2021) original daily-frequency shocks.

4 Monetary Policy and Loan-Fund Flows

In this section, we test our first three hypotheses on the effects of monetary policy on loan fund flows. We begin by testing these hypotheses looking only at loan fund flows, i.e., estimating absolute effects. Because these absolute effects could be driven by the general impact of monetary policy on investors' preference for risky debt (rather than the specific institutional features of leveraged loans as we conjecture), we then replicate our analysis using high-yield bond funds as a control group, i.e., we estimate relative effects to strengthen our identification.

4.1 The *absolute* effects of monetary policy shocks on loan-fund flows

4.1.1 The interest rate channel

Our Hypothesis 1 posits that monetary policy shocks have a positive impact on loan-fund flows through an interest-rate channel linked to the floating-rate feature of leverage loans; that is, by increasing reference rates and therefore the income stream of leveraged loans, hikes lead to inflows, while cuts lead to outflows. To test this hypothesis, we estimate the following monthly regression at the share-class level:

$$\text{Flow}_{it} = \beta\,\text{FG Shock}_t + \theta\,\text{Flow}_{it-1} + \phi\,\text{Controls}_{it-1} + \alpha_i + \gamma\,\text{Macro Factors}_t + \varepsilon_{it}\,, \tag{1}$$

where Flow_{it} is the net percentage flow of class i in month t relative to the class TNA in month $t-1$, and FG Shock is Swanson (2021) forward-guidance surprise (our proxy for monetary policy shocks). The coefficient of interest is β, estimating the sensitivity of loan-fund flows to monetary policy shocks, which we expect to be positive.

We include lagged flows as a regressor to control for serial correlation. "Controls" is a vector of additional time-varying controls, including the logarithm of TNA, the expense ratio, and the percentage of the fund portfolio invested in cash. It also includes the lagged net return and its interaction with a negative-return dummy to control for the effect of past performance and allow for a differential sensitivity to positive and negative performance. Consistent with this choice, in Appendix B, we show that loan funds' flow-performance relation is indeed significantly concave.

"Macro Factors" is a set of time-varying macroeconomic controls which includes the VIX to control for broad changes in investors' risk aversion and market uncertainty, the excess bond premium from Gilchrist and Zakrajsek (2012) to control for variation in investors' risk appetite in corporate debt markets, and the unemployment rate to control for fluctuations in economic activity. Finally, we include share-class fixed effects (α_i) to control for unobserved cross-sectional heterogeneity.

Regression (1) is estimated on the sample of loan fund share classes from January 2000 to December 2023. Results are in Table 2; standard errors are clustered at the share-class level to be robust to serial correlation. Column (1) reports the baseline results from regression (1). Consistent with our Hypothesis 1, loan-fund investors positively respond to monetary policy shocks: a one-unit increase in Swanson (2021) forward-guidance surprise increases loan fund flows by 0.34 pp (p-value < 0.01).[15] This effect is economically important because it corresponds to 8% of the inter-quartile range of loan funds' monthly flows in our sample.[16] It is also comparable in magnitude (but with the opposite sign) to the effect of monetary policy on bond-fund flows documented in the literature (Feroli *et al.* 2014; Brooks *et al.*, 2018; Fang, 2022).[17]

Columns (2) and (3) show the results of two important robustness checks, namely when we augment regression (1) to include portfolio rating fixed effects and rating-by-month fixed effects, respectively. Portfolio credit rating fixed effects control for the effect of changes in the fund risk profile on investor flows. Portfolio rating-by-month fixed effects, in turn, allow the effect of this possible confounding factor to be time-varying.[18] The estimates remain statistically significant at the 1% level and quantitatively similar, suggesting that our findings are not driven by variation in the credit risk of fund portfolios or by changes in the way investors respond to this risk over time. For example, if we control for portfolio rating-by-time fixed effects, a one-unit increase in the forward-guidance shock leads to monthly inflows in loan funds of 0.28 pp (p-value < 0.01).

[15]In our sample, the standard deviation of the forward-guidance shock is approximately one (0.92).

[16]The inter-quartile range of loan funds' monthly flows in our sample is 4.4. pp.

[17]Feroli *et al.* (2014), for instance, find that a one-standard-deviation increase in their monetary policy surprise (Wright, 2012) leads to monthly outflows from bond funds of about 0.2%.

[18]Portfolio credit rating fixed effects are implemented as a separate dummy for each rating category from Below B to AAA and Unrated; rating-by-month fixed effects are implemented as a separate dummy for each rating category in each month, except for the B-rated category, which we use as a baseline to avoid collinearity with the monetary policy shock the other macro variables.

4.1.2 The asymmetric effects of positive and negative shocks

Our Hypothesis 2 posits that the effect of positive monetary policy shocks (hikes) on loan fund flows is smaller in magnitude than that of negative shocks (cuts); the reason is that positive surprises are associated with an increase in leveraged loans' refinancing that dampens the effect of the interest-rate channel on the income stream of leveraged loans by compressing loan spreads. Consistent with this conjecture, in Appendix C, we document that following positive monetary policy shocks, leveraged loan borrowers are more likely to refinance their loans and, conditional on refinancing, to obtain lower spreads on their loans.

To test Hypothesis 2, we run regression (1) on our monthly panel of loan-fund share classes from 2000 to 2023, estimating separate coefficients for positive and negative monetary policy shocks. Results are in Table 3; standard errors are clustered at the share-class level to control for serial correlation.

While both positive and negative monetary policy shocks have a significant effect on loan funds flows, the magnitude of the effect of positive shocks is smaller, consistent with Hypothesis 2. A one-unit increase in Swanson (2021) forward guidance shock leads to a monthly inflow in loan funds of 0.17 pp (p-value $= 0.03$), whereas a one-unit decrease leads to a monthly outflow of 0.5 pp (p-value < 0.01). Not only is the effect of negative monetary policy shocks larger in magnitude (11% of the inter-quartile range of monthly flows against only 4% for the effect of positive shocks), but it is also more precisely estimated.

In Columns (2) and (3), we replicate our analysis adding portfolio rating fixed effects and rating-by-month fixed effects, respectively. Results are largely unchanged, suggesting that our findings are not driven by variation in the credit risk of fund portfolios or by changes in the way investors respond to this risk over time. For example, when including rating-by-month fixed effects (our most general regression specification), a one-unit increase in Swanson (2021) forward guidance shock leads to monthly loan fund inflows of 0.15 pp (p-value = 0.08), whereas a one-unit decrease leads to monthly outflows of 0.42 pp (p-value < 0.01).

4.1.3 Rate floors and the nonlinearity of the interest-rate channel

Hypothesis 3 posits that the effect of the interest-rate channel of monetary policy on loan fund flows is smaller when short-term rates are at the ZLB due to the presence of rate floors in loan contracts. When reference rates are below the floor, loan rates do not reset and, therefore, the interest rate channel has no impact on the income stream of leveraged loans. We can think of this hypothesis as a way to strengthen the identification of the interest rate channel.

Rate floors are different across loans and even though they do not change during the life of the loan, they change over time, depending on market conditions. Since we do not have information on the average rate floors in fund portfolios, we formulate Hypothesis 3 using the ZLB as a cutoff. At the ZLB, short-term rates are most likely below any floor and, therefore, rate floors are binding; as a result, during these periods, fund flows should display smaller sensitivity to monetary policy surprises. Above the ZLB, there is a range of short-term rates in which loan reference rates are still below at least some floors; overall, however, the flow sensitivity to monetary policy surprises should be higher.[19]

Since rate floors were widely introduced at the beginning of 2010, to test Hypothesis 3, we estimate regression (1) on 2010-2023.[20] We then split this period in two separate sub-samples and estimate the regression separately on each sub-sample: on periods when short-term rates were at the ZLB (January 2010-December 2015 and March 2020-March 2022), and on periods when short-term rates were above the ZLB.

Results are in Table 4; odd columns report the results for ZLB periods, while even columns report those for above-ZLB periods. Standard errors are clustered at the share class level to control for serial correlation.

Consistent with Hypothesis 3, Swanson (2021) forward guidance shocks have a small and insignificant effect on loan fund flows at the ZLB but have a large and significant effect above the ZLB. Based on our baseline specification (Columns (1) and (2)), a one-unit increase in this measure of monetary policy shocks does not lead to significant inflows at the ZLB (0.14 pp with p-value = 0.11) but leads to significant monthly inflows of 0.25 pp (p-value < 0.01) above the ZLB.

Again, we see that the effects are practically unchanged if we include portfolio rating fixed effects (Columns (3) and (4)) and rating-by-month fixed effects (Columns (5) and (6)), suggesting that our results are not driven by variation in the credit risk of fund portfolios or by changes in the way investors respond to this risk over time. For example, according to the specification with rating-by-month fixed effects, the impact

[19] If anything, the regressions on above-ZLB periods should *underestimate* the true sensitivity above floor rates, exactly because reference rates were still below their floors for some time during these periods.

[20] "After anemic new issuance volumes in 2008 and 2009, [...] the bank loan market re-opened robustly in 2010, inspired by a novel and protective floating-rate feature, the LIBOR floor." DDJ Capital Management (2015).

of monetary policy shocks on loan funds flows at the ZLB is even smaller than in our baseline results (0.01 pp with p-value = 0.94), while the impact above the ZLB is the same (0.26 pp with p-value < 0.01).

4.2 Identification using high-yield bond funds as control

4.2.1 The *differential* effects of monetary policy on loan-fund flows

One potential concern with the results of Section 4.1 is that they may be driven by the general impact of monetary policy on investors' risk appetite and, therefore, on their overall choice between equity and debt mutual funds, rather than by leveraged loans' specific institutional features. Monetary policy easing leads to risk-on periods, characterized by higher stock returns, lower stock-market volatility, and tighter equity premia (Bernanke and Kuttner, 2005; Bauer *et al.*, 2023); low policy rates, in particular, incentivize investors to shift from debt to high-dividend equity funds (Daniel *et al.*, 2021). This channel, in principle, could explain why negative monetary policy shocks lead to significant outflows from loan funds.

To control for the general effect of monetary policy on all debt funds, we compare loan-fund flows with the flows in the other debt-fund category with similar credit-risk profile: high-yield corporate bond funds. As we shown in Table 1, loan funds and high-yield bond funds have similar characteristics, suggesting that high-yield bond funds are a good control group; importantly, consistent with Banegas and Goldenring (2019), the average portfolio credit rating is similar in the two fund types. By using high-yield bond funds as reference group, we therefore control both for the common effect of the risk-taking channel of monetary policy on debt funds relative to equity funds and for its differential effects across debt funds due to different risk exposures.

All our hypotheses about the effects of monetary policy on loan fund flows in absolute terms should also hold relative to high-yield bond fund flows. The reason is that high-yield bonds do not share the institutional features of leveraged loans that generate those predictions; namely, high-yield bonds do not have floating rates, are less often renegotiated, and do not have rate floors. Indeed, consistent with the interest rate channel also working in relative terms, Columns (4)–(6) of Table A1 in Appendix A show that monetary policy shocks have a positive impact on loan funds' returns relative to those of high-yield bond funds.

To test Hypothesis 1, we estimate the *differential* effect of monetary policy shocks on loan fund flows relative to high-yield bond fund flows, irrespective of the sign of the shocks or the level of short-term rates. Namely, we modify regression (1) as follows:

$$\begin{aligned}\text{Flow}_{it} = {} & \beta\,\text{Loan}_i \times \text{FG Surprise}_t + \theta\,\text{Flow}_{it-1} + \phi\,\text{Controls}_{it-1} + \\ & \gamma\,\text{Loan}_i \times \text{Macro Factors}_t + \alpha_i + \mu_t + \varepsilon_{it}\,,\end{aligned} \tag{2}$$

where Loan is a dummy variable for share classes belonging to loan funds.[21] As in regression (1), Flow_{it} is share class i's percentage net flow in month t, and we include its lagged value as independent variable to control for serial correlation. In addition to all the variables used in regression (1), the vector of controls also includes the interaction of the loan-fund dummy with the share class past net return, allowing for a differential effect

[21] A few share classes (13 out of 2,074) in our sample switch from being part of a loan fund to being part of a high-yield bond fund, or vice versa; for these share classes, we use the value of the loan-fund dummy in the previous month. Excluding these observations does not affect our results.

of positive and negative returns. As we show in Appendix B, investor flows respond to the past performance of loan funds more strongly than to that of high-yield bond funds, with the differential effect being even stronger for negative returns.

The vector of controls in regression (2) also includes a fund's lagged portfolio duration and its interaction with the monetary policy shocks. The reason is that bonds have longer durations than leveraged loans (3.6 versus 0.5 years in our sample); as a result, they are more affected by the effect of monetary policy on discount rates. For example, by decreasing discount rates, a negative policy shock would increase bond valuations relative to loans and, therefore, the returns of high-yield bond funds relative to loan funds. This discount-rate channel would lead to outflows (inflows) from loan funds relative to high-yield bond funds following negative (positive) shocks, confounding our hypothesis tests. Including portfolio duration and its interaction with the monetary policy variable allows us to control for this confounding factor.[22]

As in regression (1), we include share-class fixed effects (α_i) to control for unobserved cross-sectional heterogeneity; in this tighter specification, however, we can also include time (month) fixed effects (μ_t), thus controlling explicitly for unobserved time-varying common factors, such as the possible changes in risk appetite predicted by the risk taking channel of monetary policy. Finally, we add the interactions of the loan-fund dummy with the Macro Factors in regression (1)—the VIX, excess bond premium, and unemployment rate—to allow these variables to have differential effects on loan and high-yield bond funds.

[22]Brooks *et al.* (2018) and Fang (2022), in fact, show that the impact of monetary policy on bond-fund flows depends on portfolio duration.

The coefficient of interest in regression (2) is β, which represents the differential sensitivity of loan-fund flows to monetary policy shocks relative to flows in high-yield bond funds. Column (1) of Table 5 shows the results and is the equivalent of Column (1) of Table 2 (where we report the absolute sensitivity of loan-fund flows). As in Table 2, Columns (2) and (3) report the results when we add portfolio credit rating and rating-by-month fixed effects. Standard errors are clustered at the share-class level to control for serial correlation.

Consistent with the estimates of the absolute effect in Table 2, the differential effect of monetary policy shocks on loan-fund flows is also positive and important across specifications. A one-unit increase in the Swanson (2021) forward guidance surprise leads to additional monthly flows in loan funds of 0.5–0.52 pp of fund TNA (p-value < 0.01 in all specifications), relative to high-yield bond funds. This evidence reinforces the prior of the existence of an interest rate channel of monetary policy working through leveraged loans' floating-rate feature (Hypothesis 1). This effect is also economically important, representing 11–12% of the inter-quartile range of monthly flows.

For robustness, in Appendix D, we replicate Table 5 controlling for the other types of monetary policy shocks developed by Swanson (2021): the federal funds rate and LSAP surprises. Results are in Table D1; the effect of Swanson (2021) forward guidance shocks on loan-fund flows relative to high-yield bond-fund flows is practically unchanged (0.54 pp per unit shock with p-value < 0.01), whereas neither the federal funds rate nor the LSAP shocks have significant effects, consistent with the discussion in Section 2 and supporting our choice to focus on the effects of forward guidance.

Next, we repeat the test of Hypothesis 2, on the asymmetric effects of positive and negative monetary policy shocks. Similar to what we do in the analysis of absolute effects, we estimate regression (2) allowing positive and negative shocks to have different effects on loan-fund flows; this time, however, the effects are measured relative to those on high-yield bond-fund flows. Results are in Table 6, the equivalent of Table 3.

Consistent with Hypothesis 2 and the results on absolute effects in Table 3, negative monetary policy shocks have a stronger effect than positive ones. Across all specifications, a one-unit decrease in Swanson (2021) forward guidance shock leads to additional monthly outflows from loan funds of 1.2 pp (p-value < 0.01), relative to high-yield bond funds; this effect is economically important as it represents 27% of the inter-quartile range of these funds' monthly flows. In contrast, the differential effect of positive shocks across the two fund types is insignificant; this evidence suggests that the compression of loan spreads caused by the increase in refinancing associated with positive monetary policy shocks may offset the increase in reference rates caused by these shocks through the interest rate channel.[23]

Finally, we repeat the test of Hypothesis 3, on the non-linearity of the interest rate channel as a function of short-term rates. Similar to Table 4 for the analysis of absolute effects, Table 7 shows the differential effect of monetary policy on loan-fund flows relative to high-yield bond-fund flows, at the ZLB and above the ZLB separately. Consistent with Hypothesis 3 and the evidence in Table 4, the impact of monetary policy on relative flows is insignificant when short-term rates are at the ZLB (and hence likely below any

[23]Although some corporate bonds have callable options, due to their fixed-income nature, they will likely be "called" when interest rates decline (the opposite of what we document for leveraged loan refinancing). As a result, negative monetary policy shocks could lead to a drop in the income stream of bond funds, which in turn would lead investors to flow into loan funds. That is, bond callability could bias our estimates of the effect of negative monetary policy shock on loan funds' relative flows downward. By identifying a significant effect, the results in Table 6 add support to Hypothesis 2.

rate floor); in contrast, above the ZLB, the effect is significant and important: a one-unit decrease in Swanson (2021) forward guidance shock leads to additional monthly outflows from loan funds of 0.5 pp (p-value < 0.01), 12% of flows' inter-quartile range.

For robustness, in Appendix D, we replicate Table 7 using LIBOR $< 1.1\%$ as threshold for the nonlinearity of the interest rate channel, instead of the ZLB. We choose this threshold because, in Dealscan, the mean rate floor for the leveraged term loans over 2010-2023 is 1.08%. [24] Results are in Table D2 and show that the nonlinearity of the interest rate channel as a function of short-term rates is robust to this alternative choice of the threshold: when LIBOR is below 1.1%, monetary policy shocks have no significant effect on loan-fund flows relative to flows in high-yield bond funds; in contrast, the effect is significant and close to the estimates from Table7 when LIBOR is above 1.1% (0.5 pp per unit shock (p-value < 0.05).

4.2.2 Daily frequency analysis

One potential concern with our analysis is the frequency mismatch between the monetary policy surprises, which are constructed on a daily basis around FOMC announcements, and the monthly data on fund flows. We rely on monthly fund-flow data because daily data are not available for the full sample period, 2000–2023; they are only available for a sizable share of funds from January 2010. The frequency mismatch between the dependent and independent variables exposes the monthly analysis to potential identification problems.

[24] Consistent with the discussion Appendix C, in this computation, we define a loan in Dealscan as a leveraged loan if its spread over LIBOR is greater than 275 basis points.

To address this issue, we replicate our results using daily data on fund flows from 2010 to 2023. Namely, based on regression (2), we run the following local projections (Jorda, 2005) at the daily frequency:

$$\begin{aligned}\text{Flow}_{i,t+h} =& \beta_h \,\text{Loan}_i \times \text{FG Shock}_t + \theta\, \text{Flow}_{it-1} + \phi\, \text{Controls}_{it-1} + \\ & \gamma\, \text{Loan}_i \times \text{Macro Factors}_t + \alpha_i + \mu_t + \psi_{r(i)t} + \varepsilon_{it}\,, \qquad (3)\end{aligned}$$

where $\text{Flow}_{i,t+h}$ is share class i's net percentage flow from day $t-1$ to $t+h$ relative to the class TNA on $t-1$; FG Shock_t is Swanson (2021) original forward guidance surprise on day t (equal to zero if there is no FOMC announcement on that day); and $\psi_{r(i)t}$ are portfolio credit rating-by-time fixed effects to control for the possible time-varying effect of fund risk exposure. All the other variables are defined as in regression (2).

We estimate regression (3) at different horizons, from $h = 1$ to $h = 20$ business days, roughly corresponding to one month. The object of interest is β_h, which measures the effect of a monetary policy surprise on loan-fund flows h days ahead, relative to its effect on high-yield bond-funds flows. Figure 2 shows our estimates of β_h, together with their 95% confidence intervals. Monetary policy shocks have a positive and significant impact on loan-fund flows relative to high-yield bond-fund flows, throughout the four weeks following an FOMC announcement: a one-unit drop in Swanson (2021) forward-guidance shock leads to additional outflows of 0.19 pp (p-value < 0.01) from loan funds, over the 20 days following the announcement. Importantly, this estimate is of the same order of magnitude as that obtained using contemporaneous monthly data and accounting for portfolio rating-by-time fixed effects, 0.5 pp (see Column (3) of

Table 5.

We have also run this daily frequency analysis to test Hypotheses 2 and 3. Namely, we estimate two modified versions of the local projections in equation (3): one with separate coefficients for positive and negative monetary policy shocks, and one separating periods when short-term rates are at the ZLB from periods when short-term rates are above the ZLB. The results of these robustness tests are in Figures 3 and 4.

Panel (a) of Figure 3 shows the impact of negative monetary policy shocks on loan-fund flows relative to flows in high-yield bond funds; panel (b) shows the impact of positive shocks. The effect of negative shocks is significant, indicating additional outflows from loan funds of about 0.29 pp (p-value < 0.01) at 20 days from the shock, which is of the same order of magnitude as the monthly estimate in the previous section; the effect of positive shocks, in contrast, is insignificant throughout the 20-day horizon.

Panel (a) of Figure 4 shows the impact of monetary policy shocks on loan-fund flows relative to high-yield bond-fund flows at the ZLB; panel (b) shows the impact away from the ZLB. These daily estimates corroborate the monthly estimates in the previous section: policy shocks have no significant effect at the ZLB, but their effect is significant, and of the same order of magnitude as our monthly estimates, above the ZLB.

Of course, the results of this daily analysis should be taken with caution due to the low coverage of daily data in the cross-section of funds. They do, however, support the findings from our monthly regressions, suggesting that the frequency mismatch between monthly fund-flow data and daily monetary policy surprises does not drive our results.

In sum, we find strong evidence that loan-fund flows positively respond to monetary policy shocks, consistent with the interest rate channel put forth in our hypotheses.

The effect is asymmetric: while positive surprises have no significant effect on loan-fund flows (consistent with a counteracting effect due loans' renegotiation), negative surprises lead to significant outflows from loan funds. Finally, the strength of the interest rate channel increases with the level of short-term rates, likely due to the presence of rate floors in leveraged loans. Altogether, these results confirm that loan funds' unique institutional features play an important role in monetary policy transmission. In the next section, we investigate the impact of this monetary policy transmission channel on secondary market loan prices.

5 Loan Fund Outflows and Leveraged Loan Prices

The results of Section 4 identify a link between monetary policy and investor flows in loan funds. In particular, negative monetary policy shocks (cuts) lead to large outflows, whereas positive shocks (hikes) lead to moderate or zero inflows. Investor redemptions, especially when large, will force loan-fund managers to sell some of their assets; since leveraged loans are highly illiquid, these fire sales can negatively affect market loan prices. This is our Hypothesis 4, which we test next. We end the section with a discussion of the potential implications of these market price effects for financial stability.

5.1 Loan funds' outflows and loan prices

We formally investigate the link between loan funds' outflows and loan prices using both daily loan-level pricing data and monthly aggregate price data. The high-frequency loan-level analysis allows us to identify the link between investor flows and the secondary-market prices of the loans held by loan funds, but data limitations preclude us from running this analysis on our entire sample period (see Section 3 for details). For this reason, we complement this investigation with a study of the relation between aggregate fund flows and aggregate loan prices on the entire sample.

5.1.1 Loan-level analysis

Our loan-level analysis builds on a daily panel of leveraged loans from 2019Q4 to 2022Q4; we describe this dataset and its construction in detail in Section 3 and Appendix E. For each loan-day in our panel, we observe the secondary market price, whether the loan is held by a loan fund, and the net dollar flows of the funds holding the loan, as well as the loan amount, facility size, and TNA of the funds holding the loan.

On this daily panel of leveraged loans, we run a regression *a la* Edmans *et al.* (2012) using local projections (Jorda, 2005). Namely, we regress a loan's price change at different horizons against a loan-level *flow-pressure variable* that measures the trading pressure induced by the flows in the loan funds holding the loan.

For each loan i and day t, we compute

$$\text{Flow Pressure}_{it} = \left(\sum_{f \in Funds} \frac{\text{Value}_{i,f,t-1}}{\text{Loan Size}_i} \times \frac{\$ \text{ Net Flow}_{ft}}{\text{TNA}_{f,t-1}} \right), \tag{4}$$

where $\text{Value}_{i,f,t-1}$ is the dollar amount of loan i held by fund f as of the latest available data on fund portfolios prior to day t, and Loan Size_i in the total dollar amount of the loan at origination.[25] $\$ \text{ Net Flow}_{ft}$ is fund f's dollar net flow on day t; and $\text{TNA}_{f,t-1}$ is

[25]Loan funds typically hold fractions of the total loan issued at origination. Regarding the timing and availability of portfolio data, funds file the SEC N-PORT data quarterly, but the month they report varies based on their fiscal year. To construct our daily panel, for every day in a fund's fiscal quarter, we set the fund's portfolio holdings on that day

the fund's lagged TNA.

Flow Pressure aims to measure the trading pressure on a loan price induced by the daily flows in the funds holding the loan. The pressure is negative if the funds experience outflows, as they may have to sell the loan to meet the redemptions; the pressure is positive if the funds experience inflows, as they may want to buy more of that loan. Intuitively, the absolute value of such pressure metric is higher when the funds hold a higher proportion of the loan or when they experience larger flows in absolute value.

As we argue in Section 2, the impact of inflows on the prices of loans held by the funds right before the flows should be smaller in magnitude than the impact of outflows. This is because the funds can accommodate inflows by temporarily holding cash until they find the right investment opportunity or simply by purchasing other loans. In contrast, outflows force funds to sell the loans they currently hold, either on the day of the outflow (if the redemptions are larger than the cash buffer) or in the upcoming days (to replenish their cash buffers; see Zeng, 2017).

To capture the asymmetry between the trading pressure induced by fund inflows and that induced by fund outflows, we define the following negative and positive flow-pressure measures:

$$\text{Negative Flow Pressure}_{it} = \text{Flow Pressure}_{it} \times \mathbb{1}(\text{Flow Pressure}_{it} < 0),$$

$$\text{Positive Flow Pressure}_{it} = \text{Flow Pressure}_{it} \times \mathbb{1}(\text{Flow Pressure}_{it} > 0).$$

equal to those reported at the end of the previous fiscal quarter (i.e., portfolio data on day t reflect information which is between one and 59 business days old).

We then estimate the following local projections:

$$\Delta P_{i,t+h,t-1} = \alpha_h \text{ Negative Flow Pressure}_{it} + \beta_h \text{ Positive Flow Pressure}_{it} + \gamma_h \Delta P_{i,t-1} + \mu_i + \eta_t + \varepsilon_{it}, \quad (5)$$

where $\Delta P_{i,t+h,t-1}$ is the change in the price of loan i from day $t-1$ to day $t+h$, and μ_i and η_t are loan and day fixed effects; to control for potential serial correlation in price changes, we also include $\Delta P_{i,t-1}$, the change in loan i's price from day $t-2$ to day $t-1$. Based on Hypothesis 4, we expect α_h to be positive (i.e., outflows lead to price drops), and β_h to be insignificant (i.e., no effect of inflows).

Figure 5 shows the estimates of α_h and β_h from regression (5) for $h = 1, \ldots, 20$, along with their 95% confidence intervals; that is, we estimate the impacts of negative and positive loan-fund flow pressures on the secondary-market prices of the loans held by these funds, up to a horizon of 20 business days (roughly one month). Standard errors are clustered at the loan level.

Consistent with Hypothesis 4, outflows from loan funds have a significant negative impact on the prices of the loans held by these funds. For a loan fully held by loan funds, a one-percentage-point daily outflow from these funds leads to a drop in the loan's price relative to its par value of 1.7 pp after 10 days and 1.9 pp after 20 days (p-values < 0.01). These effects are economically important as the standard deviation of loan funds' daily flows in our sample is 0.25 pp, and the standard deviations of 10-day and 20-day loan-price changes are 1.9 and 2.8 pp. In contrast, fund inflows do not significantly impact the prices of the loans held by loan funds throughout the 20-day horizon.

5.1.2 Aggregate analysis

One limitation of our loan-level price-impact analysis is that it does not encompass the entire sample period. Moreover, by focusing on the effect on the loans held by loan funds, the loan-level analysis neglects the possible spillovers to other leveraged loans. To mitigate the concerns about the external validity of our findings and quantify the broad market impact of loan-fund flows, we also investigate the relation between aggregate flows and a market-wide price index of leveraged loans that is available for most of our sample period (2002-2023), namely the S&P/LSTA U.S. Leveraged Loan 100 Index.

Figure 6 shows the time series of the S&P/LSTA U.S. Leveraged Loan 100 Index together with the cumulative flows in loan funds from 2002 to 2023. While the index shows a clear upward trend over time, it tends to drop significantly when the loan-fund industry shrinks and vice versa, suggesting that loan-fund outflows may have a negative market-wide impact on the prices of leveraged loans.

To quantify this relation, we estimate the following monthly regression from 2002 to 2023:

$$\begin{aligned}\Delta \text{Price}_t = {} & \delta + \alpha \, \text{Negative Flow}_t + \beta \, \text{Positive Flow}_t + \\ & \gamma \, \Delta \text{Price}_{t-1} + \phi \, \text{Controls}_t + \varepsilon_t \,, \end{aligned} \tag{6}$$

where Price_t is the average S&P/LSTA U.S. Leveraged Loan 100 Index in month t, normalized to 1000 at the beginning of the sample. To control for serial correlation, we take the monthly price change (ΔPrice_t) as the dependent variable and include its lagged value as control. $\text{Flow}_t < 0$ and $\text{Flow}_t > 0$ represent the negative and positive net flows across all loan funds during month t relative to the industry TNA in the previous month; note that $\text{Flow}_t < 0$ is the negative of the industry's dollar outflows. Controls_t is a vector of controls including our measure of monetary policy shocks (FG Shock) and the other macro factors used in the regressions of Section 4 (VIX, excess bond premium, and unemployment rate); we control for these variables to isolate the impact of loan-fund flows from other price effects due to factors that can also affect fund flows.

Results of regression (6) are in Column (1) of Table 8; standard errors are Newey-West with three lags. Consistent with Hypothesis 4, loan-fund outflows are associated with significant declines in the market price of leveraged loans: a one-standard-deviation increase in monthly loan-fund outflows relative to the industry size (2.3 pp) is associated with a 13-point decrease in the leveraged loan index (p-value < 0.01), amounting to 44% of the standard deviation of its monthly changes. In contrast, loan-fund inflows have no significant impact.

In Column (2) of Table 8, we estimate a variant of regression (6) designed to assess whether, as posited by Hypothesis 4, the impact of loan fund outflows on leveraged loan prices is particularly large when outflows are large. Instead of distinguishing between negative and positive flows, we regress the index monthly change against the industry net flow in that month and its interaction with a dummy for flows in the bottom decile of the distribution (i.e., the largest outflows). The results are even stronger than in Column (1): loan-fund outflows in the bottom decile of the flow distribution are associated with a significant drop in the leveraged-loan market index (14 points for a one-standard-deviation increase in outflows, with p-value < 0.01), whereas the impact of flows above the bottom decile is insignificant.

Together with the results of Section 4, our loan pricing evidence identifies a novel transmission channel of monetary policy to the secondary-market prices of leveraged loans acting through loan funds. While positive monetary policy shocks have little or no impact on loan fund flows, negative ones cause significant outflows; in turn, outflows from loan funds significantly depress the prices of the loans held by these funds.

5.2 Loan prices and loan funds' runnability

The evidence we have unveiled thus far shows that a negative monetary policy surprise will induce outflows from loan funds, and that loan fund outflows have an impact on loan prices. These price effects may have implications for financial stability. A reason is that flow-induced fire sales due to loan illiquidity can generate a first-mover advantage among loan-fund investors and, as a result, the risk of fund runs. This is a well-known reflection of funds' payoff structure: while redeeming investors get the net asset value of the fund as of the day of redemption, the portfolio readjustments caused by these redemptions typically happen in the following days (Goldstein *et al.*, 2017; Zeng, 2017; Ma *et al.*, 2022a).

That portfolio illiquidity makes open-end mutual fund runnable is well known. In particular, Goldstein *et al.* (2017) show that the flow-performance relation of corporate bond funds is concave: their outflows are sensitive to bad performance more than their inflows are sensitive to good performance, consistent with the existence of a first-mover advantage for investors. Goldstein *et al.* (2017) further show that the relation is more concave for funds holding more illiquid securities (e.g., high-yield bond funds) and during periods of market stress (consistent with liquidity in debt markets evaporating in bad times; Dang *et al.*, 2015, and Holmstrom, 2015).

The same dynamics can be observed in loan funds. In Appendix B, we show that loan funds' flow-performance relation is concave (see Table B1). Moreover, loan funds' flow-performance relation becomes even more concave during periods of negative monetary policy shocks; that is, exactly when loan funds experience outflows due to the interest-rate channel of monetary policy we identify in Section 4.

This evidence shows that loan funds are runnable and that negative monetary policy shocks—acting as a negative public signal on loan-fund performance—amplify investors' sensitivity to negative returns and therefore make loan funds more exposed to run risk, pointing to a financial stability channel of monetary policy on this industry.

6 Final Remarks

Over the last decade, we have observed a diminishing role of banks and a parallel growth of non-bank financial institutions in key segments of the credit market. To further our understanding of how monetary policy is transmitted to credit markets today, we study its effects on investor flows in open-end loan mutual funds. Loan funds are among the fastest-growing non-bank financial intermediaries in debt markets, increasing by 400% between 2000 and 2023, and are now the second-largest source of funding in the leveraged lending market.

We document that monetary policy positive (negative) shocks lead to loan funds' inflows (outflows). The effects of positive and negative shocks, however, are asymmetric: the outflows caused by negative shocks are larger than the inflows caused by positive shocks. Further, we show that loan fund outflows significantly depress the prices of the loans held by these funds, whereas inflows have no significant impact. Our results derive from the unique features of loan funds (being open-ended and investing in leveraged loans) and a set of features of leveraged loans (including their floating-rate design, their ability to be refinanced, and their illiquidity).

Taken together, our findings show a novel transmission channel of monetary policy to the secondary leveraged-loan market operating through loan funds. This channel is potentially relevant for the real economy because loan funds are an important source of leveraged lending and because leveraged loans are a sizable component of corporate credit for specific financial activities (e.g., LBOs, M&A) that are key for economic growth.

Our evidence also points to a link between monetary policy and financial stability. In particular, our finding that large loan fund outflows depress loan prices suggests that loan funds are exposed to run risk through a fire-sale mechanism. Consistent with this intuition, we show that their flow-performance relation is concave (indicating the presence of a first-mover advantage for investors), and even more so during periods of negative monetary policy shocks (exactly when loan funds tend to experience large outflows due to the effect of monetary policy on their income stream).

Figures

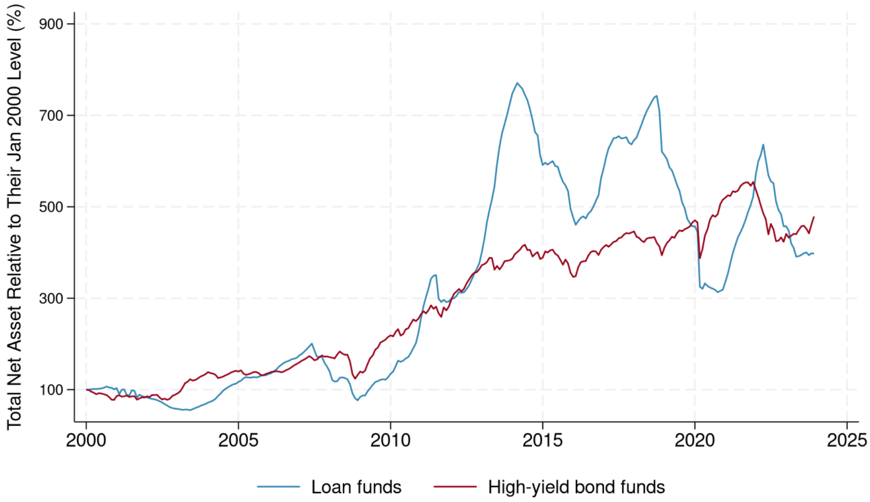


Figure 1: Loan-Fund and Bond-Fund Industry Growth. This figure displays the growth in the monthly total net assets (TNA) of loan funds and corporate bond funds, separately. The series are normalized by each industry's TNA in January 2000; the initial value is set to 100.

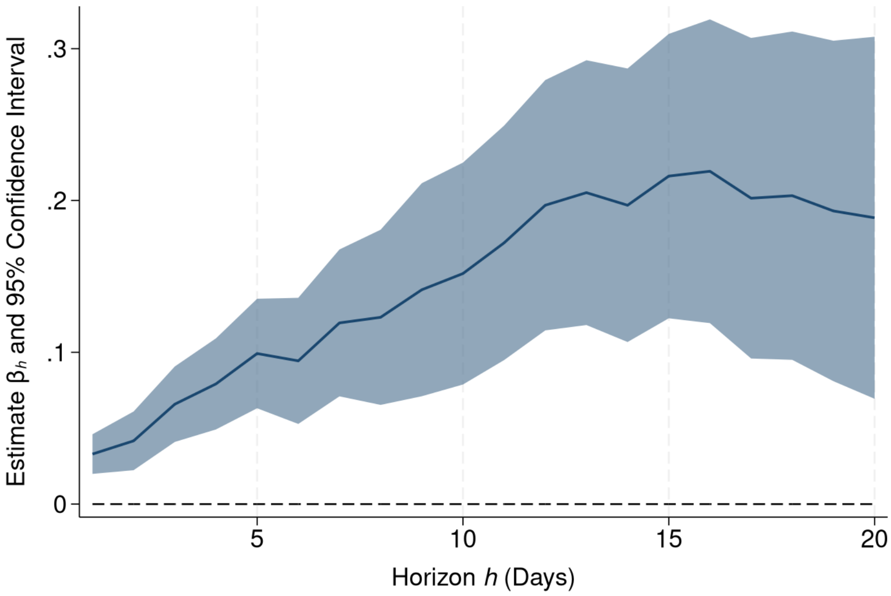
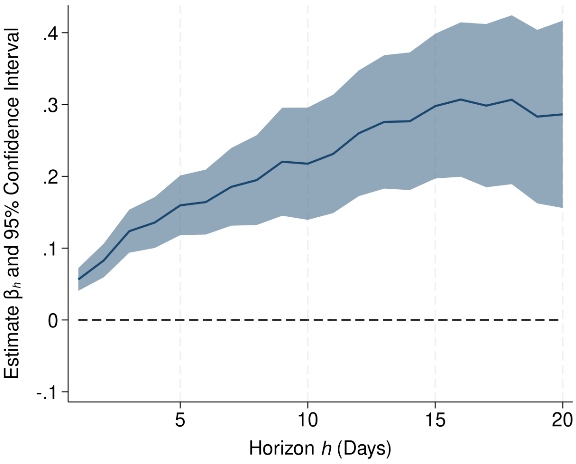
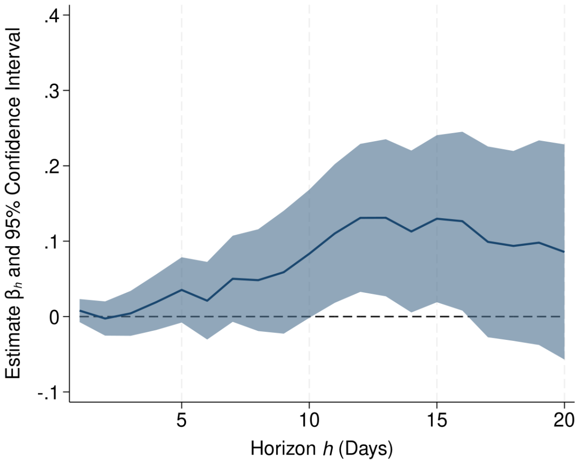


Figure 2: Effect of monetary policy shocks on loan funds' daily net flows up to h days ahead: with high yield bond fund controls. The figure shows the estimated β_h from the daily regression (3)—i.e., the effect of a forward guidance shock on loan funds' daily net flows relative to high-yield bond funds' daily net flows h days after the shock—up to $h = 20$ (four weeks) after the announcement. The solid line represents the point estimates, the shaded blue area the 95% confidence intervals. Regressions are estimated on a pooled sample of loan funds and high-yield bond funds from January 1, 2010 through December 31, 2023. The unit of observation is a share class-day. Time-varying shareclass controls include the lagged net flow as a percentage of total net assets (TNA), the lagged natural logarithm of TNA in millions (Log(TNA)), and the lagged net expense ratio in percent. Time-varying macro controls include the daily VIX, the monthly excess bond premium from Gilchrist and Zakrajšek (2012), and the monthly unemployment rate. We control for a non-linear flow-performance relation by including the net return in the prior day Return_{it-1}, $\text{I(Return<0)}_{it-1}$, $\text{I(Return<0)}_{it-1} \times \text{Return}_{it-1}$, and their interaction with the loan fund dummy. Finally, we control for the duration of the share class in the prior month Duration_{it-1} and its interaction with the FG Shock. All regressions include share-class, time, and credit rating × time fixed effects. Standard errors are clustered at the share-class level to control for serial correlation.

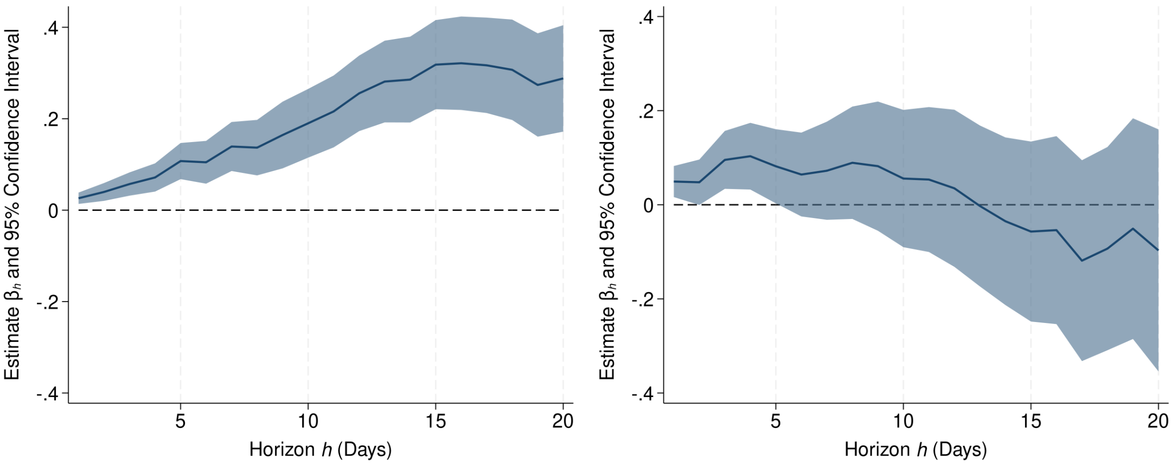


(a) FG Shock < 0



(b) FG Shock > 0

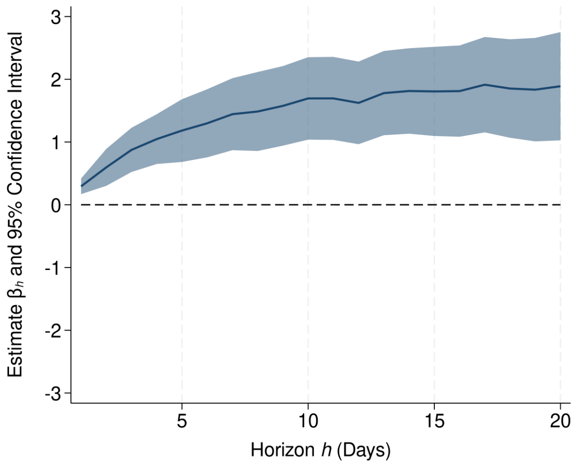
Figure 3: Effect of monetary policy shocks on loan funds' daily net flows up to h days ahead: with high yield bond fund controls and split by positive and negative shocks. The figure shows the estimated β_h from the daily regression (3)—i.e., the effect of a forward guidance surprise on loan funds' daily net flows relative to high-yield bond funds' daily net flows h days after the shock—up to $h = 20$ (four weeks) after the announcement. As in Table 6, we split the FG Shock into its negative and positive components and plot the coefficients on these terms in panel (a) and panel (b) respectively. The solid line represents the point estimates, the shaded blue area the 95% confidence intervals. Regressions are estimated on a pooled sample of loan funds and high-yield bond funds from January 1, 2010 through December 31, 2023. The unit of observation is a share class-day. Time-varying shareclass controls include the lagged net flow as a percentage of total net assets (TNA), the lagged natural logarithm of TNA in millions (Log(TNA)), and the lagged net expense ratio in percent. Time-varying macro controls include the daily VIX, the monthly excess bond premium from Gilchrist and Zakrajšek (2012), and the monthly unemployment rate. We control for a non-linear flow-performance relation by including the net return in the prior day Return_{it-1}, $\text{I(Return<0)}_{it-1}$, $\text{I(Return<0)}_{it-1} \times \text{Return}_{it-1}$, and their interaction with the loan fund dummy. Finally, we control for the duration of the share class in the prior month Duration_{it-1} and its interaction with the FG Shock. All regressions include share-class, time, and credit rating $\times$ time fixed effects. Standard errors are clustered at the share-class level to control for serial correlation.



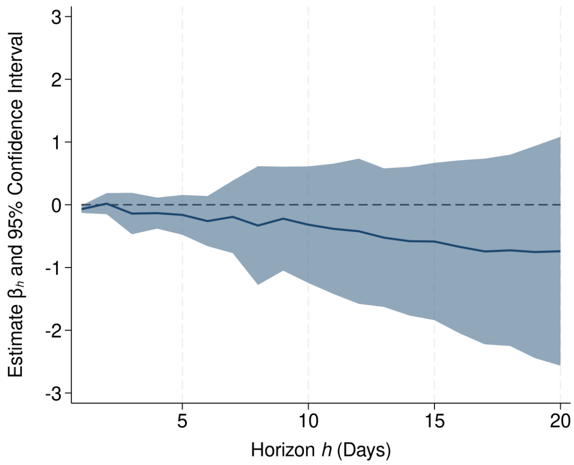
(a) Above ZLB

(b) ZLB

Figure 4: Effect of monetary policy shocks on loan funds' daily net flows up to h days ahead: with high yield bond fund controls and split by lower bound periods. The figure shows the estimated β_h from the daily regression (3)—i.e., the effect of a forward guidance surprise on loan funds' daily net flows relative to high-yield bond funds' daily net flows h days after the shock—up to $h = 20$ (four weeks) after the announcement. As in Table 7, we split the sample into periods where short-term rates are above the ZLB and periods where rates are at the ZLB, and plot the coefficients estimates from these samples in panel (a) and panel (b) respectively. The solid line represents the point estimates, the shaded blue area the 95% confidence intervals. Regressions are estimated on a pooled sample of loan funds and high-yield bond funds from January 1, 2010 through December 31, 2023. The unit of observation is a share class-day. Time-varying shareclass controls include the lagged net flow as a percentage of total net assets (TNA), the lagged natural logarithm of TNA in millions (Log(TNA)), and the lagged net expense ratio in percent. Time-varying macro controls include the daily VIX, the monthly excess bond premium from Gilchrist and Zakrajšek (2012), and the monthly unemployment rate. We control for a non-linear flow-performance relation by including the net return in the prior day Return_{it-1}, $\text{I(Return<0)}_{it-1}$, $\text{I(Return<0)}_{it-1} \times \text{Return}_{it-1}$, and their interaction with the loan fund dummy. Finally, we control for the duration of the share class in the prior month Duration_{it-1} and its interaction with the FG Shock. All regressions include share-class, time, and credit rating $\times$ time fixed effects. Standard errors are clustered at the share-class level to control for serial correlation.



(a) Negative Flow Pressure



(b) Positive Flow Pressure

Figure 5: Effect of loan fund flows on leveraged loan prices. Panel (a) and (b) show the estimated β_h from the daily loan-level regression response to negative and positive flow pressure shocks respectively, as in regression (5). The unit of observation is a loan-day. The dependent variable is the daily average asking price of a leveraged loan as a percent of par value. Each regression includes loan and day fixed effects, and each regression controls for the lagged change in price. Standard errors are clustered at the loan level. The solid line represents the point estimates, the shaded blue area the 95% confidence intervals.

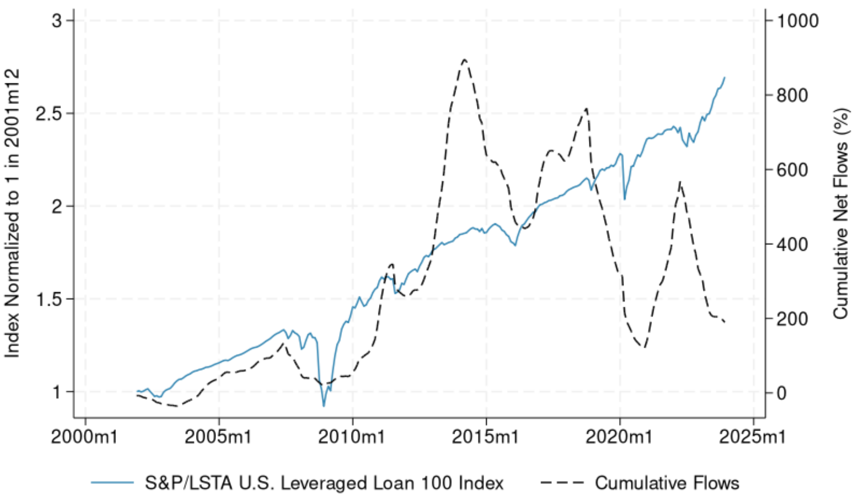


Figure 6: Market Indexes and Cumulative Flows: Loan Funds and High-yield Bond Funds. The figure shows the S&P/LSTA U.S. Leveraged Loan 100 Index normalized to 1 in December 2001, plotted against the cumulative flows in the loan fund industry as a percentage of the industry's total net assets (TNA) in December 2001.

Tables

	Loan	High-Yield Bond
Share-class Information, Month		
TNA (Millions)	477.41	426.52
	(1020.82)	(1632.51)
Flow (Percent)	.70	.79
	(9.97)	(9.33)
Expense ratio (Percent)	1.13	1.10
	(.45)	(.48)
Net return (Percent)	5.20	7.53
	(18.20)	(26.91)
Observations	26215	123336
Unique Share-classes	302	1728
Fund-Portfolio Information, Month		
Average credit rating (0–6)	1.02	1.40
	(0.17)	(0.53)
Share of unrated securities (Percent)	3.57	4.80
	(6.63)	(6.92)
Cash (Percent)	5.69	3.96
	(3.98)	(13.22)
Loan (Percent)	70.09	5.63
	(18.34)	(6.20)
Bond (Percent)	23.34	85.75
	(18.86)	(15.99)
Equity (Percent)	0.48	1.39
	(0.87)	(3.32)
Average duration (Years)	0.46	3.60
	(0.47)	(1.08)
Observations	26215	123336
Unique Funds	74	469

Table 1: Summary statistics of loan and high-yield bond funds at the share-class and fund level. Data are monthly. TNA is total net assets in millions of USD. Flow is the net flow of the share class in percent, relative to the prior month's TNA. Expense ratio is the monthly net expense ratio in percent. Net return is the monthly annualized net return of the fund's portfolio in percent. Average credit rating is the monthly average credit rating of the fund's portfolio, coded AAA=6, AA=5, A=4, BBB=3, BB=2, B=1, Below B=0. Share unrated is the monthly unrated share of the fund's portfolio in percent. Duration is the average duration of the fund's portfolio in years. Loan, Bond, Equity, and Cash are the percent of the fund's portfolio held in the respective asset category each month. Standard deviations are in parentheses. The sample is from January 2000 to December 2023.

	Flow$_{it}$		
	(1)	(2)	(3)
FG Shock$_t$	0.3360***	0.3347***	0.2814***
	(0.0512)	(0.0512)	(0.0516)
VIX$_t$	-0.1645***	-0.1632***	-0.1669***
	(0.0129)	(0.0130)	(0.0140)
EBP$_t$	0.2845	0.2349	-0.1947
	(0.1776)	(0.1746)	(0.2345)
Unemp$_t$	0.5580***	0.5522***	0.5567***
	(0.0398)	(0.0396)	(0.0409)
Flow$_{it-1}$	0.2990***	0.2986***	0.2886***
	(0.0364)	(0.0364)	(0.0342)
Controls$_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Credit Rating FE	N	Y	N
Credit Rating $\times$ Time FE	N	N	Y
Adjusted R^2	0.197	0.197	0.206
Observations	25144	25143	25130

Table 2: Flow sensitivity to monetary policy shocks. Regressions are estimated on the sample of loan funds from January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance shock from Swanson (2021). VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, and cash as a percentage of TNA. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, and I(Return<0)$_{it-1}$ $\times$ Return$_{it-1}$. All regressions include share-class fixed effects. In column (2) we add credit rating fixed effects, and in column (3) we add credit rating $\times$ time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$		
	(1)	(2)	(3)
FG Shock$_t > 0$	0.1684**	0.1683**	0.1459*
	(0.0784)	(0.0789)	(0.0825)
FG Shock$_t < 0$	0.5022***	0.4996***	0.4223***
	(0.0883)	(0.0880)	(0.0906)
VIX$_t$	-0.1636***	-0.1623***	-0.1664***
	(0.0130)	(0.0130)	(0.0140)
EBP$_t$	0.2882	0.2395	-0.1914
	(0.1778)	(0.1748)	(0.2348)
Unemp$_t$	0.5490***	0.5433***	0.5485***
	(0.0402)	(0.0401)	(0.0414)
Flow$_{it-1}$	0.2989***	0.2985***	0.2886***
	(0.0364)	(0.0365)	(0.0342)
Controls$_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Credit Rating FE	N	Y	N
Credit Rating × Time FE	N	N	Y
Adjusted R^2	0.197	0.197	0.206
Observations	25144	25143	25130

Table 3: Flow sensitivity to monetary policy shocks: split by positive and negative shocks. Regressions are estimated on the sample of loan funds from January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock > 0 is equal to the positive part of the forward guidance shock from Swanson (2021), and FG Shock < 0 is equal to its negative part. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, and cash as a percentage of TNA. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, and I(Return<0)$_{it-1}$ × Return$_{it-1}$. All regressions include share-class fixed effects. In column (2) we add credit rating fixed effects, and in column (3) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
FG Shock$_t$	0.1378	0.2462***	0.1394	0.2464***	0.0097	0.2625***
	(0.1072)	(0.0569)	(0.1069)	(0.0568)	(0.1216)	(0.0558)
VIX$_t$	-0.2102***	-0.1229***	-0.2102***	-0.1225***	-0.1909***	-0.1200***
	(0.0205)	(0.0162)	(0.0206)	(0.0163)	(0.0221)	(0.0166)
EBP$_t$	-0.9959***	-3.0924***	-1.0322***	-3.0969***	-1.1764***	-3.3878***
	(0.2600)	(0.4867)	(0.2595)	(0.4875)	(0.2841)	(0.4978)
Unemp$_t$	0.2244***	2.9833***	0.2047***	2.9646***	0.1991***	3.1511***
	(0.0627)	(0.4892)	(0.0623)	(0.4929)	(0.0663)	(0.5660)
Flow$_{it-1}$	0.3436***	0.1191**	0.3432***	0.1189**	0.3310***	0.1208***
	(0.0297)	(0.0478)	(0.0298)	(0.0478)	(0.0282)	(0.0460)
Controls$_{i,t-1}$	Y	Y	Y	Y	Y	Y
Share-class FE	Y	Y	Y	Y	Y	Y
Credit Rating FE	N	N	Y	Y	N	N
Credit Rating $\times$ Time FE	N	N	N	N	Y	Y
Sample	ZLB	Above ZLB	ZLB	Above ZLB	ZLB	Above ZLB
Adjusted R^2	0.292	0.107	0.293	0.107	0.308	0.106
Observations	11196	11142	11196	11141	11190	11139

Table 4: Flow sensitivity to monetary policy shocks: split by zero lower bound periods. Regressions are estimated on the sample of loan funds. The sample period is January 2010-December 2015 and March 2020-March 2022 (i.e., during the ZLB period) in Columns (1), (3), and (5), and January 2016-February 2020 and April 2022-December 2023 (i.e., above the ZLB period) in Columns (2), (4), and (6). The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance shock from Swanson (2021). VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, and cash as a percentage of TNA. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, and I(Return<0)$_{it-1}$ $\times$ Return$_{it-1}$. All regressions include share-class fixed effects. In columns (2) and (5) we add credit rating fixed effects, and in column (3) and (6) we add credit rating $\times$ time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$		
	(1)	(2)	(3)
Loan$_i$ × FG Shock$_t$	0.5259***	0.5282***	0.5036***
	(0.1454)	(0.1454)	(0.1487)
Loan$_i$ × VIX$_t$	-0.0895***	-0.0893***	-0.0839***
	(0.0152)	(0.0152)	(0.0157)
Loan$_i$ × EBP$_t$	-0.3471	-0.3746	-0.2654
	(0.2346)	(0.2335)	(0.2397)
Loan$_i$ × Unemp$_t$	0.1784***	0.1705***	0.1684***
	(0.0475)	(0.0478)	(0.0498)
Flow$_{it-1}$	0.1909***	0.1907***	0.1885***
	(0.0145)	(0.0145)	(0.0143)
Controls$_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Time FE	Y	Y	Y
Credit Rating FE	N	Y	N
Credit Rating × Time FE	N	N	Y
HY Bond-fund Control Group	Y	Y	Y
Adjusted R^2	0.157	0.157	0.163
Observations	129547	129547	129480

Table 5: Flow sensitivity to monetary policy shocks: with high-yield bond fund controls. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control) from January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance shock from Swanson (2021). Loan is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, I(Return<0)$_{it-1}$ × Return$_{it-1}$, and their interactions with the loan-fund dummy. Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with the FG Shock. All regressions include share-class and month fixed effects. In column (2) we add credit rating fixed effects, and in column (3) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$		
	(1)	(2)	(3)
Loan$_i$ × FG Shock$_t$ > 0	-0.1668	-0.1626	-0.2427
	(0.1888)	(0.1889)	(0.1984)
Loan$_i$ × FG Shock$_t$ < 0	1.2075***	1.2080***	1.2336***
	(0.2768)	(0.2770)	(0.2797)
Loan$_i$ × VIX$_t$	-0.0886***	-0.0884***	-0.0829***
	(0.0152)	(0.0153)	(0.0157)
Loan$_i$ × EBP$_t$	-0.3368	-0.3640	-0.2512
	(0.2345)	(0.2334)	(0.2396)
Loan$_i$ × Unemp$_t$	0.1648***	0.1572***	0.1523***
	(0.0480)	(0.0483)	(0.0503)
Flow$_{it-1}$	0.1909***	0.1907***	0.1884***
	(0.0145)	(0.0145)	(0.0143)
Controls$_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Time FE	Y	Y	Y
Credit Rating FE	N	Y	N
Credit Rating × Time FE	N	N	Y
HY Bond-fund Control Group	Y	Y	Y
Adjusted R^2	0.157	0.157	0.163
Observations	129547	129547	129480

Table 6: Flow sensitivity to monetary policy shocks: split by positive and negative shocks. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control) from January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock > 0 is equal to the positive part of the forward guidance shock from Swanson (2021), and FG Shock < 0 is equal to its negative part. Loan is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, I(Return<0)$_{it-1}$ × Return$_{it-1}$, and their interactions with the loan-fund dummy. All regressions include share-class and month fixed effects. Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with FG Shock > 0 and FG Shock < 0. All regressions include share-class and month fixed effects. In column (2) we add credit rating fixed effects, and in column (3) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Loan$_i$ × FG Shock$_t$	-0.1053	0.5235***	-0.1005	0.5274***	-0.1309	0.4932***
	(0.2903)	(0.1765)	(0.2909)	(0.1763)	(0.2969)	(0.1851)
Loan$_i$ × VIX$_t$	-0.1799***	-0.0077	-0.1799***	-0.0083	-0.1794***	-0.0078
	(0.0264)	(0.0202)	(0.0264)	(0.0202)	(0.0275)	(0.0221)
Loan$_i$ × EBP$_t$	-1.6773***	-3.7254***	-1.7115***	-3.6872***	-1.8306***	-3.5208***
	(0.3575)	(0.5360)	(0.3587)	(0.5367)	(0.3665)	(0.5849)
Loan$_i$ × Unemp$_t$	-0.2217**	2.5686***	-0.2298***	2.4912***	-0.2419***	2.2679***
	(0.0884)	(0.4829)	(0.0888)	(0.4871)	(0.0908)	(0.4762)
Flow$_{it-1}$	0.1348***	0.0931***	0.1347***	0.0925***	0.1341***	0.0903***
	(0.0224)	(0.0175)	(0.0223)	(0.0174)	(0.0222)	(0.0173)
Controls$_{i,t-1}$	Y	Y	Y	Y	Y	Y
Share-class FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Credit Rating FE	N	N	Y	Y	N	N
Credit Rating × Time FE	N	N	N	N	Y	Y
HY Bond-fund Control Group	Y	Y	Y	Y	Y	Y
Sample	ZLB	Above ZLB	ZLB	Above ZLB	ZLB	Above ZLB
Adjusted R^2	0.160	0.127	0.160	0.127	0.164	0.130
Observations	53541	46804	53541	46804	53532	46792

Table 7: Flow sensitivity to monetary policy shocks: split by zero lower bound periods and including high-yield bond funds. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control). The sample period is January 2010-December 2015 and March 2020-March 2022 (i.e., during the ZLB period) in Columns (1), (3), and (5), and January 2016-February 2020 and April 2022-December 2023 (i.e., above the ZLB period) in Columns (2), (4), and (6). The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance shock from Swanson (2021). Loan is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, I(Return<0)$_{it-1}$ × Return$_{it-1}$, and their interactions with the loan-fund dummy. Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with the FG Shock. All regressions include share-class and month fixed effects. In columns (2) and (5) we add credit rating fixed effects, and in column (3) and (6) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	ΔPrice_t	
	(1)	(2)
$\text{Flow}_t > 0$	-1.807	
	(1.154)	
$\text{Flow}_t < 0$	5.671^{***}	
	(1.611)	
Flow_t		-0.809
		(0.860)
$\mathbf{1}(\text{Bottom Decile Flows})_t \times \text{Flow}_t$		7.111^{***}
		(1.607)
ΔPrice_{t-1}	Y	Y
Controls_t	Y	Y
Adjusted R^2	0.316	0.361
Observations	263	263

Table 8: Effect of Fund Flows on Market Prices. The dependent variable is ΔPrice_t, where Price_t is the leveraged loan market price in month t computed as the monthly average of the S&P/LSTA U.S. Leveraged Loan 100 Index and rescaled to equal 1000 at the beginning of the sample. Regressions are estimated on time series of loan fund flows and leveraged loan prices. The unit of observation is a month, and the sample period is February 2002 to December 2023 for both regressions. In each month, we sum the cash flows and TNA of all loan funds and compute Flow_t as the summed flows as a percentage of summed TNA in the previous month. $\text{Flow}_t > 0$ is equal to Flow_t in all months with net inflows and zero otherwise. Analogously, $\text{Flow}_t < 0$ is equal to Flow_t in all months with net outflows and zero otherwise. $\mathbf{1}(\text{Bottom Decile Flows})_t$ is a dummy variable equal to 1 in the months with Flow_t in the bottom decile. Controls_t includes the monthly average of the daily VIX, the monthly excess bond premium from Gilchrist and Zakrajšek (2012), the monthly unemployment rate, and FG Shock, the forward guidance shock from Swanson (2021). Newey-West standard errors with three lags are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% statistical significance.

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Online Appendix to: Monetary Policy, Investor Flows, and Loan Fund Fragility

Overview

This appendix contains additional information and results for our paper "Monetary Policy, Investor Flows, and Loan Fund Fragility". Specifically, Section A below documents that monetary policy positively affects the performance of loan funds. Section B shows that investor flows in loan funds positively respond to fund past performance and that flows are more sensitive to bad performance than to good performance. Section C documents that leveraged loans are more likely to refinance following positive monetary policy shocks and that on these occasions they are more likely to secure a reduction on their interest rates. Section D shows that our main results on loan funds are robust to controlling for other monetary policy shocks and using a different threshold for LIBOR to test for nonlinear effects. Finally, Section E describes the process we followed to put together the leveraged loan prices' data that we use in our loan-level analysis of loan funds' outflows and loan prices.

Appendix A Monetary Policy and Loan Fund Performance

In this appendix, we show that monetary policy positively affect the performance of loan funds. Namely, we estimate regression (1) using share-class net returns (instead of flows) as dependent variables. Results are in Columns (1)-(3) of Table A1; standard errors are clustered at the share class level.

A one-unit drop in our measure of monetary policy shocks—Swanson (2021) forward guidance surprises—leads loan-fund returns to decrease by 0.7 pp (p-value < 0.01). Results are unchanged when we add portfolio credit rating fixed effects (Column (2)); the effect remains positive but becomes insignificant when adding portfolio rating-by-time fixed effects (Column (3)).

In the paper, to strengthen the identification of the effect of monetary policy on loan-fund flows, we use high-yield bond funds as control group (see Section 4). The idea is that monetary policy positively affects the performance of loan funds not only in absolute terms, but also relative to that of high-yield bond funds. To confirm that this is indeed the case, Columns (4)-(6) replicate regression (2) of Section 4 using class returns (instead of class flows) as the dependent variable. A one-unit drop in the Swanson (2021) forward guidance shocks leads loan-fund returns to decrease by 1.5 pp (p-value < 0.01), relative to those of high-yield bond funds (Column (4)); the decline is even greater when we include portfolio credit rating fixed effects (1.6 pp with p-value < 0.01; Column (5)) and especially portfolio rating-by-time fixed effects (2.0 pp with p-value < 0.01; Column (6)).

This evidence supports our conjecture that monetary policy shocks positively impact loan funds' performance—both in absolute terms and relative to the performance of high-yield bond funds—through an interest-rate channel due to the floating-rate feature of leveraged loans. These results suggest that the positive effect of monetary policy on the income stream of leveraged loans dominates the negative effect of monetary policy on debt valuations caused by its impact on discount rates.

	Return$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
FG Shock$_t$	0.650***	0.657***	0.159			
	(0.104)	(0.105)	(0.132)			
Loan$_i$ × FG Shock$_t$				1.542***	1.558***	1.979***
				(0.241)	(0.240)	(0.247)
VIX$_t$	-1.008***	-1.012***	-1.031***			
	(0.021)	(0.021)	(0.024)			
Loan$_i$ × VIX$_t$				0.214***	0.214***	0.273***
				(0.014)	(0.014)	(0.014)
EBP$_t$	1.903***	1.998***	-0.418			
	(0.693)	(0.712)	(0.980)			
Loan$_i$ × EBP$_t$				1.314***	1.353***	2.261***
				(0.344)	(0.345)	(0.399)
Unemp$_t$	3.273***	3.283***	2.927***			
	(0.073)	(0.073)	(0.072)			
Loan$_i$ × Unemp$_t$				-1.559***	-1.547***	-1.591***
				(0.061)	(0.061)	(0.054)
Flow$_{it-1}$	-0.148***	-0.148***	-0.110***	-0.006	-0.006	-0.009**
	(0.028)	(0.027)	(0.021)	(0.005)	(0.005)	(0.004)
Controls$_{i,t-1}$	Y	Y	Y	Y	Y	Y
Share-class FE	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	Y	Y	Y
Credit FE	N	Y	N	N	Y	N
Credit Rating × Time FE	N	N	Y	N	N	Y
HY Bond-fund Control Group	N	N	N	Y	Y	Y
Adjusted R^2	0.212	0.212	0.440	0.849	0.849	0.877
Observations	25120	25119	25110	129870	129870	129810

Table A1: Fund performance and monetary policy shocks. Regressions in Columns (1)-(3) are estimated on a sample of loan funds, and regressions in Columns (4)-(6) are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control). The sample period is January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Return$_{it}$, is the annualized net return as a percent. FG Shock is the forward guidance shock from Swanson (2021). Loan is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Flow, is the net flow as a percentage of the prior month's total net assets (TNA). Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, and I(Return<0)$_{it-1}$ × Return$_{it-1}$ in Columns (1)-(3), as well as their interactions with the loan-fund dummy in Columns (4)-(6). Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with the FG Shock in Columns (4)-(6). All regressions include share-class fixed effects, and the regressions in Columns (4)-(6) include month fixed effects. In columns (2) and (5) we add credit rating fixed effects, and in column (3) and (6) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

Appendix B Flow-Performance Relation, Run Risk, and Monetary Policy

In this appendix, we show that investor flows in loan funds positively respond to fund past performance and that the flow-performance relation is concave: flows are more sensitive to bad performance than to good performance. This evidence suggests the presence of a first-mover advantage among loan-fund investors and, therefore, that these funds are exposed to run risk, consistent with the illiquidity of leveraged loans documented in Elkamhi and Nozawa (2022) and with the price impact of loan-fund outflows documented in Section 5. Finally, we show that the flow-performance relation becomes even more concave during periods of negative monetary policy shocks, exactly when loan funds tend to experience large outflows due to the effect of monetary policy on their income stream (see Section 4); this result suggests a novel financial stability channel of monetary policy operating through loan funds.

Similar to the analysis of the flow-performance relation of bond funds in Goldstein *et al.* (2017), we estimate the following regression at the share-class level and monthly frequency, on our pooled panel of loan and high-yield bond funds from 2000 to 2023:

$$
\begin{aligned}
\text{Flow}_{it} = {} & \beta_0 \,\text{Return}_{it-1} + \gamma_0 \,\mathbf{1}\left(\text{Return}_{it-1} < 0\right) \times \text{Return}_{it-1} + \\
& + \beta_1 \,\text{Loan}_i \times \text{Return}_{it-1} + \gamma_1 \,\text{Loan}_i \times \mathbf{1}\left(\text{Return}_{it-1} < 0\right) \times \text{Return}_{it-1} + \\
& + \theta \,\text{Flow}_{it-1} + \phi \,\text{Controls}_{it-1} + \alpha_i + \mu_t + \psi_{r(i)t} + \varepsilon_{it}, \qquad (7)
\end{aligned}
$$

where Flow_{it} is the net percentage flow of class i in month t, Return_{it} is the annualized net return, $\mathbf{1}\left(\text{Return} < 0\right)$ is a dummy variable for negative returns, and Loan is a dummy variable for loan-fund share classes.[26] Controls is a vector of controls including the loan-fund dummy, the logarithm of the class TNA, and the class expense ratio. We also include lagged flows as regressor to control for serial correlation. α_i are share-class fixed effects to control for unobserved cross-sectional heterogeneity, and

[26] A few share classes (13 out of 2,074) in our sample switch from being part of a loan fund to being part of a high-yield bond fund, or vice versa; for these share classes, we use the value of the loan-fund dummy in the previous month. Excluding these observations does not affect our results.

μ_t are time fixed effects to control for unobserved time-varying common factors. $\psi_{r(i)t}$ are portfolio credit rating-by-time fixed effects to control for the possible time-varying effect of fund risk exposure (as used in Columns (3) of the tables in Section 4 (e.g., Table 2).[27]

Regression (7) allows for the flow-performance relation to have different slopes in the regions of positive and negative returns. The coefficients of interest are $\beta_0 + \beta_1$, which represents the slope of loan funds' flow-performance relation for positive returns, and $(\beta_0 + \beta_1) + (\gamma_0 + \gamma_1)$, which represents the slope for negative returns. The flow-performance relation is concave if $\gamma_0 + \gamma_1 > 0$, i.e., if the slope in the region of negative returns is steeper. Results are in Table B1, with standard errors clustered at the share-class level to control for serial correlation.

We start by estimating a simplified version of equation (7) that only includes linear return terms; that is, we drop the terms proportional to $\mathbf{1}\,(\text{Return} < 0)$ from equation (7). This regression measures the unconditional (i.e., across both positive and negative returns) average slope of the flow-performance relation. The results of this specification are reported in Column (1) and confirm that investor flows positively respond to fund performance, as widely documented in the mutual fund literature.[28] A one-standard deviation increase in lagged net returns leads to a significant increase in monthly flows of 0.53 pp (p-value < 0.01); the effect is economically important because it represents 5.29% of the standard deviation of monthly flows in our sample.

In Column (2), we turn to quantifying the differential response of loan-fund flows to good versus bad performance. The slope of loan funds' flow-performance relation is significantly steeper in the region of negative returns. In this region, a one-standard-deviation decline in returns leads to monthly outflows of 0.89 pp (p-value < 0.01), amounting to 8.9% of the standard deviation of monthly flows; in the region of positive returns, in contrast, the effect is insignificant both statistically and economically. These results suggest that there is a first-mover advantage among loan-fund investors,

[27] Portfolio rating-by-month fixed effects are implemented as a separate dummy for each rating category in each month, except for the B-rated category, which we use as a baseline to avoid collinearity with the monetary policy shock the other macro variables.

[28] See Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998) for equity mutual funds; Christoffersen and Musto (2002), Kacperczyk and Schnabl (2013), and La Spada (2018) for money market funds.

which makes loan funds exposed to run risk.

Column (3) replicates the results in Columns (2) adding the interactions of all the terms proportional to share class returns with a dummy for the months in which the measure of monetary policy shocks we use in the paper is negative. In Section 4, we show that negative shocks, by decreasing short-term rates and therefore the income stream of leveraged loans, cause significant outflows in loan funds. Positive shocks, in contrast, do not lead to significant inflows because they are associated improving economic conditions and, therefore, loan refinancing and lower loan spreads. Acting as a negative public signal on loan-fund performance, negative monetary policy shocks may make investors more attentive to negative returns and increase the risk of runs, which should be reflected in a more concave flow-performance relation.

Results in Column (3) confirm this hypothesis. The flow performance relation is even more concave when monetary policy shocks are negative. When monetary policy shocks are positive or zero, a one-standard deviation decline in net returns leads to monthly outflows of 0.62 pp in the region of negative returns (p-value < 0.01) and of only 0.46 pp in the region of positive returns (p-value $= 0.013$), confirming a concave flow-performance relation. The concavity is even greater when shocks are negative: a one-standard-deviation decline in returns leads to monthly outflows of 1.09 pp in the region of negative returns (p-value < 0.01) but has a negligible and insignificant effect in the region of positive returns.

	Flow$_{it}$ (1)	(2)	(3)
Return$_{it-1}$	0.0084***	0.0095**	0.0146***
	(0.0031)	(0.0038)	(0.0042)
Loan$_i$ × Return$_{it-1}$	0.0210***	0.0066	0.0106
	(0.0055)	(0.0075)	(0.0082)
$\mathbf{1}(\text{Return} < 0)_{it-1}$ × Return$_{it-1}$		-0.0064	-0.0311***
		(0.0088)	(0.0104)
Loan$_i$ × $\mathbf{1}(\text{Return} < 0)_{it-1}$ × Return$_{it-1}$		0.0392***	0.0397***
		(0.0126)	(0.0130)
$\mathbf{1}(\text{FG Shock} < 0)_t$ × Return$_{it-1}$			-0.0181**
			(0.0075)
$\mathbf{1}(\text{Return} < 0)_{it-1}$ × $\mathbf{1}(\text{FG Shock} < 0)_t$ × Return$_{it-1}$			0.0727***
			(0.0161)
Loan$_i$ × $\mathbf{1}(\text{FG Shock} < 0)_t$ × Return$_{it-1}$			-0.0213
			(0.0134)
Loan$_i$ × $\mathbf{1}(\text{Return} < 0)_{it-1}$ × $\mathbf{1}(\text{FG Shock} < 0)_t$ × Return$_{it-1}$			-0.0075
			(0.0247)
Loan$_i$ × $\mathbf{1}(\text{FG Shock} < 0)_t$			-0.2137
			(0.2344)
Loan$_i$ × EBP$_t$	-0.6249***	-0.4903**	-0.6237**
	(0.2363)	(0.2393)	(0.2556)
Loan$_i$ × Unemp$_t$	0.1722***	0.2028***	0.2178***
	(0.0473)	(0.0501)	(0.0507)
Loan$_i$ × VIX$_t$	-0.0974***	-0.0835***	-0.0835***
	(0.0152)	(0.0156)	(0.0157)
Flow$_{it-1}$	0.1887***	0.1885***	0.1881***
	(0.0143)	(0.0143)	(0.0143)
Flow-Performance Relation for Loan Funds			
Return$_{it-1}$	0.029***		
	(18.650)		
Return$_{it-1}$ × $\mathbf{1}(\text{Return} \geq 0)_{it-1}$		0.016*	
		(3.122)	
Return$_{it-1}$ × $\mathbf{1}(\text{Return} < 0)_{it-1}$		0.049***	
		(20.543)	
Return$_{it-1}$ × $\mathbf{1}(\text{FG Shock} \geq 0)_t$ × $\mathbf{1}(\text{Return} \geq 0)_{it-1}$			0.025**
			(6.237)
Return$_{it-1}$ × $\mathbf{1}(\text{FG Shock} \geq 0)_t$ × $\mathbf{1}(\text{Return} < 0)_{it-1}$			0.034***
			(8.563)
Return$_{it-1}$ × $\mathbf{1}(\text{FG Shock} < 0)_t$ × $\mathbf{1}(\text{Return} \geq 0)_{it-1}$			-0.014
			(0.912)
Return$_{it-1}$ × $\mathbf{1}(\text{FG Shock} < 0)_t$ × $\mathbf{1}(\text{Return} < 0)_{it-1}$			0.060***
			(9.291)
Controls$_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Time FE	Y	Y	Y
Credit Rating × Time FE	Y	Y	Y
HY Bond-fund Control Group	Y	Y	Y
Adjusted R^2	0.162	0.163	0.163
Observations	129480	129480	129480

Table B1: Flow-performance relationship. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control). The sample period is January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). Return$_{it}$ is the annualized net return as a percent. Loan is a dummy variable equal to one for loan-fund share classes. FG Shock is the forward guidance shock from Swanson (2021). VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with the FG Shock in all regressions. All regressions include share-class, month, and credit rating × time fixed effects. In the top panel, standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. In the middle panel (under *Flow-Performance Relation for Loan Funds*), we display the sum estimated coefficients to recover the overall sensitivity of loan fund flows to returns, under the corresponding conditions, and F-statistics (in parentheses) appear below the estimated coefficient sums. ***, **, and * represent 1%, 5%, and 10% statistical significance.

Appendix C Monetary Policy, Loan Refinancing, and Rate Cuts

We argued in Section (2) that the improvement in borrowers' financial conditions that typically occurs during expansionary periods makes it easier for leveraged-loan borrowers to refinance their outstanding loans with new ones that have better terms, including lower spreads. As a result, in times of positive monetary policy shocks (i.e., hikes)—typically occurring during economic expansions—we should observe an increase in leveraged-loans' refinancing and a higher incidence of rate cuts (i.e., spread reductions) associated with these refinancings. In this appendix, we investigate both of these hypotheses.

C.1 Monetary Policy and Loans' Refinancing

To investigate the relation between monetary policy shocks and loan refinancing, we estimate the following model on a panel of loan-level data from Dealscan at quarterly frequency:

$$\text{Refi}_{it} = \beta \, \text{FG Shock}_{t-1} + \phi \, \text{Controls}_{it-1} + \alpha_i + \varepsilon_{it}, \tag{8}$$

where Refi_{it} is a dummy variable equal to 100 if outstanding loan i is refinanced in quarter t and zero otherwise (we scale it to 100 to facilitate the interpretation of the results). Because Dealscan only provides information on the loan terms at origination, it does not link loans with their subsequent refinancings. For this reason, we adopted the following procedure to identify refinancings and link them to the loans they replace. We capitalize on the tranche (loan) and amendment identifiers available in the latest Dealscan data to differentiate new tranches, which we consider to be potential refinancings of existing tranches, from simple modifications of an existing tranche. For a given tranche, we define a refinancing as a new tranche that (i) has the same borrower as the original tranche, (ii) is the same type of tranche as the original (e.g., term loan, credit line), and (iii) is active before the original tranche matures and after the original tranche was last amended.[29]

[29] In some cases, we match a tranche to multiple new tranches that could potentially refinance the original tranche. In these cases, we choose the new tranche with the closest value to the original, and as a final tiebreaker, we choose the tranche with the most lenders in common with the original tranche.

FG Shock$_{t-1}$ is the sum of the monetary policy shocks we use in the paper—Swanson (2021) forward guidance surprises—in the previous quarter.[30] This is the key explanatory variable in our model: its coefficient (β) measures whether borrowers are more likely to refinance their loans following positive monetary policy shocks, as we argue in Section 2.

Regression 8 controls for a set of loan-level controls (Controls$_{it-1}$), including the log of the loan size, the loan, the number of years left to maturity, dummy variables to distinguish the loan type, its purpose, whether it has covenants, is secured by collateral, has a guarantor, has or sponsor, has a performance-pricing schedule has a rate floor, and whether it is a leveraged loan. Regression 8 also includes loan fixed effects (α_i) to focus on within-loan identification.

We estimate regression (8) on the entire universe of loans but we focus on results derived on the sample of leveraged loans because loan funds mainly invest in this type of loans. There is no unique definition of leveraged loans; some rely on the loan spread, others rely on the loan rating, and others yet rely on its type (e.g., term-B loan or higher) or its purpose (e.g., M&A or LBO financing). Since we have the loan spread for all loans in our sample, whereas the other characteristics are only available for a subset of loans, we use spreads to identify leveraged loans. Specifically, we classify a loan as a leveraged loan if its all-in-drawn spread (over LIBOR) is above 275 bps, which is the median spread for the loans in our sample for which we have credit ratings and that are rated below investment grade; using these loans' mean spread (300 bps) yields similar results.

For robustness, we also split our sample of leveraged loans depending on whether they have more or less than one year left to maturity. This exercise allows us to distinguish between near-maturity refinancings, which are more likely "mechanical," and early refinancings, which are more likely strategic. The underpinnings of our hypotheses suggest that positive monetary policy shocks should play a more important role on early refinancings than on near-maturity refinancings.

Finally, we re-estimate regression (8) on our sample of leveraged loans after we add the same macro variables that we use in the paper (Macro Factors): the VIX, the excess bond premium from

[30]Our results are robust to using the average shock instead of the sum.

Gilchrist and Zakrajsek (2012), and the unemployment rate—all lagged by one quarter, as the monetary policy shocks.

Our sample runs from 2000:Q1 until 2023:Q4, covering a total of 1,563,927 loan-quarter observations of which 695,874 are associated with leveraged loans. We identify 32,503 loan-quarter observations as instances of refinancing, of which 11,548 are associated with leveraged loans. The results of our regression (8) are in Table C1, with standard errors clustered at loan level.

Consistent with our hypothesis, following positive monetary policy shocks, borrowers are more likely to refinance their loans (Column (1)): a one-standard-deviation increase in the cumulative monetary policy shock over the previous quarter leads to a 18-bp increase in the likelihood of refinancing (p-value < 0.01); since the unconditional probability of refinancing in our sample is 2%, the effect is economically material. This result continues to hold when we restrict the sample to leveraged loans (Column (2)), albeit smaller in magnitude, which is consistent with available evidence.[31] Further, the increase in refinancing is driven by early refinancing (Column (3)) and is robust to including additional macro controls (Columns (5)). This evidence supports our conjecture that strategic refinancing activity in the leveraged-loan market is positively correlated with forward guidance surprises.

C.2 Loan Refinancing and Rate Cut

In this section, we investigate whether the loan refinancings that follow positive monetary policy shocks are associated with a reduction in loan spreads. To investigate this hypothesis, we estimate the following model on our quarterly panel of loans from Dealscan:

$$\text{Rate Cut}_{it} = \beta \, \text{Refi}_{it} \times \text{FG Shock}_{t-1} + \gamma \, \text{Refi}_{it} + \delta \, \text{FG Shock}_{t-1} + \phi \, \text{Controls}_{it-1} + \alpha_i + \varepsilon_{it}, \tag{9}$$

where Rate Cut_{it} is a dummy variable equal to 100 if the all-in-drawn spread on i experiences a reduction in quarter t and zero otherwise.[32] All of the other variables are defined as in regression (8). The variable

[31] Although Mian and Santos (2018) focus on refinancing to extend maturity, they also find that risky firms refinance less often than safer firms.

[32] As in regression (8), we scale the dependent variable to 100 to ease the interpretation of the results.

	Refi$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
FG Shock$_{t-1}$	0.1165***	0.0225**	0.0327***	0.0219	0.0233**	-0.0410
	(0.0077)	(0.0107)	(0.0111)	(0.0506)	(0.0116)	(0.0593)
VIX$_{t-1}$					-0.0325***	-0.1031**
					(0.0042)	(0.0436)
EBP$_{t-1}$					0.2589***	2.2411***
					(0.0471)	(0.4558)
Unemp$_{t-1}$					0.0671***	0.4844***
					(0.0125)	(0.0889)
Controls$_{it-1}$	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
Loan Type	All	Leveraged	Leveraged	Leveraged	Leveraged	Leveraged
Maturity	All	All	$\geq$ 1 Year	$<$ 1 Year	$\geq$ 1 Year	$<$ 1 Year
Observations	1563927	695874	650817	36952	650817	36952
Adjusted R^2	0.059	0.074	0.074	0.447	0.075	0.450

Table C1: Monetary policy and loan refinancing. Regressions are estimated on a panel of corporate loans. The sample frequency is quarterly, from 2000q1 to 2023q4. The dependent variable is a dummy variable equal to one if loan i is refinanced in quarter t and zero otherwise. We scale the dependent variable to 100 to help with the interpretation of the results. FG Shock$_{t-1}$ is the forward guidance shock from Swanson (2021) and enters in the regressions as the sum of observed shocks over the three months leading to a refinancing event. Each regression controls for loan characteristics, including the log of the loan size, the loan, the number of years left to maturity, dummy variables to distinguish the loan type, its purpose, whether it has covenants, is secured by collateral, has a guarantor, has or sponsor, has a performance-pricing schedule has a rate floor, and whether it is a leveraged loan. We identify leveraged loans as loans with an all-in drawn spread over LIBOR higher than 275 bps (the median spread for loans in our sample for which we have credit ratings and are rated below investment grade). Column (1) report results for all loans. Column (2) restricts the sample to leveraged loans. Columns (3) and (4) report results for leveraged loans depending on whether the loan has at least one year left before maturity or it has less than one-year left, respectively. Columns (5) and (6) repeat the previous two columns to include additional (lagged) macro variables (VIX, excess bond premia, and unemployment rate). All models are estimated with loan fixed effects. Reported in parentheses are standard errors clustered at the loan level. ***, **, and * represent 1%, 5%, and 10% statistical significance.

of interest in model (9) is the interaction between the refinancing dummy and the cumulative monetary policy shock in the previous quarter: its coefficient (β) tests whether refinancings are more likely associated with a reduction in loan spreads following positive monetary policy shocks.

We estimate our regression 9 on the same sample we consider to investigate loan refinancings. As we did above, we estimate our rate-cut model on the entire sample of loans (Column (1) but we then focus on the subsample of leveraged loans (Column (2)). For robustness, we estimate regression 9 on the sample of leveraged loans depending on whether loans have more or less than one year left to maturity (Columns (3) and (4)) and replicate this analysis after we add our set of macro controls (Columns (5) and (6)).

The results of our regression (9) are in Table C2; standard errors are clustered at the loan level. Consistent with our hypothesis, borrowers that refinance their loans following positive forward guidance surprises are relatively more likely to get a reduction in their loan spreads (Columns (1)): a one-standard-deviation increase in the cumulative monetary policy shock over the previous quarter leads to a 2.4 pp increase in leveraged loans' likelihood of experiencing a rate cut, conditional on refinancing early (p-value < 0.01). Since the unconditional probability of experiencing a rate cut in our sample is 1.7% and the probability conditional on refinancing is 43%, this effect is economically important. This result remains statistically significant and quantitatively similar when we restrict the sample to leveraged loans (Column (2)). Consistent with the evidence on refinancing activity in Table C1, only borrowers that refinance early are more likely to experience a rate cut (Columns (3) and (4)) following positive monetary policy shocks. Finally, our findings on refinancing are robust when we include our set of macro controls (Columns (5) and (6)).

This evidence runs counter the idea that the increase in refinancing in those instances is due to borrowers' inability to repay their loans or to covenant violations; in those cases, in fact, the spreads should increase (Roberts, 2015). In contrast, taken together, the results in Tables C1 and C2 support Hypothesis 2 of the paper: periods of positive monetary policy shocks are accompanied by an increase in leveraged loans' refinancing and a decrease in loans' spreads, which reduces the income stream of

	Rate Cut$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Refi$_{it}$ × FG Shock$_{t-1}$	1.5644***	1.3251***	1.3698***	0.7933	1.3787***	0.8548
	(0.1769)	(0.2716)	(0.2889)	(1.0599)	(0.2881)	(1.0603)
Refi$_{it}$	41.6126***	28.5450***	29.2905***	20.6095***	29.2699***	20.5640***
	(0.2633)	(0.4137)	(0.4348)	(1.9025)	(0.4343)	(1.8998)
FG Shock$_{t-1}$	0.0111***	0.0175***	0.0210***	-0.0373*	-0.0300***	-0.0934***
	(0.0043)	(0.0049)	(0.0052)	(0.0224)	(0.0056)	(0.0281)
VIX$_{t-1}$					-0.0582***	-0.1188***
					(0.0029)	(0.0265)
EBP$_{t-1}$					0.1285***	0.7234***
					(0.0285)	(0.2379)
Unemp$_{t-1}$					0.1310***	0.0583
					(0.0075)	(0.0392)
Controls$_{it-1}$	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
Loan Type	All	Leveraged	Leveraged	Leveraged	Leveraged	Leveraged
Maturity	All	All	$\geq$ 1 Year	$<$ 1 Year	$\geq$ 1 Year	$<$ 1 Year
Observations	1563927	695874	650817	36952	650817	36952
Adjusted R^2	0.256	0.192	0.195	0.438	0.196	0.440

Table C2: Monetary policy, loans' refinancing and rate cut. Regressions are estimated on a panel of corporate loans. The sample frequency is quarterly, from 2000q1 to 2023q4. The dependent variable is a dummy variable equal to one if loan i experiences a reduction in spread in quarter t and zero otherwise. We scale the dependent variable to 100 to help with the interpretation of the results. Refi$_{it}$ is a dummy variable equal to one if loan i is refinanced in quarter t and zero otherwise. FG Shock$_{t-1}$ is the forward guidance shock from Swanson (2021) and enters in the regressions as the sum of observed shocks over the three months leading to a refinancing event. Each regression controls for loan characteristics, including the log of the loan size, the loan, the number of years left to maturity, dummy variables to distinguish the loan type, its purpose, whether it has covenants, is secured by collateral, has a guarantor, has or sponsor, has a performance-pricing schedule has a rate floor, and whether it is a leveraged loan. We identify leveraged loans as loans with an all-in drawn spread over LIBOR higher than 275 bps (the median spread for loans in our sample for which we have credit ratings and are rated below investment grade). Column (1) report results for all loans. Column (2) restricts the sample to leveraged loans. Columns (3) and (4) report results for leveraged loans depending on whether the loan has at least one year left before maturity or it has less than one-year left, respectively. Columns (5) and (6) repeat the previous two columns to include additional (lagged) macro variables (VIX, excess bond premia, and unemployment rate). All models are estimated with loan fixed effects. Reported in parentheses are standard errors clustered at the loan level. ***, **, and * represent 1%, 5%, and 10% statistical significance.

loan funds. This effect reduces the income stream gains from the positive monetary policy shocks due to leveraged loans' floating-rate feature (i.e., the interest rate channel); as a result, the effect of positive monetary policy shocks on loan-fund flows is smaller in magnitude than that of negative shocks.

Appendix D Additional Robustness Checks

D.1 Controlling for other monetary policy shocks

For the reasons discussed in Section 3 of the paper, our analysis focuses on the effect of forward guidance shocks on loan-fund flows. For robustness, however, we replicate our main results controlling for the other two types of monetary policy surprises developed by Swanson (2021): the fed funds rate (FFR) and LSAP shocks. Specifically, we re-estimate regression (2) of Section 4.2 including the interactions of the loan-fund dummy with the FFR and LSAP shocks as additional controls.[33] The results of this exercise are reported in Table D1.

Across all the specifications, the coefficient on the interaction between forward-guidance shocks and the loan-fund dummy is positive and statistically significant (0.5 pp per one-unit shock, with p-value < 0.01), consistent with our hypotheses; moreover, the estimates are almost identical to those in Table 5 of the paper, which do not control for the effects of the other monetary policy shocks. FFR and LSAP shocks, in contrast, do not have a significant effect (either statistically or economically), consistent with the discussion in Section 2 and supporting our choice to focus on the effects of forward guidance.

D.2 Using LIBOR $< 1.1\%$ as threshold for nonlinear effects

In this appendix, we run an additional robustness test of Hypothesis 3 in the paper. Namely, instead of using the ZLB as a threshold to identify periods in which reference rates were likely below leveraged loans' rate floors, we use LIBOR $< 1.1\%$. We choose this threshold based on the mean rate floor for leveraged loans: in the Dealscan data, the mean LIBOR rate floor for leveraged term loans is 1.08% over the sample period, 2010-2023.[34]

Specifically, we replicate the results in Table 7 of the paper separately estimating regression (2)

[33] To facilitate the comparison of the effects across different shocks, we take the negative value of Swanson (2021) LSAP shock because this shock has the opposite sign of the other monetary policy surprises (i.e., a positive LSAP shock corresponds to monetary policy easing).

[34] Consistent with the discussion Appendix C, in this computation, we define loans in the Dealscan data as leveraged loans if their spread over LIBOR is greater than 275 basis points

	Flow_{it}		
	(1)	(2)	(3)
$\text{Loan}_i \times \text{FG Shock}_t$	0.5484***	0.5508***	0.5246***
	(0.1442)	(0.1443)	(0.1497)
$\text{Loan}_i \times \text{FFR Shock}_t$	0.0547	0.0532	0.1568
	(0.3313)	(0.3316)	(0.3426)
$\text{Loan}_i \times -\text{LSAP Shock}_t$	0.0846	0.0827	0.3139
	(0.3138)	(0.3139)	(0.2953)
$\text{Loan}_i \times \text{VIX}_t$	-0.0886***	-0.0885***	-0.0808***
	(0.0163)	(0.0164)	(0.0167)
$\text{Loan}_i \times \text{EBP}_t$	-0.3635	-0.3914*	-0.2742
	(0.2339)	(0.2327)	(0.2393)
$\text{Loan}_i \times \text{Unemp}_t$	0.1728***	0.1650***	0.1594***
	(0.0487)	(0.0490)	(0.0509)
Flow_{it-1}	0.1910***	0.1908***	0.1886***
	(0.0145)	(0.0145)	(0.0143)
$\text{Controls}_{i,t-1}$	Y	Y	Y
Share-class FE	Y	Y	Y
Time FE	Y	Y	Y
Credit Rating FE	N	Y	N
Credit Rating × Time FE	N	N	Y
HY Bond-fund Control Group	Y	Y	Y
Adjusted R^2	0.157	0.157	0.163
Observations	129547	129547	129480

Table D1: Flow sensitivity to monetary policy shocks: controlling for other monetary policy shocks and including high-yield bond funds. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control) from January 2000 to December 2023. The unit of observation is a share class-month. The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance surprise from Swanson (2021), FFR Shock is the fed funds rate surprise, and −LSAP Shock is the negative of the large scale asset purchase surprise. Loan, is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return_{it-1}, $\text{I(Return<0)}_{it-1}$, $\text{I(Return<0)}_{it-1} \times \text{Return}_{it-1}$, and their interactions with the loan-fund dummy. Finally, we control for the duration of the share class in the prior month Duration_{it-1} and its interaction with the FG Shock, FFR Shock, and −LSAP Shock. All regressions include share-class and month fixed effects. In column (2) we add credit rating fixed effects, and in column (3) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

	Flow$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Loan$_i$ × FG Shock$_t$	0.0893	0.4769***	0.0978	0.4682***	0.0269	0.4587**
	(0.2680)	(0.1716)	(0.2683)	(0.1713)	(0.2765)	(0.1814)
Loan$_i$ × VIX$_t$	-0.1985***	-0.0354*	-0.1982***	-0.0351*	-0.1945***	-0.0348*
	(0.0280)	(0.0185)	(0.0282)	(0.0185)	(0.0292)	(0.0197)
Loan$_i$ × EBP$_t$	-1.5912***	-1.9797***	-1.6042***	-1.9647***	-1.7748***	-1.8743***
	(0.3720)	(0.5687)	(0.3756)	(0.5691)	(0.3839)	(0.6001)
Loan$_i$ × Unemp$_t$	-0.1461*	0.1770*	-0.1528*	0.1594*	-0.1399	0.1490
	(0.0843)	(0.0927)	(0.0848)	(0.0925)	(0.0864)	(0.0976)
Flow$_{it-1}$	0.1355***	0.0887***	0.1354***	0.0881***	0.1347***	0.0851***
	(0.0203)	(0.0131)	(0.0203)	(0.0131)	(0.0202)	(0.0129)
Controls$_{i,t-1}$	Y	Y	Y	Y	Y	Y
Share-class FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Credit Rating FE	N	N	Y	Y	N	N
Credit Rating × Time FE	N	N	N	N	Y	Y
HY Bond-fund Control Group	Y	Y	Y	Y	Y	Y
Sample	LIBOR < 1.1	LIBOR > 1.1	LIBOR < 1.1	LIBOR > 1.1	LIBOR < 1.1	LIBOR > 1.1
Adjusted R^2	0.146	0.136	0.146	0.136	0.149	0.141
Observations	61536	38808	61536	38808	61527	38795

Table D2: Flow sensitivity to monetary policy shocks: split by LIBOR. Regressions are estimated on a pooled sample of loan funds (treatment) and high-yield bond funds (control). The sample period is January 2010-February 2017 and April 2020-March 2022 (i.e., when LIBOR was below 1.1%) in Columns (1), (3), and (5), and March 2017-March 2020 and April 2022-December 2023 (i.e., when LIBOR was above 1.1%) in Columns (2), (4), and (6). The dependent variable, Flow, is the net flow as a percentage of the prior month's total net assets (TNA). FG Shock is the forward guidance shock from Swanson (2021). Loan$_i$ is a dummy variable equal to one for loan-fund share classes. VIX is the monthly average of the daily VIX. EBP is the monthly excess bond premium from Gilchrist and Zakrajšek (2012). Unemp is the monthly unemployment rate. Controls is a set of time-varying class-level controls including the natural logarithm of TNA in millions (Log(TNA)), the net expense ratio in percent, cash as a percentage of TNA, and a dummy variable equal to one for loan-fund share classes. In addition, we control for a non-linear flow-performance relation by including the net return in the prior month Return$_{it-1}$, I(Return<0)$_{it-1}$, I(Return<0)$_{it-1}$ × Return$_{it-1}$, and their interactions with the loan-fund dummy. Finally, we control for the duration of the share class in the prior month Duration$_{it-1}$ and its interaction with the FG Shock. All regressions include share-class fixed effects. In columns (2) and (5) we add credit rating and month fixed effects, and in column (3) and (6) we add credit rating × time fixed effects. Standard errors (in parentheses) are clustered at the share-class level to control for serial correlation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

on months with LIBOR < 1.1% and on months with LIBOR > 1.1%. The results, which are reported in Table D2, show that the nonlinearity of the interest rate channel as a function of short-term rates is robust to this alternative choice of the threshold. When LIBOR is below 1.1%, monetary policy shocks have no significant effect on loan-fund flows relative to flows in high-yield bond funds; in contrast, the effect is positive and significant when LIBOR is above 1.1%: 0.5 pp per unit shock (p-value < 0.05), even in our most saturated specification (i.e., including fund portfolio credit rating-by-time fixed effects). These results are quantitatively similar to our results reported in Table (7) of the paper, which were obtained using the ZLB as the threshold.

Appendix E Construction of the Loan-Level Dataset

In this appendix, we describe how we constructed the daily panel of leveraged loan prices that we use in our loan-level analysis of loan funds' outflows and loan prices (Section 5.1). We use daily data on loan-fund share-class flows from Morningstar, security-level quarterly data on loan-fund portfolios from the Securities and Exchange Commission (SEC) Form N-PORT filings, and daily leveraged-loan pricing data from LSTA. As explained in Section 3, the resulting daily panel of loans goes from 2019Q4 to 2022Q4 because N-PORT data are only available from 2019Q4 and LSTA data end in 2022Q4.

We start by matching the loan-fund ("US Fund Bank Loan") share classes in the Morningstar dataset with the corresponding SEC N-PORT filings, based on fund names (there is no other common identifier across the two datasets); we are able to match 73 out of the 74 loan funds covered by Morningstar for 2019Q4-2022Q4.

Next, we match individual leveraged loans in the LSTA data with the loans held by loan funds, as reported in the N-PORT data. There is no clear identifier between the two datasets, and because N-PORT data are self-reported, funds may use different identifiers to refer to the same loan (e.g., 9-digit CUSIPs are not available for all loans in our sample). For these reasons, we use a fuzzy matching algorithm to identify likely matches between loans in the LSTA data and the N-PORT data.

Both the LSTA and N-PORT datasets contain the maturity date and a name for the loan. We clean the loan titles in the N-PORT data to recover the loan type (which is available in the LSTA data; e.g., Term Loan B) and filter the N-PORT data to only include leveraged loans denominated in U.S. dollars (removing other asset categories). Using the `reclink` package in Stata, we identify likely matches between loans in the LSTA and N-PORT data using exact matches on the maturity date and close matches on the loan name and type. For each loan in the N-PORT data—as identified by its name, type, and maturity date—the algorithm returns the closest match in the LSTA data and a match score between 0 and 1 that quantifies the similarity of the matching fields. We only include loans that have a matching score above 0.85, dropping N-PORT loans that are matched to multiple LSTA loans and N-PORT loans with different 9-digits CUSIPs that are matched to the same LSTA loan. As a result of our matching process, we are able to merge 31% of the loans held by loan funds from 2019Q4 through 2022Q4 with LSTA data, accounting for about 18% of the leveraged loans in LSTA.

The final step in the construction of our daily panel of loan-level prices is to incorporate data on the net percentage flows of the loan funds holding these loans. Using the mapping between LSTA and N-PORT loans and the mapping between N-PORT and Morningstar loan funds, we are able to link the loans held by loan funds with these funds' daily flows, which are available from Morningstar. Daily Morningstar data include dollar net flows and total net assets (TNA) at the share-class level, together with an internal fund identifier. For each fund-day, we sum net flows and TNA across all share classes in the fund; if flow data are missing for some of a fund's share classes on a given day, we treat the fund's net flows for that day as missing. Consistent with the empirical mutual fund literature and our analysis in Section 4, fund-day flows are trimmed between the 1st and 99th percentiles.

The final (unbalanced) loan-day panel we estimate on includes 2,351,705 observations, covering 6,337 loans over 754 business days.