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Fire-sale risk in the leveraged loan market

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ABSTRACT

Using detailed loan holding data of Collateralized Loan Obligations (CLOs), we document empirical evidence for the fire sale of leveraged loans due to leverage constraints on CLOs. Constrained CLOs are forced to sell loans downgraded to CCC or below, and thus loans widely held by constrained CLOs experience temporary price depreciation. This instability is exacerbated by diversification requirements. As the CLO market grows, each CLO's effort to diversify its portfolio leads to similarity in loan holdings among CLOs, and thus their leverage constraints simultaneously bind. CLOs' overlapping loan holdings spread idiosyncratic shocks to large borrowers to the overall leveraged loan market.

1. Introduction

The leveraged loan market — loans for borrowers with low credit quality — has been expanding rapidly since the financial crisis in 2008. The Financial Stability Board (2019) reports that the size of the leveraged loan market became almost as large as that of the high-yield corporate bond market in 2018.[1] This growth in corporate debt is so prominent that it has garnered the attention of policy makers and researchers, who are concerned about the rise of corporate leverage as a potential threat to the stability of the economy.[2] The development of the debt market is fuelled by the expansion of shadow banking and, more specifically, Collateralized Loan Obligations (CLOs). Indeed, CLOs are the largest investor class in the leveraged loan market, holding up to half of the market.[3]

In this paper, we examine the transmission of idiosyncratic shocks, such as the default of a small number of borrowers, to the overall leveraged loan market via CLOs. This transmission occurs in two steps: first, default for loan borrowers tightens leverage constraints on multiple CLOs; second, constrained CLOs simultaneously sell certain types of loans to relax their leverage constraints. This fire sale temporarily reduces the liquidity and prices of the underlying loans, and thereby damages the capital of other loan investors. Therefore, CLOs transform idiosyncratic shocks to those with a broader impact in the overall leveraged loan market.

We first provide empirical evidence for fire sales. To this end, we study institutional details of CLOs and doc-

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[1] The exact definition of leveraged loan varies across data providers and government entities. Bloomberg has a definition of leveraged loan based on credit ratings, primary use of proceeds, and credit spreads. The U.S. Federal Reserve, on the other hand, defines leveraged loan based on the use of proceeds, Debt-to-EBITDA ratio, and other criteria. See Financial Stability Board (2019) for details.

[2] See, for example, the speech of the Federal Reserve Chairman Jerome Powell on May 20, 2019, stating "Business debt has clearly reached a level that should give businesses and investors reason to pause and reflect."

[3] In the Financial Stability Board (2019), U.S. CLOs as a group hold about half of outstanding institutional leveraged loans (see its page 7). The share could be slightly less than half as CLOs may allocate a small fraction of their portfolios to assets other than those loans.

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ument contractual restrictions that drive CLOs' investment behavior. CLOs are a special purpose vehicle that invests in a diversified portfolio of loans. To fund their investment, CLOs issue debt securities with various seniority, called tranches. A variety of constraints are imposed on CLOs by contracts between CLO managers and investors to protect the investors of CLO tranches. Among these are two notable constraints on CLOs. First, CLOs are required to diversify their loan portfolio across borrowers and industries. Second, there is leverage constraint imposed on CLOs. Specifically, CLOs are required to maintain the ratio of asset to debt, called the overcollateralization (OC) ratio, above a certain threshold level. When these requirements are violated, CLOs must divert cash flows from junior claim holders to improve the ratio. This action reduces the fees paid to CLO managers, lowers the yield to CLO equity tranches, and thus hurts the reputation of CLO managers. Therefore, CLOs strive to obey these well-intended requirements that are meant to ensure the safety of CLO tranches.

We argue that CLOs with a low OC ratio are incentivized to sell loans that are marked to market in order to improve the ratio. We show that the OC ratio improves when a CLO sells its loans that are marked to market, and uses the proceeds to pay down senior tranches. If a CLO instead uses book value to evaluate its loan holding, selling the loan at the market price that is lower than the book value incurs immediate losses, which reduces any improvement in the OC ratio. Thus, the CLO is less likely to sell such loans.

CLOs use book value to evaluate loans that are rated as B or above. They also use book value for loans rated between CCC and C (CCC loans) if the CCC loan holding in their portfolio is below a certain threshold. The excess CCC loans are required to be evaluated at fair value, which is close to market price. Therefore, we examine CLO transactions for loans that are downgraded from a B rating or above to a CCC rating or below. Using an event study approach, we ask whether or not constrained CLOs (i.e., those with a low OC ratio) are more likely than unconstrained CLOs to sell downgraded loans.

Specifically, we run logit regressions of indicator variables for loan sale by a CLO on its OC ratio slack and other control variables at the loan and CLO level. We find that, over the three-month period around the month of downgrade, a CLO with low OC ratio slack is significantly more likely to sell downgraded loans than one with higher slack. Thus, we find empirical evidence supporting the argument that stress events that tighten CLOs' OC ratio constraints force them to sell downgraded loans.

To measure the market disruption due to fire sales, we study whether the market price deviates from fundamentals due to a temporary lack of liquidity and shortage of arbitrage capital. To this end, we follow the literature on fire sales (e.g., Coval and Stafford 2007; Ellul, Jotikasthira and Lundblad 2011) and assume that the fundamental values follow a random walk in the short run. This assumption implies that short-term mean-reversion in the market price reflects mispricing due to liquidity shocks. To see if the market price mean reverts, we compute abnormal returns on downgraded loans and cumulate those over the event window around downgrading weeks. To separate the abnormal returns due to fire sales and information on borrowers' fundamentals, we compare cumulative abnormal returns (CARs) between two groups of downgraded loans: loans that are widely held by constrained CLOs before downgrade, and loans that are not.

Comparing CARs, we find that loans widely held by constrained CLOs earn 3.4% lower CARs over the 20-week window leading to the downgrade than loans that are not. This difference in CARs shrinks after downgrade and becomes insignificantly different from zero 20 weeks after the downgrade. The difference in CARs upon downgrade shows that the collective action of constrained CLOs leads to temporary disruption in the loan market, moving the market price away from fundamental values. The ultimate convergence in CARs shows that the two groups of loans are of similar quality. This finding suggests that the endogenous match between constrained CLOs and poorly performing loans is not driving our results.

Our results are not driven by the choice of specific measures of CLOs' loan ownership. With alternative measures of loan ownership, including the dollar holding share of constrained CLOs, the average sales of constrained CLOs over the event window, and the sale-probability weighted sum of CLO ownership, the resulting pattern in CARs points to the same direction: loans held by constrained CLOs experience a lower price upon downgrade, which dissipates in five months.

The empirical analysis above establishes a link between OC ratio constraints on CLOs and fire sale in the leveraged loan market. Next, we argue that idiosyncratic default of leveraged loan borrowers can cause multiple CLOs to face binding OC ratio constraints at the same time. To make a case for this argument, we conduct stress tests on CLOs with hypothetical shocks. Specifically, we use security-level holding data of CLOs and examine how the OC ratio for each CLO changes under several stress scenarios. First, we consider a simple stress scenario under which the ten largest borrowers (based the total borrowing from all CLOs) default. Second, we compute simple Value-at-Risk (VaR) measures based on the simulated path of the borrower's asset value.

The result of the stress test is striking: we find that idiosyncratic default of the top ten borrowers among nearly 2,000 borrowers in our data set in 2019 leads to nearly half of CLOs violating the threshold levels of OC ratio. This fraction of CLOs violating the constraint is comparable to what we observe immediately after the financial crisis in 2008. We call this original shock idiosyncratic because the magnitude of the shock is modest and we model no direct transmission of one borrower's default to another. In fact, even though we compute VaR in a naïve way that likely underestimates default clustering, the 95%VaR leads to an even greater loss in asset values than does the top ten borrowers' default.

Why does such a modest shock affect a disproportionately large fraction of CLOs? This outcome of a stress test crucially depends on CLOs' overlapping loan holdings. We find that, despite the impressive growth of the leveraged loan market, the number of borrowers increased only modestly since 2007, while the number of CLOs tripled. However, by design, each CLO is required to diversify across borrowers. To meet the diversification requirement, CLOs' loan holdings have become increasingly similar to each other, and multiple CLOs are exposed to the same set of borrowers, especially large ones.

The growing portfolio similarity implies that CLOs are now more likely than before to be forced to trade at the same time in one direction due to idiosyncratic loan default. In our empirical analysis on fire sales, the number of constrained CLOs holding downgraded loans is the key factor driving the loan abnormal returns. Our stress tests show that a shock to the underlying loan portfolio leads to an increasing number of CLOs facing OC ratio constraints over time. Therefore, the price impact in the future may be more pronounced than what is implied from the empirical analysis which necessarily relies on historical averages. Our analytical framework that combines empirical analysis based on historical data and forward-looking analysis using stress tests reveals the potential magnitude of spillover in the leveraged loan market.

Finally, to better understand the determinant of price impact, we study the time variation in median price impact. The price impact is negatively related to buyers' capital, relative issuance of leveraged loans to high-yield bonds, new CLO issues, and foreign-exchange basis and positively associated with the aggregate loan default rate. This association explains why the price impact was less pronounced in 2020 when the COVID-19 pandemic hit the economy than in the 2008 financial crisis period. Due to the Federal Reserve's unprecedented monetary policy to directly provide credit to the private sector, the pandemic-driven shock to the leveraged loan market liquidity is alleviated through various channels, such as substitution between loans and bonds as well as foreign investors' investment in the U.S. fixed income securities.

This paper contributes to the literature on shadow banks and the role of CLOs in the leveraged loan market. Irani and Meisenzahl (2017), Irani et al. (2020) and Kundu, 2020a–c report evidence of fire sale in the loan market by banks and CLOs using different identification strategies. In particular, a contemporaneous work by Kundu, 2020c studies the impact of fire sales on defaulted loans. Loumioti and Vasvari (2018, 2019) study the effect of portfolio constraints on CLOs' performance. Unlike these papers, we study the market structure of CLOs that stems from the private sector's effort to manage credit risk and explain why fire sale is particularly important in this market.

Another related line of research examines the impact of the rise of shadow banks in the loan market. Ivashina and Sun (2011), Becker and Ivashina (2016), and Ivashina and Vallee (2020) study the effect of CLOs' loan investment on the underlying loan contracts and prices.

This paper also relates to a strand of literature that documents the impact of constrained institutional investors on asset prices (e.g., Shleifer and Vishny 1992). Evidence of fire sales by constrained investors are reported in stocks (Coval and Stafford, 2007), corporate bonds (Ellul, Jotikasthira and Lundblad, 2011), convertible bonds (Mitchell, Pedersen and Pulvino, 2007) as well as Residential Mortgage-Backed Securities (Merrill et al., 2020). In contrast, Choi et al. (2020) find little evidence for fire sales by bond mutual funds. Our paper differs because we not only study different asset classes but also highlight a unique feature of the loan market: i.e., the major investors' portfolios become increasingly similar to each other.

Our paper also contributes to the previous theoretical works on the social cost of portfolio diversification (Ibragimov et al., 2011; Wagner, 2010; 2011; Liu, 2019). These papers argue that the optimal level of portfolio diversification at the entity level may deviate from the socially optimal level, if portfolio similarity leads to inefficient liquidation of assets. We not only document empirical evidence for the potential social cost of diversification and similarity of financial intermediaries but also identify a specific mechanism that gives rise to such inefficiency.

To quantify the economic significance of fire sales, we conduct stress tests. Thus, our paper relates to the literature on estimating correlated default risk (Das et al., 2007; Koopman et al., 2008; Duffie et al., 2009), applying the estimation methods to CLOs (Nickerson and Griffin, 2017; Griffin and Nickerson, 2020), and examining the asset pricing implications of the risk (Coval et al., 2009; Benzoni et al., 2015). We contribute to the literature by documenting one of the origins of correlation across leveraged loans arising from constraints on CLOs and the commonality in collaterals.

The remainder of the paper is organized as follows: in Section 2, we describe the institutional background for CLOs and leveraged loans as well as our data; in Section 3, we show evidence that CLOs are forced to sell downgraded loans; in Section 4, we examine the price impact of fire sales by CLOs; in Section 5, we report the results of the stress tests; and in Section 6 we provide concluding remarks.

2. Institutional background and data

2.1. Institutional background

A CLO issues various tranches, or debt securities with different seniority. A tranche with the highest seniority receives cash flows from the underlying loan pool first. This senior tranche is often rated AAA at issuance by major rating agencies and on average accounts for about 65% of the initial assets of a CLO. A tranche with the lowest seniority is called an equity tranche, which pays dividends only after all of the other tranche holders have received coupons. Tranches between senior and equity tranches are junior tranches.

A loan portfolio of a CLO is managed by a CLO manager who receives fees for her service. The fees consist of senior fees that are paid before the interest payment to senior tranche holders and junior fees that are paid after payments to junior tranche holders. CLO managers select loans that a CLO buys or sells in order to achieve higher returns to investors in equity tranches and to provide steady cash flows to those in senior and junior tranches.

To safeguard senior tranche investors against default risk, numerous portfolio constraints are imposed on the management of CLOs. One key requirement is portfolio diversification. CLOs are required to calculate a "diversity score" that captures their portfolio diversity within and across industries, and to maintain the score within a certain range.[4]

Another prominent constraint is a restriction on a CLO's leverage. Specifically, CLOs are required to maintain a certain level of the OC ratio, which is the ratio of a CLO's assets to the sum of outstanding tranches that have the same or higher seniority. Thus, a senior OC ratio is the simple ratio of a CLO's asset to senior tranche outstanding, while a junior OC ratio is the ratio of a CLO's asset to the sum of senior and junior tranches outstanding. For example, consider a CLO whose asset value is \$100, and its tranches consist of 65% senior tranche, 25% junior tranche(s), and 10% equity tranche. Then, the senior OC ratio is $100/65 \approx 154\%$ and the junior OC ratio is $100/(65+25) \approx 111\%$. To reduce the risk of insolvency, CLO managers are required to maintain the OC ratio above certain thresholds.

Because the OC ratio is the ratio of a CLO's asset to debt outstanding, it is determined by changes in both assets and liabilities. We first discuss potential shocks to a CLO's asset. Because leveraged loans are illiquid, CLOs evaluate their loan holdings at the book value if the credit rating of a loan is above CCC. Defaulted loans, and CCC loans (i.e., loans rated CCC or below, but not in default) that exceed the pre-specified threshold (typically 7.5% of total asset) must be evaluated at the fair value instead of the book value, lowering the CLO's asset value and consequently the OC ratio.[5] Specifically, when total CCC loan holdings exceed the threshold, then CCC loans with a lower value are treated as excess, which must be marked to market. Therefore, to maintain a desired OC ratio, CLO managers need to avoid loans that are likely to be downgraded to CCC or below.

Next, we discuss changes in a CLO's liabilities, which are driven by the life cycle of a CLO. First, a ramp-up period occurs immediately after the closing of a CLO during which the CLO manager builds a pool of collateral by buying loans. Once the CLO's loan portfolio reaches the target level, the CLO enters the next stage called a reinvestment period. During this period, the CLO can reinvest proceeds from its initial investment into other loans. The end of a reinvestment period is the reinvestment date, after which the CLO starts to pay down its debt using the proceeds from its loan portfolio. This last period is called an amortization period, which ends as the CLO repays all its debt. Normally, a CLO repays all outstanding debt before its legal maturity.

The OC ratios are monitored on a regular basis. Typically, a CLO sends to investors a monthly trustee report that includes the latest values of the OC ratio for each tranche. Once the OC ratios fall below a pre-specified cutoff value, then the CLO must stop paying coupons to junior tranches and dividends to equity tranches, and either acquire more collateral (if the failure occurs before the reinvestment date)[6] or pay down senior tranches to improve the OC ratio. This process of comparing the OC ratio for each tranche to the threshold is called an OC ratio test.

A failure in OC ratio tests is costly for CLO managers for several reasons. First, they will not receive junior fees. Second, low OC ratios may lead to downgrades of senior and junior tranches as well as lower yield on the CLO's equity tranche. These adverse developments hurt the reputation of CLO managers, reducing the chance of launching another CLO in the future. In Internet Appendix A, we document empirical evidence showing that lower OC ratios indeed predict higher chances of CLO tranche downgrading, lower equity yield, and lower probability of launching a new CLO by the same CLO manager. Due to these potentially large costs of failure, CLOs tend to take preemptive actions to avoid violating the OC ratio requirements.[7]

Unlike banks, CLOs are lightly regulated, and thus the constraints imposed on CLOs reflect investors' efforts to reduce risks as well as rating agencies' guidelines for CLO tranche ratings. As such, while these contractual arrangements likely reduce the risk of each CLO, there is no guarantee that they are socially optimal.

2.2. Data

For data on CLO loan holdings, transactions, and OC ratio test results, we use the CLO-i data provided by Acuris. This database contains information from trustee reports for U.S. CLOs from January 2007 to December 2020. The total principal balance of CLOs in CLO-i's sample is \$568 billion in 2020, which corresponds to about 85% of the entire U.S. CLO universe.[8] In this article, we focus on the subsample of CLOs that have non-missing OC ratio test results.[9] For the analysis based on monthly data, we treat trustee reports that are published in the middle of a month as the month-end value for the nearest month-end date.

For each CLO, we compute slack in the OC ratio by taking the difference between the reported OC ratio and the threshold value. Panel A of Table 1 reports the summary statistics over time. The average CLO has an OC ratio slack for senior tranches ranging from 8.8% to 30.0% and for junior tranches ranging from 0.9% to 6.5%. As expected, the slack is lower during stress periods in 2009 and 2020 than in other periods. The average ratio of CCC loans to asset

[4] The required diversity range is set as a function of credit risk and yield on a CLO's portfolio.

[5] The threshold for CCC loans are set separately for Moody's and S&P. However, a CLO's holding of loans with only one rating agency's rating (or loans with ratings on which two agencies disagree) is restricted, and thus most loans have a credit rating from both Moody's and S&Ps. In this article, we take the lower rating of Moody's and S&P if they disagree, and use a single value of the ratio of CCC loans.

[6] Some CLOs have a specific trigger to induce CLOs to purchase more collateral, called the reinvestment OC ratio test. This threshold is typically set slightly higher than junior OC ratio tests.

[7] Figure F.1 in Internet Appendix shows the time-series of distributions of OC ratio slack, which suggests a test failure is rare in non-crisis periods.

[8] According to the Securities Industry and Financial Markets Association, the total size of the U.S. CLO market is \$662 billion in 2020.

[9] CLO-i data include a variety of test names for OC ratio tests and other tests because each CLO uses slightly different terminology for the same test. To identify OC ratio test results, we search for the words "OC" and "Overcollateralization" in the file, and manually verify that the test indeed refers to an OC ratio test. For junior OC ratio tests, we search for class D and E OC ratio tests. If only one of class D or E OC ratio tests is available, we use it as the junior OC ratio for the CLO. If both class D and E OC ratios are available, then we use the class E OC ratio test as the junior OC ratio for the CLO.

Table 1
Time-series summary statistics of CLOs.

Year	N(CLO)	Asset ($ mil)	*Slack*(S) (%)	*Slack*(J) (%)	CCC / Asset (%)
Panel A. Full Sample					
2007	19	498.0	12.7	4.9	8.5
2008	143	506.2	12.1	2.3	12.1
2009	163	493.4	8.8	0.9	11.9
2010	219	485.1	13.9	3.1	8.9
2011	235	473.3	18.2	4.4	8.7
2012	221	464.6	21.7	5.2	7.5
2013	244	445.2	30.0	6.5	7.4
2014	354	454.9	29.5	6.3	9.0
2015	428	461.1	26.9	5.9	12.2
2016	421	474.5	26.1	5.3	14.7
2017	493	531.0	11.5	4.2	13.9
2018	536	535.9	11.0	4.5	11.0
2019	643	518.7	10.9	3.8	9.9
2020	700	504.7	11.2	2.4	14.6
Panel B. CLO 1.0					
2007	19	498.0	12.7	4.9	8.5
2008	143	506.2	12.1	2.3	12.1
2009	163	493.4	8.8	0.9	11.9
2010	219	485.1	13.9	3.1	8.9
2011	231	473.3	18.3	4.3	8.4
2012	210	466.4	22.2	5.2	7.3
2013	202	438.0	33.4	6.7	7.5
2014	174	388.6	47.1	7.8	5.0
2015	137	334.3	56.3	8.6	6.8
2016	69	296.1	87.3	9.9	8.9
2017	9	271.5	82.4	13.4	9.2
2018	3	309.6	54.5	12.6	9.1
Panel C. CLO 2.0 and 3.0					
2011	4	473.0	9.4	4.8	28.2
2012	11	426.7	10.4	5.1	11.6
2013	42	479.9	14.0	5.9	6.5
2014	180	524.6	11.0	4.9	12.8
2015	291	526.2	12.0	4.7	14.8
2016	352	512.9	13.1	4.4	15.8
2017	484	536.3	10.1	4.0	14.0
2018	533	537.3	10.7	4.4	11.0

The table reports the number of CLOs in our sample, the average of assets under management, slack in senior and junior OC ratio, and the fraction of CCC loans to the CLO's assets. CLO1.0 is launched in or before December 2008, while CLO2.0 and 3.0 are launched afterwards. There is no CLO1.0 outstanding after 2018.

varies from 7.4% to 14.7%. This statistic suggests that the average CLO exceeds the threshold value for a CCC loan ratio of 7.5% most of the time. Relative to the share of these risky loans, the junior OC ratio slack is thin, which may constrain CLOs' portfolio choice once hit by adverse events. In contrast, the average CLO has ample slack for the senior OC ratio, and thus this ratio is less likely than its junior cousin to constrain CLOs.

The OC ratio is affected by the life cycle of CLOs: CLOs close to maturity tend to have a high OC ratio because they repay tranches with higher seniority first, which increases the ratio of their equity tranche to assets. To control for the mechanical changes in the OC ratio due to varying time to CLO maturity, we split the sample into two groups: CLO1.0 with a closing date on or before December 2008, and CLO2.0 and CLO3.0 with a closing date after December 2008.[10] The senior OC ratios for CLO1.0 rise substantially from 2009 to 2017 due to repayment. On the other hand, the average senior OC ratios for CLO2.0 and 3.0 remain relatively stable over time. Therefore, when one examines information in the OC ratio, it is important to account for the changes in this ratio due to debt repayment.

The top panel of Table 2 shows the cross-sectional distribution of OC ratio slack averaged over time. The average CLO has 4.3% slack against the junior OC ratio threshold, while the cross-sectional standard deviation is 3.3%. Thus, there is a significant variation across CLOs with regards to distance to OC ratio test failure.

The force that counters a relatively thin junior OC ratio slack is portfolio diversification. The middle three panels of Table 2 provide summary statistics for the average CLO's loan portfolio. On average, a CLO diversifies across 242 loans. To measure the degree of portfolio diversification across industries, we classify loans into 35 industries defined by Moody's. For each CLO in each month, we calculate loan shares by industry and compute three metrics of industry diversification: the portfolio share for an industry with the largest exposure, the sum of the top three industries in terms of portfolio shares, and the Herfindahl index of industry shares. Table 2 reports the average and distribution of these metrics across CLOs. The average CLO has the largest industry share of 14.1% and a Herfindahl index of 7.5, which are somewhat higher than an ideal portfolio that is equally spread across 35 industries. Still, CLOs manage to spread their investment across a variety of industries to reduce the risk of concentration.

Leveraged loans held by CLOs carry high default risk, as the average LIBOR spread is 3.5% and the average credit rating is B (which corresponds to a numerical rating of 15). We also calculate the breakdown of loans by credit rating as a fraction of total (book values of) loans in the data set. This breakdown shows that the average CLO has 1.4% investment-grade (IG) loans, 19.0% BB-rated loans, 64.1% B-rated loans, and 7.5% CCC loans.

Finally, the second last row of Table 2 reports portfolio turnover of CLOs. Turnover is measured by total dollar transaction volume (both buys and sells) in a month[11] divided by month-end total loan holdings. We find that the monthly turnover is 5.8% for the average CLO, which reflects an annual turnover of 72%. The high turnover rate implies that CLOs are actively managed.

For data to calculate abnormal returns on loans, we use the S&P LSTA leveraged loan index downloaded from Bloomberg, the S&P500 index from CRSP, and 3-month T-bill rates from FRED. For loans' face value, we use Dealscan, which is mapped to CLO-i data based on borrowers' name and loan maturity. To measure capital of other loan investors, we use three data sources: i) loan mutual fund data from CRSP[12]; ii) distressed/restructuring-focused

[10] In the aftermath of the financial crisis in 2008, investors' appetite for structured products substantially declined. As a result, no new issues of CLOs occur in 2009 and 2010 in our sample. CLO3.0 starts in 2014 as they follow the Volcker rule and other new regulations.

[11] Our data set includes transaction data, and thus this volume is not inferred from changes in holding data.

[12] We identify loan mutual funds using the Lipper objective code "LP".

Table 2
Time-series average of cross-sectional statistics of CLOs.

	Mean	Std.	Percentiles				
			5%	25%	50%	75%	95%
OC ratio slack:							
Slack(*S*) (%)	17.46	23.75	6.93	9.00	10.60	15.16	55.18
Slack(*J*) (%)	4.26	3.26	0.50	2.78	3.82	5.12	8.98
Loan characteristics:							
# Loans	241.9	113.6	78.9	166.7	232.6	308.6	439.3
Loan LIBOR spreads (%)	3.5	0.6	2.7	3.1	3.4	3.7	4.3
Loan maturity (years)	4.4	1.0	2.7	4.0	4.7	5.0	5.4
Average loan credit rating	15.0	1.1	14.1	14.5	14.8	15.1	17.0
Diversification across industry:							
Top 1 industry share (%)	14.1	6.2	9.5	11.2	12.8	14.8	23.2
Top 3 industry share (%)	32.9	8.2	25.3	28.6	31.3	34.7	46.1
Herfindahl index ×100	7.5	5.1	5.1	5.8	6.4	7.2	13.3
Share of loans by credit ratings (%)							
IG	1.4	1.5	0.0	0.3	1.0	1.9	4.1
BB	19.0	8.0	4.5	14.3	19.1	24.2	31.1
B	64.1	14.3	38.0	58.4	67.5	73.0	79.6
CCC	7.5	5.5	2.0	4.6	6.4	8.7	16.5
Monthly turnover (%)	5.8	7.4	0.3	2.2	4.2	6.8	16.0
Exposure to 10 largest borrowers (%)	7.9	3.8	1.1	5.4	7.9	10.2	14.0

Each year from 2007 to 2020, we compute summary statistics of loan holdings for each CLO and then calculate the average, standard deviation, and percentiles across CLOs. The table reports the time-series averages of these statistics across CLOs. *Slack*(*S*) and *Slack*(*J*) are the difference between reported OC ratios and threshold value for OC ratio tests. Each loan is given a credit rating on the numerical scale (1:AAA, 21:C), where a value of 10 or below corresponds to investment-grade (IG). Monthly loan turnover is computed by dividing the dollar transaction amount (both buys and sells) in a month by total loan holding for each CLO.

hedge fund data from the Lipper Hedge Fund Database for the fund-level information[13]; and iii) the HFR global hedge fund industry report for the aggregate hedge fund data.[14]

3. Fire sales of downgraded loans

3.1. Mechanism of fire sales

In this section, we examine whether or not CLOs constrained by a low OC ratio are forced to sell loans downgraded to a CCC rating. We hypothesize that constrained CLOs may sell their loan holdings and repay senior tranches to improve the OC ratio. This transaction is costly if the loan is held at book value on a CLO's balance sheet and the market price is below the book value. However, because CCC loans in excess of the holding limit are valued at fair value, selling excess CCC loans is a less expensive way to raise the OC ratio.

We highlight this point using a simple example. Consider a CLO whose asset value is A and outstanding amount of senior tranche is D. Then, the initial senior OC ratio is $OC^{pre} = A/D$. Furthermore, consider two sets of transactions: i) the CLO sells a loan that is held at the book value of 100 and uses the proceeds to repay the senior tranche; and ii) the CLO sells a loan that is valued using market price $P < 100$ and repays the senior tranche.

In the first case, the OC ratio after the transaction changes to

$$OC^{Post} = \frac{A - 100}{D - P}, \tag{1}$$

and it increases after the transaction (i.e., $OC^{Post} > OC^{Pre}$) if, and only if,

$$OC^{Pre} > \frac{100}{P}. \tag{2}$$

In the second case, the OC ratio changes to

$$OC^{Post} = \frac{A - P}{D - P}, \tag{3}$$

which is higher after the transactions if, and only if,

$$OC^{Pre} > 1. \tag{4}$$

Ellul et al. (2015) and Merrill et al. (2020) emphasize the importance of mark-to-market accounting in understanding fire sales, and one can see their point by comparing (2) and (4). Equation (2) shows that a CLO is less likely to sell a loan when market price P is lower. When a loan is held at the book value, the CLO suffers from losses upon sale, which sets a higher bar for selling the loan to improve the OC ratio.

However, once the loan is valued at the market price, the condition is relaxed, and (4) does not depend on the market price. In the data, condition (4) is satisfied for most

[13] We find distressed/restructuring-focused hedge funds using the indicator variable "if_bankruptcy" and "if_distressedmarkets".

[14] The HFR report provides the breakdown of assets under management by strategies. As shown in Joenväärä et al. (2021), the data coverage of the Lipper database significantly declines over time, and thus we use the "Distressed/Restructuring" category in the HFR data to measure the aggregate buyers' capital.

CLOs because the threshold for the OC ratio test is set above 100%. Thus, for them, selling a loan that is marked to market improves the OC ratio, enabling CLO managers to relax the OC ratio constraint, receive junior fees, and pay dividends to equity holders.

The OC ratio constraint does not directly depend on the quality of assets in the same way as a regulated financial institution's capital ratio. The motivation for fire sales comes from the fact that CLOs use the proceeds from loan sales to repay the investors, which results in a lower amount of debt. Because selling loans changes both the numerator and denominator of the ratio, it generally changes the ratio even if the security is marked to market. This is in contrast to regulated financial institutions such as banks and insurance firms who face the capital adequacy constraint, defined as

$$BIS \equiv \frac{E}{A^*} > \overline{BIS}, \tag{5}$$

where E is statutory capital, A^* is risk-adjusted assets that are inversely related to their quality, and $\overline{BIS}$ is the prespecified lower bound for the capital adequacy ratio.

For banks, selling securities that are marked to market does not change the statutory capital E as it is a simple exchange of cash and the loan with the equivalent value. However, exchanging low quality assets for cash reduces A^* and thus this action increases the capital ratio. Therefore, even though both CLOs and banks benefit from selling downgraded securities under mark-to-market accounting, there is a difference in mechanism: the force behind CLOs' fire sale does not depend on an ad-hoc definition of risk weights set by regulators; instead, they are driven by the mechanism to protect CLO investors by returning sales proceeds to them.

The mechanism above suggests that loans downgraded from B or above to CCC or below provide an interesting testing ground to identify fire sales. We have a testable hypothesis that CLOs sell loans that are downgraded to CCC or below because of the change in the valuation method, and that CLOs with an OC ratio closer to the lower bound are more strongly incentivized to do so. To be clear, we do not argue that the OC ratio constraint is the only reason for CLOs to sell loans rated CCC or below.[15] However, if the constraint is one of the main reasons for sales, this link helps us separate forced sales from information-driven discretionary sales. Therefore, we empirically study this link in the next section.

3.2. CLOs' transactions for downgraded loans

We start by examining sales and purchases of loans that are first downgraded from a B rating or above to a CCC rating or below. Specifically, we set an event window of 12 months before and after the downgrading month for each downgraded loan and study how CLOs trade the loan in each month.

To identify downgraded loans, we rely on CLOs' loan holding data that include the credit rating of each loan. If a downgrade is reversed in the next month, we regard it as a recording error and remove such observations from the list of downgraded loans. If we find the same loan downgraded to CCC or below multiple times over the life of the loan, then we only use the first downgrade as the downgrading event.

We examine net loan transaction volume by CLOs around downgrade months for the average downgraded loan. As shown in Fig. 1, the net volume (buys minus sells) turns negative when the loan is downgraded and reaches a trough one month after downgrade, and slowly reverts toward zero over the next 12 months. Overall, the figure shows that downgrading to a CCC rating and below significantly increases CLOs' loan sales.

Table 3 presents summary statistics of loan transactions by CLOs. Panel A reports the transactions by credit rating on the trade date. In our sample period, CLOs trade 51,860 loans in more than 2 million transactions. The average number of transactions per month is 0.80, and 52% of the transactions are CLO buys. The breakdown by credit rating shows that trade characteristics for IG, BB, and B-rated loans are similar to each other, while those for CCC loans are characterized by a low percentage of CLO buys (31%) and a lower transaction price. The panel also presents CLOs' transaction volume as a percentage of the loan amount outstanding, which is the product of CLOs' portfolio turnover and CLOs' loan holding share. This is the turnover rate of loans but the numerator is restricted to CLOs' trade rather than overall transaction volume. Using all loans, CLOs' loan trade in a month accounts for 3.0% of loan amount outstanding. This is large relative to the market-wide turnover rate of 6.7%.[16] In particular, CLOs' trade is more important among B-rated loans. Thus, CLOs' share in the leveraged loan market is significant both in terms of holdings and transactions.

Panel B of Table 3 reports the same statistics for the subsample of loans that are downgraded from an above-CCC rating to a CCC rating or below. The downgraded loans are transacted more actively than other loans with the average number of trades at 1.05 per month. Consistent with the constraint on OC ratio, CLOs become the net sellers of these loans after downgrade with the average percentage of CLO buy transactions decreasing from 52% before downgrade to 28% afterwards.

3.3. Identifying fire sales

To examine the link between the OC ratio and CLOs' tendency to sell, we predict CLOs' loan sales with its OC ratio slack, controlling for other characteristics of CLOs and loans. Table 2 shows that the junior OC ratio slack is much

[15] For example, once a CLO violates the 7.5% threshold, it faces another portfolio constraint that prohibits the CLO from investing in loans that worsen the ratio of CCC loans to its asset.

[16] To estimate the market turnover rate, we take the ratio of quarterly loan transaction volume (market statistic published by the Loan Syndications and Trading Association) to the loan amount outstanding in the S&P LSTA index. We take the average of this quarterly data to obtain the estimate of market-wide turnover rate. We do not have non-CLOs' transaction volume data by rating, so we multiply overall volume with the fraction of amount outstanding by rating in the S&P LSTA index to estimate the volume by rating.

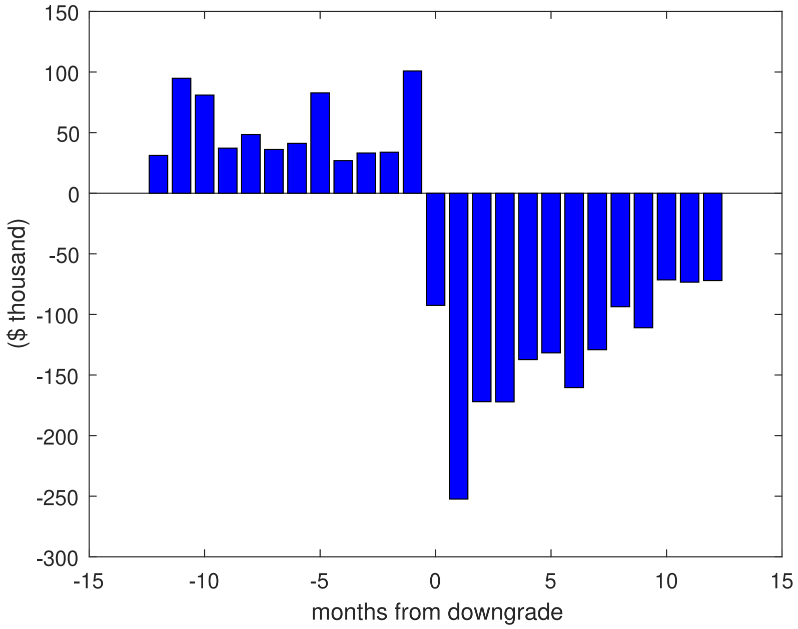

Fig. 1. CLOs' Net Purchase of Loans Downgraded to CCC or Below. This figure presents the difference between the total purchases and sales of the loans that are rated BB or above and downgraded to CCC or below in month 0. For each downgraded loan, we sum all CLOs' net purchase for each loan in each month and then take the average across loans.

smaller than the senior OC ratio slack, and thus we focus on the former in the following analysis. Furthermore, in Section 2.2, we show that the OC ratio mechanically changes as CLOs repay their debt after their reinvestment dates. To focus on changes to the OC ratio due to asset quality rather than scheduled repayment of CLOs' debt, we limit our sample to CLOs that are before their reinvestment date. Finally, we only use CLOs that have a CCC loan ratio above 5%.

In Figure 2, we plot the probability of selling downgraded loans around the downgrading month ($m = 0$) as well as the three-month moving averages. For each downgraded loan, we compute the fraction of CLOs who sell the loan m months before and after the downgrade for $m = 0, \ldots, 12$, separately for three groups of CLOs classified based on the OC ratio slack. Then we take the average across loans to obtain estimates for the selling probability. The figure shows that CLOs with a low OC ratio (i.e., those in the bottom tercile) tend to sell downgraded loans more than those with a high OC ratio (in the top tercile) around the downgrading months. The difference between the two groups of CLOs is particularly pronounced between months 0 to 2, suggesting that constrained CLOs tend to react more aggressively to downgrades.

We formally test this observation by running multivariate logit regressions. Specifically, we regress loan sale dummies for loan j by CLO i over the window $[m_0, m_1]$:

$$D^{SELL}_{i,j,m_0 \to m_1} = f\Big(bSlack(J)_{i,m_0-1} + \gamma_0 X_{j,m_0-1} + \gamma_1 Y_{i,m_0-1} + \gamma_2 FE_{q(m_0-1)} + \varepsilon_{i,j,m_0 \to m_1}\Big), \quad (6)$$

where $D^{SELL}_{i,j,m_0 \to m_1}$ is a dummy variable that equals one if CLO i sells loan j at least once during the event window and zero otherwise, $Slack(J)_{i,m_0-1}$ is junior OC ratio slack in percentage form, X_{j,m_0-1} is loan-level control variables, Y_{i,m_0-1} is CLO-level control variables, $FE_{q(m_0-1)}$ is calendar year-quarter fixed effects, and $f(\cdot)$ is a logit function.

Because Fig. 1 shows more pronounced loan sales around the downgrade months, we use three sets of dummy variables over event windows $[-3, -1]$, [0,2], and [3,5]. To alleviate the effect of outliers, we remove observations with an OC ratio slack below the 0.5 percentile or above the 99.5 percentile.

We estimate the logit model in (6) using the maximum likelihood method. To account for the potential model misspecification, we compute standard errors robust to misspecification.[17] In the regression, the loan-level control includes the credit rating before downgrade (AAA:1, B-:16) and the time to maturity of the loan in years. The CLO-level control includes each CLO's time to reinvestment date, the logarithm of the CLO's assets under management, age of the CLO manager measured as the time since the manager first appears in the database, logarithm of

[17] We compute the robust standard errors as follows: let $l(\theta)$ be a log likelihood function with a vector of parameter θ. Then the first-order condition to maximize the likelihood is

$$E\left[\frac{\partial l(\theta)}{\partial \theta}\right] = 0.$$

Treating this equation as GMM moment conditions, the variance of estimated parameters $\hat{\theta}$ is given by:

$$\sigma^2(\hat{\theta}) = \frac{1}{T} E\left[\frac{\partial^2 l(\theta)}{\partial \theta \partial \theta'}\right]^{-1} E\left[\left(\frac{\partial l(\theta)}{\partial \theta}\right)\left(\frac{\partial l(\theta)}{\partial \theta}\right)'\right] E\left[\frac{\partial^2 l(\theta)}{\partial \theta' \partial \theta}\right]^{-1}.$$

This formula does not require the information matrix equality which holds under the assumption that the likelihood function is correctly specified.

Table 3
Summary statistics of loan transactions by CLOs.

Panel A. Trade by Credit Rating on the Trade Date

Rating	IG	BB	B	CCC-	NR	All
Number of loans	1,169	11,146	33,370	9,972	7,794	51,860
Number of trades	15,261	376,392	1,485,769	160,901	45,603	2,098,927
Number of trades per month	0.19	0.92	1.02	0.50	0.18	0.80
% Buy trades	50.58	53.36	54.72	30.90	44.64	52.22
Average trade characteristics						
Price (per $100 par)	97.63	98.54	97.65	87.88	90.41	96.81
Size ($ million)	2.77	2.43	2.17	1.68	2.56	2.20
Maturity (years)	4.74	5.10	4.99	4.06	3.76	4.89
Share of CLO transactions						
Turnover for Avg. CLO (%)	5.24	5.35	5.44	5.62	9.54	5.77
CLO holding shares (%)	11.58	29.99	77.46	40.56	25.12	51.40
CLO trade / Market (%)	0.61	1.60	4.21	2.28	2.40	2.97

Panel B. Subsamples for Loans Downgraded to CCC or Below

	All	Before Down-grade	After Down-grade
Number of loans	2,908	2,908	2,908
Number of trades	395,449	279,423	107,798
Number of trades per month	1.05	1.25	0.80
% Buy trades	44.86	51.73	28.27
Average trade characteristics			
Price (per $100 par)	93.35	96.13	86.98
Size ($ million)	1.95	2.01	1.76
Maturity (years)	4.54	4.83	3.84

This table provides summary statistics of our transaction data. % Buy trades is percentage of the number of CLOs' buy transactions to the number of CLOs' total transactions. In Panel A, we classify transactions based on the credit rating of the loan on a transaction date. Turnover for Avg. CLO is the time-series average of the cross-sectional mean portfolio turnover for each rating. CLO holding shares are the dollar amount held by CLOs scaled by the amount outstanding. CLO trade / Market is the ratio of monthly CLO transaction volume scaled by the market size, which equals the product of the CLO turnover and CLO holding share. In Panel B, we use a subsample of loans that are downgraded to CCC or below. The sample period is from January 2007 to December 2020.

the manager's total assets under management (which is greater than the CLO's asset if the manager manages more than one CLO), and ratio of the CLO's CCC loan holding to its asset.

3.4. Empirical evidence on fire sales

The first two columns of Table 4 report estimated slope coefficients in (6) and the associated marginal effects for loan sales between months 0 and 2. We find that the junior OC ratio slack is negatively associated with the probability of loan sales. The estimated marginal effect on the slack is −0.48 percentage points. The time-series averages of cross-sectional standard deviation and the interquartile range of junior OC ratio slack are 3.26% and 2.34%, respectively (Table 2). Thus, a one-standard deviation decrease in OC ratio slack (a change from the 75th percentile to the 25th) leads to a 1.56 (1.12) percentage point higher chance of selling downgraded loans. These effects are nontrivial given that the unconditional probability of selling downgraded loans over this three-month window is 13.27% in our sample.

We also consider the case that a CLO with the junior OC ratio in the top tercile of the distribution moves to the bottom tercile. We run a logit regression in (6), replacing the linear OC ratio slack variable with a dummy variable that equals 1 if the CLO is in a particular tercile defined by OC ratio slack. This regression specification accounts for a potential nonlinear link between OC ratio slack and sales of downgraded loans.

Columns 3 to 4 in Table 4 report the estimated slope coefficients for the two dummy variables corresponding to the bottom and middle OC ratio slack terciles (and thus the top tercile is the omitted category) as well as the associated marginal effects. The estimated marginal effect on the bottom tercile dummy is 3.53 percentage points. Thus, if a CLO receives a shock that moves its OC ratio from the top to the bottom tercile, the chance of selling a downgraded loan increases by 3.53 percentage points.

Among the set of control variables we employ, we find that CLOs with a longer time to reinvestment date, shorter manager experience, and larger manager assets under management are more likely to sell these loans. These estimates show that it is important to control for a CLO's

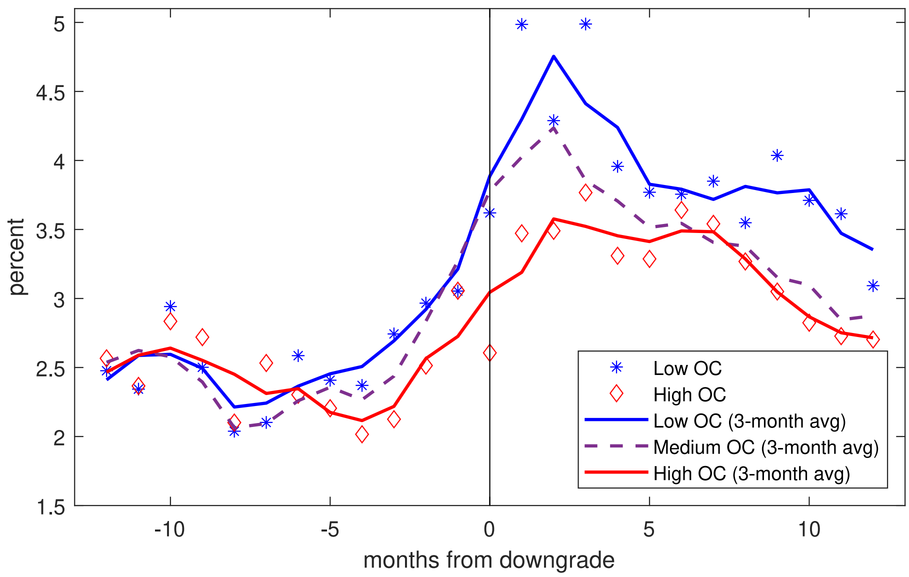

Fig. 2. Average Probability of Selling Downgraded Loans Around Downgrading Months. The figure presents the probability of selling loans downgraded to CCC or below in month 0. For each downgraded loan, we compute the fraction of CLOs who sell the loan m months before and after month 0 for $m = 0, \ldots, 12$, separately for three groups of CLOs based on OC ratio slack. The cutoff for high, medium, and low OC is the 67th and 33rd percentiles of the distribution in a month. We then take the average across loans to compute the average probability of selling the loan.

Table 4
Determinants of sales of downgraded loans.

	Months 0 to 2				Months −3 to −1		Months 3 to 5	
	b	$m(b)$	b	$m(b)$	b	$m(b)$	b	$m(b)$
Slack(J)	−4.62	−0.48			−1.59	−0.12	−3.96	−0.38
	(−3.76)	(−3.77)			(−0.90)	(−0.90)	(−3.35)	(−3.36)
Dummy: *Slack(J)* <33rd pct			34.08	3.53				
			(6.49)	(6.53)				
Dummy: 33rd pct≤ *Slack(J)* <67th pct			25.64	2.65				
			(5.30)	(5.31)				
Rtg	−2.47	−0.26	−2.49	−0.26	−0.24	−0.02	−6.67	−0.64
	(−2.29)	(−2.29)	(−2.30)	(−2.30)	(−0.17)	(−0.17)	(−5.66)	(−5.68)
LoanMat	−2.04	−0.21	−2.08	−0.22	−4.47	−0.33	9.16	0.88
	(−0.72)	(−0.72)	(−0.73)	(−0.73)	(−1.30)	(−1.30)	(2.99)	(3.00)
CLOMat	3.08	0.32	3.44	0.36	4.56	0.34	5.24	0.50
	(2.58)	(2.58)	(2.87)	(2.87)	(3.02)	(3.03)	(4.11)	(4.12)
log *CLOSize*	4.64	0.48	4.89	0.51	17.24	1.27	−8.98	−0.86
	(0.71)	(0.71)	(0.75)	(0.75)	(1.99)	(1.99)	(−1.26)	(−1.26)
MgrAge	−4.10	−0.42	−4.20	−0.43	−3.82	−0.28	−4.94	−0.47
	(−9.19)	(−9.23)	(−9.35)	(−9.39)	(−5.75)	(−5.78)	(−10.11)	(−10.22)
log *MgrSize*	17.25	1.79	17.18	1.78	19.58	1.44	15.36	1.47
	(6.78)	(6.80)	(6.75)	(6.77)	(5.62)	(5.66)	(5.94)	(5.96)
CCCRatio	−2.12	−0.22	−2.10	−0.22	−0.38	−0.03	0.09	0.01
	(−3.82)	(−3.84)	(−3.79)	(−3.80)	(−0.57)	(−0.57)	(0.24)	(0.24)
Time FE	Yes		Yes		Yes		Yes	
$\bar{R}^2$	4.02		4.15		3.45		2.37	
N	36,092		36,092		29,555		36,433	

This table reports the estimates for the slope coefficients and marginal effects of logit regressions of loan sales for loan j by CLO i in window $[m_0, m_1]$:

$$D^{SELL}_{i,j,m_0\to m_1} = f\left(bSlack(J)_{i,m_0-1} + \gamma_0 X_{j,m_0-1} + \gamma_1 Y_{i,m_0-1} + \gamma_2 FE_{q(m_0-1)} + \varepsilon_{i,j,m_0\to m_1}\right),$$

where $D^{SELL}_{i,j,m_0\to m_1}$ is a dummy variable which equals one if CLO i sells loan j at least once during the event window and zero otherwise, $Slack(J)_{i,m_0-1}$ is the junior OC ratio slack in percentage form, X_{j,m_0-1} is loan-level control variables (*Rtg* is a numerical rating variable before downgrade and *LoanMat* is time to loan maturity), Y_{i,m_0-1} is the CLO level control variables (*CLOMat* is time to reinvestment date, *CLOSize* is assets under management, *MgrAge* is the age of the CLO manager, *MgrSize* is total assets under management for the manager, and *CCCRatio* is the ratio of CCC loans to assets under management), Time FE is year-quarter fixed effects, and $f(\cdot)$ is a logit function. b is estimated slope coefficients multiplied by 100, $m(b)$ is marginal effect in percent, values in parentheses are t-statistics robust to model misspecification, $\bar{R}^2$ is pseudo R-squared, and N is the number of observations. For this analysis, we only use CLOs before their reinvestment date and a CCC-ratio above 5%.

and CLO manager's characteristics to tease out the effect of binding OC ratio constraints on CLOs.

Columns 5 to 8 show the estimates for the logit regression of sales over the windows preceding or following the downgrade, including months −3 to −1 and months 3 to 5. Our estimates show that the estimated marginal effects in (6) are more pronounced in magnitude for the later event window than earlier windows. This pattern of marginal effects suggests that in general, constrained CLOs do not try to front run to sell loans before downgrades occur. To understand this better, in Internet Appendix B we compare CLOs who sell earlier and later, as well as buyers and sellers. We find that those who sell loans earlier are less constrained and have higher managers' age and assets under management.[18]

Finally, to reinforce our interpretation of the link between the OC ratio and the probability of selling downgraded loans, we examine whether CLOs with a low OC ratio redeem their senior tranche in the near future or not. To this end, we regress negative changes in senior tranche outstanding on the OC ratio slack as well as the same set of CLO-level control variables and time-fixed effects as in (6). Table 5 reports the estimated coefficients of the OLS regression of senior tranche redemption, showing that the OC ratio slack is negatively associated with future redemption at the three-, six-, and twelve-month horizons. This suggests that a CLO with a low OC ratio is more likely to redeem its senior tranche, confirming that one of the motivations for a CLO to sell a downgraded loan is to improve its OC ratio by reducing the denominator.

The evidence in this section suggests that CLOs with a lower junior OC ratio are more likely to sell loans that are downgraded to a CCC rating or below. Because such a sale is motivated by constraints on CLOs rather than the fundamental value of loans, we regard it as fire sale. However, the results in this section focus on constraints on *individual* CLOs and their trading behavior. To evaluate the externality posed by fire sales, one has to study the consequence of *collective* actions of CLOs, to which we turn in the next section.

Table 5
Predicting redemption of senior tranches.

$h =$	3	6	12
$Slack(J)$	−0.01	−0.03	−0.04
	(−1.91)	(−2.32)	(−2.51)
$CLOMat$	−0.22	−0.53	−1.25
	(−1.50)	(−1.92)	(−3.56)
$\log CLOSize$	−0.23	−0.40	−1.53
	(−1.34)	(−1.42)	(−2.39)
$MgrAge$	0.02	0.08	0.19
	(1.59)	(2.03)	(3.30)
$\log Mgrsize$	0.14	0.17	0.10
	(0.97)	(0.84)	(0.41)
$CCCRatio$	0.07	0.08	0.09
	(4.37)	(4.13)	(2.97)
Time FE	Yes	Yes	Yes
$\bar{R}^2$	0.06	0.11	0.13
N	33,450	32,096	28,717

This table reports the estimates for the OLS regression coefficients of senior tranche redemption by CLO i in window $[t, t+h]$:

$$-\left(\frac{S_{i,t+h} - S_{i,t}}{S_{i,t}}\right) = bSlack(J)_{i,t} + \gamma_1 Y_{i,t} + \gamma_2 FE_{q(t)} + \xi_{i,t\to t+h},$$

where $S_{i,t}$ is senior tranche outstanding for CLO i in month t, $Slack(J)_{i,t}$ is the percentage of junior OC ratio slack to the CLO's asset, $Y_{i,t}$ is the CLO level control variables ($CLOMat$ is time to reinvestment date, $CLOSize$ is assets under management, $MgrAge$ is the age of the CLO manager, $MgrSize$ is total assets under management for the manager, and $CCCRatio$ is the ratio of CCC loans to assets under management), and Time FE is year-quarter fixed effects. The estimated slope coefficients are multiplied by 100 and thus the left-hand side variables are percentage changes. Values in parentheses are t-statistics Hansen-Hodrick adjusted for overlapping observations, $\bar{R}^2$ is adjusted R-squared, and N is the number of observations. For this analysis, we only use CLOs before their reinvestment date and a CCC-ratio above 5%.

4. Price impact on downgraded loans

A class of investors' collective action to buy or sell specific securities may lead to a temporary deviation of the security's price away from fundamentals, if the investor class has a large volume share in transacting the security and arbitrage capital does not flow to the market soon enough. Based on this argument, we examine whether or not downgraded loans held by a greater number of constrained CLOs (i.e., CLOs with a below-median OC ratio in each month) experience a temporary price decrease greater than other downgraded loans. This hypothesis reflects the rapid growth of CLOs and their increasingly overlapping loan portfolios, which we document in Section 5. We show that, due to portfolio similarity across CLOs, a shock to a few underlying borrowers affects a large number of CLOs, propelling them to trade at the same time. Therefore, the key factor that exacerbates the price impact is whether or not the loan is held by a large number of constrained CLOs.

To distinguish the price decrease due to news about fundamentals from the price decrease due to illiquidity, one must take a stand on a model of fair values and examine if a market price deviates from them. Following Coval and Stafford (2007), we assume that loan prices follow a random walk over the short horizon and examine whether or not CARs revert back to zero some time after the event. If the decrease in a price is due to temporary liquidity shocks, then the price should mean revert as arbitrage capital flows in.

4.1. Estimating price impact

We start by describing the empirical framework to examine the price impact of CLOs' loan transactions. First, we

[18] In Internet Appendix, we examine whether the tendency to sell loans differs across the subsample of cohorts of CLOs. In Table F.4, we repeat the estimates for (6) for months 0 to 2, using three cohorts of CLOs classified by their deal closing date. The estimated marginal effect on the dummy corresponding to the tercile with the lowest OC ratio is 1.41, 9.16, and 3.13 percentage points for CLO1.0, 2.0, and 3.0, respectively. The estimates for CLO1.0 and CLO3.0 are similar to the full sample results of 3.53 percentage points in Table 4, while the estimate for CLO2.0, which has the smallest sample size, is higher. Thus, facing downgrades amid the COVID-19 pandemic, CLO2.0 reacts more aggressively than CLO3.0. Still, CLO3.0 sells amid the pandemic at least as much as CLO1.0 after the financial crisis. As a result, we do not see a decline in marginal effects over time.

compute abnormal returns on each downgraded loan in the sample and cumulate them within the event window around the downgrade. To test whether a CLO's forced sale inflicts a price impact, we compare CARs on two groups of loans: those widely held by constrained CLOs and those that are not. By using loans not widely held by constrained CLOs as the control group, we examine the price impact on loans that are held by a large number of constrained CLOs and are likely to be sold upon downgrade. The remainder of the section explains these steps in detail and presents empirical results.

First, we compute abnormal returns on downgraded loans by regressing their returns on aggregate market factors and control variables. To precisely estimate the regression coefficients, we compute loan returns at the weekly frequency using CLOs' transaction prices. If multiple transactions occur on the same day, then we take the average across transactions to obtain the daily price series. We treat the last daily observation in a week as an end-of-the-week price and compute log weekly returns when observations in two subsequent weeks are available. To eliminate the effect of outliers on the estimates, we remove prices below \$5 per \$100 face amount.[19]

Following the spirit of Ellul et al. (2011)[20], we run regressions of weekly returns on loan j:

$$\begin{aligned}\Delta \log P_{j,w+1} = {} & \alpha + \beta IDX_{w+1} + \gamma_1 (S_{j,w+1} - S_{j,w}) \\ & + \gamma_2 (S_{j,w+1} \log Q_{j,w+1} - S_{j,w} \log Q_{j,w}) \\ & + \varepsilon_{j,w+1}, \end{aligned} \tag{7}$$

where IDX_{w+1} is a vector of benchmark returns including a return on the S&P LSTA leveraged loan index, the 3-month T-bill rate, and a return on the S&P500 index; $S_{j,w}$ is an indicator variable that is 1 (-1) when a CLO buys (sells) loan j; and $Q_{j,w}$ is the dollar volume of the transaction. $\varepsilon_{j,w+1}$ measures abnormal returns in week $w+1$ due to temporary liquidity shocks because we subtract the regression intercept, returns attributable to market-wide movements in loan prices, and market microstructure noise from observed returns.

We run the regression separately for the four groups of loans using the data from before week -20 and after week 20. The regression coefficients using the data from before week -20 are used to compute abnormal returns from weeks -20 to -1, and the coefficients based on the data from after week 20 are used to compute abnormal returns from week 0 to 20. The four groups are defined by credit rating before downgrade and maturity. Specifically, we double-sort loans based on: i) whether the rating before downgrade is B- or not; and ii) whether the time to maturity is above the median or not. By estimating (7) at the group level rather than the individual loan level, we impose an assumption that the slope coefficients are constant across loans in the same group. While this assumption is somewhat restrictive, it also helps improve the accuracy of coefficient estimates with our relatively small sample in which we only observe prices when transactions occur. Estimating (7) separately before and after downgrading is motivated by the insight of Merton (1974) that default risk is the key determinant for a loan's sensitivity to underlying shocks. Because default risk changes upon downgrading to CCC or below, we run regressions separately to allow for the slope coefficients in (7) to change in week 0.

We then cumulate the estimated abnormal returns $\hat{\varepsilon}_{i,w}$ in (7) for each loan from week -20 to 20 to compute a CAR. In a week when $\hat{\varepsilon}_{i,w}$ is missing, we carry over the CAR from the previous week. To ensure the consistency of the coefficient estimates and return observations, we use loans that trade at least twice in weeks -20 to -1 and at least twice in weeks 0 to 20, and have at least five return observations throughout the event window for this analysis, which gives 838 downgraded loans in the sample.

To evaluate whether the CARs mean revert after downgrade, we split the sample of downgraded loans into two groups based on the number of constrained CLOs (whose OC ratio is below the median in a month) holding the loan using the median as a cutoff value. We then take the average of CARs across loans within each group.

Table 6 reports mean cumulative abnormal returns (MCARs) for the two groups of loans over the event window. The average loan with a below-median number of constrained CLOs has a -5.13% MCAR from week -20 to week 0 (downgrading week), while for loans with an above median number of CLOs the MCAR is -8.49% in week 0 and -4.98% at the end of the event window. Due to the selling pressure of CLOs with a low OC ratio, these loans experience a greater decline in prices around the downgrading week but recover a part of the loss in subsequent weeks.[21] The difference in MCARs between the two groups of loan is -3.35% at week 0 with a t-statistic of -2.93. More importantly, the difference between the two groups converges to around zero at the end of the event window. Specifically, the MCAR difference is -0.33% at week 15 and 0.76% at week 20, and both estimates are insignificantly different from zero. This convergence shows that the additional price decline on loans with an above median number of constrained CLOs is only temporary. Combining the evidence of transactions by constrained CLOs, the decline in price upon downgrade likely reflects CLOs' forced sales of loans.

Figure 3 plots MCARs for loans with an above and below median number of constrained CLOs. The price of loans with high (constrained) CLO ownership declines more than that of loans with low ownership up to the week of downgrading. After that, MCARs on loans with high (constrained) CLO ownership stabilize and mean revert such that the difference between the two groups shrinks toward zero by the end of the event window.

[19] \$5 correspond to the 1st percentile of the distribution for transactions of downgraded loans.

[20] This regression specification follows Ellul et al. (2011), but we add a factor that proxies for aggregate loan market returns.

[21] Because we estimate (7) using weeks before -20 and after 20, the regression intercept does not necessarily capture the returns upon downgrade. Thus, the CAR at the end of the event window is not guaranteed to end up being zero. Should we estimate (7) using returns from -20 to 20, then residuals mechanically sum to zero. Ultimately, for our purposes, what matters is the difference between the two groups rather than the levels for each group.

Table 6
Mean cumulative abnormal returns around downgrades.

Begin week	End week	Below-median number of constrained CLOs MCAR (1)	Below-median number of constrained CLOs t-statistic	Above-median number of constrained CLOs MCAR (2)	Above-median number of constrained CLOs t-statistic	Difference MCAR (2)-(1)	Difference t-statistic
−20	−16	−0.13	(−1.51)	−0.45	(−2.70)	−0.32	(−1.73)
−15	−11	−0.78	(−4.12)	−0.50	(−1.46)	0.27	(0.72)
−10	−6	−1.26	(−3.77)	−1.82	(−3.28)	−0.56	(−0.92)
−5	−1	−2.84	(−5.19)	−5.31	(−6.24)	−2.47	(−2.48)
0	0	−5.13	(−6.54)	−8.49	(−7.91)	−3.35	(−2.93)
1	5	−5.26	(−6.16)	−8.10	(−6.48)	−2.84	(−2.17)
6	10	−5.68	(−6.09)	−7.29	(−5.31)	−1.62	(−1.12)
11	15	−6.07	(−5.96)	−6.40	(−4.33)	−0.33	(−0.21)
16	20	−5.74	(−5.26)	−4.98	(−3.25)	0.76	(0.47)

For each downgraded loan, we compute an abnormal return as residuals of a regression of a loan return in week w,

$$\Delta \log P_{i,w+1} = \alpha + \beta IDX_{w+1} + \gamma_1 (S_{i,w+1} - S_{i,w}) + \gamma_2 (S_{i,w+1} \log Q_{i,w+1} - S_{i,w} \log Q_{i,w}) + \varepsilon_{i,w+1},$$

where IDX_{w+1} is a vector of benchmark returns including a return on the S&P LSTA leveraged loan index, the 3-month T-bill rate, and a return on the S&P500 index; $S_{i,w}$ is the indicator variable which is 1 (−1) when a CLO buys (sells) loan i; $Q_{i,w}$ is the dollar volume of the transaction. We run the regression separately for four groups of loans using the data before week −20 and after week 20. The regression coefficients using the data before −20 is used to compute abnormal returns from week −20 to −1, and the coefficients based on the data after week 20 is used to compute abnormal returns from week 0 to 20. The four groups are defined by credit rating before downgrade being B- or above, and time to maturity above or below median. We then cumulate $\varepsilon_{i,w}$ for each loan from week −20 to 20 to compute cumulative abnormal returns. Week 0 is the week when the loan is downgraded to CCC or below. Finally, we take the average across loans separately for loans held by below-median number of constrained CLOs and above-median number of constrained CLOs. Constrained CLOs are defined as those with below-median junior OC ratio slack at the end of month $t-2$ (where month t is the downgrading month). MCAR is in percent. For this analysis, we use loans that trade at least twice in week −20 to −1 and at least twice in week 0 to 20 and have at least five return observations throughout the event window, which gives the number of loans of 838. Values in parentheses are t-statistics, which are computed by block bootstrapping simulation with calendar weeks sampled with replacement.

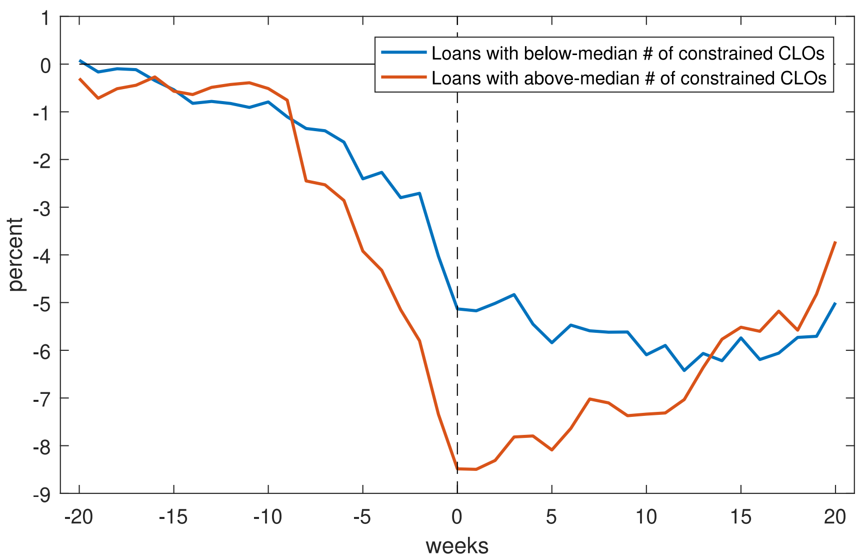

Fig. 3. Mean Cumulative Abnormal Returns Around the Downgrade Event. For each downgraded loan, we compute an abnormal return by running a regression of a loan return in week w:

$$\Delta \log P_{i,w+1} = \alpha + \beta IDX_{w+1} + \gamma_1 (S_{i,w+1} - S_{i,w}) + \gamma_2 (S_{i,w+1} \log Q_{i,w+1} - S_{i,w} \log Q_{i,w}) + \varepsilon_{i,w+1}$$

where IDX_{w+1} is a vector of benchmark returns including a return on the S&P LSTA leveraged loan index, the 3-month T-bill rate, and a return on the S&P500 index; $S_{i,w}$ is the indicator variable which is 1 (−1) when a CLO buys (sells) loan i; $Q_{i,w}$ is the dollar volume of the transaction. We then cumulate $\hat{\varepsilon}_{i,w}$ for each loan from week −20 to 20 to compute cumulative abnormal returns. Week 0 is the week when the loan is downgraded to CCC or below. Finally, we take the average across loans that trade in each event window separately for those held by below- and above-median number of constrained CLOs. For this analysis, we use loans that trade at least twice in week −20 to −1 and at least twice in week 0 to 20 and have at least five return observations throughout the event window, which gives the number of loans of 838.

Table 7
CLOs' loan transaction volume around downgrades.

Begin week	End week	Below-median number of constrained CLOs			Above-median number of constrained CLOs		
		Buy (1)	Sell (2)	Net (2)-(1)	Buy (1)	Sell (2)	Net (2)-(1)
Panel A. Average Volume (per week, per loan) in Million Dollars							
−20	−16	1.27	1.17	0.10	2.28	1.80	0.47
−15	−11	1.53	1.54	−0.01	2.55	2.24	0.31
−10	−6	1.61	1.85	−0.24	2.16	2.56	−0.40
−5	−1	1.15	1.80	−0.65	2.06	3.82	−1.76
0	0	0.64	2.39	−1.75	1.23	5.38	−4.15
1	5	0.60	2.03	−1.43	1.20	4.57	−3.37
6	10	0.95	2.31	−1.36	1.07	3.80	−2.73
11	15	0.77	2.05	−1.28	0.93	3.54	−2.60
16	20	0.78	1.93	−1.15	1.08	3.52	−2.43
Panel B. Average Volume (per week, per loan) Scaled by Loan Issue Amount (%)							
−20	−16	0.61	0.33	0.28	0.29	0.24	0.04
−15	−11	0.46	0.41	0.05	0.57	0.33	0.24
−10	−6	0.51	0.39	0.12	0.39	0.41	−0.02
−5	−1	0.44	0.42	0.03	0.32	0.54	−0.22
0	0	0.25	0.61	−0.36	0.16	0.94	−0.78
1	5	0.18	0.60	−0.43	0.20	0.67	−0.47
6	10	0.26	0.63	−0.37	0.17	0.76	−0.59
11	15	0.22	0.43	−0.20	0.13	0.55	−0.42
16	20	0.18	0.44	−0.26	0.18	0.55	−0.37

For each loan, we compute the sum of all buys and sells by CLOs in a week. We then take the average across downgraded loans separately for loans held by below-median number of constrained CLOs before downgrade and loans with above-median number of constrained CLOs. In Panel A, the unit is million dollars per week per loan. In Panel B, each observation is scaled by the face value of the loan at issuance.

To confirm that the loans held by the greater number of constrained CLOs indeed face more intense selling pressure, we compute the dollar volume for each downgraded loan every week and take the average separately for the two groups of loans. Table 7 reports the average weekly volume, including CLO buys and CLO sells. For both groups of loans, the sales volume increases from week −20 to the week of downgrade (week 0), but the magnitude is different. In the week of downgrade, the average sell is $2.39 million for loans held by a below median number of constrained CLOs and $5.38 million for loans with an above median number of constrained CLOs. Net volume (buy minus sell) is also lower for loans held by an above median number of CLOs. To dig deeper into the significance of transaction volume, Panel B reports the dollar volume scaled by the loan's issue amount. In the downgrading week, 0.94% of the loans widely held by constrained CLOs are sold, which is greater than the group of loans in the control group. We argue that this volume is economically significant relative to the market-wide weekly turnover of 1.5%. Because the value 0.94% only captures the sale of the loan by CLOs in our sample, we must adjust this value for two issues: first, for each sell there is a buy, so to compare with the turnover rate, we need to multiply 0.94% by two; second, the sample of CLOs with non-missing information for OC tests is less than half of the entire sample (as we later show in Table 10). Should we have non-missing data for all CLOs, the dollar volume would be greater than 0.94%, arguably twice as large. Therefore, the sales volume of 0.94% in the week of downgrade is likely to be abnormally large when compared to the available market statistics.

The convergence of the difference in CARs at the end of the event window is important for addressing reverse causality concerns in interpreting the price impact. Without convergence, one could argue that a CLO manager with poor skill is likely to have a low OC ratio and invest in loans with low expected recovery so that these loans earn low returns upon downgrade. If this is the case, the manager's lack of skill drives the CLO's OC ratio and low CARs on the loans held by the CLO, and thus there is no causal link between the OC ratio and price impact. However, we argue that such interpretation is less plausible because the difference in CARs would be persistent if a manager's poor selection skill drives the results.

4.2. Alternative measures of constrained CLO ownership

In the previous section, we use how many constrained CLOs own downgraded loans as a measure of stress because the distinguishing feature of CLOs is their tendency to simultaneously face constraints. However, this measure may reflect the omitted characteristics of borrowers or loans and does not depend on the dollar value of the loans held by CLOs. Thus, we create three alternative measures that share the same spirit but capture slightly different aspects of constrained CLOs' ownership of downgraded loans: first, we calculate the constrained CLOs' holding share as the ratio of the dollar value of the loan held by constrained CLOs (which have a below median OC ra-

Table 8
Determinants of cumulative abnormal returns upon downgrade: alternative measures of ownership.

τ	Ownership	Maturity	Rating Before Downgrade	Log Loan Size	Log Borrower Size	Year FE	$\bar{R}^2$
Panel A. Number of Constrained CLOs							
−16	0.33	−0.08	−0.11	0.28	−0.22	Yes	0.03
	(1.25)	(−0.71)	(−0.44)	(0.97)	(−0.72)		
−1	−1.53	−0.76	−0.27	−0.08	0.40	Yes	0.08
	(−2.15)	(−2.72)	(−0.32)	(−0.12)	(0.47)		
0	−2.17	−0.89	−1.00	0.36	0.44	Yes	0.08
	(−2.81)	(−2.74)	(−1.10)	(0.48)	(0.49)		
5	−1.46	−0.31	−1.07	0.65	1.49	Yes	0.05
	(−1.67)	(−0.82)	(−1.08)	(0.76)	(1.52)		
20	0.72	0.37	0.76	1.00	2.71	Yes	0.05
	(0.68)	(0.79)	(0.74)	(1.01)	(2.41)		
Panel B. Share of Loans Held by Constrained CLOs							
−16	−0.06	−0.11	−0.08	0.31	−0.08	Yes	0.03
	(−0.29)	(−0.88)	(−0.35)	(0.87)	(−0.25)		
−1	−2.15	−0.97	−0.12	−1.63	0.85	Yes	0.09
	(−3.01)	(−3.12)	(−0.15)	(−2.14)	(1.00)		
0	−2.64	−1.17	−0.77	−1.87	1.09	Yes	0.10
	(−3.54)	(−3.32)	(−0.88)	(−2.18)	(1.22)		
5	−1.70	−0.57	−0.90	−0.89	1.97	Yes	0.06
	(−2.12)	(−1.36)	(−0.93)	(−1.01)	(2.02)		
20	−0.57	0.28	0.83	0.96	3.12	Yes	0.05
	(−0.62)	(0.57)	(0.80)	(0.87)	(2.70)		
Panel C. Share of Loans Sold by Constrained CLOs							
−16	0.01	−0.08	0.12	0.38	−0.09	Yes	0.03
	(0.02)	(−0.68)	(0.42)	(1.05)	(−0.26)	–	
−1	−1.40	−0.86	0.71	−1.51	0.11	Yes	0.09
	(−1.78)	(−2.64)	(0.79)	(−1.72)	(0.12)		
0	−2.38	−1.09	−0.05	−1.79	−0.06	Yes	0.10
	(−3.00)	(−2.93)	(−0.05)	(−1.88)	(−0.07)		
5	−0.66	−0.36	−0.44	−0.01	1.14	Yes	0.05
	(−0.66)	(−0.83)	(−0.37)	(−0.01)	(1.06)		
20	0.08	0.29	1.45	1.18	3.53	Yes	0.06
	(0.07)	(0.56)	(1.06)	(0.98)	(2.84)		
Panel D. Probability of Sell-Weighted Holdings of All CLOs							
−16	0.02	−0.09	−0.09	0.37	−0.14	Yes	0.03
	(0.13)	(−0.77)	(−0.38)	(1.15)	(−0.49)		
−1	−1.09	−0.86	−0.31	−1.21	0.36	Yes	0.08
	(−2.22)	(−2.90)	(−0.37)	(−1.68)	(0.47)		
0	−1.20	−0.98	−1.07	−0.99	0.22	Yes	0.08
	(−2.08)	(−2.84)	(−1.18)	(−1.15)	(0.27)		
5	−0.70	−0.34	−1.14	−0.16	1.16	Yes	0.05
	(−1.19)	(−0.84)	(−1.15)	(−0.18)	(1.30)		
20	0.35	0.40	0.79	1.42	2.77	Yes	0.06
	(0.57)	(0.84)	(0.77)	(1.41)	(2.68)		

This table reports estimated slope coefficients, associated t-statistics, and adjusted R-squared for a regression,

$$CAR_{j,\tau} = b_{0,\tau} + b_{1,\tau} \log Ownership_j + \gamma Ctrl_j + u_{j,\tau},$$

where $CAR_{j,\tau}$ is cumulative abnormal returns on loan j from 20 weeks before the downgrade to τ in percent, $Ownership_i$ is a CLO ownership measure for loan j, including the number of constrained CLOs that own loan i, the ratio of constrained CLOs' holding of loan j to its issue amount, the ratio of the average sales volume by constrained CLOs to the loan's issue amount, and the sale probability-weighted sum of CLO ownership (including constrained and unconstrained CLOs). $Ctrl_j$ is a set of control variables, including maturity (the time to maturity of the loan in years), a credit rating before loan i is downgraded to CCC or below (AAA=1,…, B-=16), the logarithm of loan's face value, and the logarithm of the total dollar loan amount outstanding for the borrower. The regressions include year fixed-effects and standard errors are adjusted for heteroskedasticity.

Table 9
Drivers for the price impact in the financial crisis and 2020.

	Buyers'	Fed's Intervention					Total
	Capital	LoanBond	FXBasis	NewCLO	NegDefault		
Panel A. Univariate Regressions							
b	−0.602	−0.037	−0.351	−0.722	−8.036		
$t(b)$	(−4.21)	(−4.58)	(−3.51)	(−3.90)	(−2.04)		
$\bar{R}^2$	0.050	0.022	0.023	0.030	0.015		
Changes from the Financial Crisis Period to 2020						(a)	−12.909
Change	6.196	7.123	9.628	3.608	0.375		
Change $\times b$	−3.733	−0.260	−3.380	−2.607	−3.012	(b)	−12.992
						(b)/(a)	100.6%
Changes from the Post-Crisis Period to 2020						(a)	3.153
Change	−10.769	−54.657	4.805	−3.239	−0.190		
Change $\times b$	6.488	1.999	−1.687	2.340	1.528	(b)	10.668
						(b)/(a)	338.3%
Panel B. Multivariate Regressions							
b	−0.577	−0.030	−0.263	0.293	2.087		
$t(b)$	(−3.93)	(−2.66)	(−2.54)	(1.06)	(0.48)		
$\bar{R}^2$			0.066				
Changes from the Financial Crisis Period to 2020						(a)	−12.909
Change	6.196	7.123	9.628	3.608	0.375		
Change $\times b$	−3.577	−0.212	−2.534	1.056	0.782	(b)	−4.485
						(b)/(a)	34.7%
Changes from the Post-Crisis Period to 2020						(a)	3.153
Change	−10.769	−54.657	4.805	−3.239	−0.190		
Change $\times b$	6.216	1.626	−1.265	−0.948	−0.397	(b)	5.232
						(b)/(a)	165.9%

The table reports the difference in price impact, measured by the negative of cumulative abnormal returns (%) in the downgrading week for loans downgraded to CCC or below. Using the downgraded loans in or before 2019, we run a regression of the negative of downgrading-week (week 0) CAR in percent observed in month t on macro variable in that quarter and loan-level control variables,

$$\text{Price Impact}_{j,t}(= -CAR_{j,0,t}) = a + bY_{q(t)} + \gamma Ctrl_{j,t} + \varepsilon_{j,t},$$

where $Y_{q(t)}$ is a macro variable including buyers' capital (the sum of loan mutual funds' asset and distressed-focused hedge funds asset divided by the total leveraged loan outstanding in percent), LoanBond (new issuance of leveraged loans minus high-yield bonds in billion dollars), FXBasis (foreign-exchange basis averaged across nine currencies in basis points), NewCLO (assets under management of newly-issued CLOs scaled by the CLO outstanding in the previous quarter in percent), and NegDefault (the negative of the fraction of dollar value defaulted to the amount outstanding). The control variables include credit rating before downgrade, time to maturity, log loan and borrower size. The number of observations is 504 and values in parentheses are t-statistics adjusted for heteroskedasticity.

tio) to the loan's face value; second, we use the ratio of sales by constrained CLOs averaged over the event window to the loan's face value; and third, we use the sale probability-weighted sum of CLO ownership including both constrained and unconstrained CLOs for the loan.[22]

Using these alternative measures, we regress CARs up to week τ on a proxy for the ownership by constrained CLOs (*Ownership*). Specifically, for $\tau = -16, \ldots, 20$, we run

$$CAR_{j,\tau} = b_{0,\tau} + b_{1,\tau} \log Ownership_j + \gamma Ctrl_j + u_{j,\tau}, \tag{8}$$

where $CAR_{j,\tau}$ is the cumulative abnormal returns on loan j from 20 weeks before the downgrade to week τ in percent; and $Ctrl_j$ is a vector of control variables including the time to maturity of the loan in years, a numerical credit rating variable (AAA:1, B-:16) before downgrading, the logarithm of the loan's face value, and the logarithm of total loan amount outstanding for the borrower. These right-hand-side variables are measured at the end of month $t-2$, where t is the downgrading month.

Table 8 reports the estimated coefficient of the CAR on the alternative measures for CLOs' ownership of downgraded loans. Panel A repeats our main results using the number of constrained CLOs that hold the downgraded loans as a regressor. In downgrading weeks, the slope coefficient on this ownership proxy is estimated at −2.17, i.e., a one log-unit increase in the number of constrained CLOs who own the loan before the downgrade leads to a 2.17 percentage point fall in abnormal returns. Consistent with the results in the previous section, this effect dissipates at the end of the event window.

[22] Specifically, we define

$$Ownership_j = \frac{\sum_i x_{ij} Prob_{ij0}}{F_j},$$

where x_{ij} is the dollar holding value of CLO i for loan j two months before downgrade, $Prob_{ij0}$ is the probability of sale in months [0,2] for CLO i, and F_j is the face value of loan j.

Table 10
Growth of CLOs and overlapping loan holdings.

Year	N(CLO)	N(B)	Total Holding ($ bil.)	Avg. N(CLO) per Borrower	Avg. N(CLO) per Borrower (Top 10)	Avg. N(B) per CLO
Panel A. CLOs with Test Results						
2007	19	1,076	6.8	4.2	14.7	237.0
2008	143	2,123	54.5	13.3	107.8	196.8
2009	163	2,193	62.4	13.8	134.1	186.2
2010	219	2,341	84.5	17.1	181.0	182.8
2011	235	2,311	91.1	18.1	194.7	178.3
2012	221	2,223	85.6	16.9	173.0	169.6
2013	244	2,271	91.7	17.3	175.7	161.2
2014	354	2,305	133.1	24.8	228.4	161.2
2015	428	2,275	158.9	32.0	299.7	170.0
2016	421	2,103	153.9	38.3	289.7	191.4
2017	493	2,091	223.4	56.1	365.8	238.0
2018	536	1,696	259.9	83.1	442.4	262.8
2019	643	1,629	278.5	104.6	494.9	265.0
2020	700	1,812	280.0	105.9	569.2	274.2
Panel B. All CLOs						
2007	96	1,707	21.1	7.3	42.4	130.0
2008	296	2,620	86.5	17.7	175.0	156.6
2009	349	2,811	100.6	17.7	217.0	142.4
2010	470	3,077	141.8	22.5	313.7	147.5
2011	471	3,061	142.4	21.4	309.2	139.3
2012	469	3,177	140.2	19.7	297.2	133.7
2013	518	3,091	146.9	20.4	286.3	122.0
2014	666	3,142	206.7	29.0	356.5	136.7
2015	757	3,187	250.7	37.0	470.5	155.8
2016	792	3,050	254.7	44.4	480.9	170.8
2017	955	3,288	390.7	60.5	604.6	208.3
2018	1,066	3,030	502.2	85.5	801.3	243.1
2019	1,278	3,243	545.9	97.4	904.0	247.2
2020	1,441	3,455	567.9	105.2	1052.4	252.3

This table provides the year-end summary statistics for the CLO market as a whole. Panel A reports our sample of CLOs with non-missing OC ratio test results and Panel B reports the statistics for the entire sample. N(CLO) is the number of CLOs, N(B) is the number of unique borrowers, total holding is the sum of all loans held by CLOs, Avg. N(CLO) per Borrower is the number of CLOs that holds loan for a borrower averaged across borrowers, Avg. N(CLO) per Borrower (Top 10) is the number of CLOs that hold a loan for a borrower averaged across ten largest borrowers in a month, and Avg. N(B) per CLO is the number of borrowers that a CLO holds averaged across CLOs.

In Panel B, we replace this pressure variable with the loan holding share of the constrained CLOs. We find that the results are quite similar to the main results in Panel A. In a week of downgrade, a one log-unit increase in the ownership share corresponds to a −2.64 percentage point fall in CARs. Similarly, in Panels C and D, the loading on the forced sale scaled by loan face value and the sale probability-weighted loan ownership also generates a temporary decline in abnormal returns. The loading on *Ownership* variable is significantly negative in the week of downgrade (week 0) for all alternative specifications and insignificantly positive at the end of the event window except for Panel B, which ends with −0.57. Therefore, our finding that constrained CLOs' ownership affects CARs of downgraded loans does not depend on our specific choice of ownership measures.

4.3. Time series of price impact and covid-19 crisis

In this section, we study the time-series variation in price impacts. We define the price impact as the negative of the CAR in a downgrade week. The top panel of Figure 4 plots the median price impact across loans downgraded in each quarter in the sample as well as the number of loans downgraded. It shows that the price impact in 2020 is not much greater than other periods despite the pandemic-driven panic in March. When we take the simple average of price impact in downgrade weeks, the average in 2020 is 4.41%, for the post-financial crisis period (2010–2019) is 1.26%, and for the crisis period (2008–2009) is 17.31%. Therefore, despite the increasing overlap in loan holdings, the price impact in 2020 is much less pronounced than in the crisis period. Given the severity of the pandemic shock and the number of downgraded loans[23], the absence of a spike in price impact begs further investigation. To this end, in addition to CLOs' increased capital buffer since the financial crisis, we consider two factors

[23] Figures F.2 and F.3 in Internet Appendix show that CLO issuance indeed falls and more tranche downgrading occurs in 2020. However, Griffin and Nickerson (2020) document that all tranche downgrades are junior ones and no senior tranches are downgraded in 2020.

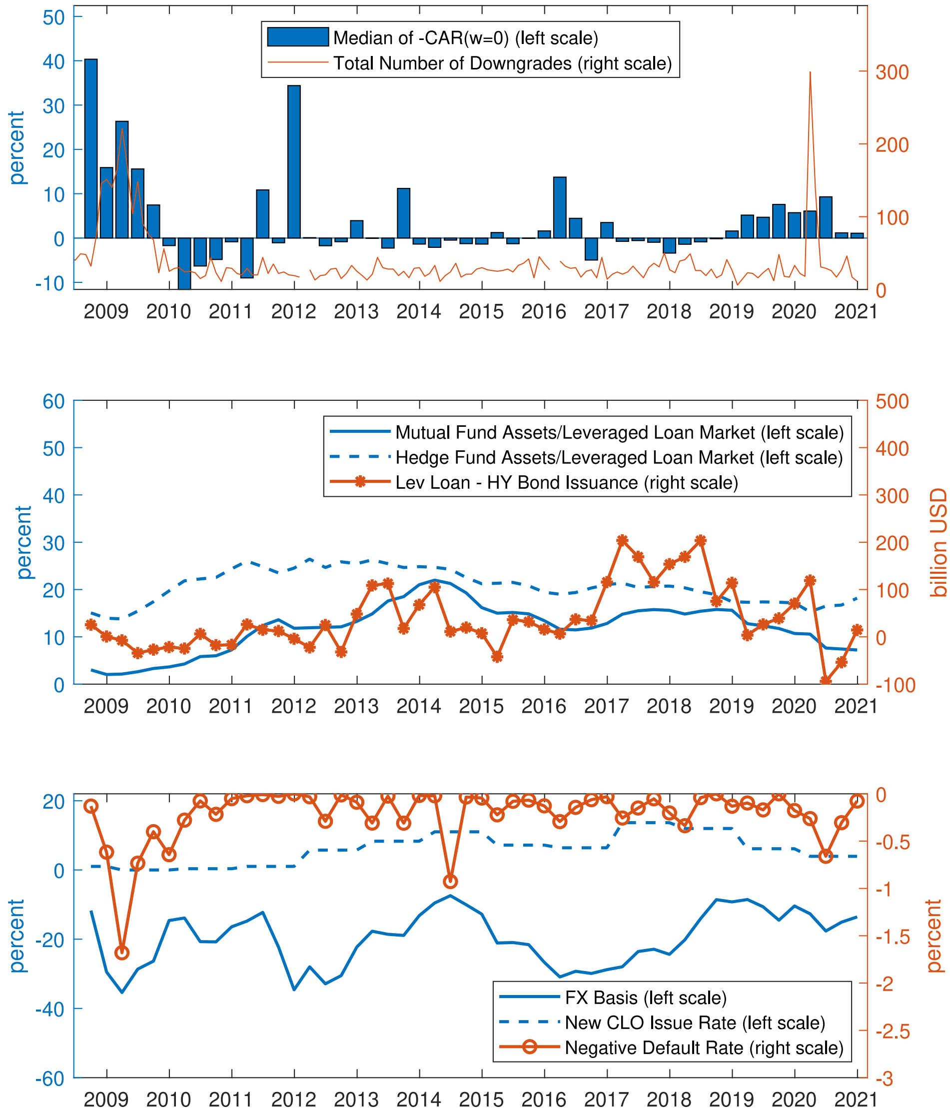

Fig. 4. Price Impact on Downgraded Loans and Factors Driving the Impact. For each downgraded loan satisfying the criteria to compute a CAR, we calculate the median CAR in the week of downgrade across loans that are downgraded in a given quarter. The top panel shows the negative of the median CAR upon downgrade and the number of downgraded loans (which include those we do not calculate CARs). In the middle and bottom panel, we plot the factors affecting the price impact. Each variable is defined in the note to Table 9.

that might have alleviated the shock in 2020: buyers' capital and the Fed's intervention.

We measure buyers' capital using the sum of loan mutual funds' assets and distressed (or restructuring) focused hedge funds' assets from the HFR report scaled by the leveraged loan market size. All else equal, ample non-CLO buyers' capital implies lower price impact.

Measuring the impact of the Fed's intervention in the loan market is more challenging. As explained in Nozawa and Qiu (2021), facing the pandemic, the Fed took a series of unprecedented actions to supply credit to the private sector, including purchasing corporate bonds and exchange-traded funds (ETFs) based on them. However, the Fed did not directly buy leveraged loans or CLOs. Thus, even though the Fed's intervention likely improved the market sentiment for credit-sensitive securities, identifying the exact channel through which the Fed's program affected the leveraged loan market is difficult. Still, we test several mechanisms through which the Fed's program might have indirectly helped the leveraged loan market. First, because the Fed purchased high-yield corporate bonds and ETFs, the substitution of leveraged loan issuance with high-yield bond issuance might have alleviated supply-demand imbalances in the leveraged loan market. Thus, we measure the substitution effect by the difference in dollar issuance between leveraged loans and high-yield bonds.

Second, related to the first effect, the Fed's support for the high-yield bond market likely prevents some borrowers from defaulting. More default of borrowers would have decreased the OC ratio of CLOs as well as the capital of other loan buyers. Thus, the Fed's policy might have alleviated the price impact through a lower borrower default rate. As such, we use the dollar value of leveraged loan default scaled by the total amount outstanding as a proxy for the intervention effect on borrowers. We multiply the default rate by (-1), so a higher value corresponds to a better state.

Third, as McCrone et al. (2020) argue, the Fed's swap line with foreign central banks in 2020 alleviates the U.S. dollar funding pressure. Absent the swap line, the foreign-exchange basis (FX basis) would plummet into negative territory, which would reduce the profits for foreign investors who invest in the U.S. fixed income securities using basis swaps. Thus, all else equal, a higher FX basis would provide support to fixed income markets in the U.S. Thus, we use the FX basis averaged over nine major currencies[24] as a proxy for the impact of the Fed's intervention in 2020.

Lastly, the Fed's Term Asset-Backed Securities Loan Facility (TALF) introduced in 2020 accepts newly issued static (i.e., not actively managed) CLOs' senior tranches as collateral. This facility makes it easier for CLO investors to invest in CLO tranches and thus stimulates new CLO issues. Because newly issued CLOs are less likely to be constrained than those issued before 2020, they could help purchase leveraged loans including those rated at or below CCC. Thus, we use the dollar values of assets under management for newly issued CLOs scaled by the existing CLOs' total assets in the previous quarter as a measure of CLO issuance activities.

Therefore, in total, we have one proxy for buyers' capital and four proxies for the Fed's actions that may affect price impacts at the aggregate level. Panels B and C of Fig. 4 show time-series plots of these variables. To examine whether these proxies relate to price impacts, we run a panel regression of price impact on loan j downgraded in month t:

$$\text{Price Impact}_{j,t} (= -CAR_{j,0,t}) = a + bY_{q(t)} + \gamma Ctrl_{j,t} + \varepsilon_{j,t}, \tag{9}$$

where $Y_{q(t)}$ is a macro variable or a vector of five macro variables. The set of control variables comprises of the credit rating before downgrade, time to maturity, log loan and borrower size.

To explain the performance of loans in 2020, we estimate (9) using all loans downgraded before 2019. We then examine whether the estimated coefficients $\hat{b}$ interacted with the changes in $Y_{q(t)}$ from the baseline period to 2020 explain the changes in price impact averaged within the baseline period and within 2020. In other words, we compare $\overline{\text{Price Impact}}_{2020} - \overline{\text{Price Impact}}_{Base}$ and $\hat{b}(\bar{Y}_{2020} - \bar{Y}_{Base})$. For the baseline period, we consider a) the financial crisis period (2008Q3 to 2009Q4) and b) the post-crisis period (2010Q1 to 2019Q4).

Table 9 presents the estimated slope coefficients, associated t-statistics, and adjusted R-squared for regression (9) when each proxy is used separately (Panel A) or jointly (Panel B). Furthermore, the table also reports the changes in macro variables $(\bar{Y}_{2020} - \bar{Y}_{Base})$ and the average price impact $\overline{\text{Price Impact}}_{2020} - \overline{\text{Price Impact}}_{Base}$ using each baseline period. Panel A shows that when we use each proxy separately, all macro variables are negatively associated with price impacts: an increase in those variables reduces price impacts on downgraded loans by alleviating the liquidity shortage in the leveraged loan market. Furthermore, these variables are higher in 2020 than in the financial crisis period. For example, buyers' capital in 2020 is higher than the crisis period by 6.2 percentage points. Because the slope of buyers' capital is -0.602, it explains a $6.2 \times (-0.602) = -3.7$ percentage point reduction in price impact. Extending this logic, loan-bond substitution, FX basis, new CLO issues, and a lower default rate respectively explain -0.3, -3.4, -2.6, and -3.0 percentage points out of the total change in price impact of -12.9 percentage points.

Panel A also shows the comparison between the relatively calm post-crisis period (2010Q1 to 2019Q4) and 2020. The difference is explained by lower buyers' capital (-10.7 percentage points), lower loan issuance (-$54 billion), lower new CLO issue rates (-3.2 percentage points), and higher default rate (0.19 percentage points) in 2020. The FX basis in 2020 is higher than the baseline, and thus it does not help explain the higher price impact in 2020. However, other factors seem to mostly explain why the price impact is more pronounced in 2020 than in the quiet period of 2010–2019.

In Panel B, we use all five proxies in a multivariate regressions in (9) and estimate the marginal contribution of each factor. Now, the loading on new CLO issues and the default rate lose statistical significance, but the point estimates for buyers' capital, loan-bond substitution, and FX basis remain similar to those in the univariate regressions in Panel A. Even in this multivariate regression, the five factors in total explain 35% of the change in price impacts in 2020 from the crisis period and 166% of the change from the post-crisis period.

Our proxies for the Fed's intervention are admittedly indirect ones, and the buyers' capital measure is an endogenous outcome of the market conditions (a topic we discuss further in Section 5.4). Nonetheless, our proxies for buyers' capital and the Fed's policy actions help explain why we did not see a pronounced price impact in the leveraged loan market during the pandemic-driven recession in 2020.

5. Economic significance of fire sales

5.1. Risks in the past and in the future

In the previous section, we document compelling evidence for the fire sale of leveraged loans. However, one may argue against the economic significance of our findings. First, given the ample evidence of fire sales in other markets, what is unique about the loan market? Second, the loans downgraded to a CCC rating are those with low credit quality and thus already have a low price. Why, then, should we be so concerned about additional 3.4%

[24] We use Australian Dollars, British Pounds, Canadian Dollars, Euros, Danish Krone, Japanese Yen, Norwegian Krone, Swedish Krone, and Swiss Francs.

(temporary) price discounts due to liquidity shortage as a source of risk?

We address the first concern about the uniqueness of our findings by emphasizing the synchronous trading induced by the diversity constraint, which is unique to CLOs. To highlight its prominence, we conduct stress tests on CLOs. We consider *hypothetical* shocks to CLOs' loan portfolios and study how those shocks spread across various CLOs and affect their OC ratio. In designing stress tests, we take into consideration the key characteristics of CLOs' loan portfolios, which have similarity in loan holdings due to the diversification requirement. The overlapping loan holdings imply that an idiosyncratic shock to a few large borrowers can affect a large fraction of CLOs. To emphasize the importance of overlapping portfolio holdings, we consider a deliberately simple scenario in which the ten largest borrowers (defined by the total borrowing from CLOs as a whole) default with a loss-given default of 50%[25], and show that the price impact under this scenario can be larger than observed in the historical data. We argue that this scenario corresponds to a mild shock because only ten borrowers out of nearly 2,000 borrowers default and there is no contagion of the defaults to other firms in the related industry. However, this scenario is admittedly arbitrary, and the likelihood of such an event occurring is not clear. Therefore, we also employ a classic procedure to derive 95% and 99% Value-at-Risk of underlying loan pools over the one-year horizon. The details for the implementation of stress tests are provided in Appendix A.[26]

5.2. Portfolio similarity

We first study the characteristics of the CLO loan portfolios that drive the results of the stress tests. Table 10 provides summary statistics for the aggregate CLO market. Panel A is the subsample of CLOs with non-missing OC ratio test results. The total value of CLO loan portfolios rises from \$6.8 billion in 2007 to \$280.0 billion in 2020. Despite the impressive growth in the CLO market, the number of unique borrowers in our sample increases only moderately, from 1,076 firms in 2007 to 1,812 firms in 2020.

Each CLO is well diversified to protect senior tranche investors. Throughout the sample period, the average number of borrowers to which each CLO is exposed is around 200. Because the number of CLOs grows faster than the number of borrowers, for each CLO to achieve the same level of diversification the CLOs end up being exposed to the same borrower. As a result, the average number of CLOs exposed to a borrower increases over time. In 2007, the average borrower is held by 4.2 CLOs, while in 2020, the average borrower is held by 105.9 CLOs. This commonality in loan holding is even more striking as we examine the ten largest borrowers in terms of total dollar amount of borrowing. In 2020, the top ten borrowers are on average held by 569 CLOs out of 700 CLOs in our sample. Therefore, the growth of the CLO industry is accompanied by an increase in the overlap of their portfolios, exposing CLOs to similar sets of borrowers. Panel B of Table 10 reports the same statistics for all CLOs in the CLO-i data, which confirms the same trend.[27]

We emphasize that those loans to the top ten borrowers are widely held by CLOs, but their total size is not overwhelming when compared with CLOs' total loan holdings. In the last row of Table 2, the average CLO has only 7.9% exposure to those ten borrowers. This fraction is less than half of the average senior OC ratio slack. Thus, the direct impact of the default of those borrowers on the default risk of CLOs' debt securities is likely to be small.

5.3. Results of stress tests

In this section, we outline the results of the stress tests; more details can be found in Appendix A. Three panels in Fig. 5 present the time series of the percentage of CLOs that would fail junior OC tests, fail senior OC tests, and become insolvent under our stress scenario as well as in the historical data.

The top panel of Fig. 5 shows that failure in junior OC ratio tests is rare between 2010 and 2019. Under the scenario in which the top ten borrowers default, CLOs' asset value and OC ratio decline and the failure rate increases. The fraction of CLOs that would fail junior OC tests under stress peaks in 2009, and then declines until the middle of 2015. After 2015, this ratio starts to increase until the end of the sample. The estimated fraction of CLOs that would fail the junior OC test under stress is 44% in December 2019, which is as high as what is observed in 2009. Thus, before the pandemic hits the market, the default of only ten borrowers is predicted to cause a failure of junior OC tests at least as widespread as what actually occurred after the financial crisis. As the impact of the COVID-19 pandemic unfolds in 2020, the fraction of actual CLOs failing the test increases to around 20%, which reflects the impact being mitigated by the Fed's intervention.

This increase in the failure rate since 2015 reflects the fact that each CLO's loan portfolio becomes similar to the

[25] For reference, the Moody's average recovery rate for senior secured loan (1st lien) during recessions is 56.78% (average of 1992, 2002, 2008, and 2009). Furthermore, Becker and Ivashina (2016) and Billett et al. (2016) show a rising share of so-called covenant-lite loans, or loans without maintenance covenants, in the leveraged loan market. Because covenant-lite loans are likely to have a lower recovery rate, we argue that 50% recovery adequately represents the rates during a business cycle trough, which is the relevant period for our scenario of large borrowers' default. Standard and Poor's (2019) shows that US first lien covenant-lite institutional loans had a median average recovery rate of 63.5% over 2015–2017 compared to 84.1% for non-covenant-lite institutional syndicated loans. Given that their sample period is during booms, recoveries during recessions are likely to be even lower.

[26] Internet Appendix C lists those top ten borrowers at the end of each year in the sample.

[27] One concern about the growth in the average number of CLOs per borrower is that the increase may simply reflect the better coverage of CLO-i data over time. To see the effect of improved coverage, we compute the ratio of the total loan holdings in CLO-i data to the total outstanding CLOs reported by SIFMA. Because a large increase in coverage of CLO-i data occurs in 2008, we compare 2008 and 2020. In SIFMA, the total balance is \$308.3 billion in 2008 and \$662.3 billion in 2020. Thus, the data coverage in terms of dollar value increases nearly threefold from 28.1% (=86.6/308.3) in 2008 to 85.8% (=567.9/662.3) in 2020. Over the same period, the number of CLOs per issuer increases from 17.7 to 105.2, or by about six times. Thus, improved data coverage is unlikely to fully explain the increasing trend in the number of CLOs per borrower.

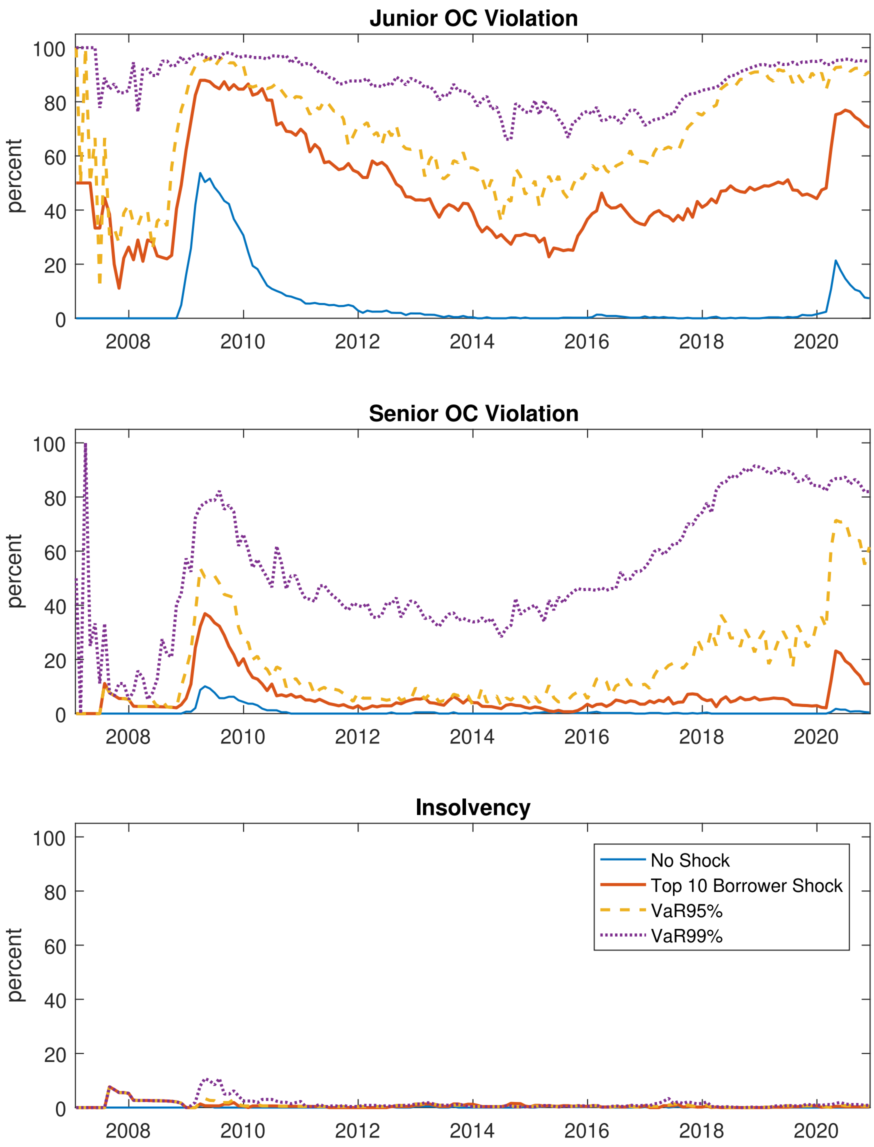

Fig. 5. Percentage of CLOs That Would Fail the OC Tests Under Stress. The figure plots the percentage of CLOs that violate the overcollateralization tests under variety of risk scenarios. "No Shock" is the percentage of CLOs that violate OC ratio tests in the historical data. "Top 10 Borrower Shock" is the percentage if ten largest borrowers default. "VaR95%" and "VaR99%" are the percentages under the 95% and 99% VaR scenarios, respectively.

others over time. As a result, even though the fraction of CLOs that actually fail junior OC tests remains close to zero between 2015 and 2019, the hypothetical failure rate under a stress event increases over the same period. In contrast, the middle and bottom panels of Figure 5 show that, with the top ten borrowers' defaults, the fraction of CLOs that would fail senior OC tests or become insolvent remains small over our sample period. These results show that portfolio diversification has both bright and dark sides; diversification reduces the risk of insolvency of CLO senior tranches, but the similarity across CLOs leads to more widespread failure of junior OC ratio tests after shock.

Now we turn to the two other stress scenarios using VaR. We find that the aggregate credit loss due to the VaR95% shock is greater than the loss from the top ten borrower defaults. As a result, the fraction of CLOs failing junior and senior OC ratio tests after receiving these shocks is always higher than the results using top ten borrower defaults. In Appendix A, we argue that our procedure to calculate VaR likely underestimates the default clustering. Therefore, despite the relatively high concentration of loans to these large borrowers, their default is still idiosyncratic and thus the direct effect is not as severe as under VaR, which accounts for the correlated default. This small magnitude of the original shocks makes our finding that as many as 44% of CLOs would fail junior OC ratio tests even more striking.

Finally, we discuss the implication of the stress test results on fire sales. Suppose that the top ten borrowers default in 2019. The number of CLOs with valid test results in 2019 in Table 10 is 643, and thus this shock increases the number of constrained CLOs from near zero to 283 ($= 0.44 \times 643$). If we use the estimated sensitivity of CARs to the number of constrained CLOs in Panel A, Table 8, the price impact is likely to be much higher than the estimates in the historical data reported in Table 6. Because the OC ratio test failure of so many CLOs has not yet happened, to what extent we can extrapolate the coefficient estimates in (8) to evaluate the impact of the stress scenario on downgraded loans is not clear. However, given the findings thus far, the large increase of constrained CLOs predicted in our stress scenario is likely to exacerbate the price reaction upon downgrade in the absence of policy intervention.

5.4. Systemic risk

Systemic risk arises when a group of investors' fire sale imposes negative externality on other investors, who face tightening constraints due to lower market prices. CLOs' fire sale of downgraded loans per se is likely to have little impact on other CLOs because many of CLOs' assets are held at book value. But how about other loan investors? We examine the possibility that the fire sale affects other investors, such as mutual funds and hedge funds, whose capital is more sensitive than that of CLOs to market price variation. According to Lee et al. (2019), mutual funds and hedge funds respectively hold 21% and 4% of B-rated syndicated loans and 21% and 8% of loans rated below CCC in 2018. These figures suggest that they are potentially important buyers of loans sold by CLOs. However, when they face outflows due to lower returns, their ability to provide liquidity can diminish, which amplifies the price impact. To verify this claim, we first provide evidence that CLOs' fire sales can affect the leveraged loan market as a whole rather than just downgraded loans, and then examine how the associated price declines affect other investors' capital through a flow-return relationship.

Because CLOs use book value, they may be inclined to sell loans that carry low book value to realize gains and increase the OC ratio. In Internet Appendix E, we estimate a logit regression of loan sales on the loan's book-value ranking in a CLO's portfolio, and find that a loan in the lowest book-price tercile is 0.36% more likely to be sold than a similar loan in the same CLO's portfolio. The effects vary across credit ratings, and the point estimate is 0.82%, 1.09%, and 0.13% for IG-rated, BB-rated, and B-rated loans, respectively.[28] With the increased probability of sales for loans rated above CCC, we estimate a decrease in price that is consistent with the evidence in our main results, where downgraded loans experience a 3.35% lower price due to fire sales (Table 6).

To provide a simple estimate for the price impact on loans rated above CCC, we consider the price impact per unit of the quantity sold for each rating category R,

$$\lambda = \frac{(\text{Price Impact})_R}{(\text{Quantity Fire-Sold})_R/(\text{Loan Amount Outstanding})_R}, \qquad (10)$$

$$= \frac{(\text{Price Impact})_R}{\Delta\text{Prob[Sell]}_R \times (\text{CLO Holding})_R/(\text{Loan Amount Outstanding})_R},$$

$$= \frac{(\text{Price Impact})_R}{\Delta\text{Prob[Sell]}_R \times (\text{CLO Holding Share})_R}.$$

The equation above shows that, once we know λ, the probability of sales, and the CLO holding share, we can then calculate the price impact for each rating category.

Table 11 reports the price impact, an increase in the probability of sales due to lower book value, and the shares of CLOs' loan holdings. The last column is for CCC loans, where we know the price impact is 3.35% and the probability of sale is 3.53% (see Table 4). Based on this estimate, we infer λ using Eq. (10). The other columns show the price impacts backed out from the value of λ (assumed to be common across ratings), the magnitude of gains trading, and the CLO loan ownership shares. As the increase in sales probability due to gains trading is more pronounced for BB-rated loans, their price impact is estimated at a higher level (0.76%) than IG- and B-rated loans (0.22% and 0.23%).

To estimate the impact of fire sales on the overall loan market, we take the weighted average of the price impact across credit ratings. For the weights, we use the rating shares in the S&P LSTA Leveraged Loan Index averaged from 2007 to 2020 reported in the last row of Table 11, which leads to the weighted average of 0.88%.

Next, we assess how the lower prices of leveraged loans due to CLOs' fire sale spill over to other investors' capital. To this end, we estimate the sensitivity of fund flows to the leveraged loan index. The spillover effect is quantified by the product of the estimated price impact in the overall loan market and the sensitivity we estimate below.

To estimate the sensitivity, we calculate the fund flow for each fund following Coval and Stafford (2007)[29], and run a panel regression of fund flows on the past flows and the loan index returns,

$$Flow_{f,q} = a + \sum_{l=1}^{L} b_{F,l} Flow_{f,q-l} + \sum_{l=1}^{L} b_{R,l} R_{q-l} + \varepsilon_{f,q}. \qquad (11)$$

We estimate (11) for $L = 1$ and $L = 4$. Standard errors are clustered by calendar quarters.

Table 12 reports the estimated coefficients and the adjusted R-squared of the regression in (11). We find that the estimated flow sensitivity b_R is generally positive but not precisely estimated. For example, in the regression with $L = 1$, the response of mutual funds' flow to a one-percent increase in R_{q-1} is estimated at 0.34% ($t = 1.23$), while that for hedge funds is 0.19% ($t = 1.62$). The insignificant coefficients of the past returns arise because, unlike Coval and Stafford (2007), we use the loan market returns rather

[28] In Internet Appendix Table F.8, we report evidence that CLOs strategically sell CCC loans that are not recently downgraded when they face downgrades of other loans. The magnitude of this strategic sale is, however, smaller than the sale of downgraded loans.

[29] For mutual funds, the flow variable, $Flow_{f,q}$ is calculated as $Flow_{f,q} = \frac{TNA_{f,q} - (1+R_{f,q})TNA_{f,q-1}}{TNA_{f,q-1}}$, where $TNA_{f,q}$ is the total net asset for fund f in quarter q. In estimating the regression in (11), we restrict the sample to observations that satisfy $-0.5 \leq \frac{TNA_{f,q} - TNA_{f,q-1}}{TNA_{f,q-1}} \leq 2$. For hedge funds, the flow is defined as $Flow_{f,q} = \frac{A_{f,q} - (1+R_{f,q})A_{f,q-1}}{A_{f,q-1}}$, where $A_{f,q}$ is the reported or estimated asset value of the fund. As in the mutual fund flows, we use observations only when they satisfy $-0.5 \leq \frac{A_{f,q} - A_{f,q-1}}{A_{f,q-1}} \leq 2$.

Table 11
Estimated price impact on each rating group.

		IG	BB	B	CCC
Price Impact (%)	(a)×(b)×(c)	0.22	0.76	0.23	3.35
Probability of Forced Sell (%)	(a)	0.82	1.09	0.13	3.53
CLO Loan Holding Share (%)	(b)	11.58	29.99	77.46	40.56
λ	(c)		2.34		
Weights in the Leveraged Loan Index (%)		7.2	34.5	43.4	14.9

This table reports the price impact on loans due to fire sales and an increase in probability of sales due to downgrade (for CCC loans) or to gains trading (for IG, BB, and B-rated loans). λ is price impact per unit of the share of loans that are sold, which is calculated using the CCC loan sample. The weights in the leveraged loan index is the average from 2007 to 2020.

Table 12
Panel regressions of fund flows on lagged flows and the loan index returns.

	Mutual Funds		Hedge Funds	
	b	$t(b)$	b	$t(b)$
Panel A. Regression on the Returns and Flows in the Previous Quarter				
$Flow_{q-1}$	0.00	(1.94)	0.18	(11.77)
R_{q-1}	0.34	(1.23)	0.19	(1.62)
Intercept	4.58	(3.63)	0.01	(0.02)
$\bar{R}^2$	0.00		0.08	
N	11,132		20,522	
Panel B. Regression on the Returns and Flows in the Previous Four Quarters				
$Flow_{q-1}$	0.01	(3.60)	0.12	(10.07)
$Flow_{q-2}$	0.00	(2.25)	0.09	(9.46)
$Flow_{q-3}$	0.00	(0.17)	0.05	(5.76)
$Flow_{q-4}$	0.00	(1.05)	0.03	(4.31)
R_{q-1}	0.46	(1.45)	0.23	(2.87)
R_{q-2}	0.31	(1.10)	0.11	(1.18)
R_{q-3}	0.48	(3.12)	0.12	(1.51)
R_{q-4}	0.30	(1.51)	0.06	(0.96)
Intercept	1.59	(1.19)	−1.59	(−3.79)
$\bar{R}^2$	0.03		0.09	
N	10,299		16,234	
(Long-Run Coefficients of Flow)				
ε^{Flow}	0.01	(2.05)	0.39	(9.94)
ε^{R}	1.04	(1.18)	0.64	(2.60)

The table shows the estimates for the panel regression of quarterly fund flows on lagged fund flows and the loan index returns for different fund types. Mutual funds are loan participation funds and hedge funds are distressed or restructuring funds. N is the number of observations. $\bar{R}^2$ is the adjusted R-squared. The long-run coefficients are the VAR-implied sensitivity of the fund's cumulative long-run flow to a shock to quarterly flow and returns. To calculate the long-run flow response, we estimate a VAR, $Y_{f,q} = B_0 + B_1 Y_{f,q-1} + \varepsilon_{f,q}$, with a state vector $Y_{f,q} = \left(Flow_{f,q} \quad \dots \quad Flow_{f,q-3} \quad R_q \quad \dots \quad R_{q-3}\right)$. The long-run response of the flow is calculated as the first row of the matrix $B^L = B_1(I - B_1)^{-1}$. The standard errors of B^L are calculated using the Delta method.

than the funds' own returns. In Internet Appendix Tables F.10 and F.11, we show that the coefficients of the funds' own returns are significantly positive.

Panel B of Table 12 presents the regression with $L = 4$. Because the fund flow depends on index returns lagged over the past four quarters, we summarize the response by examining the implied long-run coefficient of the flow on the shock to the quarterly flow and returns. To this end, we estimate a VAR,

$$Y_{f,q} = B_0 + B_1 Y_{f,q-1} + \varepsilon_{f,q},$$

with a state vector $Y_{f,q} = \left(Flow_{f,q} \quad \dots \quad Flow_{f,q-3} \quad R_q \quad \dots \quad R_{q-3}\right)$. The long-run response of the flow is calculated as the first row of the matrix $B^{LR} = B_1(I - B_1)^{-1}$. The standard errors of B^{LR} are calculated using the Delta method.

As shown in the last rows of Table 12, a one-percentage point shock to the quarterly flow and loan index returns leads to an increase in long-run mutual fund flow of 0.01% ($t = 2.05$) and 1.04% ($t = 1.18$), while the same shock leads to an increase in long-run hedge fund flow of 0.39% ($t = 9.94$) and 0.64% ($t = 2.60$), respectively. Because the sensitivity to the past index return is positive, a lower return due to fire sales reduces flows to mutual and hedge funds. For example, a 0.88% lower return on the loan index due to fire sales leads to a reduction of flow of 0.91% for mutual funds and 0.56% for hedge funds in the long run. The magnitude of the reduction is more pronounced for mutual funds than for hedge funds, but the effect on mutual funds is not statistically significant due to large flow volatility. In sum, we see some suggestive, if not definitive, evidence for CLOs' fire sales contributing to systemic risk.[30]

As we show above, with no Fed intervention the price impact in 2020 would have been greater, which would result in a greater loss of capital for non-CLO loan investors. The lower level of buyers' capital in turn magnifies the price impact, and this interaction contributes to systemic risk. As it turned out, the Fed's intervention more than offset the initial shock, which made the price impact of fire sales small to begin with. One caveat for the Fed's role in managing systemic risk is that the loan market participants, including CLO managers, may anticipate the Fed's bailout and thus take on more risk in their portfolios during booms. Therefore, one needs caution in drawing strong conclusions on the role of the Fed based only on the observed price impact and the Fed's policy reactions.[31]

6. Conclusion

In this paper, we examine the effect of OC ratio constraints facing CLOs on the underlying leveraged loan market. We show that failing the OC ratio test is costly for CLO managers, as it reduces management fees and hurts the performance of CLO tranches. To prevent the OC ratio from falling, CLOs sell CCC loans and repay senior tranches. Although CLOs are net sellers of CCC loans throughout the sample period, we find that CLOs with a lower OC ratio are even more likely to sell CCC loans than CLOs with a higher OC ratio. Thus, the reputation concerns of CLO managers combined with contractual agreements between CLOs and investors to keep each CLO safe lead to the fire sale of downgraded loans.

Next, we document that constrained CLOs' collective sales of downgraded loans lead to a shortage of liquidity in the leveraged loan market and a more pronounced decline in loan prices than control groups. Because this additional price decline reverts to zero in five months, it likely represents the selling pressure of constrained CLOs. Importantly, the price impact depends on how widely such a loan is held by constrained CLOs before the downgrade, and thus a stress event in which many CLOs are constrained at once likely poses significant price pressure on CCC loans.

The impact of fire sales is potentially exacerbated by a CLO's efforts to diversify within a limited space of borrowers, which leads to similarities in portfolio holdings across CLOs. While diversification reduces the risk of insolvency for a CLO's senior tranches, it transforms a modest idiosyncratic shock that hits a small group of borrowers to a widespread shock that impacts the underlying loan market, particularly for the segment of the market with low credit quality.

To highlight the effect of portfolio similarity, we consider a hypothetical shock of ten large borrowers defaulting for idiosyncratic reasons. We show that such a shock would lead to widespread violation of junior OC ratio tests, with the fraction of CLOs that would have negative junior OC slack being as large as the level seen during the aftermath of the financial crisis. This transmission of shock is an unexpected consequence of CLOs' collective efforts to diversify their portfolios. Because of the similarity across CLOs, their leverage constraints and thus their trading behavior become more synchronized, which could amplify the price movements of a risky segment of the leveraged loan market.

We do not argue that the transmission of shock is the only systemic risk concerning CLOs. Indeed, there can be widespread consequences of tightened OC ratio constraints on CLOs due to stress events. On the one hand, CLO investors, including systemically important financial institutions, suffer from reduced regulatory capital due to lower prices and downgrades of the CLO tranches they hold. Our results suggest that, because of their similarity, a downgrade of a CLO is likely to coincide with a downgrade of another CLO.[32] On the other hand, leveraged loan borrowers will also feel pain as they find it difficult to refinance the loan due to the poor performance of CLO tranches, reduced appetite of CLO investors to originate more CLOs, and a resulting decrease in new CLO issues. Analysis of these systemic risks remains an important topic for future research.

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Appendix A. Stress tests on CLOs

A1. Design of stress tests

In this section, we describe a stress test on CLOs and quantify how many CLOs would fail OC ratio tests when a stress event occurs. For each CLO, we consider both senior and junior OC ratio tests. We compute slack in the OC ratio for each CLO as well as shocks to its loan portfolio. We

[30] In Internet Appendix F, we document empirical evidence that the OC ratio of CLOs from which a borrower borrows is positively associated with the future asset and sales growth of the firm. Thus, CLOs contribute to systemic risk by selling loans as well as through their impact on borrowers' growth.

[31] If hedge funds and mutual funds face tightening constraints due to outflows, who can alleviate them? Lee et al. (2019) report the breakdown of loan holdings by investor types for syndicate loans rated CCC or below as of 2018. CLOs, mutual funds, and hedge funds in total hold about 60% of the market, and the rest is held by other types of investors, including domestic banks (10%), foreign banks (5%), finance companies (5%), large asset managers (3%), and private equity (2%). As regulated banks are unlikely buyers of these risky loans in times of stress, finance companies, asset managers, and private equity are potential liquidity providers.

[32] In Internet Appendix A, we study the probability of downgrades for CLO tranches.

then examine how the slack changes and how many CLOs would fail OC ratio tests after the shock.

We define dollar slack for senior and junior OC ratio tests for CLO i in month t as

$$\$Slack(S)_{i,t} = A_{i,t} - \$Thres(S)_{i,t}, \tag{A.1}$$

$$\$Slack(J)_{i,t} = A_{i,t} - \$Thres(J)_{i,t}, \tag{A.2}$$

where $A_{i,t}$ is the value of the CLO's loan portfolio on its balance sheet, and $\$Thres(S)_{i,t}$ and $\$Thres(J)_{i,t}$ are the threshold for senior and junior OC ratio tests expressed in dollars, respectively. We then scale the slack by asset value and express it in percent,

$$Slack(\cdot)_{i,t} = \frac{\$Slack(\cdot)_{i,t}}{A_{i,t}} \times 100 \tag{A.3}$$

If $Slack(S)_{i,t} < 0$, then CLO i fails the senior OC ratio test.

Our data set does not have $A_{i,t}$, and thus we infer $A_{i,t}$ from amount outstanding for CLO tranches and reported OC ratios.[33] This procedure accounts for the fact that loans rated B and above are recorded at book value while excess CCC loans and defaulted loans are evaluated at fair value.

Although this is not our main focus, we also compute the slack relative to insolvency, an event in which the asset value goes below the outstanding amount of senior tranches (i.e., the senior OC ratio falls below 100%),

$$\$Slack(Def)_{i,t} = A_{i,t} - S_{i,t}. \tag{A.5}$$

If $\$Slack(Def)_{i,t} < 0$, then we regard CLO i as insolvent.

Next, we consider shocks to a CLO's asset value under several stress scenarios. In each scenario, we consider shocks to an underlying pool of loans. After the shocks, the dollar slack changes to,

$$\begin{aligned}\Delta\$Slack(S)_{i,t} &= \$Slack(S)_{i,t} - Shock_{i,t},\\ \Delta\$Slack(J)_{i,t} &= \$Slack(J)_{i,t} - Shock_{i,t},\\ \Delta\$Slack(Def)_{i,t} &= \$Slack(Def)_{i,t} - Shock_{i,t}.\end{aligned}$$

In the empirical analysis below, we characterize the distribution of these slacks after the shocks and examine how the shocks affect OC ratio tests for various CLOs.

To quantify potential shocks, we consider two stress scenarios. First, we use a simple stress scenario under which the top ten borrowers default with loss given default of LGD_D. Every month, we choose the ten largest borrowers in terms of the total dollar loan amount held by the entire universe of CLOs. Then, shocks under this scenario for CLO i in month t are

$$Shock_{i,t} = \sum_{j \in B_t(Top10)} H_{ijt} LGD_D.$$

where H_{ijt} is CLO i's dollar loan amount to borrower j and $B_t(Top10)$ is the set of top ten borrowers in month t.

Now we explain the procedure to calculate Value-at-Risk. In our set up, a borrower would default if its asset returns R_b fall below a threshold value. Then the probability of default for borrower b with credit rating r is:

$$P[R_b < D(r)] = p_{default},$$

where $D(r)$ is the default threshold for a firm with rating r. Similarly, the probability of loan downgrade from a B rating and above to a CCC rating and below and the probability of upgrades from a CCC rating or below to an above-CCC rating satisfy

$$P[D(r) \le R_b < D_{down}(r)] = p_{downgrade},$$
$$P[D_{up}(r) \le R_b] = p_{upgrade}.$$

We assume that R_b follows a standard normal distribution with a one-factor structure:

$$R_b = \sqrt{\rho}W + \sqrt{1-\rho}Z_b,$$

where W and Z_b are an i.i.d. standard normal random variable. We back out the default, upgrading, and downgrading thresholds ($D(r), D_{up}(r)$, and $D_{down}(r)$, respectively), such that the resulting probability matches Moody's historical one-year default and transition probability.[34]

We simulate W and Z_b 10,000 times every month and compute the loss for a CLO's portfolio under path m,

$$\begin{aligned}Shock_{i,t}(m) = &\sum_{j \in B_{i,t}} H_{ijt} I_{j,t}(R_b(m) < D(r)) LGD_D\\ &+ \Delta H_{it}(CCC) LGD_{CCC},\end{aligned} \tag{A.6}$$

where

$$\Delta H_{it}(CCC) = H_{it}^{Post}(CCC) - H_{it}^{Pre}(CCC), \tag{A.7}$$

$$H_{it}^{Pre}(CCC) = \max\left(0, \sum_{j \in B_{it}(CCC)} H_{ijt} - 0.075 \sum_{j \in B_{it}} H_{ijt}\right), \tag{A.8}$$

$$\begin{aligned}H_{it}^{Post}(CCC) = \max\Bigg(0, &\sum_{j \in B_{it}(CCC)} H_{ijt}\\ &+ \sum_{j \in B_{it}} H_{ijt}[I_{j,t}(D(r) \le R_b(m) < D_{down}(r))\\ &- I_{j,t}(D_{up}(r) \le R_b(m))] - 0.075 \sum_{j \in B_{it}} H_{ijt}\Bigg),\end{aligned} \tag{A.9}$$

[33] We back out the value of assets for CLO i in month t using the OC ratio reported in our data set:

$$A_{i,t} = OC(S)_{i,t} \times S_{i,t}, \tag{A.4}$$

where $S_{i,t}$ is the outstanding dollar amount of the senior note. To compute the slack, we need the cutoff value for assets in dollars. We compute this cutoff value by:

$$\$Thres(S)_{i,t} = Thres(S)_{i,t} \times S_{i,t},$$

where $Thres(S)_{i,t}$ is the reported threshold for senior OC ratio. For a junior tranche, we back out the junior notes outstanding and all notes outstanding above the junior notes using the reported junior OC ratio and asset value inferred from (A.4):

$$S_{i,t} + J_{i,t} = \frac{A_{i,t}}{OC(J)_{i,t}}.$$

Then, the dollar threshold is given by

$$\$Thres(J)_{i,t} = Thres(J)_{i,t} \times (S_{i,t} + J_{i,t}).$$

[34] For this exercise, we use Average Cumulative Issuer-Weighted Global Default Rates by alphanumeric Rating and Average One-Year Alphanumeric Rating Migration Rates from 1983 to 2017 in Moody's (2018).

where B_{it} is a set of loans held by CLO i in month t, $I(\cdot)$ is an indicator function, $H_{it}^{Pre}(CCC)$ is the amount of CCC loan holdings in excess of 7.5% of CLO i's total assets before shocks, $H_{it}^{Post}(CCC)$ is the excess CCC loan holding after shocks, and LGD_{CCC} is one minus the fair value (in percent) of CCC loans. The 95th and 99th percentiles of $Shock_{i,t}(m)$ give the 95% and 99% VaR.

In the main analysis, we use $\rho = 0.24$, $LGD_D = 0.5$, and $LGD_{CCC} = 0.1125$, but provide robustness results in Internet Appendix D for other values. To estimate ρ, we follow Coval et al. (2009) and use stock return correlation. Specifically, we use the daily stock returns for the firms whose market value is below the median CRSP universe. We then compute ρ by regressing daily individual stock returns on market returns in each month and take the median across stocks. Finally, we compute the average during the stress period (July 2007 to April 2009) to obtain the estimate of ρ. To obtain an estimate for LGD_{CCC}, we compute the simple average over all transaction prices of CCC loans in our sample and use this value as an estimate for the fair value which is held constant over time and across CCC loans. To avoid an extreme estimate of VaR, we only compute VaR for CLOs with at least 50 loans in their portfolio.

VaR computed using the methodology above crucially depends on the assumption of normally distributed asset values and thus likely underestimates the true tail risk of a portfolio of defaultable debts. For example, Duffie et al. (2009) argue that one has to account for unobservable comovement in the probability of default across borrowers ('frailty') to accurately estimate default clustering. Nickerson and Griffin (2017) implement (Duffie et al., 2009)'s model on CLOs to evaluate rating agencies' credit rating on CLO tranches. For us, the goal of computing VaR is to show that our main stress scenario of ten large borrowers defaulting is a moderate idiosyncratic shock that is smaller than any reasonable estimate of tail events. As such, our VaR estimates are meant to provide a lower bound for the default risk of senior tranches and we do not speak directly to how likely the default of CLO senior tranches is, which is sensitive to the modelling assumption.

A2. Further results of stress tests

In this section, we present the results of the stress scenarios on CLOs' OC ratio slack. Panel A of Table A.1 presents the summary statistics of scaled slack, $Slack(\cdot)_{i,t}$, in the historical data without stress scenarios. The fraction of dollar slack to an asset value for the average CLO is 3.2% and 8.6% for junior and senior OC tests, while the average slack is 20.8% against insolvency. Thus, if the credit loss under stress tests is less than 3.2% of the average CLO's loan holdings, then the CLO does not violate any OC test. On the other hand, if the credit loss exceeds 20.8%, then this CLO is not able to pay to the senior tranche investors in full.

Now we examine the effect of the stress scenarios including top ten borrowers' default and the 95 and 99% VaR, which are reported in Panels B to D of Table A.1. Panel B presents the distribution of OC slack after the top ten borrowers default. When these large borrowers default, the OC slack for CLOs declines. As a result, the average CLO has nearly zero slack (−0.1%) for junior OC test. Looking across the distribution, the median CLO has −0.1% slack, and the 25th percentile CLO has −1.5% slack. After the shock, 52.2% of CLOs have negative slack, implying that nearly half of the CLOs in the sample would fail the junior OC ratio test. In contrast, the average CLO still has positive slack for senior OC ratio tests (5.2%) and only 6.7% would fail the senior OC ratio test. Lastly, under this stress scenario, no CLOs are insolvent.

The results thus far suggest that the idiosyncratic default of the top ten borrowers leads to widespread violation of junior OC ratio tests. It is important to note that such results are based on CLOs' *actual* loan holdings information, even though the shock itself is hypothetical. To understand how portfolio diversification and overlapping ownership of loans drive our results, we next calculate changes in OC ratio slack based on *hypothetical* holdings as a benchmark.

The first benchmark is perfect diversification. In this case, each CLO perfectly diversifies across all borrowers and allocates loans to each borrower proportional to the size of the borrower. As a result, the portfolio weight of each loan becomes identical across CLOs. This is an extreme case of perfect diversification; holding the universe of borrowers fixed, all CLOs become identical in terms of the portfolio composition. In this case, the only heterogeneity across CLOs is the amount outstanding of tranches and thresholds for OC ratio tests.

The fourth to sixth rows in Panel B of Table A.1 report the results of stress tests using these hypothetical portfolio holdings. The resulting change in OC ratio slack is remarkably similar to the test results based on actual holdings. For example, the fraction of CLOs failing junior OC ratio tests under this assumption is 61.2%, close to 52.2% for actual holdings. This similarity suggests that, though CLOs diversify over 200 borrowers in reality, the degree of diversification is comparable to the hypothetical case in which each CLO diversifies over the entire universe of borrowers.

This diversification leads to two consequences under a stress scenario. First, because CLOs are well diversified, senior tranches are unlikely to default. Improved safety for senior tranches is the whole point of forming CLOs, and the current portfolio holding suggests that CLOs to some extent achieve this goal. Second, as CLOs are diversified inside the limited universe of borrowers, diversification leads to similarities among CLOs. Therefore, the default of only (top) ten borrowers out of the universe of around 2,000 borrowers leads to the widespread violation of junior OC ratio tests. The similarity in CLOs' portfolio holdings implies that, when an OC ratio constraint on one CLO tightens, the constraints on the other CLOs would start to bind at the same time. Thus, portfolio diversification leads to comovement in OC ratio failure across CLOs.

The second benchmark is the case with little diversification of loan holdings. In this hypothetical case, we assign the total loss due to the top ten borrowers' default (at the aggregate level) randomly to individual CLOs. Specifically, each month, we pick a CLO and assume that it invests fully in one of the ten borrowers that default. We keep choosing CLOs randomly until the cumulative loss assigned to

Table A1
Percentage slack of overcollateralization tests: stress tests.

$\Delta Slack$		Mean	Percentiles					%(< 0)
			5%	25%	50%	75%	95%	
Panel A. Slack without shocks								
	$OC(J)$	3.2	0.1	2.2	3.2	3.9	7.3	4.4
	$OC(S)$	8.6	3.5	5.6	6.4	8.3	23.9	0.0
	Def	20.8	13.8	18.1	20.1	21.7	31.7	0.0
Panel B. Top 10 borrowers default								
Actual holdings	$OC(J)$	−0.1	−4.1	−1.5	−0.1	1.1	4.1	52.2
	$OC(S)$	5.2	−0.4	2.0	3.4	5.4	19.2	6.7
	Def	17.4	9.8	14.6	16.8	18.8	27.9	0.0
Fully difersified	$OC(J)$	−0.2	−3.1	−1.1	−0.3	0.4	3.8	61.2
	$OC(S)$	5.2	0.4	2.2	2.9	4.7	20.6	3.0
	Def	17.4	10.3	14.8	16.7	18.2	28.4	0.0
Not difersified	$OC(J)$	0.1	−3.0	2.0	3.1	3.8	7.2	8.0
	$OC(S)$	5.5	1.3	5.5	6.3	8.1	23.6	4.2
	Def	17.6	9.4	17.8	20.0	21.6	31.5	3.8
Panel C. VaR95% shock								
Actual holdings	$OC(J)$	−1.8	−6.1	−3.2	−1.8	−0.4	2.9	80.0
	$OC(S)$	3.2	−2.7	0.0	1.6	3.8	17.0	24.4
	Def	15.5	8.7	12.8	14.9	17.0	25.6	0.0
Panel D. VaR99% shock								
Actual holdings	$OC(J)$	−5.3	−10.3	−7.2	−5.5	−3.5	0.2	94.5
	$OC(S)$	−0.3	−7.0	−4.0	−2.0	1.0	14.1	68.5
	Def	12.0	4.9	9.0	11.2	13.8	22.7	1.2

The table shows summary statistics of OC ratio slack as a percentage of assets under management. Slack is the difference between a reported OC ratio for a CLO and its threshold values. The threshold values are the cutoff values of OC tests for senior ($OC(S)$) and junior ($OC(J)$) tranches, while the threshold for insolvency (Def) is 100% of senior tranches. %(< 0) is the percentage of CLOs with negative slack among all CLOs. "Actual holdings" is the slack when shocks are assigned to each CLO based on its actual loan holdings. "Fully-diversified" is the case in which we assume all CLOs are fully diversified and identical and assign the total loss of the underlying loans in proportion to the assets under management of each CLO. "Not diversified" is the case in which we assume each CLO invests in one loan and assign defaulted loans randomly across CLOs. The number of observations is 53,960 CLO-months.

the selected CLOs equals the total loss that would occur in the month under the stress scenario. This hypothetical loan ownership leads to a bifurcation of the fate of CLOs under stress. A lucky CLO who happens not to own any of the ten defaulted borrowers suffers no loss, while an unlucky CLO who is assigned a defaulted borrower would see its portfolio value to plummet.

The last three rows in Panel B of Table A.1 reports the effect of the top ten borrowers' defaults on OC ratio slack in this case of little diversification. Because we fix the size of the total shock, the average effect in this case is not very different from the two other cases. Specifically, the average slack for junior OC, senior OC, and insolvency tests are 0.1%, 5.5% and 17.6%, which are similar to the results using actual loan holding. However, the difference in loan ownership leads to different distribution of OC ratio slack across CLOs. With little diversification, only 8.0% of CLOs would fail the junior OC ratio test after the shock, which is much lower than 52.2% failure rate with the actual loan ownership. On the other hand, 3.8% of CLOs become insolvent after the shock without diversification, higher than zero insolvency rate based on the actual ownership. The stark difference between the results based on actual holdings and the hypothetical holdings with little diversification confirms our argument that CLOs actual holdings resemble the case of perfect diversification.

In sum, we describe the key feature of CLOs' loan holding: overlapping loan investment among CLOs induced by the rapid growth in CLOs' assets under management and diversification requirements. This feature of the data is the key in understanding the transmission of idiosyncratic defaults of large borrowers to a widespread shock in the underlying leveraged loan market.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.05.003.

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