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Negative externalities of mutual fund instability: Evidence from leveraged loan funds

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ABSTRACT

The market for leveraged loans that provide debt financing for risky companies has been on an exceptional growth path over the last decade. With the increased presence of investment funds in this market, however, come increased concerns – namely, whether a sharp rise of redemptions by fund investors could set off a cascade of drops in secondary loan prices and whether these price falls could trigger further redemptions, ultimately fueling a downward price and liquidity spiral? This paper provides evidence consistent with the view that in times of loan market stress, fund flows and loan price returns have been pro-cyclical, i.e., have reinforced each other's movements. Furthermore, fund outflows foster market illiquidity. Importantly, the paper identifies lending by CLOs as a channel through which outflow-induced price dislocations in the secondary market transmit to corporate borrowing, making it harder for leveraged companies to rollover their existing debt exactly at a time when liquidity is needed most (in market downs).

1. Introduction

In part because of the ongoing period of depressed global interest rates and investors' search for yield, an increasing number of investment funds, especially open-end mutual funds, have turned to less liquid but higher-yielding asset classes like leveraged loans or high-yield bonds that provide financing for risky firms. Over the last decade, the assets under management (AUM) of leveraged loan mutual funds offered to retail investors more than doubled, from \$54.3 billion in December 2010 to \$130.2 billion at the end of 2019, according to data from Lipper. As shown in Fig. 1, investor flows into these funds have generally been highly correlated with loan market returns (i.e., the change in the average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index – the LLI100).[1] In particular, over the period from January 2013 to December 2019, aggregate net monthly flows (inflows minus outflows) and market returns show a contemporaneous correlation of 37.1%.

This correlation prompts the question of whether a positive feedback process is at work, in which flows cause market returns (via price impact) and past market returns cause future flows (via feedback trading or return chasing). Such a feedback loop could be a source of cyclical instability, exacerbating market movements and contributing to price volatility. Feedback loops in the leveraged loan market are likely one-sided, operating only in falling markets. While loan funds invest in illiquid assets with long settlement periods, these funds offer their investors liquid redemption terms. Frequently, fund investors can even buy or sell their shares on the same day. This kind of "liquidity mismatch" between fund assets and liabilities and the resulting run-incentives of fund investors have the ability to cause a "death spiral" of mass investor redemptions that lead to deep price discounts, which, in turn, trigger further investor withdrawals (see Morris and Shin 2004, 2014 and Chen et al. 2010). These outflows and the accompanying fire sales may create major price dislocations in the secondary market, which can spill over to corporate access to finance, making it harder for leveraged companies to rollover their existing debt, thereby potentially leading to destabilizing financial shocks.[2]

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[1] The S&P/LSTA Leveraged Loan 100 Index is a daily index for the U.S. market that consists of 100 facilities (mostly term loans, both amortizing and institutional) and intends to mirror the market-weighted performance of the largest institutional leveraged loans in an effort to reflect the most-liquid side of the market. The index is published by S&P's Leveraged Commentary & Data (LCD) unit, dates back to 2002, and the pricing source are average bid quotes from the LSTA/LPC mark-to-market service.

[2] One implication of such a downward price spiral is a much stronger correlation between investor flows and market returns in downside markets. Indeed, the pattern shown in Fig. 1 points in this direction: in months with negative LLI100 bid returns, flows and returns are highly positively correlated ($\rho = 64.1\%$, significant at the 1% level), indicating that negative net flows (i.e., outflows) go hand in

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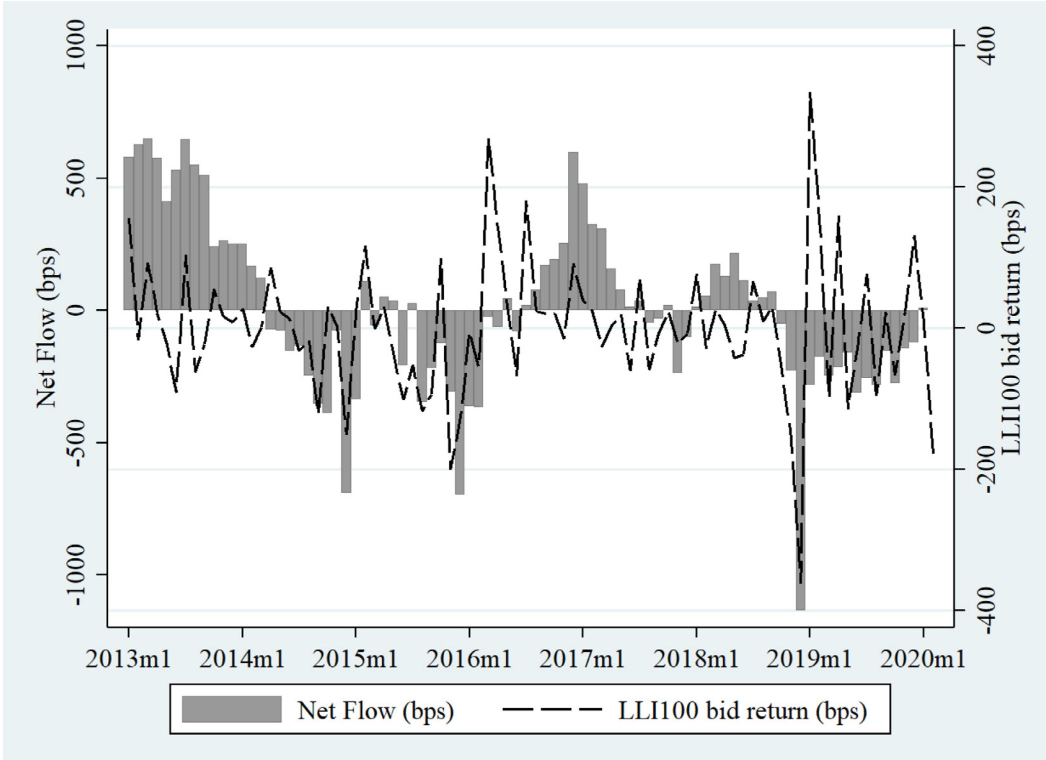

Fig. 1. Monthly aggregate net fund flows and loan market returns. Monthly data on aggregate net flows (i.e., inflows minus outflows) of retail loan mutual funds is from LCD. These funds encompass continuously offered, closed-end funds, exchange-traded closed-end funds (ETFs), and traditional daily-access funds. The flows are normalized by the fund's aggregate AUM at the end of the previous month. Loan market returns measure the relative change in the par-weighted average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index (LLI100).

This discussion motivates the paper's two main research questions: Does a feedback loop describe the relation between loan fund flows and market returns, and if true, does the flow-return relation spill over to corporate borrowing (and what is the channel of such a transmission)?

The paper starts with bilateral vector autoregressions (VARs) to examine the short-term dynamics between retail fund flows and loan market returns. VARs are particularly beneficial in this context because they rely on a minimal number of assumptions about the overall model structure. My daily fund flow and market return data span the period from August 2013 to December 2019, or 1627 trading days, a much longer and more comprehensive sample than the ones used in previous studies of daily equity mutual fund flow series (e.g., Ben-Rephael et al. 2011, Edelen and Warner 2001).[3] I rely on impulse response functions (IRFs) to simulate the typical reaction over time of one variable to unforecastable changes ("shocks" or "innovations") in the other variable within the bilateral VAR. To investigate a possible (temporary or permanent) price impact of flows, I look at IRFs that simulate the return response to a one standard deviation (1-SD) shock to flows. The main results from these IRFs are as follows.

First, in line with the importance of "run-on-the-fund" and "fire sale" dynamics in illiquid markets, loan price reactions to fund outflows (but not inflows!) are statistically significant and economically meaningful. In monetary terms, a $65 million net outflow shock at a particular day evaporates $295 million of market value in the LLI100 after eight days. Second, loan prices respond to net outflows not immediately, but with some delay (of more than one trading week). This reflects an inherent characteristic of less liquid markets in which prices are stale and slow to fully incorporate new information. Third, a large part (up to 50%) of the initial price reaction is transitory, reflecting price noise, which is only slowly corrected after more than two trading weeks. This represents strong evidence in favor of the price pressure hypothesis of fund redemptions.

To study feedback trading or return chasing behavior of loan fund investors, I estimate IRFs that simulate the flow response to a 1-SD shock to market returns. The results reveal an asymmetric response of net inflows and outflows to shocks in loan prices, consistent with the dominance of run-like incentives and first-mover advantages among loan fund investors in falling markets. While an unexpected 17.3 basis points (bps) decrease of the average daily bid price among the 100 LLI100 facilities raises aggregate net fund outflows by about $87 million (1.5 times its mean) over the next four trading weeks, the return chasing behavior is much less pronounced in rising markets. The accumulated responses of inflows

hand with price decreases. In contrast, flows and returns are almost uncorrelated in rising markets ($\rho = -14.3\%$, not significant). Reinforcing the short-term dynamics of downward price spirals in the loan market, when measured at a daily frequency over the period from August 2013 to December 2019, the contemporaneous flow-return correlation amounts to 52.8% (significant at 1%) in down-markets, and to −2.5% (not significant) in up-markets.

[3] A central advantage of this study is the availability of *daily* aggregate net fund flows obtained from LCD. This data allows for the cleanest possible identification of a causality from flows to price movements (i.e., price impact) and of future flow reactions to past price adjustments (i.e., feedback trading). The alternative use of lower, weekly or monthly, frequency data would seriously constrain any causal interpretation of the results because over the course of a month, for example, there are likely confounding fundamental shocks that simultaneously affect both, flows and market returns.

to upward shocks in returns are three to five times smaller and only weakly statistically significant.

In sum, the evidence so far strongly supports the view that a positive feedback effect of market-wide returns and aggregate retail loan fund flows operates on a daily level in the loan market. In line with previous theoretical and empirical literature (e.g., Chen et al. 2010, Goldstein et al. 2017), however, this feedback loop is limited to falling markets, and thereby contributes to the destabilizing dynamics of a downward spiral in market prices.

In the second part of the paper, I identify a possible channel through which such fund outflow-induced price dislocations transmit to corporate credit supply. More precisely, I rely on a central prediction of the *securities trading crowding-out lending* theories of Diamond and Rajan (2011) and Shleifer and Vishny (2010): price shocks in the secondary market transmit through higher expected returns to the primary market and cause loan investors with stable liabilities to reduce credit supply. The theory in Diamond and Rajan (2011) distinguishes two types of lenders (or loan investors): those with short-term, unstable, and liquid liabilities and others with more stable long-term, illiquid funding. While the first group is exposed to liquidity shocks and subsequent fire sale dynamics, the later partially insulate assets from non-fundamental price shocks. Loan mutual funds and exchange-traded funds (ETFs) are representative of the first type, and asset-backed securities called collateralized loan obligations (CLOs) correspond to the second.[4]

CLOs in their role as the largest leveraged loan investors are especially meaningful in this context because, in sharp contrast to loan mutual funds and ETFs, they are generally not required to mark-to-market their portfolio assets and CLO liabilities are not redeemable on short notice. Hence, CLOs are ideally suited to act as secondary market price insulators in the sense of (Chodorow-Reich et al., 2021) and to buy up the fire sales of loan mutual funds. However, if CLOs face funding restrictions, more buying in the secondary market necessarily comes with a contraction of credit supply to the corporate sector.

I start with micro (i.e., facility) level evidence of contrarian behavior by CLOs relative to loan funds. More specifically, the results suggest that CLOs as a group are partially absorbing the aggregate selling pressure of loan mutual funds, in line with the view that CLOs are taking advantage by buying up fund fire sales. I then show that funds sell as a response to outflows. Hence, outflows are the driving force behind fund fire sales.

Next, I test directly whether loan trading crowds out lending by CLOs in market downturns when fund outflows gain momentum. My measure of credit crowding-out is LENDING_SHARE, defined as the ratio of CLOs' credit supply (i.e., primary market loan purchases) to total (i.e., primary and secondary market) loan purchases. Hence, a lower value of LENDING_SHARE suggests that new credit is crowded out by loan purchases in the secondary market. Multivariate time series regressions at the weekly and monthly frequency reveal an asymmetric effect of flows on credit crowding-out. For example, while current week LENDING_SHARE falls by 15.2% (significant at 1%) if last week net outflows increased by 1%, it only rises by 8.0% (not significant) for a 1% upward shift in past week net inflows. Furthermore, the 2-week effect is 5.5% and significant for outflows, but essentially zero (−0.2%) and insignificant for inflows.

Finally, I perform a *CLO loan trading crowding-out lending* difference-in-difference type analysis at the firm level. The firm level results are particularly insightful because, by holding the borrower and time fixed, I can control non-parametrically for all observed and unobserved time-varying firm level heterogeneity like loan demand or credit risk. This should mitigate any endogeneity concerns. The analysis reveals that purchases of outstanding facilities of a firm by CLOs during cheap markets crowds out new CLO credit supply to the same firm. This crowding-out effect is economically strong and statistically significant at both, the weekly and monthly level. In sum, all the above evidence is consistent with the idea that fund redemptions and the associated price dislocations exert a negative externality on lending by CLOs in the primary market.

This paper contributes by informing the regulatory debate on financial stability and real sector implications of investment funds' exposure to leveraged loans. For example, in its 2019 Financial Stability Review, the German central bank raised the concern that investment funds can amplify financial shocks via an indirect contagion mechanism (see Deutsche Bundesbank, 2019, pp. 100–105). The worry here is that in episodes of market turmoil, fund investors have run-like incentives to redeem their shares as early as possible, especially if the fund holds relatively illiquid and risky assets like leveraged loans and high-yield bonds. The empirical evidence in this paper corroborates the concerns of regulators around the world with respect to leveraged loan fund instability, flow-return self-sustaining dynamics, and associated negative externalities on credit supply.[5]

More broadly, the paper contributes to our understanding of institutional investors' behavior during fire sale episodes. Procyclical behavior of loan fund investors in downturns amplifies downward price spirals, and consequently might force loan fund managers to first sell higher-quality investment grade bonds to raise cash (and prevent fire sale discounts), thereby ultimately "propagating the crisis" across the entire fixed income sector. Manconi et al. (2012) provide evidence in line with such cross-sector contagion of bond funds during the global financial crisis, and Greenwood et al. (2015) model spillover effects of fire sales through common asset exposures within the banking sector.

An extensive empirical literature examines the fire sale mechanism and associated spillover effects within the equity or bond mutual fund context (see Chernenko and Sunderam 2020, Choi et al. 2020 and Falato et al. 2020b, for recent contributions). These studies largely support the view that fire sales impose a negative externality on peer funds holding fire-sold assets. This paper extends the literature on flow-return feedback effects in the context of fire sales to leveraged loan funds that have received little attention so far. That way, the paper relates to fire sales in the corporate bond market due to investment constraints on insurance companies (e.g., Ellul et al. 2011). However, structural differences between (high-yield) bonds and (leveraged) loans warrant a separate study of loan funds. In addition, by focusing on CLO credit supply, the paper also broadens the scope of the fire sale literature to spillover effects on corporate access to finance.

Barrot et al. (2016) show that individual investors provide liquidity to the stock market in case of fire sales by institutional in-

[4] CLO is the name of an asset-backed security set up to hold and manage pools of leveraged loans (almost exclusively term loans B, C, etc.), and to a lesser extent high-yield bonds. These investments are financed through the issuance of several debt and (one or two) equity tranches that have rights to the collateral and payment stream, in descending order. CLOs are issued by a special purpose vehicle/entity (SPV/SPE).

[5] The concern that investment funds holding illiquid and risky assets might pose similar risks to financial stability than banks is popular among regulators around the world. For example, the Bank for International Settlements notes: *"Moreover, given that mutual funds are a major buyer, mark-to-market losses could spur fund redemptions, induce fire sales and further depress prices. These dynamics may affect not only investors holding these loans, but also the broader economy by blocking the flow of funds to the leveraged credit market."* (BIS Quarterly Review 2018, p. 11). The Financial Stability Board (2019, p. 24) concludes that *"even if at fund level liquidity risks may be adequately managed, if these funds in the aggregate experienced large-scale redemptions resulting in a need to sell leveraged loans, they could act procyclically and these sales could produce disruptive price impacts in the leveraged loan market."*

vestors. My results suggest that CLOs "lean against the wind" and serve as liquidity providers when fund outflows trigger downward price spirals. This way, the paper connects with a broader literature that examines the cyclical investment behavior of institutional investors. While the classical textbook buy-side investor is assumed to stabilize markets, i.e., to buy when prices fall and to sell when prices rise, recent empirical evidence provides a more nuanced picture. Timmer (2018), for example, finds that banks and investment funds respond pro-cyclically to debt security price changes, whereas insurance companies and pension funds act like contrarian investors. I show that neither loan fund managers nor their investors are contrarian, especially during crises, and that their behavior seems to amplify downward price and liquidity spirals. My findings are also consistent with Feroli et al. (2014) who provide evidence consistent with a feedback loop between mutual fund flows for certain fixed income securities and aggregate market prices.

The paper also extends the recent literature on strategic complementarities and financial fragility of funds holding illiquid assets (e.g., Chen et al. 2010, Goldstein et al. 2017, Falato et al., 2020a). While these papers concentrate on asymmetric flow-performance relations at the individual fund level and do not focus on market price implications, my paper highlights the potential for major price dislocations through aggregate fund flows during large-scale redemption periods. Furthermore, because loan funds "stress-test" the liquidity mismatch and fragility concern relative to equity and bonds funds, potentially meaningful run-on-the-fund incentives and the implications thereof should be most clearly visible in this context.

Finally, this paper provides a rare empirical test of the *securities trading crowding-out lending* theory developed in Diamond and Rajan (2011) and Shleifer and Vishny (2010). Abbassi et al. (2016) analyze securities trading by German banks and the associated spillovers to the supply of credit and provide evidence in line with the theoretical predictions. However, while these authors differentiate banks according to their trading expertise, contrasting the behavior of loan investors with relatively stable (CLOs) and unstable liabilities (loan funds and ETFs) is likely more in line with the two-investor setting envisaged by Diamond and Rajan (2011).

The remainder of the paper is organized as follows: In the next section, I characterize leveraged loans, describe the role of investment funds in the loan market, and detail the liquidity mismatch concern. While Section 3 provides information on the daily fund flow and loan market price return series used, Section 4 investigates whether a feedback effect of market-wide returns and aggregate fund flows operates on a daily level in the loan market. Section 5 studies the negative externality of fund outflow-induced price shocks in the secondary loan market on lending by CLOs in the primary market, and Section 6 gives a summary and conclusions.

2. Institutional background

A syndicated loan is a commercial credit structured, arranged, and administered by one or several commercial or investment banks, known as arrangers or agents. This paper looks at the leveraged or non-investment grade segment of the syndicated loan market, i.e., loans to risky borrowers. Such leveraged loans are typically packaged into two broad structures: institutional tranches and pro rata tranches. Institutional tranches comprise first- and second-lien, non-amortizing ("bullet"), fully funded facilities (called term loans B, C, D, etc.) structured specifically for institutional investors like CLOs, mutual funds/ETFs, credit hedge funds, pension funds and insurance companies. Pro rata debt includes unfunded revolving credit ("revolvers") and amortizing facilities (term loans A), which are packaged together and usually syndicated to banks. As shown in Fig. IA.1 in the Internet Appendix, the institutional part of the U.S. primary leveraged loan market experienced a tremendous growth over the last decade, with institutional outstandings more than doubling since 2010, crossing the $1 trillion threshold for the first time at $1.006 trillion in April 2018, and catching up the U.S. high-yield bond market. At the end of 2019, the outstanding par of U.S. institutional facilities amounts to $1.2 trillion, of which about 15% is held by retail mutual funds.

Internet Appendix Fig. IA.2 highlights the most important investors in the institutional loan segment together with their market shares. Traditionally, CLOs have been the dominant player with a current primary market share of approximately 70%, followed by loan mutual funds. These mutual funds are also known as prime funds in the U.S. because they were originally offered to investors as a money-market-like fund that intends to approximate the prime rate. Loan funds can be separated into two broad categories: closed-end and open-end. Closed-end funds are either continuously offered or exchange-traded. In the former case, investors can buy into these funds each day at the fund's net asset value (NAV), but redemptions are allowed only at a monthly or quarterly frequency rather than each day. Investors in ETFs, in turn, can buy and sell shares anytime on a stock exchange, but may not redeem them. Importantly, because buying and selling ETF shares on an exchange (in the secondary market) does not necessitate cash flows into or out of ETFs, these fund structures do not necessarily exhibit the same first-mover advantage or run risks as open-end mutual funds.[6] Finally, traditional open-end mutual funds are so-called "daily-access" funds into which investors can buy or redeem shares each day at the fund's NAV. Obviously, these funds are exposed to the strongest form of liquidity mismatch and run-like incentives.

As indicated in Internet Appendix Fig. IA.3, retail loan funds' AUM peaked at slightly more than $180 billion in November 2018, but since then have experienced a downward momentum, falling to $130 billion in December 2019. Fig. IA.4 displays the growth path in the number of funds, separately for ETFs and open-end (daily-access)/closed-end (monthly or quarterly tendered) structures. Currently, 121 funds are offered to investors, 50 ETFs and 71 open-end/closed-end pools. Approximately 75 different asset managers operate in this market.

In addition to the structures discussed above that satisfy retail investor demand, other forms of pooled investment vehicles like credit (or distressed) hedge funds, high-yield bond funds, and privately managed credit funds (e.g., separately managed accounts) tailored to the particular requirements of insurance companies and pension funds are important players in the leveraged loan space. Together, their primary market share is about 12% in 2019 (see Fig. IA.2).

Leveraged loans are inherently different from their natural peers, high-yield bonds, in several important ways. First, loans are bilateral contracts, not registered securities overseen by securities laws and regulators. Second, while some derivative products like loan credit default swaps (LCDS) do exist, there is no easy way to short a specific loan, at least not in the cash market. Most importantly, however, due to their nature as non-standardized contracts, the sale of a loan takes much longer to settle than the sale of high-yield bonds, which typically settle in three business days. This delayed settlement window may cause a potential liquidity mismatch

[6] The ETF sponsor interacts only with selected broker-dealers (called "authorized participants – APs") to create/redeem ETF units, which can be exchanged "in kind" for the underlying basket of securities. However, given the features associated with leveraged loans (physical contracts rather than securities, and relatively long settlement periods), in-kind redemptions with an AP are frequently replaced by cash redemptions. Hence, the usual arbitrage mechanism is impaired for loan ETFs, which likely limits the price impact of ETF outflows.

for mutual funds offering daily liquidity, requiring fund managers to secure sufficient liquidity to cover redemptions over extended settlement periods. As a result, efficient liquidity risk management is key to successfully managing a loan mutual fund.

Managers of loan funds have several tools available to manage fund liquidity risk. Typically, holding a slice of the portfolio in liquid assets (cash and high-grade bonds) acts as the first level of defense for a fund facing withdrawals. Second, by increasing the share of liquid and larger loans (e.g., the 100 loans that make up the S&P/LSTA Leveraged Loan 100 Index) with generally faster settlement, the portfolio manager gains additional flexibility to raise cash within the portfolio. Third, in the U.S., loan mutual funds have the ability to borrow (up to 33% of NAV under the Investment Company Act of 1940). Typically, loan funds (or their fund complexes) establish a bank loan facility from a group of large banks. By limiting the use of permissible leverage during normal times, portfolio managers can retain maximum flexibility to draw down their loan facilities to meet redemptions during periods of market stress, if necessary.

All these tools are adequate to alleviate pro-cyclical behavior of mutual funds, that is, the tendency to sell leveraged loans in times of large-scale redemptions. Whether, at the end, the retail loan mutual fund sector as a whole acts pro-cyclical and has the necessary size to cause major price dislocations in the leveraged loan market is ultimately an empirical question, one this paper intends to address.

3. Data

3.1. Measuring fund flows and market returns

An important innovation in my analysis is the use of aggregate net fund flows (i.e., inflows minus outflows) measured at a *daily* frequency. Standard & Poor's (S&P's) Leverage Commentary and Data (LCD) unit compiles this data. Importantly, I have no information on the flows of any specific fund or on inflows and outflows separately. LCD estimates aggregate fund flows based on data they receive directly from a number of mutual fund complexes. In particular, they collect daily fund flow series for a representative sample of loan funds, and then take the weighted-average AUM change each day from contributors and extrapolate it to the Lipper AUM universe to provide a "Lipper-style" daily reading of inflows minus outflows. The retail loan fund population covered by Lipper increased over my sample period. As of December 2019, the universe of loan funds reporting to Lipper comprises 92, of which 31 are closed-end and 61 are open-end, with total AUM of $126.7 billion. Lipper sources data from these funds to calculate its own weekly series of aggregate net fund flows (the Lipper "weekly reporters" series). This popular fund flow series serves as the main indicator of marginal investor demand sentiment among loan market professionals.

However, not all funds report their assets and asset value changes to Lipper each week. As estimated by LCD, at the end of 2019, the total number of loan or prime funds amounts to 121, with AUM of $130.2 billion. Of these, 50 are exchange-traded and 71 are open-end/closed-end with either daily, monthly, or quarterly redemption periods. LCD extrapolates its daily fund flows also to this "total" universe of loan funds.

Are the daily fund flow estimates reliable? While there is no ultimate answer to this question, some limited empirical evidence substantiates the use of LCD's daily flows.[7] At the bottom line, any systematic measurement errors or noise in flow estimates should bias me against detecting evidence of a meaningful short-term feedback loop between flows and returns. Hence, my findings most likely underestimate the real extent of price pressure and feedback trading present in the loan market.

S&P and the Loan Syndications and Trading Association (LSTA) developed a class of popular indices for the U.S. leveraged loan market. The most widely followed one is the S&P/LSTA U.S. Leveraged Loan 100 Index (LLI100) that tracks the market-weighted performance of the 100 largest and liquid facilities (mostly term loans) of the institutional loan universe. Importantly, market weightings and loan return calculations rely on indicative dealer bid quotes, not traded prices. The LLI100 serves as a common benchmark for the performance measurement of major loan fund managers and as a basis for passive investment vehicles such as ETFs. For example, the Invesco Senior Loan ETF invests at least 80% of its total assets in the facilities that make up the LLI100. Since most of the trading activity in the secondary loan market is concentrated in LLI100 constituents, and in order to avoid analysis problems arising from infrequent trading, and stale or missing dealer quotes, I focus on the LLI100 index to proxy for loan market returns. For each trading day, I calculate the par-weighted average bid price across all constituent facilities. I denote daily relative changes (in bps) of this average bid price by RET.

3.2. Properties of daily flows and returns

My sample period extends from August 2013 to December 2019, covering a total of 1627 trading days. Table 1 presents summary statistics on daily returns and flows. As shown in Panel A, the average RET is small, only 0.03 bps a day, or 7.5 bps annually, and on a typically day, the average bid across the 100 most-liquid facilities does not move at all. This is expected as individual loan prices are not supposed to change unless the loan's default risk shifts. If such shifts are mainly idiosyncratic in nature, RET, as a measure of market-wide default risk, remains unaffected.

Compared to the small average price movements, however, returns appear to be excessively volatile, with a daily standard deviation (SD) of 18.2 bps, approximately 292.5 bps on an annual basis. This extremely low mean-to-SD ratio is unlikely to be due to frequent daily shifts in systematic default risk. Instead, temporary changes in market technicals like demand and supply imbalances caused by retail fund flows might be a more plausible explanation.

Panel B presents descriptive statistics for flows. Over the sample period, outflows are more frequent and pronounced than inflows. On approximately 60% (951 out of 1627) of the days net aggregate flows to retail loan funds are negative, and the average of these flows (the variable NET_FLOWS) is negative: -$15.6 million, with a SD of $138.1 million. I follow previous literature (e.g., Ben-Rephael et al. 2011) and normalize the net flows by funds' AUM. Since I have only monthly data on the funds' aggregate AUM, I use the AUM of the previous month for the normalization of this months' daily flows. I denote the normalized flows by NFLOWS. The SD of this daily ratio is 9.8 bps, and on a typical day, funds loose on aggregate 1.4 bps of their previous months' AUM, which appears negligible. However, in the worst 5% of days, outflows are more than ten times larger (i.e., the 5% percentile of the daily flow distribution is −16.6 bps).

As argued above, a feedback loop is more likely to operate in falling markets, ultimately leading to a downward price spiral. To capture this idea, I separate NFLOWS into net outflows and net inflows. In particular, the variable OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise. By

[7] I benchmark LCD's daily flows against their weekly peers from Lipper. That is, I sum up the daily flows for each trading week and calculate the time-series correlation between this series and Lipper's weekly reporters series. The high pairwise correlation of 92% verifies that the daily estimates closely match the weekly flow dynamics, further reinforcing the accuracy of daily flows.

Table 1
Descriptive statistics. The table reports the summary statistics of the daily return and flow sample. The data span the period from August 2013 to December 2019, a total of 1627 trading days. RET is the relative change (in bps) of the par-weighted average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index. NET_FLOWS denotes dollar net flows (inflows minus outflows) aggregated across all prime funds. NFLOWS are NET_FLOWS normalized by previous month total fund AUM. OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise.

	Obs.	Mean	Median	Std. dev.	5%	95%
Panel A: Daily par-weighted average bid returns (in bps)						
LLI100 (‘RET’)	1627	0.03	0.00	18.15	−17.64	13.42
Panel B: Daily fund flows						
NET_FLOWS ($ million)	1627	−15.64	−20.87	138.07	−233.85	200.81
NFLOWS (bps)	1627	−1.29	−1.41	9.76	−16.59	14.03
OUTFLOWS (bps)	1627	−4.05	−1.41	6.73	−16.59	0.00
INFLOWS (bps)	1627	2.76	0.00	5.24	0.00	14.03

Table 2
Partial autocorrelations of flows and returns. The partial autocorrelation is the univariate correlation after controlling for the correlation at previous lags. The data span the period from August 2013 to December 2019, a total of 1627 trading days. RET is the relative change (in bps) of the par-weighted average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index. NET_FLOWS denotes dollar net flows (inflows minus outflows) aggregated across all prime funds. NFLOWS are NET_FLOWS normalized by previous month total fund AUM. OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise.

Lag:	1	2	3	4	5	6	7	8	9	10
Panel A: Returns										
LLI100 (‘RET’)	0.224[a]	0.105[a]	0.046	-0.002	0.007	-0.010	0.018	0.005	-0.004	0.005
Panel B: Fund flows										
NFLOWS	0.768[a]	0.296[a]	0.122[a]	0.140[a]	0.089[a]	0.068[a]	0.029	0.039	0.050	0.017
OUTFLOWS	0.721[a]	0.295[a]	0.039	0.079[a]	0.067[a]	0.030	-0.026	0.042	0.033	0.031
INFLOWS	0.733[a]	0.265[a]	0.216[a]	0.196[a]	0.143[a]	0.110[a]	0.107[a]	0.062[a]	0.087[a]	0.019

[a] Significant at 0.05 level, two-tailed test.

construction, the SDs of OUTFLOWS (6.7 bps) and INFLOWS (5.2 bps) are lower than the one for NFLOWS (9.8 bps).[8]

Table 2 shows the partial autocorrelations of returns (Panel A) and flows (Panel B). Partial autocorrelations measure the univariate correlation after controlling for the correlation at previous lags. The statistically significant positive autocorrelation of RET at lags 1 and 2 indicates that information in past LLI100 bid returns is relevant for future returns. This could reflect some degree of quote staleness or infrequent trading demand even among the 100 most-liquid facilities in the loan market. Although none of these autocorrelations appears economically large, I control for such time-series dependencies in my analysis below. More importantly, however, all net flow variables exhibit high positive autocorrelations, with significant lags up to order nine for INFLOWS, five for OUTFLOWS and six for NFLOWS. Moreover, the first-order correlations are particularly high, exceeding 70% in each case. These autocorrelations imply that large components of the flows are predictable on the basis of past flows.[9]

4. Empirical results

4.1. How a shock to retail loan fund flows affects prices

Fig. 1 presents preliminary evidence of a one-sided feedback loop between flows and returns. While the flow-return pattern shown in the figure reveals no sign of synchronization in market upswings, three episodes of severe market turmoil characterized by simultaneous strong outflows and large price drops are eye-catching. Over the last two months of 2018, the average LLI100 bid price crashed by about 5.2% and retail funds lost almost 14% of their beginning of period AUM. In November 2015, the market dropped by 2.0% and the corresponding outflows amount to 3.1% of AUM. Finally, in December 2014, the LLI100 experienced a price decrease of 1.5% and fund outflows sum to 7%. Importantly, all of these numbers are sizeable in view of the fact that the typical monthly market return amounts to 4 bps (standard deviation: 98 bps) and the typical monthly net flows are 13 bps (standard deviation: 317 bps). Hence, these stress episodes are a first indication of a feedback process strong enough to sustain a downward spiral in loan prices.

For a more rigorous examination, I employ a set of bilateral vector autoregressions (VARs). In particular, the following analyzes rely on impulse response function (IRF) simulations to estimate the dynamic relations between NFLOWS and RET. The recursive VAR system based on optimal lag tests[10] includes L lags of NFLOWS and RET:

$$NFLOWS_t = \alpha_1 + \sum_{i=1}^{L} \beta_i\, NFLOWS_{t-i} + \sum_{i=1}^{L} \gamma_i\, RET_{t-i} + \varepsilon_t \tag{1}$$

$$RET_t = \alpha_2 + \sum_{i=1}^{L} \lambda_i\, NFLOWS_{t-i} + \sum_{i=1}^{L} \delta_i\, RET_{t-i} + \eta_t .$$

I present impulse responses using a Cholesky ordering of the VAR that places fund flows first and returns second. That is, I assume the causality runs from NFLOWS to RET, meaning that, at time t_0, a shock to NFLOWS (represented by ε_t in Eq. (1)) affects RET but a shock to RET does not affect NFLOWS contemporane-

[8] For all the series in Table 1, I can reject the null hypothesis of a unit root at all common significance levels, using Dickey-Fuller tests with various lags in the augmented regression. Hence, returns and flows are generated by stationary processes. This is an important prerequisite for the application of VARs in Section 4.

[9] Additional unreported tests reveal no material difference in flows or returns across days of the week. Hence, no apparent “day-of-the-week” characteristics in either flows or returns will affect my analysis.

[10] I employ the following lag-order selection statistics: a likelihood-ratio test statistic, the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC), and the Hannan and Quinn information criterion (HQIC). All lag-order selection statistics are estimated for a series of VARs of order 1 through a preset maximum lag of three weeks (15 trading days). In each case, I choose the lag number indicated by the simple majority of the applied criteria as optimal. Typical lags are eight or ten. Again, all results are qualitatively unchanged for different choices of the optimal lag order. See Lütkepohl (2005) for more information on lag-order selection statistics.

Table 3
Cumulative impulse response functions – baseline results. The table shows cumulative orthogonalized impulse response functions (IRFs) from three different bilateral vector autoregressions (VARs). The data span the period from August 2013 to December 2019, a total of 1627 trading days. Columns (1) and (4) are from a VAR of RET and NFLOWS, columns (2) and (5) from a VAR of RET and OUTFLOWS, and columns (3) and (6) from a VAR of RET and INFLOWS. The Cholesky ordering of each VAR places fund flows first and returns second. The optimal lag order is chosen individually for each VAR, based on lag order selection statistics. Columns (1) to (3) report the simulated response of RET (in bps) to a one standard deviation innovation in NFLOWS, OUTFLOWS, and INFLOWS, respectively. Columns (4) to (6) report the simulated response (in bps) of NFLOWS, OUTFLOWS, and INFLOWS, respectively, to a one standard deviation innovation in RET. See Table 1 for variable definitions. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Cumulative orthogonalized IRFs					
	How a shock to flows affects RET			How a shock to RET affects flows		
Days	NFLOWS (1)	OUTFLOWS (2)	INFLOWS (3)	NFLOWS (4)	OUTFLOWS (5)	INFLOWS (6)
0	2.591***	3.118***	0.102	0.000	0.000	0.000
	(0.432)	(0.432)	(0.435)	(0.000)	(0.000)	(0.000)
1	4.427***	4.914***	0.595	0.795***	0.587***	0.149*
	(0.672)	(0.670)	(0.683)	(0.144)	(0.110)	(0.079)
2	5.908***	6.865***	0.296	1.608***	1.250***	0.220
	(0.881)	(0.876)	(0.898)	(0.254)	(0.197)	(0.134)
3	7.088***	7.969***	0.427	2.319***	1.804***	0.332*
	(1.068)	(1.063)	(1.090)	(0.367)	(0.293)	(0.182)
4	8.027***	8.897***	0.720	2.745***	2.283***	0.274
	(1.235)	(1.229)	(1.257)	(0.476)	(0.386)	(0.228)
5	8.739***	10.247***	0.045	3.426***	2.771***	0.471*
	(1.383)	(1.380)	(1.402)	(0.587)	(0.480)	(0.274)
6	11.036***	11.254***	2.568*	3.874***	3.123***	0.590*
	(1.514)	(1.518)	(1.520)	(0.701)	(0.574)	(0.321)
7	11.349***	11.415***	2.744*	4.333***	3.519***	0.714*
	(1.632)	(1.645)	(1.614)	(0.818)	(0.670)	(0.370)
8	11.379***	11.210***	2.918*	4.471***	3.785***	0.640
	(1.734)	(1.763)	(1.678)	(0.936)	(0.763)	(0.421)
9	11.598***	11.141***	3.232*	4.915***	4.109***	0.837*
	(1.802)	(1.855)	(1.705)	(1.053)	(0.855)	(0.474)
10	10.649***	10.015***	2.897*	5.100***	4.240***	0.967*
	(1.775)	(1.868)	(1.626)	(1.172)	(0.943)	(0.528)
11	10.301***	9.431***	2.863*	5.411***	4.457***	1.066*
	(1.821)	(1.936)	(1.655)	(1.299)	(1.036)	(0.586)
12	10.013***	8.837***	2.844*	5.713***	4.659***	1.168*
	(1.882)	(2.011)	(1.718)	(1.425)	(1.128)	(0.642)
13	9.851***	8.379***	3.010*	6.008***	4.860***	1.257*
	(1.956)	(2.098)	(1.788)	(1.548)	(1.215)	(0.697)
14	9.727***	8.033***	3.092*	6.286***	5.045***	1.355*
	(2.032)	(2.186)	(1.857)	(1.667)	(1.298)	(0.752)
15	9.674***	7.743***	3.266*	6.557***	5.220***	1.441*
	(2.109)	(2.273)	(1.928)	(1.782)	(1.376)	(0.806)
16	9.656***	7.464***	3.446*	6.811***	5.373***	1.537*
	(2.185)	(2.358)	(1.996)	(1.893)	(1.448)	(0.860)
17	9.549***	7.191***	3.547*	7.045***	5.524***	1.618*
	(2.261)	(2.440)	(2.063)	(2.000)	(1.516)	(0.913)
18	9.417***	6.885***	3.626*	7.263***	5.654***	1.706*
	(2.336)	(2.520)	(2.133)	(2.103)	(1.579)	(0.965)
19	9.255***	6.594**	3.708*	7.481***	5.779***	1.791*
	(2.410)	(2.596)	(2.200)	(2.203)	(1.637)	(1.018)
20	9.061***	6.258**	3.744*	7.686***	5.884***	1.876*
	(2.483)	(2.669)	(2.270)	(2.299)	(1.691)	(1.069)

ously.[11] Hence, the destabilizing dynamics are driven by the decisions of investors as reflected in their fund flows. The assumption behind this ordering is that shocks to flows on a given day are exogenous to changes in valuations on that day. After the initial day, however, the VAR allows for arbitrary correlations between the innovations to flows and returns.

The accumulated impulse response of RET to a 1-SD shock to NFLOWS is presented in Table 3, Column (1). See Fig. 2 (bottom left chart) for a graphical representation. The shock size amounts to 5.7 bps of aggregate fund AUM or \$84 million. As can be seen in the table, the contemporaneous effect of this shock to NFLOWS on RET is 2.6 bps. This t_0 response is followed by an accumulated effect from day 1 to day 9 of about 9.0 bps, significantly different from zero at the 1% level. Based on the average LLI100 par amount of \$258.5 billion over my sample period, the \$84 million flow shock results in a valuation effect of about \$300 million (=0.00116*258.5). In other words, each dollar of unexpected net outflows (inflows) lowers (raises) the market value of LLI100 loans on average by about 3.6 dollars after ten days. This continuation effect is not only statistically significant, but also economically large. After day 9, however, a reversal effect dominates, summing up to 2.5 bps until day 20, leaving the permanent shock response at 9.1 bps (significantly different from zero with a t-statistic of 3.65). Hence, approximately 78.4% of the $t_0 - t_9$ valuation response of 11.6 bps is permanent, 21.6% is temporary.

[11] It is important to note that all the results in this paper remain qualitatively unchanged if I change the identifying assumption and employ an ordering that puts returns before flows. However, by using data on a daily frequency and by looking at a decentralized OTC market with limited pre- and post-trade transparency, it should be easier to defend the assumption that flow movements cause price adjustments contemporaneously, but not vice versa.

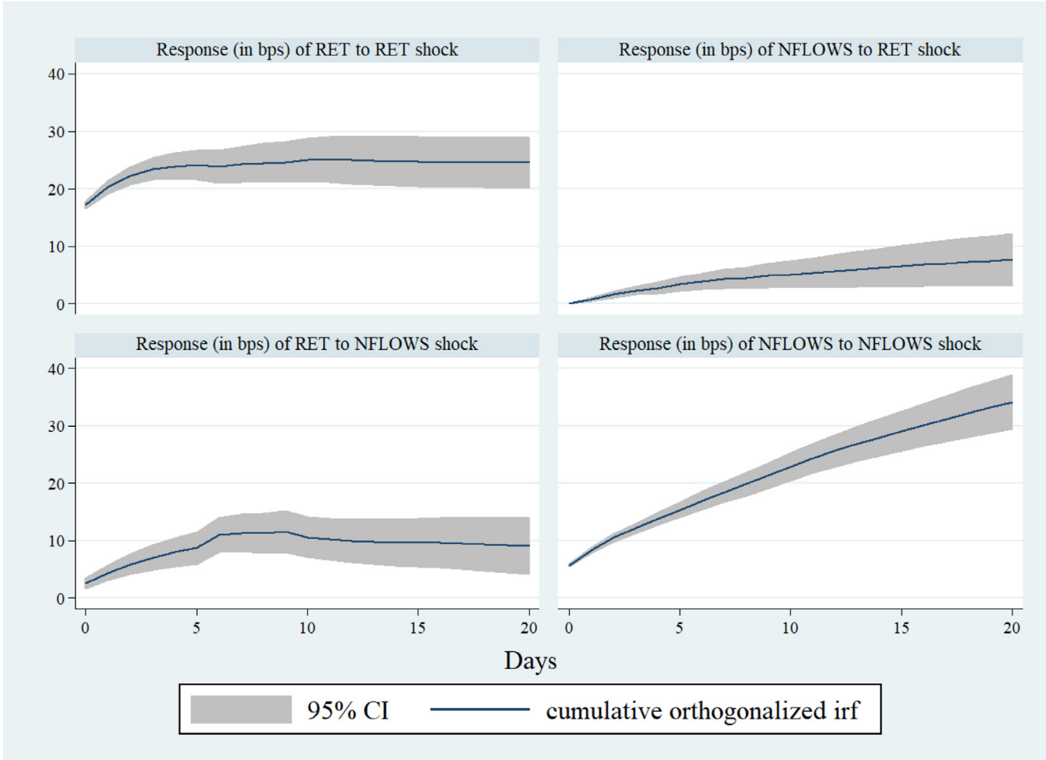

Fig. 2. Cumulative orthogonalized impulse response functions from a VAR of RET and NFLOWS. A bilateral VAR with two endogenous variables, RET and NFLOWS, and ten lags of each variable is estimated on daily data over the period August 2013 to December 2019 (1627 trading days). The Cholesky ordering of the VAR places fund flows first and returns second. RET denotes the daily relative change (in bps) of the average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index. NFLOWS is the aggregate net daily flow (inflow minus outflow) of loan mutual funds. The figure has four charts detailing the cumulative response over 20 days to one-standard deviation innovations of: flows to flows (top left), flows to returns (top right), returns to flows (bottom left), and returns to returns (bottom right).

The evidence so far is consistent with the notion that flow-induced trading by retail loan funds exerts a large pressure on secondary (LLI100) loan prices. The accumulated ten-day effect of 11.6 bps corresponds to almost 500 times the mean daily change in the par-weighted average LLI100 bid price (i.e., 0.02 bps, the mean of RET) or to 63.7% of the daily standard deviation of RET (18.2 bps). Slightly more than one fifth of this price impact appears to be temporary price noise, which slowly reverses within the next ten trading days.

Recent arguments and results in the literature on strategic complementarities and financial fragility of funds holding illiquid assets (e.g., Chen et al. 2010, Goldstein et al. 2017) raise an even more subtle implication of fund flows: the price impact of negative NFLOWS (i.e., OUTFLOWS) should exceed the one of positive NFLOWS (i.e., INFLOWS). The point here is that loan funds are highly liquid instruments with short (often daily) redemption periods, meaning investors can enter and exit positions easily. If these funds invest most of their AUM in illiquid assets, a liquidity mismatch results and the associated first-mover advantage could cause a run-on-the-fund phenomenon (as shown in Goldstein et al. 2017, for bond funds).

In a downturn, when fund share redemptions gain momentum, a fund becomes a forced seller into an illiquid market where only a few investors are willing to buy at cents on the dollar. Forced selling, the associated losses, and the inability still to meet redemptions can cause mutual funds and ETFs to collapse, sowing the seeds for a distinct downward price spiral. Even worse, fire sales and major price dislocations in the loan market can spill over to the corporate sector, making it harder for leveraged companies to obtain funding. Further support for such an asymmetric response of prices to OUTFLOWS and INFLOWS comes from the fire sale literature (e.g., Coval and Stafford 2007, Manconi et al. 2012 and Ellul et al. 2011) studying liquid public markets: vast evidence suggests that institutional selling pressure imposes a much stronger temporary price distortion than institutional buying demand.

I test for asymmetric responses of prices to INFLOWS and OUTFLOWS by modifying the VAR system of Eq. (1). More precisely, I estimate a VAR separately for INFLOWS and OUTFLOWS (instead of NFLOWS). Recall that OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise. The accumulated impulse response of RET to a 1-SD shock to OUTFLOWS (4.4 bps or $65 million) and INFLOWS (3.2 bps or $47 million) is presented in Table 3, Columns (2) and (3), respectively. See the bottom left charts in Figs. 3 and 4 for a graphical illustration of these IRFs.

Interestingly and as predicted by the run-on-the-fund and fire sale view widely held among practitioners, regulators and academics, only aggregate net outflows impose a (partially reversed) pressure on prices. While the contemporaneous response of prices to net outflows is 3.1 bps and the accumulated $t_0 - t_7$ effect amounts to 11.4 bps, all statistically significant at the 1% level, the corresponding responses of prices to net inflows are small and never significant at conventional levels. In particular, an innovation of 4.4 bps in OUTFLOWS lowers the average price of LLI100 facilities by 11.4 bps within the next seven days. Again an economically large effect given the mean (0.02 bps) and standard deviation (18.2 bps) of RET.[12] In monetary terms, a $65 million net outflow shock at a particular day evaporates $295 million (= 0.00114*258.5) of market value in the LLI100 after eight days (from day 0 to day

[12] Recall that the variable OUTFLOWS is defined on a negative scale. Hence, to get the effect of a 1-SD increase in net outflows on RET, we must multiply the corresponding impulse responses by −1.

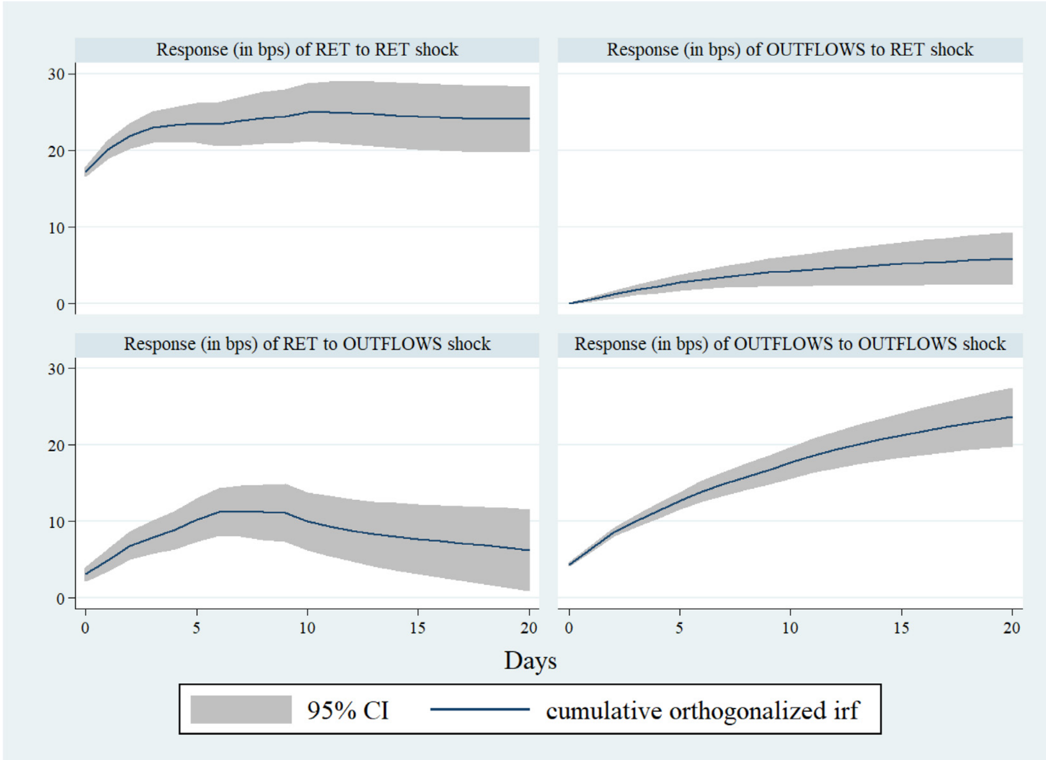

Fig. 3. Cumulative orthogonalized impulse response functions from a VAR of RET and OUTFLOWS. A bilateral VAR with two endogenous variables, RET and OUTFLOWS, and ten lags of each variable is estimated on daily data over the period August 2013 to December 2019 (1627 trading days). The Cholesky ordering of the VAR places fund flows first and returns second. RET denotes the daily relative change (in bps) of the par-weighted average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index. OUTFLOWS is the aggregate net daily outflow of loan mutual funds. In particular, OUTFLOWS equals NFLOWS if NFLOWS is negative, and zero otherwise. The figure has four charts detailing the cumulative response over 20 days to one-standard deviation innovations of: outflows to outflows (top left), outflows to returns (top right), returns to outflows (bottom left), and returns to returns (bottom right).

7). Also noteworthy is the pronounced reversal of 5.1 bps (= 11.4 – 6.3) up to day 20 (significant at the 1% level), suggesting that about 44.7% of the t_0-t_7 accumulated response reflects temporary price noise which is not immediately corrected.

4.2. How a shock to prices affects flows

The previous section looked at one dimension of the broad relationship between loan market price returns and loan fund flows: the effect of daily fund flows on market returns (i.e., changes in the LLI100 average bid price). A positive-feedback process, however, requires two-way self-sustaining dynamics between flows and returns, where the market moves in response to the investors' behavior while fund investors themselves react to past market movements. To investigate the second part of these dynamics, I examine how a shock to RET (represented by η_t in Eq. (1)) affects NFLOWS. Recall that by design (i.e., the Cholesky ordering) innovations to RET cannot contemporaneously affect flows.

Column (4) in Table 3 reports the accumulated impulse response of NFLOWS to a 1-SD shock (17.3 bps) of RET, and the top right chart in Fig. 2 illustrates this IRF. The four trading weeks effect (up to day 20) of this shock amounts to 7.7 bps, or about 80% of the daily standard deviation (9.6 bps) of NFLOWS. All responses are also highly (at 1%) statistically significant. In monetary units, a 17.3 bps return surprise on a given day causes $113 million of additional net inflows into investment funds over the next four weeks. Hence, in line with the presence of a strong feedback loop, net fund flows respond positively to past market returns over the full projection interval. This finding is also consistent with many papers reporting return chasing behavior among mutual fund investors at the individual fund level (e.g., Chevalier and Ellison 1997, Sirri and Tufano 1998).

However, the concave flow-performance relation identified in the literature for funds holding more illiquid assets implies that impulse responses are stronger for OUTFLOWS than for INFLOWS. I test this prediction using the VARs estimated separately for OUTFLOWS and INFLOWS. The corresponding impulse response functions are presented in Columns (5) and (6) of Table 3, and are graphically depicted in the top right charts of Figs. 3 and 4. As can be seen, the shock response of OUTFLOWS resembles closely the pattern observed for NFLOWS. The four-week effect sums to 5.9 bps or $86.7 million, significant at 1%. That is, an unexpected 17.3 bps decrease of the average daily bid price among the 100 LLI100 facilities raises aggregate net fund outflows by about $87 million over the next four weeks. In contrast, the return chasing behavior is much less pronounced among net inflows. The accumulated responses of INFLOWS in Column (6) are three to five times smaller (summing up to just 1.9 bps at day 20) and only weakly (at 10%) statistically significant. This asymmetric response of net inflows and outflows to shocks in loan prices is consistent with the dominance of run-like incentives and first-mover advantages among loan fund investors.

In sum, the evidence so far strongly supports the view that a positive feedback effect of market-wide returns and aggregate retail loan fund flows operates on a daily level in the loan market. In line with theoretical predictions about spillover effects of investor redemptions in falling markets, however, this feedback loop exacerbates the selling pressures in a run-like episode and thereby contributes to the destabilizing dynamics of a downward spiral in asset prices.

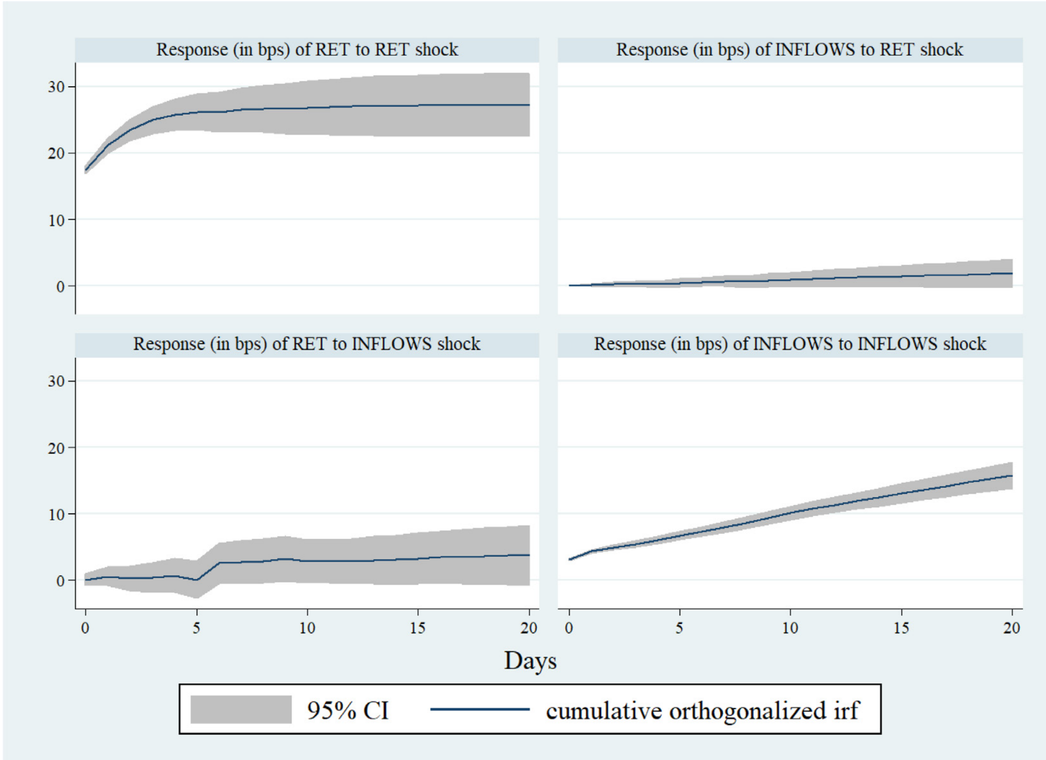

Fig. 4. Cumulative orthogonalized impulse response functions from a VAR of RET and INFLOWS. A bilateral VAR with two endogenous variables, RET and INFLOWS, and ten lags of each variable is estimated on daily data over the period August 2013 to December 2019 (1627 trading days). The Cholesky ordering of the VAR places fund flows first and returns second. RET denotes the daily relative change (in bps) of the par-weighted average bid price across the 100 constituent facilities of the S&P/LSTA Leveraged Loan 100 index. INFLOWS is the aggregate net daily inflow of loan mutual funds. In particular, INFLOWS equals NFLOWS if NFLOWS is positive, and zero otherwise. The figure has four charts detailing the cumulative response over 20 days to one-standard deviation innovations of: inflows to inflows (top left), inflows to returns (top right), returns to inflows (bottom left), and returns to returns (bottom right).

4.3. Additional results

4.3.1. Price impact of unexpected and expected net flows

In additional analyzes detailed in the Internet Appendix (Section A), I look deeper into the price pressure effects of fund flows. Net flows are highly persistent and strongly predictable by their own lags and by past market returns. This motivates the question whether prices respond differently to anticipated and unanticipated fund flows. I address this issue by dividing net flows into expected and unexpected components and estimate separate bilateral VARs of RET and expected and unexpected OUTFLOWS and INFLOWS, respectively. The results are revealing. In short, while unexpected inflows contain new information that permanently affects prices, expected inflows appear to be uninformative about market fundamentals, a finding in line with previous literature (e.g., Warther 1995). Net outflows, in turn, whether they are anticipated or not, do not transmit value-relevant information to the market. Instead, they cause fire sale episodes that temporarily destabilize prices.

4.3.2. Price impact across different time periods and market segments

In Section B of the Internet Appendix, I test for time-series variation in the return response to outflow shocks and its link to market liquidity by dividing the full sample period almost equally. Viewing the more recent period from January 2017 to December 2019 as being characterized by higher market liquidity, the temporary price impact of outflow shocks should be less significant and reversed faster during this period. Indeed, this is what I find. In addition, with respect to cross-sectional variation in price responses, the prediction would be that fund flow-induced fire sales depress predominantly the prices of facilities largely held by loan mutual funds. Vice versa, the prices of those (small, illiquid, and high-risk) facilities that are outside the typical investment universe of loan funds should be less affected by fund outflows. VARs with return series of ratings-based (BB, B, CCC) sub-indices of the broad S&P/LSTA index indicate that price responses to outflow shocks are much more pronounced among the 100 largest and most-liquid facilities contained in the LLI100 index, and weaker, both economically and statistically, for non-LLI100 facilities.

4.3.3. How a shock to retail loan fund flows affects market liquidity

In another set of bilateral VARs (see Section C in the Internet Appendix for details), I look at systematic variation in loan market liquidity and its relation to retail fund flows. My primary interest here is to examine the collateral value or funding constraints view of liquidity supply (e.g., Brunnermeier and Pedersen 2009, Gârleanu and Pedersen 2007, Gromb and Vayanos 2002). The collateral value of dealer inventories, and, hence, dealers' funding constraints act as the underlying channel in this theory. Loan price shifts induce wealth changes that, in turn, affect market liquidity. This channel operates asymmetrically because it is exactly in down markets where liquidity providers are likely to hit their wealth or financing constraints. If fund flows cause price movements, they should also affect market liquidity via the collateral value or funding liquidity channel. My findings strongly support this prediction and are in line with the previous results on market returns. While the liquidity response to innovations in (unexpected or expected) inflows is weak and mostly insignificant, outflow shocks, anticipated or not, adversely affect liquidity. Hence, large-scale fund redemptions foster market illiquidity.

4.4. Robustness

I run several robustness checks (for the sake of brevity, results from these tests are not reported in detail):

- The feedback loop could just reflect a joint response of returns and flows to variation in a common factor like market-wide uncertainty, risk aversion or credit risk premia. I address this concern by including the CBOE volatility index VIX as an exogeneous variable into the VAR.[13] The VIX has been shown to capture variation in credit spreads and/or credit risk premia, e.g., (Berndt et al., 2018). I replicate the VARs from Table 3 with the contemporaneous VIX index level added as an exogeneous variable and present the results in Table IA.7 of the Internet Appendix. While all previous findings remain qualitatively unchanged and statistically highly significant, the economic significance is somewhat lower. For example, the accumulated $t_0 - t_7$ effect of a 1-SD shock to OUTFLOWS amounts to 11.4 bps without VIX (Column (2) in Table 3), and to 8.7 bps with VIX (Column (2) in Table IA.7). The subsequent price reversal is even stronger in case of VIX, suggesting that all the price reaction to outflow shocks is temporary. Moreover, return chasing is also slightly less pronounced: while the four-week response of OUTFLOWS to a 1-SD return surprise sums to 5.9 bps in Table 3, it is lower at 4.3 bps in Table IA.7.
- As explained previously, LCD extrapolates the daily fund flow data they obtain from contributing fund families to the Lipper loan fund universe, and to a "total" universe that also includes the AUM of funds not reporting on a weekly basis to Lipper. I replicate all analyzes using these total-style daily fund flows. Results remain qualitatively unchanged.
- In addition to bid quote changes, I approximate returns by market value changes of the LLI100. The market value of a facility is the product of its current par and the average (across all quoting dealers) bid. Hence, market value returns also capture principal repayments. While the results still hold, I note that bid quotes are a purer measure of price pressure.
- I reassess the short-term dynamic relations between flows and returns by OLS time-series regressions with Newey-West standard errors. That is, I regress flows on lagged flows and returns and vice versa for market returns as dependent variable. In the return regression, the sum of coefficients for the first six lags of OUTFLOWS is positive (t-statistic: 2.06), and negative for lags 7-10 (t-statistic: -2.1), consistent with the price impact-and-reversal pattern observed previously. INFLOWS, in contrast, are unrelated to future returns. Moreover, the predictive power of past returns is stronger for outflows than for inflows, in line with the prevalence of feedback trading in down markets.[14]

5. Externalities of fund outflow-induced fire selling and price dislocations

In this section, I try to cleanly identify the mechanism by which a fund outflow-induced downward spiral in secondary market loan prices imposes a negative externality on credit supply. I start with direct evidence that CLOs partially stabilize loan prices by buying facilities that funds unload and that funds sell as a response to outflows. Next, I investigate the central prediction of the *trading crowding-out lending* theory put forth in Diamond and Rajan (2011) and Shleifer and Vishny (2010): the fragility of lenders with unstable liabilities (loan mutual funds) puts a negative externality on the credit supply of lenders with more stable liabilities (CLOs). During a crisis, because of mutual fund outflow-induced fire sales in the secondary loan market, the returns from investing in loans trading at temporarily depressed prices are higher than the returns from lending, assuming that primary and secondary markets are not fully integrated and that primary loan price discounts do not adjust immediately to changes in expected trading returns. Consequently, in the presence of funding constraints, CLOs reduce credit supply as they withdraw funds from lending to profit from trading opportunities. This is exactly what I find, both in time-series regressions and in borrower-level analyzes.

5.1. Do CLOs absorb loan mutual fund selling pressure?

According to data from LCD (see Internet Appendix Fig. IA.2), CLOs account for 71% of primary loan market allocations in 2019, compared to 52% at the 2008 distressed peak. This is important as it suggests that the stability of the loan market depends to a large degree on the cyclicality of CLO manager's trading behavior. Hence, do CLOs stabilize market prices by buying facilities that funds are selling, or do they reinforce price pressure in market downturns?

On the one hand, and in sharp contrast to mutual funds, CLOs are generally not required to mark-to-market their portfolio assets.[15] This structural feature makes CLOs relatively sticky in terms of forced selling and potentially limits the vicious cycle of loan fund redemptions and price drops. On the other hand, while CLOs are typically not forced to sell, they are unlikely to be buyers of deeply distressed debt and are far from being the buyer of last resort. This is because CLOs often include specific provisions when purchasing loans below a documented threshold price, typically 80% of par, with these loans referred to as "discount obligations" (DO). Importantly, CLOs are disincentivized to buy DOs because they must be carried at their purchase price in the calculation of par coverage ratios. Hence, the ability of CLOs to absorb selling pressure is likely limited to non-DOs, i.e., facilities trading above 80.

To gauge the cyclical trading behavior of CLOs, I extract all trade information contained in CLO trustee reports available from the database CLO-i of Creditflux. My trade sample for the following analysis is limited to the 5.5 years from July 2010 to December 2015. I drop (1) trades with missing information on traded par amount, price or trade day, (2) transactions wrongly classified as secondary market trades (i.e., primary assignments, restructurings), (3) trades in facilities with no dealer quotes from Markit, and (4) trades in instruments other than term loans (e.g., bonds, letters of credit, mezzanine tranches) or in facilities that cannot be clearly identified. The final sample includes about 142,000 secondary market trades of CLOs in term loans.

To gain insights into loan trading by funds, I employ the CRSP mutual fund database that provides information on facility par amounts held by SEC registered funds on a monthly basis.[16] I infer trades from changes in par amounts held from month to month, and exclude par changes that are due to facility repayments, restructurings and refinancings. Information on contractual par re-

[13] I am indebted to an anonymous referee for suggesting this robustness check.

[14] I also run Granger causality tests after the estimation of each VAR model. These tests indicate that flows Granger-cause returns and that returns Granger-cause flows. This is true for NFLOWS, OUTFLOWS, and even INFLOWS. Significance levels are typically 1% or better. However, Granger causality tests are just Wald tests that the coefficients on all the lags of an endogenous variable in a VAR that is not the dependent variable in an equation are jointly zero. Hence, they tell us nothing about the form of the dynamic relation between flows and returns.

[15] CLO managers must mark-to-market the following positions: (1) CCC-rated loans in excess of an allowed 7.5% CCC portfolio bucket, (2) discount obligations (i.e., positions bought at a depressed price, normally below 80% of par), and (3) defaulted loans. All other positions are held at par.

[16] Loan or prime funds are identified in CRSP by the Lipper style code "LP" (for loan participation funds).

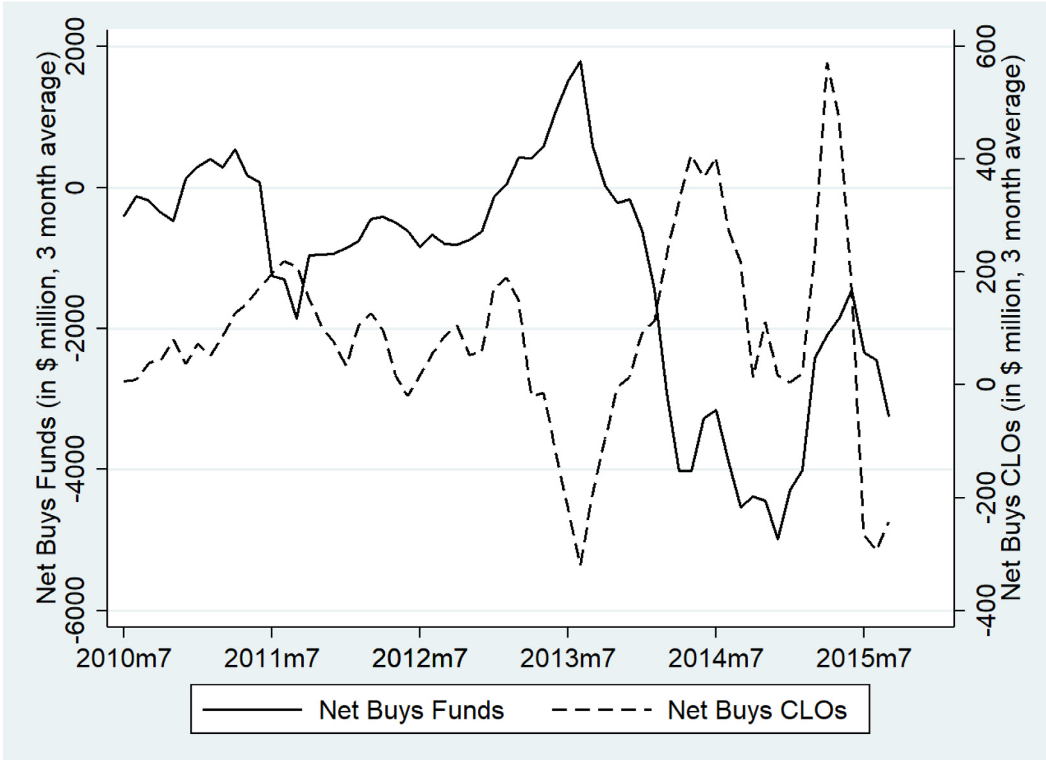

Fig. 5. Aggregate net buys of loan funds and CLOs. Net buys are defined as $BUYS_t - SELLS_t$, where $BUYS_t$ is the aggregate par of all secondary market term loan buys in month t, and $SELLS_t$ is the aggregate par of term loan sells in month t. Net buys are calculated separately for loan funds and CLOs across facility-months with a least one loan fund trade in the facility. Trading behavior of loan funds is inferred from monthly holding reports (i.e., 13f reports) of funds that file with the SEC. Trades are assumed to equal changes in facility par amounts between subsequent holding reports, adjusted for repayments, refinancings, and restructurings. Data source for fund holding reports is CRSP. Data for CLO trades is from trustee reports in CLO-i. Both monthly time series are from July 2010 to December 2015 (66 months). The figure shows three-month moving averages.

payment schemes of facilities is obtained from DealScan. This data is available to me up to January 2016.

Fig. 5 depicts the monthly pattern of net buys (i.e., the par bought minus the par sold) aggregated separately for loan funds and CLOs across a common set of facilities. Except for about the last twelve months, both series clearly move in opposite directions. The pairwise correlation is −0.62 from July 2010 to December 2014, and less negative at −0.29 for the extended period until December 2015. Hence, when funds are net sellers, CLOs are net buyers on average. In the 50 months during which funds are selling in excess of buying, they typically sell $1.3 billion more than what they buy. Of these $1.3 billion net selling, CLOs buy on net $101 million (or 7.5%). I note that this number likely underestimates the price support from CLOs because (1) CLO-i lacks complete coverage of CLOs and/or trustee reports, (2) CLO trades are excluded due to missing or incomplete information on the traded facility, trade day or traded par, and (3) not all facilities in the non-standardized CLO trustee reports can be matched with CRSP. Despite these caveats, Fig. 5 provides preliminary evidence suggesting a market price insulator role of CLOs.

To assess CLOs' and funds' directional trade more formally, I compute for each traded facility i the following aggregate order imbalance measure by summing up the par of all buy and sell trades in month t:[17]

$$NET\_BUYING_{it} = \frac{BUYS_{it} - SELLS_{it}}{BUYS_{it} + SELLS_{it}}. \quad (2)$$

NET_BUYING is calculated separately for trades by CLOs and funds, and I include facility months only when the facility is traded by at least one fund in that month. My final sample contains 17,664 facility x month observations over the period from July 2010 to December 2015.

Column (1) in Table 4 presents the results from a simple univariate regression of CLO_NET_BUYING on FUND_NET_BUYING. Standard errors are double clustered at the facility and month level. Importantly, the estimated coefficient is significantly negative indicating that CLOs and funds trade in opposite directions. If funds as a group increase their net buying of a facility by one SD (0.859), CLOs' net buying of the same facility decreases on average by about 2.9%, or slightly less than the sample mean (3.1%) of CLO_NET_BUYING. I include facility and month fixed effects in Column (2) to control for the possibility that CLOs and funds might prefer facilities with different characteristics (like ratings, maturity, seniority, or covenants) and mechanically trade more or less across time due to fixed reinvestment periods or par repayment schedules. While the adjusted R^2 increases to 14%, the coefficient on FUND_NET_BUYING remains negative and significant (at 1%). Column (3) investigates whether CLOs respond asymmetrically to fund trading. If CLOs partially absorb the selling pressure of funds, the association between fund and CLO trading should be particularly strong for facilities unloaded by funds. To test this prediction, the variable SELLING (BUYING) equals FUND_NET_BUYING if FUND_NET_BUYING is negative (positive), and zero otherwise. Hence, SELLING (BUYING) is defined on a negative (positive) scale. Column (3) replaces FUND_NET_BUYING by SELLING and BUYING. The coefficient for SELLING turns out negative and significant (at 10%) while BUYING is also negative but insignificant. This indicates that almost all of the effect of FUND_NET_BUYING is driven by CLOs' buying of facilities dropped by funds, and not CLOs' selling of facilities funds are eager to buy. A one SD (0.234) increase in funds' selling of a facility is associated with 77 bps (or about one

[17] I also assess the trade direction by using the number of (buy or sell) trades instead of the traded par. Results are similar for this alternative measure.

Table 4
Trading behavior of CLOs and loan mutual funds – micro level evidence. The table shows OLS regressions, estimated on a facility x month level over the period from July 2010 to December 2015. The dependent variable is $CLO\_NET\_BUYING_{it}$, defined as $(BUYS_{it} - SELLS_{it})/(BUYS_{it} + SELLS_{it})$, where $BUYS_{it}$ is the aggregate par of all secondary market buys of facility i by CLOs in month t, and $SELLS_{it}$ is the aggregate par of facility i sold by CLOs in month t. $FUND\_NET\_BUYING_{it}$ is defined similarly for trades by loan funds. $SELLING_{it}$ ($BUYING_{it}$) equals $FUND\_NET\_BUYING_{it}$ if $FUND\_NET\_BUYING_{it}$ is negative (positive), and zero otherwise. $SELLING\_D_{it}$ is a dummy variable that takes on the value one if $FUND\_NET\_BUYING_{it}$ is negative, and zero otherwise. Standard errors (in parentheses) are double-clustered at the facility and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$FUND\_NET\_BUYING_{it}$	−0.034**	−0.022***		
	(0.016)	(0.008)		
$BUYING_{it}$			−0.010	
			(0.021)	
$SELLING_{it}$			−0.033*	
			(0.019)	
$SELLING\_D_{it}$				0.043***
				(0.015)
Month FE	No	Yes	Yes	Yes
Facility FE	No	Yes	Yes	Yes
Adj. R^2	0.001	0.143	0.143	0.143
N	17,664	17,664	17,664	17,664

fourth of the mean of CLO_NET_BUYING) more net buying of the same facility by CLOs.

Funds typically trade in the same direction, either solely selling or buying a facility in a given month. As a result, the empirical distribution of FUND_NET_BUYING is bimodal, with peaks at −100% and 100%. To account for such commonality in fund trading, Column (4) replaces BUYING and SELLING by the dummy SELLING_D, which takes on the value one if FUND_NET_BUYING is negative, and zero otherwise. CLO_NET_BUYING is 4.3% (or 1.4 times its mean) larger for facilities sold by funds compared to facilities funds are buying. This difference is highly significant. In sum, the evidence in Table 4 is consistent with the view that CLOs partially stabilize prices during market stress by buying facilities that funds unload.

5.2. Do funds trade in response to flows?

The central premise of this paper is that aggregate flows cause loan market returns through a trading channel, i.e., funds sell if they face outflows and buy in response to inflows. This premise might be incorrect if an efficient liquidity risk management partially insulates funds' loan trading from flows (especially outflows). In this case, fund trading is to some degree discretionary and less sensitive to flows, thereby raising the possibility that the relation between (daily) flows and returns detected previously operates through a different, e.g. an information-based, channel. For example, frequent daily changes in systematic default risk might affect flows (but not trades) and dealer quotes simultaneously. However, while systematic default risk is unlikely to change at a daily frequency, it is nevertheless revealing to study the association between fund trading and net flows. To gauge the aggregate trading behavior of loan funds, I add up $FUND\_NET\_BUYING_{it}$ across all facilities traded in a given month.

Fig. 6 depicts the monthly time series (67 months, from July 2010 to January 2016) of loan fund net buying and net fund flows. Obviously, both series are highly correlated contemporaneously with a correlation coefficient of 77% (significant at 1%). Hence, while funds on aggregate are frequently net sellers over the period considered, selling in excess of buying is more pronounced when funds face outflows compared to inflows. Table 5 presents results from time-series OLS regressions with $FUND\_NET\_BUYING_t$ as dependent variable.[18] Column (1) reveals that fund trading is to some degree persistent, with the first lag of $FUND\_NET\_BUYING_t$ being significantly positive. More importantly, Columns (2) and (3) show a positive and highly significant contemporaneous and predictive relation between net flows and net buying. For example, 1% more net flows last month predict 2.7% additional net fund buying this month. Even flows two months ago are significantly positive, implying that funds face difficulties to adjust immediately to flows that are by themselves persistent. Column (4) tests whether funds respond differently to inflows and outflows. If funds are successful in managing redemption risk, fund trading of facilities should be less sensitive to outflows than inflows. However, this prediction does not turn out: while a 1% increase in outflows lowers net buying by 6.3%, 1% more inflows raise net buying by 7.9%. Importantly, the difference between both coefficients is not significant. In sum, Fig. 6 and Table 5 are strongly suggestive of funds trading on aggregate in response to flows.

5.3. Crowding-out effects in CLO lending

5.3.1. Time-series evidence

The previous sections provide direct evidence that CLOs stabilize market prices by buying facilities that funds are selling, and that funds sell as a response to outflows. In the absence of unlimited access to funding, however, increased buying in the secondary market necessarily comes with a reduced lending capacity. This, in turn, implies that CLOs' aggregate loan purchases in the secondary market crowd out CLO lending exactly at times when new credit is needed most, i.e., in market downturns characterized by fund outflows and depressed loan prices. I measure time-series variation in crowding-out behavior through the variable LENDING_SHARE, which is the ratio of CLOs' credit supply (i.e., primary market loan purchases) to total (i.e., primary and secondary market) loan investments by CLOs. If purchases of depressed facilities crowd out new lending, LENDING_SHARE should be positively associated with market returns: relatively less (more) lending but more (less) buying in times of cheap (rich) secondary markets.

To investigate the cyclical lending and loan purchasing behavior of CLOs, I collect information on primary and secondary market investments from monthly trustee reports of all CLOs contained in the database CLO-i of Creditflux. My sample of CLO trustee reports in this section is from January 2013 to December 2019. Based on the information in the trustee reports, I calculate the amount of primary and secondary market loan purchases aggregated across all CLOs with available reports in CLO-

[18] Due to the small sample size, the results in Table 5 are only suggestive and must be interpreted with caution. In particular, the Dickey-Fuller test cannot reject the null hypothesis of a unit root for FUND_NET_BUYING with two or more lags in the augmented regression.

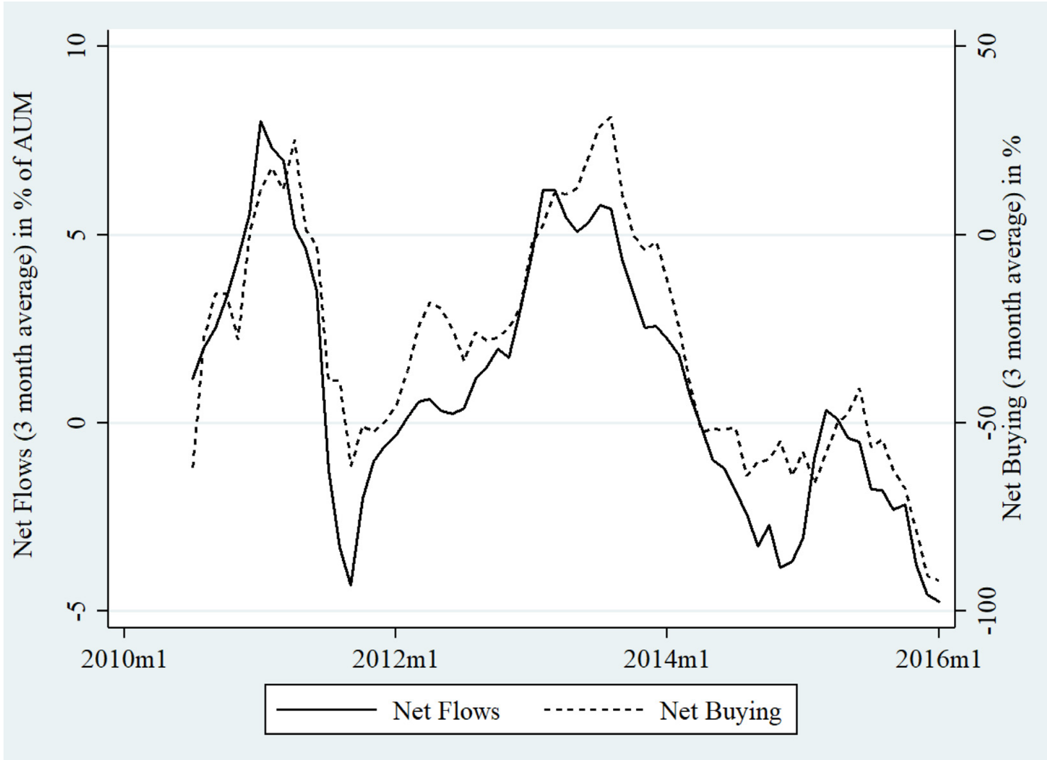

Fig. 6. Aggregate loan fund net buying and net fund flows. NET_BUYING_t is defined as $(BUYS_t - SELLS_t)/(BUYS_t + SELLS_t)$, where $BUYS_t$ is the aggregate par of all loan fund secondary market term loan buys in month t, and $SELLS_t$ is the aggregate par of loan fund term loan sells in month t. Trading behavior of loan funds is inferred from monthly holding reports (i.e., 13f reports) of funds that file with the SEC. Trades are assumed to equal changes in facility par amounts between subsequent holding reports, adjusted for repayments, refinancings, and restructurings. Data source for fund holding reports is CRSP. Both monthly times series are from July 2010 to January 2016 (67 months). The figure shows three-month moving averages.

Table 5
Aggregate loan fund trading and net fund flows. The table shows time-series OLS regressions, estimated on a monthly basis over the period from July 2010 to January 2016 (67 months in total). The dependent variable is $FUND\_NET\_BUYING_t$, defined as $(BUYS_t - SELLS_t)/(BUYS_t + SELLS_t)$, where $BUYS_t$ is the aggregate par of all loan fund secondary market term loan buys in month t, and $SELLS_t$ is the aggregate par of loan fund term loan sells in month t. NFLOWS are monthly aggregate net fund flows normalized by previous month total fund AUM. OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise. Newey-West (1987) standard errors are in parentheses, the number of lags is automatically determined according to Newey and West (1994). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$FUND\_NET\_BUYING_{t-1}$	0.544***	0.063	−0.174	0.045
	(0.121)	(0.097)	(0.105)	(0.093)
$NFLOWS_t$		7.182***	4.986***	
		(1.040)	(1.399)	
$NFLOWS_{t-1}$			2.687***	
			(1.427)	
$NFLOWS_{t-2}$			2.685***	
			(0.887)	
$OUTFLOWS_t$				6.322***
				(1.889)
$INFLOWS_t$				7.909***
				(2.178)
Adj. R^2	0.273	0.571	0.632	0.566

i.[19] Table 6 presents the results of OLS time-series regressions of LENDING_SHARE on price returns, loan mutual fund flows, and control variables. To be consistent with the short-term flow-return dynamics shown in Section 4, the regressions in Table 6 are executed at the weekly frequency and include lagged returns (and flows).

The benchmark specification in Column (1) confirms the prediction. The coefficient on 1-week lagged RET is positive and highly significant. A one standard deviation increase in average bids predicts a 0.31 standard deviations higher LENDING_SHARE next week. Hence, at times when the secondary market becomes expensive (bids rise), CLOs spend a larger fraction of each invested dollar for new loans instead of buying existing ones. However, while the contemporaneous coefficient is negative (but insignificant) at −5.2, the sum of the two (i.e., the t and t-1) coefficients

[19] Because offshore vehicles like CLOs or hedge funds suffer adverse tax consequences from buying loans directly in the primary market, a special transfer mechanism ("primary assignment") applies to primary purchases of these important investor types. In a primary assignment, the lead arranger or transfer agent parks the desired loan on its books for some time after loan issuance, and subsequently transfers it to these investors through an assignment. Importantly, these primary assignments are primary purchases, not secondary market trades. I use a special clustering algorithm designed to identify primary assignments in trustee reports. Details on the algorithm are available from the author upon request.

Table 6
Regressions of relative investment allocations between primary and secondary loan markets by CLOs – weekly aggregates. This table reports the results of OLS time-series regressions of primary versus secondary loan market investments by CLOs on price returns, loan mutual fund flows, and control variables. LENDING_SHARE denotes the weekly ratio of primary market investments (i.e., new lending) to total (primary plus secondary) loan investments aggregated across all CLOs with available trustee reports in CLO-i. Price returns (RET) are based on relative changes in par-weighted average bid quotes of facilities contained in the LLI100 index. NFLOWS denotes weekly net flows (inflows minus outflows) aggregated across all prime funds and normalized by previous month total fund AUM. OUTFLOWS (INFLOWS) equals NFLOWS if NFLOWS is negative (positive), and zero otherwise. Further control variables are the CBOE VIX, the term spread, the short-rate, and the credit spread. The sample period is weekly from January 2013 to December 2019. Newey-West (1987) standard errors are reported in parentheses, the number of lags is automatically determined according to Newey and West (1994). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $LENDING\_SHARE_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.809***	0.528***	0.697***	0.604***	0.658***	0.761***
	(0.006)	(0.051)	(0.094)	(0.048)	(0.049)	(0.080)
$LENDING\_SHARE_{t-1}$		0.347***	0.298***	0.251***	0.211***	0.196***
		(0.060)	(0.059)	(0.058)	(0.057)	(0.059)
RET_t	−5.211	−2.969	−4.721	−2.072	−3.896	−4.525
	(4.313)	(3.910)	(3.774)	(3.084)	(2.865)	(3.000)
RET_{t-1}	13.106***	11.187***	9.651***	8.621***	6.527**	6.219**
	(3.413)	(4.313)	(3.863)	(3.274)	(2.764)	(2.750)
$NFLOWS_t$				−10.761***		
				(4.042)		
$NFLOWS_{t-1}$				12.686***		
				(4.008)		
$OUTFLOWS_t$					−9.703**	−9.772**
					(4.361)	(4.405)
$OUTFLOWS_{t-1}$					15.162***	14.915***
					(4.323)	(4.268)
$INFLOWS_t$					−8.141	−8.816
					(7.695)	(8.196)
$INFLOWS_{t-1}$					7.976	8.584
					(7.523)	(7.992)
Controls	No	No	Yes	No	No	Yes
Adj. R^2	0.060	0.178	0.199	0.231	0.251	0.249
N	357	357	357	357	357	357

is positive and significant at 10%.[20] The 1-SD effect of RET is 0.19 standard deviations of LENDING_SHARE over two weeks.

Column (2) controls for the one-week lag of the dependent variable, and Column (3) additionally includes various proxies for market uncertainty and standard fixed income (credit) risk premia (CBOE volatility index VIX, short rate, term spread, credit spread).[21] As a result, the adjusted R^2 jumps to 20%. More importantly, however, while the predictive relation becomes weaker, it is still significant at 1%, and the 2-week effect remains positive and significant (at 10%). Consistent with credit crowding-out effects due to loan purchases in the market, CLOs lend relatively less when the secondary market becomes cheap (bids fall).

The next column directly investigates the fund flow channel of CLO credit contraction, i.e., whether CLOs take advantage of outflow-induced fire selling by loan mutual funds and ETFs in market downs. Past week net flows ($NFLOWS_{t-1}$) turn out to be a significant positive predictor of LENDING_SHARE. A one standard deviation increase in net flows this week predicts a rise of 1.2 standard deviations in LENDING_SHARE next week. While the contemporaneous relation is again negative (and significant), the 2-week effect is positive (1.9) and significant at 1%, implying that a 1-SD shift in NFLOWS raises LENDING_SHARE by 0.18 standard deviations over two weeks.

While the previous finding of a positive relation between LENDING_SHARE and fund flows is fully consistent with the lending crowding-out story, the theory in Diamond and Rajan (2011) and Shleifer and Vishny (2010) has an even more subtle implication: relative primary versus secondary market investment allocations (i.e., the credit crowding-out effect) of lenders with stable liabilities (CLOs) should respond asymmetrically to flows. If CLOs absorb the aggregate selling pressure of investors with unstable short-term liabilities (loan mutual funds), outflows should decrease the relative lending activity of CLOs much more than inflows increase it because it is exactly in down markets where attractive expected returns from buying up fire sells (i.e., providing liquidity in the secondary market) can be achieved. I test this asymmetric response of relative investment allocation decisions to fund flows in Column (5) where I replace NFLOWS by separate variables for OUTFLOWS and INFLOWS.

The results are revealing and in line with asymmetric effects on lending crowding-out due to fund flows: while current week LENDING_SHARE falls by 15.2% (significant at 1%) if last week net outflows increased by 1%, it only rises by 8.0% (not significant) for a 1% upward shift in past week inflows. Furthermore, the 2-week relation is positive at 5.5% and significant for OUTFLOWS, but essentially zero (-0.2%) and insignificant for INFLOWS. These results remain unchanged if I include the standard set of controls in Column (6).

Table IA.8 in the Internet Appendix replicates the regressions of Table 6 at the monthly frequency to study the longer-term dynamic relations between LENDING_SHARE, price returns, and fund flows. The results reveal that the crowding-out effect of CLO lending due to loan purchases in the secondary market also operates at the monthly level. More precisely, the monthly evidence confirms

[20] The negative contemporaneous coefficient could be viewed as the result of a potential simultaneity bias due to a two-way causal contemporaneous relation between aggregate CLO net trading and market price changes. While it is reasonable that CLOs' weekly net buying or selling moves average prices in the same direction at the same time, LENDING_SHARE is not a measure of CLOs' aggregate trading direction. It looks at the relative allocation of investments (i.e., loan purchases) between primary and secondary markets and neglects any loan selling by CLOs or the total amount invested. Hence, LENDING_SHARE is unlikely to affect market prices directly.

[21] The short rate is the 3-month Treasury-bill yield, the term spread is the spread between 10-year Treasury constant maturity and 3-month Treasury constant maturity yields, and the credit spread is the spread between Moody's Baa corporate bond yields and the 10-year Treasury constant maturity yield.

Table 7

Borrower-level regressions of CLO lending and secondary market investing. This table reports the results of OLS regressions of VOLUME (in $ million) on an indicator for the market segment and the borrower's previous period trade price level in the secondary market. Periods are weeks in the first two columns, and months in the remaining two columns. To calculate VOLUME, I aggregate the par of all CLO buys at the borrower x time level. For each borrower and each period, I separate between the par bought by all CLOs in the primary market via new loan allocations and the par bought in the secondary market through the purchase of existing loans. Hence, for each borrower (i) and time (t) pair, VOLUME takes on two values: the par bought in the primary and the par bought in the secondary market. Data on CLO buying behavior is collected from CLO trustee reports contained in the database CLO-i of Creditflux. PM is a dummy variable taking on the value one for the primary market, and zero else. TRADED_PRICE gives the average price (in % of par) paid by CLOs in period t-1 for outstanding facilities of borrower i. The sample is based on all borrower x time pairs over the period from January 2013 to December 2019 that fulfill the following two conditions: (1) the borrower offers a new loan in period t, and has outstanding (i.e., old) loans traded in periods t and t-1, (2) at least one CLO buys an old loan in period t-1. Standard errors (in parentheses) are double-clustered at the borrower and time level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Week level		Month level	
	(1)	(2)	(3)	(4)
Constant	4.966***		11.951***	11.951***
	(0.384)	4.966***	(0.812)	(0.744)
		(0.378)		
PM_{kit}	8.011***		28.334***	
	(0.768)	−103.483***	(1.624)	−404.683***
		(15.601)		(44.683)
PM_{kit} *				4.352***
$TRADED\_PRICE_{it-1}$		1.122***		(0.452)
		(0.161)		
Borrower x Time FE	Yes	Yes	Yes	Yes
Adj. R^2	0.03	0.03	0.07	0.07
N	18,944	18,944	15,444	15,444

that fund outflows are a central channel behind the severe contraction of CLO lending in down markets. If loan funds face net outflows of one standard deviation (1.8% of previous months' AUM), CLOs reduce their relative allocation to new loan supply by 0.53 standard deviations (significant at 1%). In contrast, buying demand by funds does not significantly affect relative lending by CLOs.

In sum, the above results are consistent with the idea that excessive selling by retail accounts is absorbed by CLOs at the costs of a lower lending share of each dollar invested, highlighting a negative spillover from fund investor redemptions to CLO credit supply.

5.3.2. Borrower-level evidence

While the previous analysis is suggestive of a meaningful spillover effect from fund redemptions to corporate access to finance via the CLO lending channel, it does not account for the dynamics of loan demand by borrowers or time-series changes in the characteristic mix of borrowers or loans offered in the primary market. For example, the average borrower or loan entering the primary market during secondary market booms could look quite different from the one appearing on the market at times of stress. If CLOs on aggregate have preferences for specific loan or borrower features and these features are more prevalent during market booms or busts, a spurious correlation between CLO lending volumes and market returns or fund outflows might emerge. That is, CLOs lend less during market downs not because of higher expected returns from buying in the secondary but simply because of fewer new loans offering the desired features. Moreover, falling prices in the secondary market and fund outflows could signal a worsening economic outlook characterized by fewer investment opportunities for leveraged borrowers and, hence, less loan demand. This could also explain the time-series findings.

I address these concerns in this section by use of a borrower-level analysis. That is, I aggregate the par of all CLO buys at the borrower x time level. I use both, weekly and monthly aggregation. For each borrower and each time period (i.e., week or month), I separate between the par bought by all CLOs in the primary market via new loan allocations and the par bought in the secondary market through the purchase of existing loans. I restrict the analysis to borrower x time observations that fulfill the following two conditions: (1) the borrower offers a new loan in period t, and has outstanding (i.e., old) loans traded in periods t and t-1, (2) I observe at least one CLO buy of an old loan in period t-1. The first condition guarantees the existence of a primary and a secondary market for the same borrower at the same time, and the second condition enables me to capture the current secondary market pricing of the borrower. Over the period from January 2013 to December 2019, 9472 borrower x week and 7722 borrower x month observations satisfy these conditions. I run the following regression on both samples:

$$VOLUME_{kit} = \beta_0 + \beta_1 * PM_{kit} + \beta_2 * PM_{kit} * TRADED\_PRICE_{it-1} + FE_{it} + e_{kit}, \quad (3)$$

where the index k denotes the market segment, i.e., either the primary (k = PM) or the secondary (k = SM) market. My sample design yields two values for the loan par bought by CLOs (the variable VOLUME in $ million) for each borrower (i) and time (t) pair, the par bought in the primary and the par bought in the secondary market. PM is a dummy variable taking on the value one for the primary market, and zero else. TRADED_PRICE gives the average price paid by CLOs in period t-1 for outstanding facilities of borrower i, and FE_{it} denotes borrower x time fixed effects. I lag TRADED_PRICE by one period to mitigate simultaneity and/or reverse causality concerns. Also note that the fixed effects absorb the level effect of TRADED_PRICE.

The above setting enables me to look at the relative allocation of CLO money between the primary and the secondary market of the same borrower at the same time, and whether this allocation varies with the borrower's current secondary market pricing level. By holding the borrower and time fixed, I control nonparametrically for all observed and unobserved time-varying borrower-level heterogeneity. This should mitigate any endogeneity concerns. The variable of interest is the interaction between PM and TRADED_PRICE: β_2 should be positive if a lower pricing level for a given borrower in the secondary market contracts the supply of credit from CLOs for this borrower.

Table 7 reports the results, in the first two columns for weekly aggregates and in the last two for monthly numbers. Standard errors are double-clustered at the borrower and time level. Column (1) contains a benchmark specification without the interaction term. The significant coefficient of 8.0 on PM indicates that for the average borrower in an average week, CLOs lend $8.0 million more compared to the amount ($5.0 million) they invest in the borrower's existing facilities. In Column (2), the interaction between the market segment dummy and the secondary price level is included. While the coefficient on PM is negative (and significant), the interaction obtains a positive and highly significant coefficient, as predicted. Hence, if the outstanding facilities of a borrower are relatively cheap on average (i.e., TRADED_PRICE is at its 10% percentile: 97.5% of par), the lending volume of CLOs is just $5.72 million (=1.12*97.5–103.48) above the secondary allocation for the same borrower at the same time. In contrast, if the borrower is expensive (i.e., TRADED_PRICE is at its 90% percentile: 100.8% of par), CLOs on aggregate buy $9.42 million more of the borrower's new loan relative to what they invest in the borrower's existing facilities. That is, moving from the 10% to the 90% percentile in secondary market pricing increases the relative loan supply of CLOs by 65%, holding borrower and time fixed. A similar 10% to 90% percentile shift in facility pricing is associated with a $12.7 million (or 59%) rise in relative credit supply at the month level (see Column (4)).

In sum, the borrower-level analysis strongly supports the premise that lending by CLOs acts as a channel through which price dislocations in the secondary market, caused by fund redemptions, transmit to corporate credit supply. This is exactly what is predicted by the trading crowding-out lending story put forth in Diamond and Rajan (2011) and Shleifer and Vishny (2010).

6. Conclusion

Leveraged loans provide debt financing to companies with elevated default risk from virtually all major industries around the world. At the end of 2019, the outstanding par of leveraged loans (pro rata and institutional tranches) exceeds $2.4 trillion globally, with about $1.8 trillion issued to U.S. companies. Adverse impacts on these highly leveraged companies' abilities to refinance their existing debt likely creates serious destabilizing effects for the U.S. economy. One potential source of such distortion could be the increased presence of investment funds in the leveraged finance market.[22] The point of concern here is the liquidity mismatch between fund assets and liabilities, which could trigger a run-on-the-fund scenario, similar to the incentives faced by depositors in a bank run. In such a scenario, investor redemption requests might exhaust cash in the portfolio, thus causing fund managers to fire sell existing fund assets to raise the required cash. If opportunistic buyers like distressed debt or hedge funds are unable or slow to support the market, a destabilizing feedback loop of fund redemptions and funds liquidating loans at deep discounts could take effect. Such a feedback process might lead to self-sustaining downward price spirals in stress episodes when two conditions hold simultaneously: aggregate outflows cause future price declines (i.e., fund flows exert price pressure), and past price drops elicit further outflows (i.e., fund investors chase market returns).

To test for a feedback loop between aggregate fund flows and loan market returns, this paper makes use of a unique and newly available time series of aggregate net daily loan fund flows that span the period from August 2013 to December 2019. Bilateral vector autoregressions are estimated to study the price impact of fund flows and the feedback trading behavior of fund investors. In sum, the paper's evidence is consistent with the view that in times of loan market stress, fund flows and loan price returns have been pro-cyclical, i.e., have reinforced each other's movements. The findings also support the collateral value theory of liquidity supply, predicting a one-sided effect of flows on market liquidity: while there is no association between inflows and market bid-ask spreads, outflow shocks cause loan prices to decrease and market liquidity to fall.

Do secondary loan market price dislocations transmit to corporate access to finance, and if they do, what is the mechanism underlying such a transmission? The paper provides several pieces of evidence in line with lending by CLOs acting as such a transmission channel. In short, CLOs on aggregate reduce their lending (and increase their purchases of outstanding loans) at times when funds face outflows, market prices are falling and expected returns from buying loans in the market are higher. Because CLOs are by far the largest lenders of leveraged loans, these results highlight the economic significance of the externality imposed by loan fund redemptions.

[22] The Financial Stability Board (2019, p. 23) reports that as of December 2018, U.S. registered open-end (including ETFs) and closed-end investment funds held approximately $216 billion in leveraged loans directly, and additional $63 billion through their exposures to CLOs. More than 80% of these holdings are concentrated in open-end funds. The aggregate market share of U.S. investment funds amounts to 12% of outstanding U.S. leveraged loans (pro rata + institutional) and to 8% of U.S. CLOs.

CRediT author statement for

"Negative externalities of mutual fund instability: Evidence from leveraged loan funds"

Thomas Mählmann (single author): All.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2021.106328.

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