# Fire-Sale Risk in the Leveraged Loan Market *

Redouane Elkamhi† Yoshio Nozawa‡

University of Toronto

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**Abstract**

Using detailed loan holding data of Collateralized Loan Obligations (CLOs), we document empirical evidence for 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 constraint binds simultaneously. CLOs' overlapping loan holdings spread idiosyncratic shocks to large borrowers to the overall leveraged loan market.

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†Rotman School of Management, Toronto, ON M5S 3E6, Canada; redouane.elkamhi@rotman.utoronto.ca.

‡Rotman School of Management and UTSC, Toronto, ON M5S 3E6, Canada; yoshio.nozawa@rotman.utoronto.ca.

# 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 constraint. 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 document contractual restrictions that drive CLOs' investment behavior.

[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.

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, there 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 fees paid to CLO managers, lowers yield to CLO equity tranches, and thus hurts reputation of CLO managers. Therefore, CLOs strive to obey to these well-intended requirements which 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 instead a CLO uses book value to evaluate its loan holding, selling the loan at the market price (which is generally lower than the book value) incurs immediate losses, which reduce an 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 the fair value, which is close to a market price. Therefore, we examine CLO transactions for loans that are downgraded from B rating or above to 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 to sell downgraded loans than unconstrained CLOs are.

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.

A tendency for an individual investor to sell her holdings would not disrupt the financial market if her market share is small, and there are other investors who take the opposite side of the trade. However, as we emphasized above, the holding share of CLOs in the leveraged loan market is significant. Furthermore, we show that CLOs trade loans actively with the average annual portfolio turnover of more than 70%, which accounts for nearly half of the overall transaction volume. Therefore, if multiple CLOs face constraints at the same time, then their collective action can disrupt the overall CCC loan market, and potentially impact market prices in the short run.

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 shot-term mean-reversion in the market price reflects mispricing due to liquidity shocks. To see if market prices mean reverts, we compute abnormal returns on downgraded loans, and cumulate those over the event window around downgrading weeks. In order 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 in 20 weeks after the downgrade. The difference in CARs upon downgrade shows that 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 the entire CLOs default. Second, we compute simple Value-at-Risk (VaR) measures based on the simulated path of 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 right after the financial crisis in 2009. 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 the top ten borrowers' default does.

Why does such a modest shock affect a disproportionately large fraction of CLOs? This outcome of a stress test depends crucially 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 now CLOs are more likely to be forced to trade at the same time in one direction due to idiosyncratic loan default than they used to be. 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 is likely to be more pronounced than what is implied from the empirical analysis which necessarily relies on historical averages. Our analytical framework which 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.

This spillover of shocks becomes a systemic event if fire sale of a group of investors imposes significantly negative externality on other agents in the economy. We find suggestive evidence that the price decline due to fire sale may lead to capital outflow from loan mutual funds and distressed/restructuring-focused hedge funds. Furthermore, constrained CLOs' loan ownership negatively affects borrowers' growth. Taken together, the spillover of shocks could contribute to systemic risk in the 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, 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 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, and 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,b,c) report evidence of fire sale in the loan market by banks and CLOs using different identification strategies. 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 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. Munday et al. (2018), Loumioti (2019) and Chernenko, Erel, and Prilmeier (2021) examine the characteristics and performance of nonbank lending. From the asset pricing perspective, Cordell, Roberts, and Schwert (2020) and Elkamhi, Li, and Nozawa (2020) study how CLO tranches are priced.

This paper also relates to a strand of literature that documents the impact of constrained institutional investors on asset prices. Theoretically, various models assert that investors hit by idiosyncratic liquidity shocks affect asset prices (Shleifer and Vishny, 1992), especially in over-the-counter markets (Duffie, Gârleanu, and Pedersen, 2005; Duffie, Gârleanu, and Pedersen, 2007; He and Milbradt, 2014). Empirically, 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 not only because we study different asset classes, but also because we highlight a unique feature of the loan market that the major investors' portfolios become increasingly similar to each other, which can exacerbate the price impact.

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 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 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, there are numerous portfolio constraints imposed on management of CLOs. One key requirement is portfolio diversification. CLOs are required to calculate "diversity score" which captures their portfolio diversity within and across industries, and to keep 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

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

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 assets 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 keep the OC ratio above certain thresholds.

Since 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. Since leveraged loans are illiquid, CLOs evaluate their loan holdings at the book value if credit rating of a loan is above CCC. Defaulted loans, and CCC loans (i.e. loans that are 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 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 have to be marked to market. Therefore, to maintain a desired level of the 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, there is a ramp-up period right 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

[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 rating that two agencies disagree on) 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.

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 go 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 many 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 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. Because of 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 risk of each CLO, there is no guarantee that they are socially optimal.

[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 A1 in Appendix shows the time-series of distributions of OC ratio slack, which suggests that the test failure is rare in non-crisis periods.

## 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 collects 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 covers 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.

Table 1 presents summary statistics of OC ratio tests and risk measures for the average CLO in our sample. In Panel A, the number of CLOs increases from 19 in 2007 to 700 in 2020, while the average CLO has around $500 million of assets under management, which is stable during our sample period. These statistics imply that assets under management for CLOs as a whole grew rapidly over our sample period.

For each CLO, we compute slack in the OC ratio by taking the difference between the reported OC ratio and the threshold value. The average CLO has OC ratio slack for senior tranches ranging from 8.8% to 30.0% and that 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 varies from 7.4% to 14.7%. This statistic suggests that the average CLO exceeds the threshold value for 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 to constrain CLOs

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

[9] CLO-i data includes 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 OC ratio tests. For junior OC ratio test, we search for OC ratio tests for class D and E OC ratio tests. If only one of class D or E OC ratio tests are available, we use it as junior OC ratio for the CLO. If both class D and E OC ratios are available, then we use class E OC ratio test as junior OC ratio for the CLO.

than its junior cousin is.

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 the CLO's maturity, we split the sample into two groups: CLO1.0 with a closing date in 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 relatively thin junior OC ratio slack is portfolio diversification. If a CLO's portfolio is well diversified, it is unlikely that multiple defaults happen at the same time and significantly reduce the OC ratio. In contrast, poor portfolio diversification leads to a higher risk of significant deterioration in the OC ratio.

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

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

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 3.7% of investment-grade (IG) loans, 19.0% of BB-rated loans, 64.1% of B-rated loans and 7.5% of 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 equals 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 hedge fund data from the Lipper Hedge Fund Database for the fund-level information;[13] iii) the HFR global hedge fund industry report for the aggregate hedge fund data.[14]

[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".

[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 declines over time significantly, and thus we use "Distressed/Restructuring" category in the HFR data to measure the aggregate buyers' capital.

# 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 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 which is held at the book value of 100, and uses the proceeds to repay the senior tranche ii) the CLO sells a loan which is valued using market price $P < 100$ and repays the senior tranche.

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

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

and it increases after the transactions (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). (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, the condition (4) is satisfied for most 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, to receive junior fees, and to pay dividends to equity holders.

The OC ratio constraint does not depend directly on the quality of assets in the same way as a regulated financial institution's capital ratio does. The motivation for fire sales comes from the fact that CLOs use the proceeds from loan sales to repay to the investors, which results in a lower amount of debt. Since 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 pre-specified 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 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 the OC ratio closer to the lower bound are more strongly incentivized to to do. 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, and this is why we study this link empirically 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 B rating or above to 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 credit rating of each loan. If a downgrade is reversed in the next month, we regard it as recording errors and remove such observation from the list of downgraded loans. If we find the same

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

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 Figure 1, the net volume (buys minus sells) starts to decrease one month before downgrade, and reaches a trough two months after downgrade, and reverts toward zero slowly over the next 12 months. Overall, the figure shows that downgrading to CCC rating and below increases CLOs' loan sales significantly.

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 times, 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 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 which are downgraded from above-CCC rating to CCC rating or below. The downgraded loans are

[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.

transacted more actively than other loans, with the average number of trades at 1.05 times 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 smaller than that of the senior one, and thus we focus on junior OC ratio slack in the following analysis. Furthermore, in Section 2.2, we show that the OC ratio changes mechanically as CLOs repay their debt after reinvestment dates. In order 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 the reinvestment date. Finally, we only use CLOs that have the 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 $[m_0, m_1]$:

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

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 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, $f(\cdot)$ is a logit function.

Since Figure 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 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 credit rating before downgrade (AAA:1, B-:16) and 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, the logarithm of the manager's total assets under management (which is greater than the CLO's asset if the manager manages more than one CLO), and the ratio of the

[17] We compute the robust standard errors as follows: let $l(\theta)$ be log likelihood function with a vector of parameter $\theta$. 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, 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.

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 dummy variables which 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 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 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 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 the future redemption at the three-, six- and twelve-month horizon. 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

[18] In Appendix, we examine whether the tendency to sell loans differs across the subsample of cohorts of CLOs. In Table A4, 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 CLO 1.0, 2.0 and 3.0, respectively. The estimates for CLO 1.0 and CLO3.0 are similar to the full sample results of 3.53 percentage points in Table 4, while the estimate for CLO 2.0, which has the smallest sample size, is higher. Thus, facing downgrades amid the COVID-19 pandemic, CLO 2.0 reacts more aggressively than CLO 3.0 does. Still, CLO 3.0 sells amid the pandemic at least as much as CLO 1.0 does after the financial crisis. As a result, we do not see a decline in marginal effects over time.

likely to sell loans that are downgraded to 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, which we turn to in the next section.

# 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 the loan is held by a large number of constrained CLOs or not.

In order to distinguish the price decrease due to news about fundamentals from the price decrease due to illiquidity, one has to 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 CARs revert back to zero some time after the event or not. 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 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 held widely by constrained CLOs, and those that are not. By using loans not held widely 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 estimate the regression coefficients precisely, we compute loan returns at the weekly frequency using CLOs' transaction prices. If there are multiple transactions occurring 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 five dollars per 100 dollar face amount.[19]

Following the spirit of Ellul, Jotikasthira, and Lundblad (2011)[20], we run regressions of weekly returns on loan $j$:

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

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

[19] Five dollars correspond to the 1 percentile of the distribution for transactions of downgraded loans.
[20] This regression specification follows Ellul, Jotikasthira, and Lundblad (2011), but we add a factor that proxies for aggregate loan market returns.

indicator variable which is 1 (-1) when a CLO buys (sells) loan $j$; $Q_{j,w}$ is 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 before week -20 and after week 20. The regression coefficients using the data before week -20 are used to compute abnormal returns from weeks -20 to -1, and the coefficients based on the data 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 at 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 where 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. Since 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 below-median number of constrained CLOs has -5.13% MCAR from week -20 to week 0 (downgrading week), while a MCAR for loans with above median number of CLOs 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 the subsequent weeks.[21] The difference in MCARs between the two groups of loan is -3.35% in 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% in week 15 and 0.76% in 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 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 at the end of the event window.

To confirm that the loans held by the greater number of constrained CLOs indeed face

[21] Since 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.

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 below median number of constrained CLOs, and \$5.38 million for loans with above median number of constrained CLOs. Net volume (buy minus sell) is also lower for loans held by 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%. Since the value 0.94% captures only the sale of the loan by CLOs in our sample, we have to 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 with the available market statistics.

The convergence of the difference in CARs at the end of the event window is important in 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 if a manager's poor selection skill drives the results, then the difference in CARs would be persistent.

## 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 face constraints simultaneously. 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 below median OC ratio) 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; 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 $\tau$ on a proxy for the ownership by constrained CLOs ($Ownership$). Specifically, for $\tau = -16, \ldots, 20$, we run

$$CAR_{j,\tau} = b_0 + b_1 \log Ownership_j + \gamma Ctrl_j + u_{j,\tau}, \tag{8}$$

where $CAR_{j,\tau}$ is cumulative abnormal returns on loan $j$ from 20 weeks before the downgrade to week $\tau$ in percent, $Ctrl_j$ 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.

[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 $i$, $F_j$ is the face value of loan $j$.

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: 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.

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 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%, while that for the post-financial crisis period (2010-2019) is 1.26%, and that 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 that might have alleviated the shock in 2020: buyers' capital and Fed's intervention.

We measure buyers' capital using the sum of loan mutual funds' assets and distressed/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 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 helped the leveraged loan market indirectly. First, since 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, Fed's support for the high-yield bond market likely prevents some borrowers from defaulting. Should there be more default of borrowers, it would have decreased the OC ratio of CLOs as well as the capital of other loan buyers.

[23] Figures A2 and A3 in Appendix show that indeed CLO issuance falls and there are more tranche downgrading in 2020. However, Griffin and Nickerson (2020) show that all tranche downgrades are junior ones and no senior tranches are downgraded in 2020.

Thus, Fed's policy might have alleviated the price impact through a lower borrower default rate. Thus, we use the negative dollar value of leveraged loan default scaled by the total amount outstanding as a proxy for the intervention effect on borrowers. We use the negative default rate, so the 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, foreign-exchange basis (FX basis) would plummet into a 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 Fed's intervention in 2020.

Lastly, 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. Since 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 Figure 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 $t$:

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

[24] We use Australian Dollars, British Pound, Canadian Dollars, Euro, Danish Krone, Japanese Yen, Norwegian Krone, Swedish Krone, and Swiss Franc.

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

To explain the relatively good 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 ($\bar{X}_{2020} - \bar{X}_{Base}$) 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. Since 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 explains -0.3, -3.4, -2.6, -3.0 percentage points out of the total change in price impact of $-12.9$ percentage points, respectively.

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. 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 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 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 CCC rating are those with low credit quality and thus have a low price anyway. Then, why should we be so concerned about additional 4% (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 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 loss-given default of 50%, [25] and show that the price impact under this scenario is larger than what is 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 C.[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

[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. Since covenant-lite loans are likely to have lower recovery rate, we argue that 50% recovery represents the rates during a business cycle trough adequately, 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]A6 in Appendix D lists those top ten borrowers at the end of each year in the sample.

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: it increases 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 each CLO is exposed to is around 200. Since the number of CLOs grows faster than the number of borrowers, in order for each CLO to achieve the same level of diversification, CLOs end up being exposed to the same borrower. As a result, the average number of CLOs that are 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 CLO industry accompanies an increase in the overlap of their portfolios, making CLOs exposed to similar sets of borrowers.

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.

Panel B of Table 10 reports the same statistics for all CLOs in the CLO-i data. Once we include CLOs with missing OC ratio information, the sample size is nearly twice as large as our final sample in Panel A. However, the trend in the average number of CLOs per borrower in Panel B is similar to the one for our sample in Panel A. The average borrower is held by more CLOs over time, and the average number of CLOs per borrower increases from 7.3 in 2007 to 105.2 in 2020.[27]

[27] One concern about the growth in the average number of CLOs per borrower is that the increase may

## 5.3 Results of Stress Tests

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

The top panel of Figure 5 shows that failure in junior OC ratio tests is rare between 2010 and 2019. Under the scenario where the top ten borrowers default, then 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 which 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 it actually occurred after the financial crisis. As the impact of COVID-19 unfolds in 2020, the fraction of actual CLOs failing the test increases to around 20%, which reflects the impact being mitigated by Fed's intervention.

This increase in the failure rate since 2015 reflects the fact that each CLO's loan portfolio becomes similar to the others over time. As a result, even though the fraction of CLOs that actually fail junior OC tests remains close to zero between 2016 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

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.[28] Since there is a large increase in coverage of CLO-i data 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 from 28.1% (=86.6/308.3) in 2008 to 85.8% (=567.9/662.3) in 2020, a nearly threefold increase. Over the same period, the number of CLOs per issuer increases from 17.7 to 105.2, about six times as large. Thus, an improved data coverage is unlikely to fully explain the increasing trend in the number of CLOs per borrower.

period. These results show that there are bright and dark sides of portfolio diversification. Diversification reduces the risk of insolvency of CLO senior tranches, but the similarity across CLOs leads to more wide-spread 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. Finally, under the relatively simple scenario we consider, no CLOs become insolvent (i.e., the asset value goes below the senior tranche outstanding) after the shock.

Comparing the scenarios with top ten borrower defaults and VaR, we find that the aggregate impact of top ten borrower defaults is not as severe as that of VaR. In Appendix C, 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 the ones 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 649, 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. Since the OC ratio test failure of so many CLOs has not happened yet, it is not clear to what extent we can extrapolate the coefficient estimates in (8) to evaluate the impact of the stress scenario on downgraded loans. 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 to market price variation than CLOs'. According to Lee et al. (2019), mutual funds and hedge funds hold 21% and 4% of B-rated syndicated loans, and 21% and 8% of loans rated below CCC in 2018, respectively. 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 show 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.

Since 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 Appendix F, 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.[29] With the increased probability of sales for loans rated above CCC, we estimate a decrease in price

[29] In Appendix Table A8, 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.

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 $R$,

$$\begin{aligned}
\lambda &= \frac{(\text{Price Impact})_R}{(\text{Quantity Fire-Sold})_R/(\text{Loan Amount Outstanding})_R}, \\
&= \frac{(\text{Price Impact})_R}{\Delta\text{Prob[Sell]}_R \times (\text{CLO Holding})_R/(\text{Loan Amount Outstanding})_R}, \\
&= \frac{(\text{Price Impact})_R}{\Delta\text{Prob[Sell]}_R \times (\text{CLO Holding Share})_R}.
\end{aligned} \tag{10}$$

The equation above shows that, once we know $\lambda$, the probability of sales and the CLO holding share, then we can 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 $\lambda$ using equation (10). The other columns show the price impacts backed out from the value of $\lambda$ (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),[30] and run a panel regression of fund flows on the past flows and the loan index returns,

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

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 $b_R$ are 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 than the funds' own returns. In Internet Appendix Tables A10 and A11, we show that the coefficients of the funds' own returns are significantly positive.

Panel B of Table 12 presents the regression with $L = 4$. Since 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.

[30]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 $-0.5 \leq \frac{A_{f,q} - A_{f,q-1}}{A_{f,q-1}} \leq 2$.

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 $Y_{f,q} = \begin{pmatrix} Flow_{f,q} & \dots & Flow_{f,q-3} & R_q & \dots & R_{q-3} \end{pmatrix}$. 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. Since 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.

As we show above, should there be no Fed's 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, 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 a strong conclusion on the role of the Fed based only on the observed price impact and the Fed's policy reactions.[31]

[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

Furthermore, we argue that CLOs can contribute to systemic risk in the economy beyond the financial market because they function as shadow banks. Much like banks, there is a connection between CLO managers and certain borrowers, which makes it difficult for borrowers to switch lenders. This effect is more pronounced for smaller firms who do not issue corporate bonds. In Appendix Section G, we document empirical evidence that the OC ratio of CLOs that a borrower borrows from is positively associated with the future asset and sales growth of the firm. Thus, CLOs not only contribute to systemic risk by selling loans but also through their impact on borrowers' growth.

# 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 are. 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. Since 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

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. They include 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.

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 the CLO's senior tranches, it transforms a modest idiosyncratic shock that hits a small group of borrowers to a wide-spread 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, and the fraction of CLOs that would have negative junior OC slack is 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 CLO tranches they hold. Our results suggest that a downgrade of a CLO is likely to coincide with a downgrade of another CLO, because of their similarity.[32] On the other hand, leveraged loan borrowers will also feel pain as they find it difficult to

[32]This effect may be even more alarming considering that systematically important banks are the largest investors in CLO AAA tranches (Financial Stability Board, 2019) and hence these securities constitute an important fraction of the banks' economic/regulatory capital. This potential risk of correlated downgrades that we identify in the high-quality CLO tranches may engender serious concerns for financial markets through the implied effects on banks. In Appendix A, we study the probability of downgrades for CLO tranches.

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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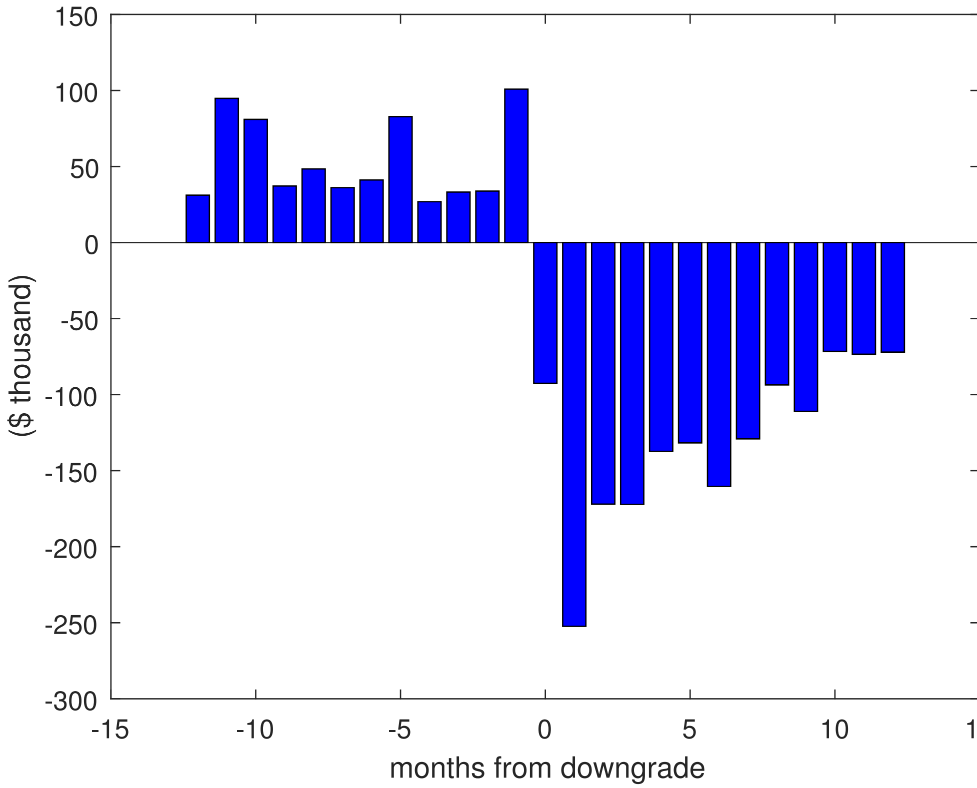
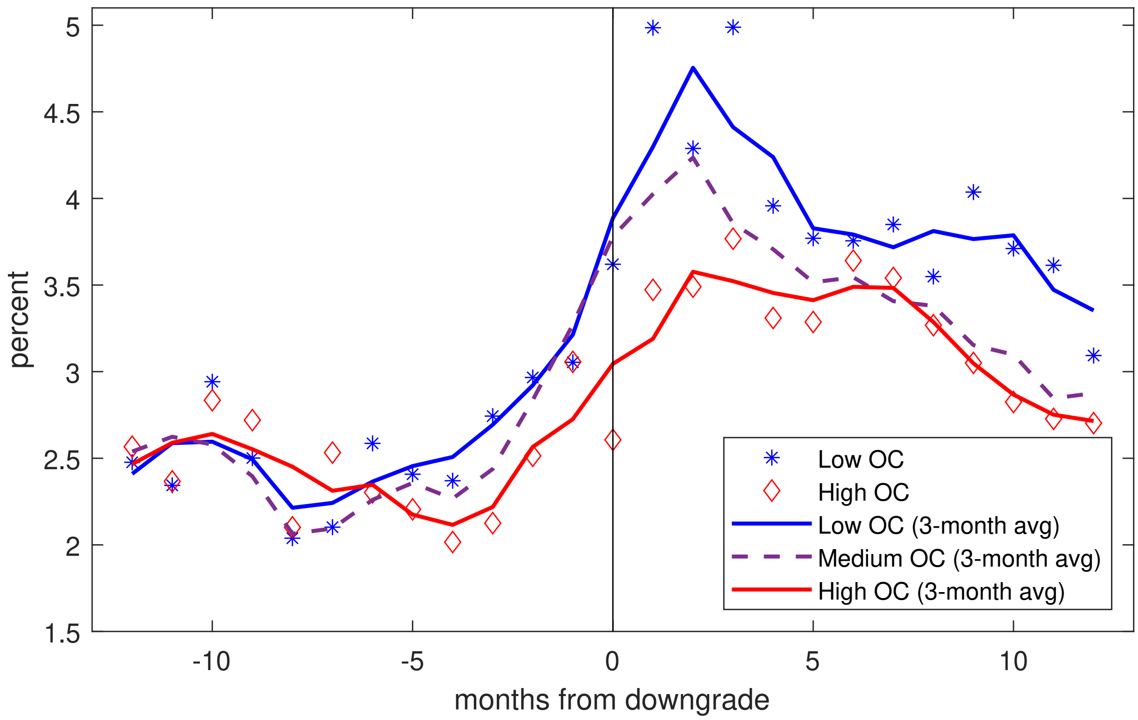
**Figure 1: CLOs' Net Purchase of Loans Downgraded to CCC or Below**



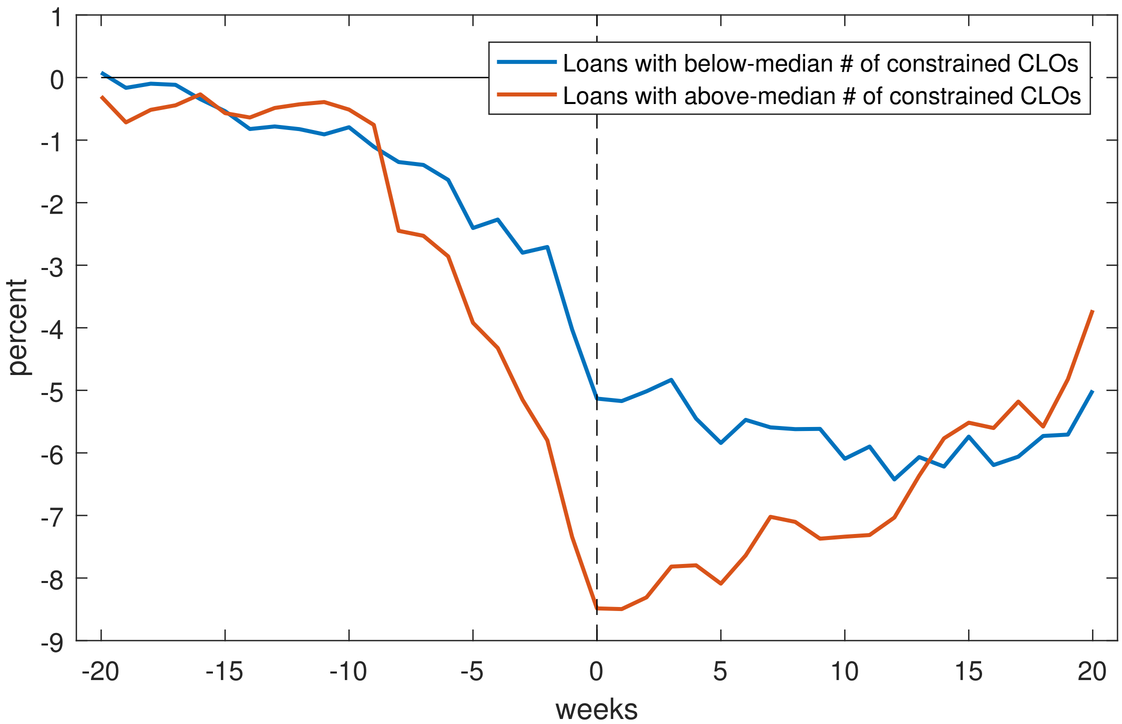

This figure presents the difference between the total purchases and sales of the loans that are rated BB or above, and downgraded to CCC or below in month 0. For each downgraded loan, we sum the purchase and sales by all CLOs from months $-12$ to 12, and then take the average across loans.

**Figure 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.

**Figure 3: Mean Cumulative Abnormal Returns Around the Downgrade Event**

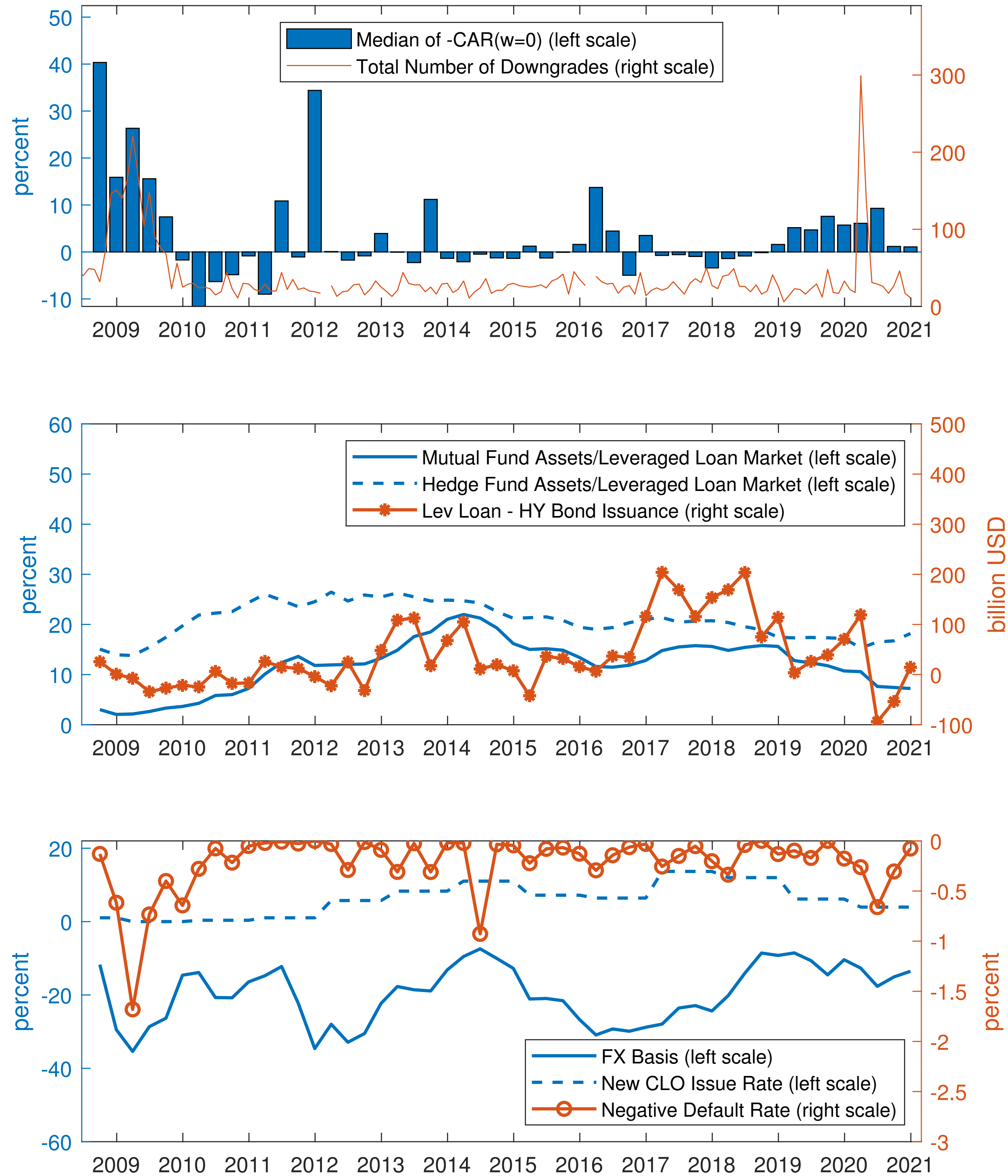



For each downgraded loan, we compute an abnormal return by running a regression of a loan return in week $w$:

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

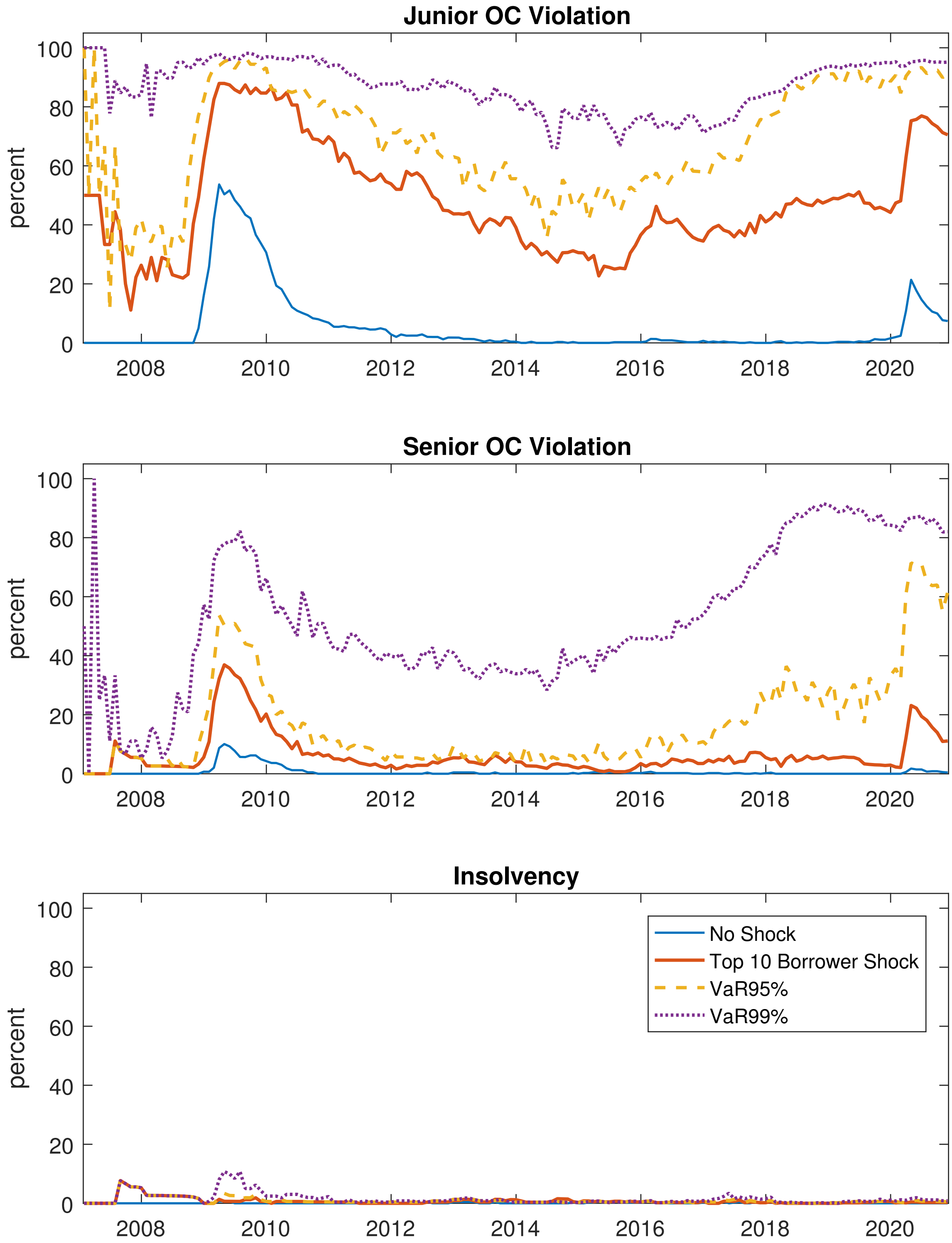
where $IDX_{w+1}$ is a vector of benchmark returns including a return on the S&P LSTA leveraged loan index, the 3-month T-bill rate, and a return on the S&P500 index; $S_{i,w}$ is the indicator variable which is 1 (-1) when a CLO buys (sells) loan $i$; $Q_{i,w}$ is the dollar volume of the transaction.
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 at least five return observations throughout the event window, which gives the number of loans of 838.

**Figure 4: Price Impact on Downgraded Loans and Factors Driving the Impact**




For each downgraded loans 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.

**Figure 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 scenario, respectively.

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.

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 | 3.7 | 5.7 | 0.0 | 0.6 | 1.7 | 5.1 | 12.3 |
| 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.

**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 is equal to the product of the CLO turnover and CLO holding share. In Panel B, we use subsample of loans that are downgraded to CCC or below. The sample period is from January 2007 to December 2020.

**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: | | | 34.08 | 3.53 | | | | |
| $Slack(J)$ <33rd pct | | | (6.49) | (6.53) | | | | |
| Dummy: 33rd pct≤ | | | 25.64 | 2.65 | | | | |
| $Slack(J)$ <67th pct | | | (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, $LoanMat$ 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, $CCCRatio$ is the ratio of CCC loans to assets under management), Time FE is year-quarter fixed effects, $f(\cdot)$ 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 the reinvestment date, and the CCC-ratio above 5%.

**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, $CCCRatio$ 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 so 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 the reinvestment date, and the CCC-ratio above 5%.

**Table 6: Mean Cumulative Abnormal Returns Around Downgrades**

| Begin week | End week | Below-median number of constrained CLOs | | Above-median number of constrained CLOs | | Difference | |
|---|---|---|---|---|---|---|---|
| | | MCAR (1) | $t$-statistic | MCAR (2) | $t$-statistic | MCAR (2)-(1) | $t$-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 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.

## 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.

**Table 8: Determinants of Cumulative Abnormal Returns Upon Downgrade: Alternative Measures of Ownership**

| $\tau$ | 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) | | |

**Table 8, Continued**

| $\tau$ | Ownership | Maturity | Rating Before Downgrade | Log Loan Size | Log Borrower Size | Year FE | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|
| 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:

$$CAR_{j,\tau} = b_0 + b_1 \log Ownership_j + \gamma Ctrl_j + u_{j,\tau}$$

where $CAR_{j,\tau}$ is cumulative abnormal returns on loan $j$ from 20 weeks before the downgrade to $\tau$ in percent, $Ownership_i$ is a CLO ownership measures 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, and 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), and 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' Capital | Fed's Intervention: LoanBond | FXBasis | NewCLO | NegDefault | | Total |
|---|---|---|---|---|---|---|---|
| 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 | | |
| Explain | -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 | | |
| Explain | 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 | | |
| Explained | -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 | | |
| Explained | 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), 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.

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 OC ratio tests available, 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.

**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 |
| $\lambda$ | (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, an increase in probability of sales due to downgrade (for CCC loans) or to gains trading (for IG, BB and B-rated loans). $\lambda$ is price impact per unit of the share of loans that are sold, 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) |
| $\hat{R}^2$ | 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) |
| $\hat{R}^2$ | 0.03 | | 0.09 | |
| N | 10,299 | | 16,234 | |
| (Long-Run Coefficients of Flow) | | | | |
| $\varepsilon^{Flow}$ | 0.01 | (2.05) | 0.39 | (9.94) |
| $\varepsilon^{R}$ | 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 funds. N is the number of observations. $\hat{R}^2$ is the adjusted R-squared. The long-run coefficients are the VAR-implied sensitivity of the fund's cumulative long-run flow to the shock to 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 $Y_{f,q} = \begin{pmatrix} Flow_{f,q} & \dots & Flow_{f,q-3} & R_q & \dots & R_{q-3} \end{pmatrix}$. 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.

# Appendices

## A Consequence of Low OC Ratios on CLO Performance

### A.1 Probability of Downgrades for CLO Tranches and Yield on Equity Tranche

In this section, we examine how a low OC ratio affects CLOs' performance. Since we do not observe the market prices of CLO tranches, we use proxies for returns on investment in CLO tranches. For senior and junior CLO tranches, we use credit rating as a measure of a tranche's value. A downgrade of CLO tranches implies a decline in the fundamental value of the tranche. Since a lower OC ratio reflects a higher default risk of underlying loan pools, it should be associated with a higher chance of CLO tranche downgrade. For equity tranches, there is no credit rating assigned, and thus we use equity yield as a measure of investment performance. Equity yield is a quarterly distribution to equity investors divided by the equity tranche outstanding. When a CLO fails an OC ratio test, it must divert cash from its equity tranche to purchase more collateral or pay down senior tranches, and thus we hypothesize that a lower OC ratio predicts lower equity yield.

To empirically examine the link between OC ratio and CLOs' performance, we use quarterly panel data at the CLO-quarter level. Table A1 reports the summary statistics of the measures of CLO performance and their predictors. The first performance measure is the dummy variable that equals one if a CLO deal has at least one tranche downgraded during a quarter, and zero otherwise. The first two rows of Table A1 show that the unconditional probability of downgrade in a given quarter is 2.68% using S&P's credit rating, and 3.49% of Moody's rating. In the empirical analysis below, we use a combined downgrading dummy which equals one if either S&P or Moody's downgrades in a quarter. The second performance measure is the annualized equity yield: the third row of Table A1 shows that the average equity yield is 17.2% in our sample period, with a standard deviation of 21.1%.

Figure A2 shows the time-series variation in the CLO performance measures at the aggregate level. The top panel shows the average equity yield, which is low in the aftermath of the financial crisis, increases since then until the peak of 2013, and then slowly declines towards the end of the sample period. The bottom panel shows the total number of CLOs that experience at least one tranche downgraded either by S&P or Moody's in a quarter. There is a pronounced increase in downgrades during the period between 2009 and 2010 and in 2020, and the number is low in between the two stress periods. Therefore, in the empirical analysis below, we split the sample into a normal period (2011-2019) and stress period (2008-2010 and 2020) to see if the link between the OC ratio and performance changes between these two periods.

We run an OLS regression of equity yield, and a logit regression of downgrading of CLO $i$'s tranches in quarter $q+1$ on its quarter-$q$ OC ratio slack:

$$y_{i,q+1} = bSlack(J)_{i,q} + \gamma_1 Y_{i,q} + \gamma_2 FE_q + \varepsilon_{i,q+1}, \tag{12}$$

$$D^{Downgrade}_{i,q+1} = f\left(b\Delta Slack(J)_{i,q-4\to q} + \gamma_1 Y_{i,q} + \gamma_2 FE_q + \varepsilon_{i,q+1}\right), \tag{13}$$

where $Slack(J)_{i,q}$ is the slack on junior OC rate in percent, $Y_{i,q}$ is the CLO-level control variables including time to reinvestment date, the logarithm of the CLO's assets under management, age of the CLO manager, the logarithm of total assets under management for the manager, the ratio of CCC loans to assets under management, $FE$ is year-quarter fixed effects, $f(\cdot)$ is a logit function. Since the downgrade reflects changes in the quality of underlying loan portfolios, we use changes in the OC ratio slack in (13). By including year-quarter fixed effects, we compare the performance across CLOs at a given point in time, and ask whether CLOs with higher junior OC ratio slack than others perform better than those with lower slack in the following quarter or not.

For the OLS regression of equity yields, standard errors are clustered at the CLO level to account for potential serial correlation in error terms. We estimate the logit model in (13) using the Maximum Likelihood method. To account for the potential model misspecification, we compute standard errors robust to misspecification.

The first three columns of Table A2 present the estimated slope coefficients for (12). The loading on the OC ratio is 0.27, implying that a one percentage point increase in the OC ratio predicts a 0.27 percentage point increase in equity yield. These effects are robust to including other measures of the quality of CLO portfolios, such as the ratio of CCC loans to assets. The loading on the OC ratio is 0.82 during the stress period and 0.24 in normal time. Although the sample size is relatively small, the greater point estimate for the stress period suggests that the impact of a low OC ratio matters more in times of stress. In our stress test in Table A5, the junior OC ratio for the average CLO falls 3.3 percentage points when the top ten borrowers default. This shock translates into a 2.7 percentage point decline in equity yield during the stress period, but only a 0.8 percentage point decline in normal time.

The last three columns of Table A2 report the estimates for (13). Using the full sample, the probability of downgrade is negatively associated with changes in the OC ratio. Thus, a CLO with a low OC ratio is more likely to have their debt downgraded in the future than other CLOs are. Similar to the results on earnings yield, the estimated effect is more pronounced in the stress period (-2.0) than normal time (-1.7).

The empirical analysis above shows that a lower OC ratio is likely to hurt the investment performance of CLO tranches. Although the low performance directly affects CLO managers who might retain some of CLO tranches themselves, the greater impact arises through new CLO issues, which we turn to next.

## A.2 Probability of Launching a New CLO

In this section, we study whether a CLO's past performance predicts the launch of new CLOs by the same manager in the future. In the mutual fund literature, fund flows are known to be positively correlated with the fund's past returns (e.g. Coval and Stafford (2007)). This relationship suggests that investors increase fund allocation based on the past performance of the investment vehicle. For CLOs, there are no fund flows because investors cannot redeem funds from CLOs. Thus, the flow-performance relationship arises as a link between the launch of new CLOs and their past performance.

To empirically show the link, we study the cross-sectional relationship between a CLO manager's past performance and the likelihood of launching a new CLO in the future. We construct a dummy variable which equals one if CLO manager $m$ launches at least one CLO in a quarter and zero otherwise, and predict this variable with the manager's characteristic in the previous quarter. Specifically, using the manager-quarter-level panel data, we run a logit regression

$$D_{m,q+1}^{Launch} = f\left(b_1 D_{m,q}^{Downgrade} + b_2 \log y_{m,q} + \gamma_1 Y_{m,q} + \gamma_2 FE_q + \varepsilon_{m,q+1}\right), \tag{14}$$

where $D_{m,q}^{Downgrade}$ is a dummy variable that equals one if at least one CLO of manager $m$ is downgraded in quarter $q$, $\log y_{m,q}$ is the logarithm of the average equity yield for manager $m$, $Y_{m,q}$ is the CLO manager-level control variables including age of the CLO manager and the logarithm of total assets under management for the manager, $FE$ is year-quarter fixed effects, $f(\cdot)$ is a logit function. In (14), we ask whether a CLO manager's past performance predicts the launch of a new CLO by the same manager in the next quarter. As in the previous section, we estimate (14) using the Maximum Likelihood method, and compute $t$-statistics robust to model misspecification.

Table A3 reports estimation results for the logit regression in (14). In the first two columns, the estimated marginal effect on downgrading dummy is -4.4, implying that when at least one CLO managed by a given manager experiences a rating downgrade, then the manager is 4.4 percentage points less likely to launch a new CLO in the next quarter. Given the unconditional probability of launching a new CLO is 23%, this effect is economically significant.

The next two columns report the point estimates on the average equity yield. The marginal effect is 2.66, implying that a one standard deviation increase in equity yield from the sample average predicts a 2.0 percentage point higher chance of launching a new CLO ($= 2.66 \times \log((18 + 20)/18)$). The control variables also predict the launch of new CLOs with a reasonable sign: a manager with lower age and more CLOs in the past is more likely to launch a new CLO. The link between past performance and the launch of a new CLO survives after controlling for these variables. The pseudo R-squared of the logit regression is high, ranging between 0.22 and 0.23, suggesting that the model captures the determinants of new CLO issues well.

In sum, we show that a lower OC ratio is associated with lower performance of CLOs in the subsequent period, which in turn predicts a lower likelihood of launching new CLOs. When there are fewer CLOs launched, there are fewer buyers of underlying leveraged loans. This is one channel through which OC ratio constraints affect underlying loan markets. While empirical evidence is useful, the limited sample period forces us to rely primarily on cross-sectional relationship between OC ratio constraints and loan demand. However, a more interesting question is on time-series relationships. When an economy enters recession, constraints bind to many CLOs at once. However, this question is difficult to address using a purely empirical approach due to the limited sample period, and thus we conduct a stress test instead.

# B Further Analysis on CLOs' Transaction of Downgraded Loans

In this section, we study CLOs who buy downgraded loans with those who sell. Furthermore, we compare CLOs who sell downgraded loans earlier with those who sell later. We use the subsample of CLOs who buy or sell loans over the period six months before and after the downgrade, and calculate the average characteristics for transactions in month $m = -6, \ldots, 6$. The characteristics include the CLO's OC ratio slack, transaction price, and loan's maturity as a proxy for risk.

In Panel A, Figure A4, we plot the number of observations separately for CLO buys and sells. Here, the unit of analysis is loan-CLO-month. We see that CLO sells and buys are similar in months $[-6, -1]$, but the number of observations for sell becomes much higher than buys once the loans are downgraded. Nonetheless, the number of buy transactions after downgrade is not zero, and thus it is interesting to compare the characteristic of buys and sells in months $[0, 6]$.

Panel B shows the average OC ratio for CLOs buying or selling loans around downgrading months. After downgrade (in months $[0, 6]$), the average OC ratio for buyers is higher than sellers. Thus, less constrained CLOs purchase downgraded loans, possibly to take advantage of fire sales. Panel C presents the average transaction prices. We observe that after downgrade, the gap in price between buy and sell widens. This wider bid-ask spread suggests that less constrained CLOs' opportunistic purchase is not enough to provide adequate liquidity in this market. As a result, non-CLO liquidity providers charge higher fees after downgrade to benefit from liquidity shortages. Finally, in Panel D, we plot the average maturity for downgraded loans bought and sold by CLOs. It appears that opportunistic CLOs prefer to buy loans with longer maturity than sellers.

Next, we turn to study early versus late sellers. We calculate the average of the characteristics conditional on a CLO selling the loan in month $m$. Figure A5 shows the average of the six characteristics we use to predict fire sale in Table 4. We see that CLOs who sell earlier tend to have a higher OC ratio slack, longer CLO maturity, higher CLO manager's age, greater CLO manager's assets under management (AUM), and lower CCC ratio. The figure suggests that less constrained CLOs (with high OC slack and a low CCC ratio) take action sooner rather than later, which is somewhat puzzling: if all CLO managers are forward-looking and equally capable, more constrained CLOs should act sooner than less constrained ones. This pattern can be potentially explained by the skill of CLO managers. If the skill is positively correlated with a manager's age and AUM, then the heterogeneous skill can generate variation in when to sell. The fact that a CLO manager with longer experience and greater AUM sells sooner corroborates this conjecture.

# C Stress Tests on CLOs

## C.1 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 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

$$\$Slack(S)_{i,t} = A_{i,t} - \$Thres(S)_{i,t}, \tag{15}$$

$$\$Slack(J)_{i,t} = A_{i,t} - \$Thres(J)_{i,t}. \tag{16}$$

where $A_{i,t}$ is the value of the CLO's loan portfolio on its balance sheet, $\$Thres(S)_{i,t}$ 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,

$$Slack(\cdot)_{i,t} = \frac{\$Slack(\cdot)_{i,t}}{A_{i,t}} \times 100 \tag{17}$$

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 the book value, while excess CCC loans and defaulted loans are evaluated at the fair value.

Although this is not our main focus of the paper, 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 goes below 100%),

$$\$Slack(Def)_{i,t} = A_{i,t} - S_{i,t}. \tag{19}$$

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

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

$$A_{i,t} = OC(S)_{i,t} \times S_{i,t}, \tag{18}$$

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 (18):

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

Then, the dollar threshold is given by

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

Next, we consider shocks to a CLOs' 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:

$$\Delta \$Slack(S)_{i,t} = \$Slack(S)_{i,t} - Shock_{i,t},$$

$$\Delta \$Slack(J)_{i,t} = \$Slack(J)_{i,t} - Shock_{i,t},$$

$$\Delta \$Slack(Def)_{i,t} = \$Slack(Def)_{i,t} - Shock_{i,t}.$$

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 $t$ is

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

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 $R_b$ go 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 B rating and above to CCC rating and below, and the probability of upgrades from CCC rating or below to above-CCC rating satisfy:

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

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 $D(r), D_{up}(r), D_{down}(r)$ 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 CLOs' portfolio under path $m$,

$$Shock_{i,t}(m) = \sum_{j \in B_{i,t}} H_{ijt} I_{j,t}(R_b(m) < D(r)) LGD_D + \Delta H_{it}(CCC) LGD_{CCC}, \tag{20}$$

where

$$\Delta H_{it}(CCC) = H_{it}^{Post}(CCC) - H_{it}^{Pre}(CCC), \tag{21}$$

$$H_{it}^{Pre}(CCC) = \max\left(0, \sum_{j \in B_{it}(CCC)} H_{ijt} - 0.075 \sum_{j \in B_{it}} H_{ijt}\right), \tag{22}$$

$$\begin{aligned} H_{it}^{Post}(CCC) = \max\Bigg(0, &\sum_{j \in B_{it}(CCC)} H_{ijt} + \sum_{j \in B_{it}} H_{ijt}[I_{j,t}(D(r) \leq R_b(m) < D_{down}(r)) \\ &- I_{j,t}(D_{up}(r) \leq R_b(m))] - 0.075 \sum_{j \in B_{it}} H_{ijt}\Bigg), \end{aligned} \tag{23}$$

[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 of a CCC loan. 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 Appendix E for other values. To estimate $\rho$, we follow Coval, Jurek, and Stafford (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 $\rho$ 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 $\rho$. 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 borrower defaults is a moderate idiosyncratic shock, which 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.

## C.2 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 A5 presents the summary statistics of scaled slack, $Slack(\cdot)_{i,t}$ and $\Delta Slack(\cdot)_{i,t}$ 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 CLOs' loan holdings, then the average 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 borrower defaults and the 95- and 99-% VaR, which is reported in Panels B to D of Table A5. Panel B presents the distribution of OC slack after the top ten borrowers default. When these large borrowers default, 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 25-th 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 would be 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 A5 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, as 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 defaults (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 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 A5 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 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 resembles 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.

# D List of Top Ten Borrowers

Table A6 reports the ten largest borrowers as measured by total borrowing from the entire CLOs. As we conduct stress tests every month, these lists change every month. To save space, we report the list as of December in each year.

# E Robustness Checks for VaR Results

Table A7 reports the OC ratio slack after the 95% and 99% VaR shocks with $\rho = 0.1, 0.2, \ldots, 0.5$. The table shows that, even with a low value of $\rho$ such as $\rho = 0.1$, a VaR95% shock would lead to 55% of CLOs failing the junior OC ratio test after the shock. This fraction increases as we increase $\rho$ from 0.1 to 0.5, reaching 90% with $\rho = 0.5$. These results highlight that shocks generated from VaR would cause a large fraction of CLOs to fail junior OC ratio tests regardless of the parameters we use.

# F Empirical Analysis on Gains Trading For Loans Rated B- or Above

As discussed in the text, CLOs hold loans rated above CCC at book value, and thus changing prices for those loans do not affect CLOs' asset value and their OC ratio. However, as Ellul et al. (2015) show, allowing investors to carry assets at a historical cost encourages them to engage in gains trading. When a loan's book value is lower than the market value, a CLO can sell the loan to realize the gain and increase their asset value.

We then mimic the logit regression for downgraded loans and regress a sales dummy on loans' book values:

$$D_{i,j,t}^{SELL} = f\left(b_0 D_{i,j,t-1}^{BP} + b_1 D_{i,j,t-1}^{\Delta Slack} + b_2 D_{i,j,t-1}^{BP} D_{i,j,t-1}^{\Delta Slack} + \gamma_0 X_{j,t-1} + \gamma_1 Y_{i,t-1} + \gamma_2 FE_{q(t)} + \varepsilon_{i,j,t}\right),$$

where $D_{i,j,t-1}^{BP}$ is a vector of dummy variables which comprises of two dummies, one which equals 1 if CLO $i$'s book value of loan $j$ is less than the 33rd percentile of the loans held by CLO $i$ in month $t-1$ and zero otherwise, and the other corresponding to the book value between the 33rd and 67th percentiles; $D_{i,j,t-1}^{\Delta Slack}$ is a dummy variable which equals one if a 12-month change in junior OC ratio slack for CLO $i$ is above median and zero otherwise; $X_{j,t-1}$ is loan-level control variables ($Rtg$ is a numerical rating variable, $LoanMat$ is time to loan maturity); $Y_{i,t-1}$ 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, $CCCRatio$ is the ratio of CCC loans to assets under management); Time FE is year-quarter fixed effects, $f(\cdot)$ is a logit function. Unlike the regression for downgraded loans, there are no shocks that help us (even weakly) infer the causality; and thus if we use the level of the OC ratio rather than changes, it is difficult to distinguish whether the OC ratio changes gains trading or gains trading changes the OC ratio. Therefore, we use changes in the OC ratio over the past 12 months to distinguish constrained and unconstrained CLOs.

Table A9 reports the estimated coefficients for the logit regressions, estimated for all loans above CCC, IG-rated loans only, BB-rated loans only, B-rated loans only, with and without interaction terms with the OC ratio. In the first two columns, we estimate the regression using all loans above CCC rating. We find that the loading on the tercile dummy for a low book value predicts an increase in loan sales significantly. Relative to loans with a high book value, those in the lowest tercile are 0.36% more likely to be sold, which is nontrivial given the unconditional sales probability of 3.31%. Thus, controlling for loan and CLO characteristics, a loan's relative ranking in terms of a historical cost within the CLO's portfolio matters in deciding which loans to sell. This increased sales probability for a loan with a lower book value provides evidence for gains trading.

The next six columns in Table A9 report the results when we run the logit regression separately for IG-rated loans, BB-rated loans, and B-rated loans. We find that the marginal effect is 0.82% for IG-rated loans, 1.09% for BB-rated loans, and only 0.13% for B-rated loans. As we show below, CLOs collectively own much higher shares of B-rated loans than IG- or BB-rated loans. It appears that CLOs try to avoid gains trading in B-rated loans that are mainly held by other CLOs, and sell IG- or BB-rated loans instead.

The last two columns of Table A9 report the results using all loans above CCC, including the interaction term between low book values and high OC ratio. We find that the interaction term is negative, and the marginal effect is estimated at -0.15%. Thus, a CLO with a higher OC ratio is less likely to engage in gains trading, and this provides support for the interpretation that part of the reasons why CLOs sell loans with a lower price is to improve the OC ratio, just like the fire sales of downgraded loans.

# G Empirical Analysis on Borrowers' Growth

To examine the effect of the OC ratio constraints facing CLOs on borrowers' growth, we follow the spirit of Chodorow-Reich (2013) and run a panel regression of firm $c$'s growth on lenders' OC ratio slack:

$$g_{c,y+1} = \gamma OC(J)_{c,y} + \beta X_{c,y} + \rho g_{c,y} + u_{c,y+1}, \tag{24}$$

where $g_{c,y+1}$ is the growth rate in total assets or sales for firm $c$ in year $y+1$,[35] $OC(J)_{c,y}$ is the loan-volume weighted average OC-ratio slack of CLO managers lending to firm $c$ in

[35] For firms with a fiscal year ending in December, we use the growth from December in year $y$ to December in year $y+1$. For those with a fiscal year ending in non-December months, we use the growth from year $y+1$ to $y+2$.

December of year $y$, and $X_{c,y}$ is the vector of control variables including the log book-to-market ratio, three dummies for firm size, three dummies for firm age, industry and year fixed effects. For a firm with a missing value of the book-to-market ratio, we set it to zero and include a dummy for the missing value. For this exercise, we limit the sample to borrowers in nonfinancial industries and merge the CLO data set with Compustat based on borrower's name.

If lenders' health matters for borrowers' growth, then we expect that parameter $\gamma$ to be positive and that a lower value of slack makes it less likely for a CLO manager to extend a new loan to the firm, hindering the growth. As we control for year and industry fixed effects, the difference in growth likely reflects the lenders' health rather than unobservable macro- or industry-level shocks which simultaneously affect firm growth and CLOs' OC ratio slack.

Importantly, we measure $OC(J)$ using all CLO managers with at least one CLO with non-zero loan balance to the borrower $c$. This is because the sticky borrower-lender relationship should exist between CLO managers and borrowers, rather than between CLOs and borrowers. If a manager familiarizes herself to a borrower through due diligence while lending through a CLO under management, she would be equally likely to extend a new loan to the borrower through the existing CLO or another CLO which currently does not have a direct exposure. Thus, what matters is the manager-level OC ratio slack rather than the individual CLO-level slack. Therefore, we first aggregate CLO-level slack at the manager level, then take the loan volume-weighted average across *managers* for each borrower.

Table A12 presents the estimated coefficients, regression R-squared and the number of observations for the regression in (24). When we just include the lagged left-hand side variable as a control, the estimated coefficient on $OC(J)$ is 0.30 and 0.32 for asset and sales growth, respectively. Economically, a one-percentage point increase in the slack this year predicts an about 0.30 percentage point rise in assets and sales next year. This is economically important, as under the stress tests, the OC ratio could drop as many as five percentage points for the average CLO under 95% VaR, and the (unconditional) average asset and sales growth rates are 2.9% and 3.4%, respectively.

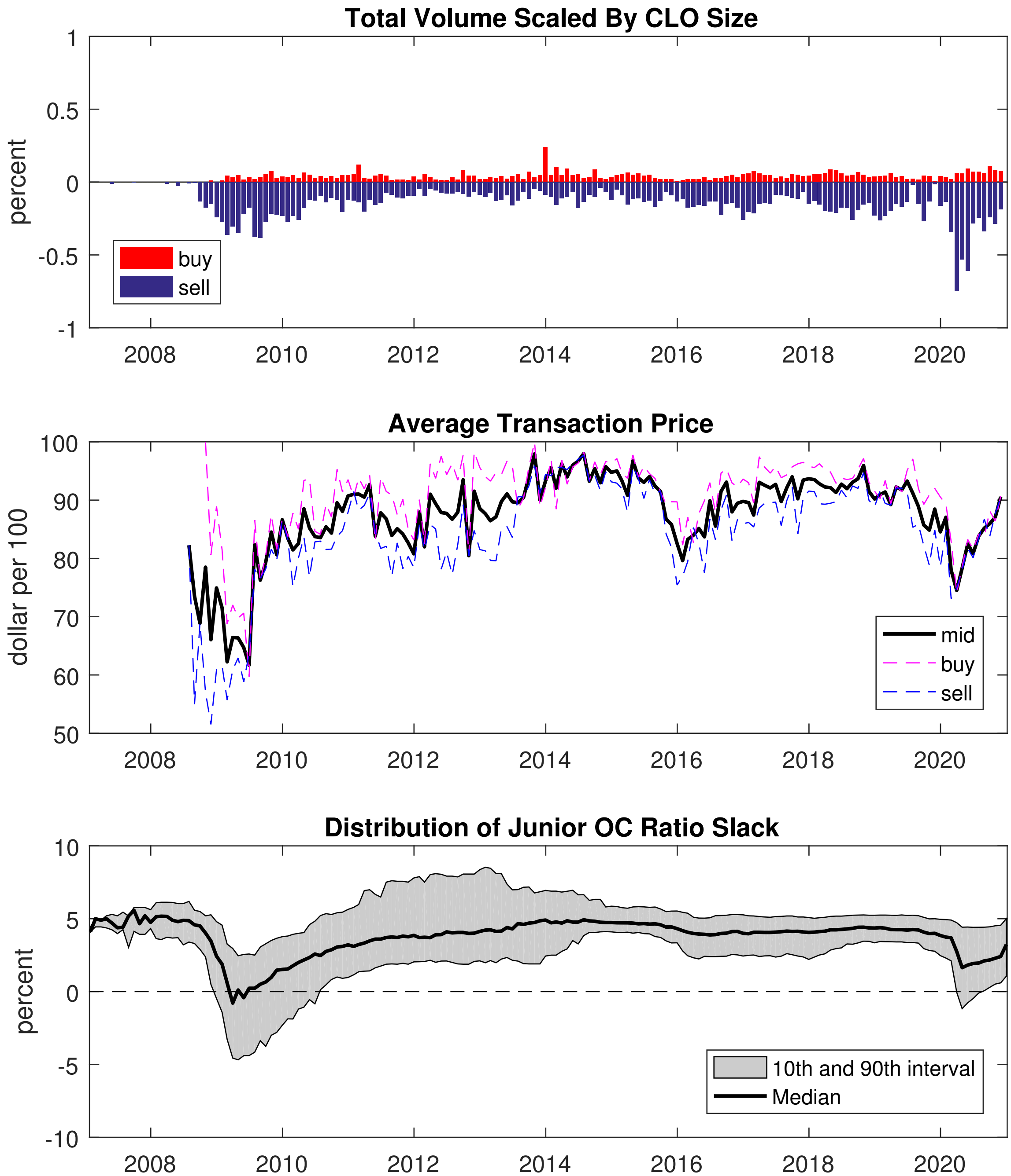
After including industry and year-fixed effects, these estimates decrease to 0.18 and 0.30, respectively. With all controls such as the book-to-market ratio and firm size, the estimated coefficients are still 0.21 and 0.32, both statistically significant. Therefore, we observe an interesting correlation between lenders' health and borrowers' growth next year, suggesting that the deterioration of lenders' financial health may spill over to borrowers in the leverage loan market.

If lenders' OC ratio slack affects borrowers' growth, the effect should be more pronounced for small firms with limited access to alternative means of finance. Thus, we extend the previous analysis by studying the subsample of firms who have not issued corporate bonds. The first regression in Table A13 shows the estimates for the specification with the most extensive controls using this subsample. The estimated coefficients on $OC(J)$ increase to 0.38 and 0.49 from the main results of 0.21 and 0.32 (in Table A12) for asset growth and sales growth, respectively. Since issuing corporate bonds entails some fixed costs such as registering the issue to the Securities and Exchange Commission, it is more difficult for firms that have not issued corporate bonds to find alternative sources of funds when the existing lenders face constraints. Our analysis supports this hypothesis, as firms without access to the bond market are more sensitive to financial constraints on CLOs.

The second regression of Table A13 includes the interaction terms between $OC(J)$ and borrowers' size dummies. $D_{Asset,n}$ is one if a firm is in the $n$-th tercile in terms of total assets. We include the interaction between $OC(J)$ and the size dummies to study a heterogeneous reaction to lenders' constraints based on borrowers' size. The estimated coefficients for $OC(J)$ for the first, second, and third terciles are 0.44, 0.13, and 0.11 for asset growth, and 0.49, 0.22, and 0.28 for sales growth. Therefore, the effects of constraints on CLOs are more pronounced for small borrowers than large borrowers. Information asymmetry is more severe for smaller firms and thus they are likely to face difficulty in finding alternative lenders when existing lenders face financial constraints to extend new loans.

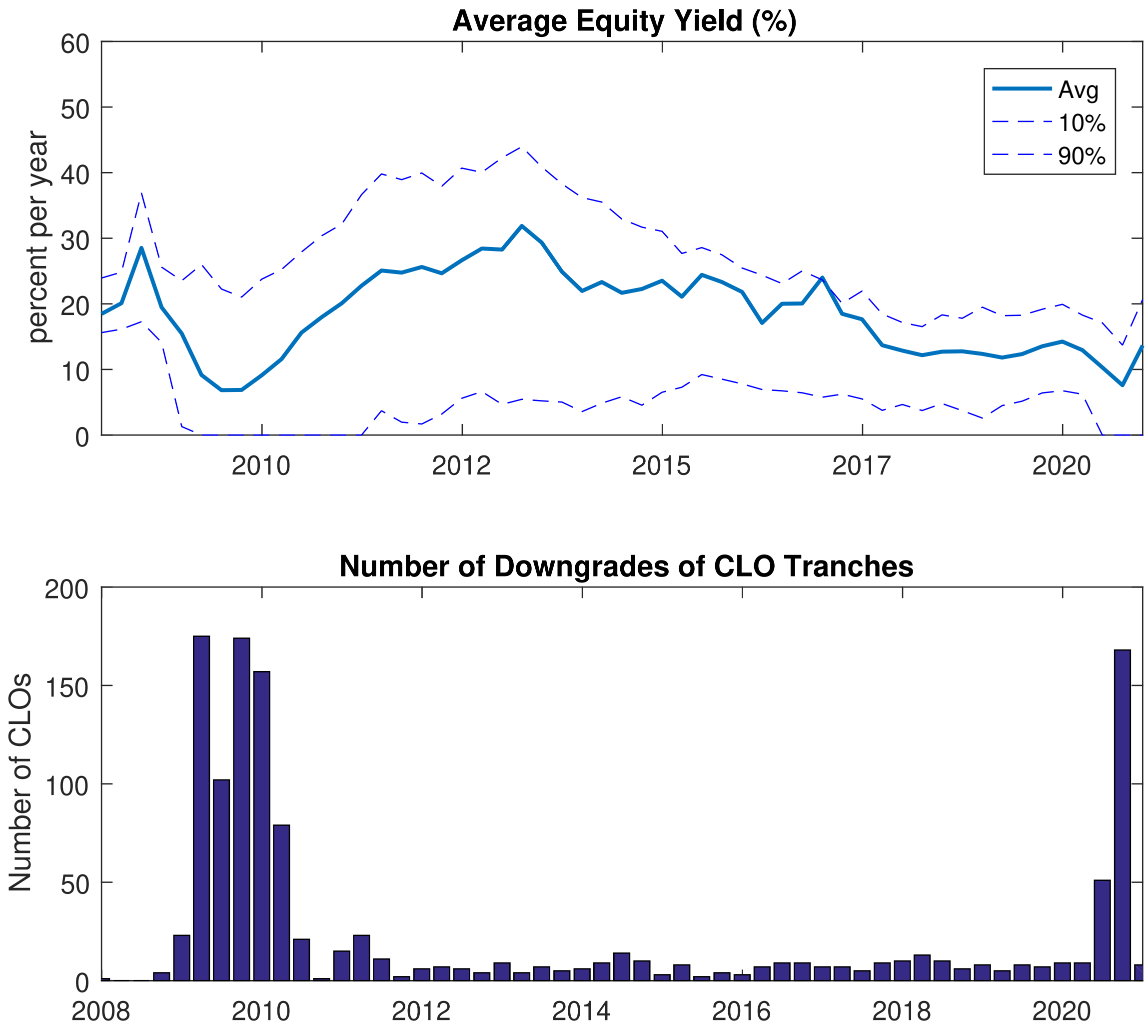
Taken together, we find evidence for the linkage between CLOs' OC ratio slack and borrowers' growth. The link suggests that shocks to CLOs' leverage constraint may spill over to the real economy through their lending activities.

**Figure A1: CLOs' Purchases and Sales of CCC Loans**



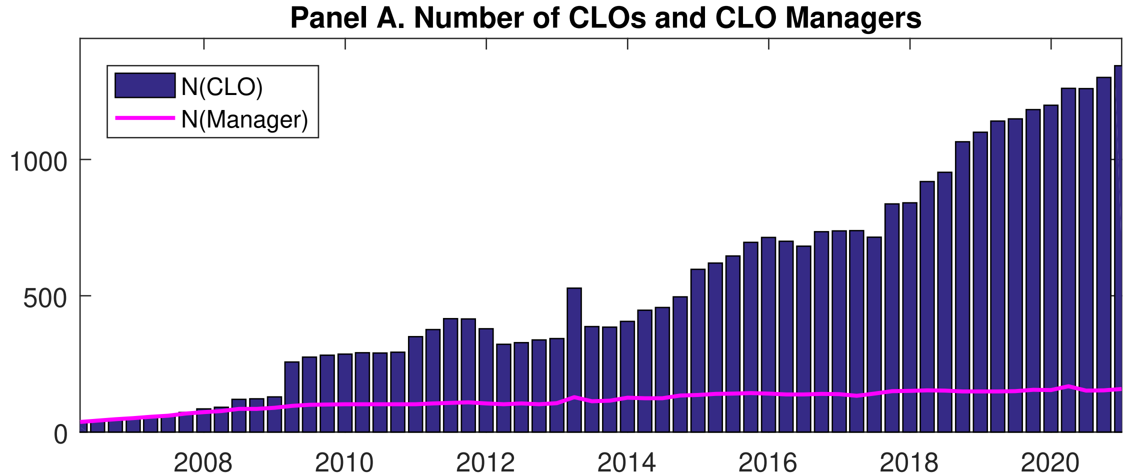

The top panel plots total purchase and sales of CCC loans (loans that are rated at or below CCC, but not in default) by CLOs, scaled by the CLO's asset size. The middle panel plots the average of transaction prices. Every month, we take the simple average of purchase price and sales price of loans. The mid price is the average of the purchase and sales price in each month. The bottom panel plots the median junior OC slack (the difference between junior OC ratio and the threshold) as well as the 10th and 90th percentiles.

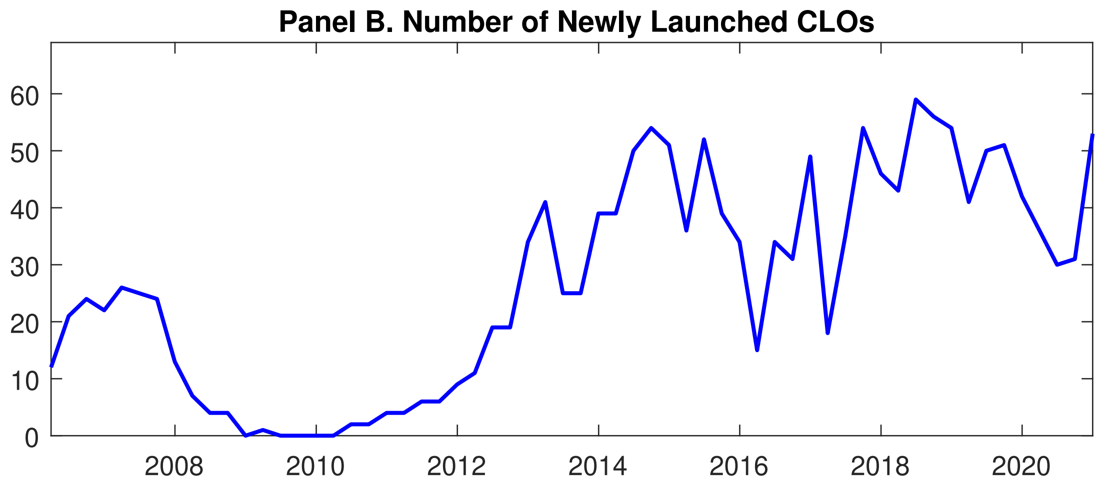
**Figure A2: Equity Yield and Downgrades of CLO Tranches**




The top panel plots equity yield of CLOs averaged for each CLO manager in sample. The solid line plots the average equity yield for the average manager, and dashed lines plot the 10th- and 90th-percentiles. The bottom panel plots the number of CLOs that experience at least one tranche downgraded by either S&P or Moody's. The data is quarterly from 2008 to 2020.

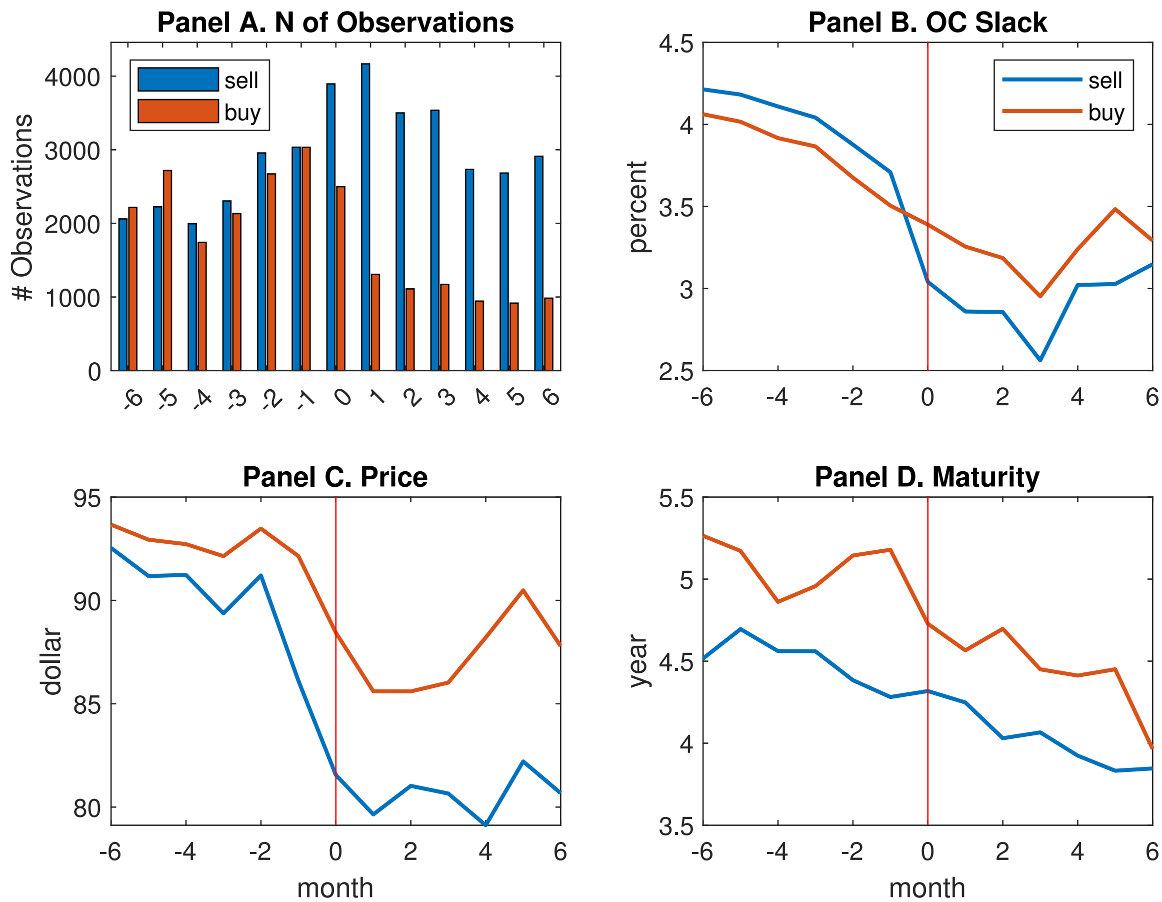
**Figure A3: Number of CLOs Outstanding, CLO managers, and New CLO Issues**



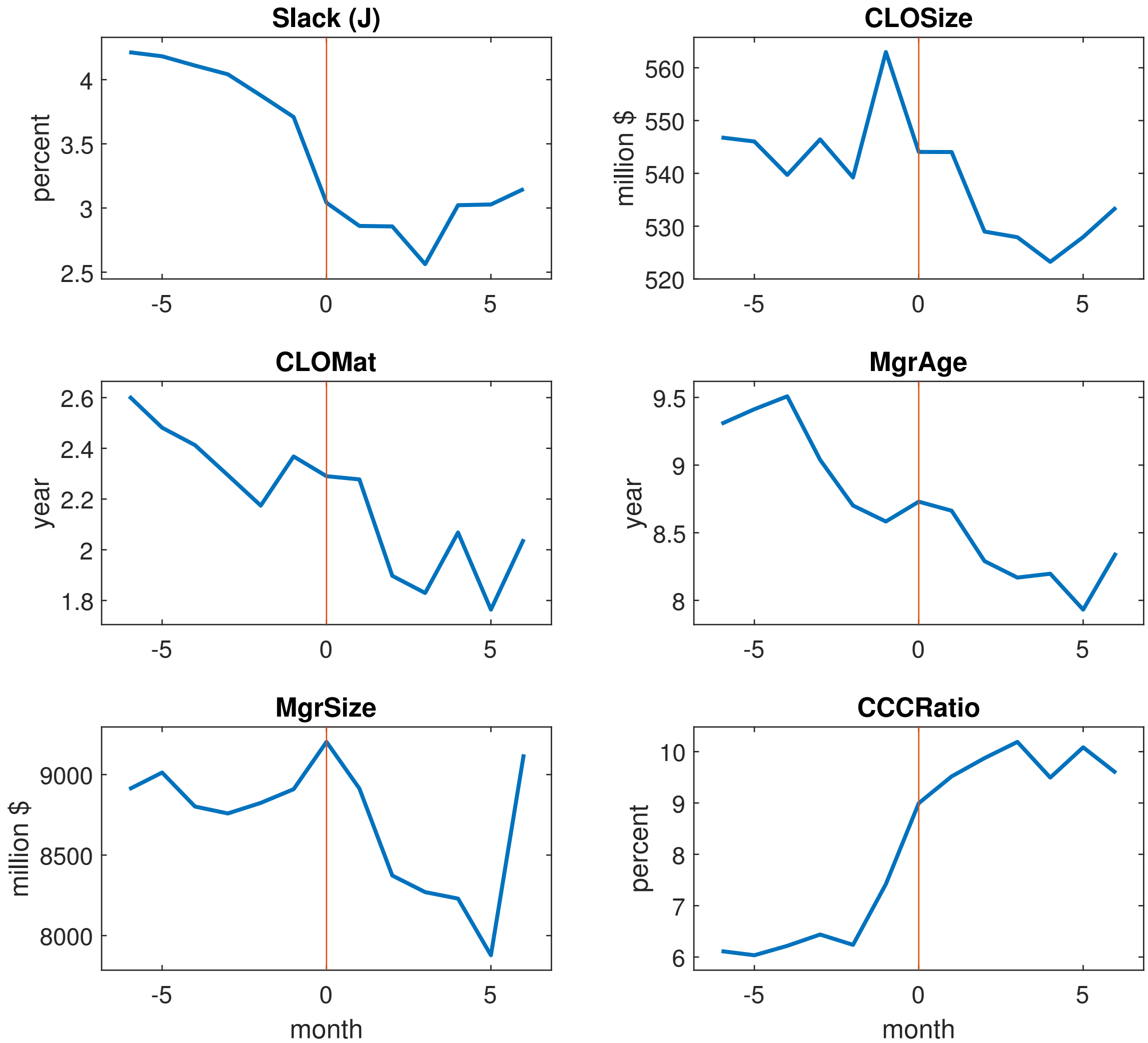

The top panel plots the number of CLO deals outstanding as well as CLO managers that have at least one CLO outstanding. The bottom panel plots the number of newly-issued CLO deals in each quarter from 2006 to 2020.

**Figure A4: Characteristics of CLOs That Buy and Sell Downgraded Loans**




For each downgraded loans, we select CLOs who buy or sell the loan over the period six months before and after the downgrade. The figure shows the number of observations (in loan-CLO-month), and the average characteristics of the CLOs that sell the loan in month $m$, where 0 is the downgrade month.

**Figure A5: Characteristics of CLOs That Sell Downgraded Loans**




For each downgraded loans, we select CLOs who sell the loan over the period six months before and after the downgrade. The figure shows the average characteristics of the CLOs that sell the loan in month $m$, where 0 is the downgrade month.

**Table A1: Summary Statistics for CLO Equity Yield and Tranche Downgrading**

| | Mean | Std | Percentiles | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 5 | 25 | 50 | 75 | 95 | 99 |
| $D^{Downgrade}$ (S&P) $\times 100$ | 2.68 | 16.16 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| $D^{Downgrade}$ (Moody's) $\times 100$ | 3.49 | 18.35 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| $y$ (%) | 17.22 | 21.09 | 0.00 | 0.00 | 9.02 | 14.47 | 20.78 | 36.43 | 95.74 |
| $D^{Launch} \times 100$ | 23.00 | 42.00 | 0 | 0 | 0 | 0 | 0 | 100 | 100 |
| $Slack$ (%) | 4.65 | 9.54 | -6.82 | 0.00 | 2.94 | 4.14 | 5.02 | 10.60 | 33.25 |
| $\Delta Slack$ (%) | 0.16 | 10.94 | -14.59 | -3.83 | -0.81 | -0.02 | 0.81 | 5.97 | 24.25 |
| $CLOMat$ (years) | 1.38 | 2.77 | -5.59 | -3.37 | -0.45 | 1.58 | 3.31 | 5.57 | 7.32 |
| $MgrAge$ (years) | 7.81 | 4.12 | 0.50 | 1.50 | 4.67 | 7.51 | 10.76 | 14.51 | 19.01 |
| $\log CLOsize$ | 19.85 | 0.56 | 17.49 | 18.72 | 19.72 | 19.95 | 20.14 | 20.51 | 20.80 |
| $\log Mgrsize$ | 22.15 | 1.02 | 19.24 | 20.19 | 21.53 | 22.32 | 22.87 | 23.56 | 23.79 |
| $CCCRatio$ (%) | 6.99 | 5.58 | 0.00 | 0.90 | 3.69 | 5.93 | 8.75 | 16.32 | 27.25 |

This table reports the summary statistics calculated across the quarterly panel data of CLOs from 2008Q1 to 2020Q4. Downgrade is the dummy variable which equals one if at least one tranche of a CLO is downgraded in a quarter. $y$ is equity yield, which is annualized distribution to equity tranches divided by their outstanding amount. $CLOMat$ is time to a CLO's reinvestment date, $MgrAge$ is the age of the CLO manager, $CLOsize$ is assets under management, $Mgrsize$ is total assets under management for the manager, and $CCCRatio$ is the ratio of CCC loans to assets under management. $D^{Launch}$ is the panel data at the manager-quarter level which equals one if a CLO manager launches a new CLO in the quarter, and zero otherwise.

**Table A2: Predicting Equity Yield and Tranche Downgrading**

| | OLS regressions of equity yield | | | | Logit regressions of downgrading dummies | | |
|---|---|---|---|---|---|---|---|
| | All | '11 - '19 | '08 - '10, '20 | | All | '11 - '19 | '08 - '10,'20 |
| $Slack(J)$ | 0.27 | 0.24 | 0.82 | $\Delta Slack(J)$ | -1.58 | -1.66 | -2.00 |
| | (4.73) | (4.44) | (2.14) | | (-4.10) | (-4.32) | (-1.24) |
| $CLOMat$ | 0.02 | -0.26 | 0.94 | $CLOMat$ | -17.30 | -29.72 | -6.46 |
| | (0.25) | (-2.36) | (5.70) | | (-5.64) | (-6.91) | (-1.45) |
| $\log CLOSize$ | 1.71 | 2.77 | 1.46 | $\log CLOSize$ | 30.49 | 45.13 | 23.42 |
| | (3.64) | (3.31) | (4.05) | | (2.21) | (2.83) | (1.01) |
| $MgrAge$ | 0.15 | 0.13 | 0.08 | $MgrAge$ | 0.11 | -0.04 | 0.36 |
| | (2.80) | (1.70) | (2.25) | | (0.08) | (-0.01) | (0.24) |
| $\log Mgrsize$ | -0.12 | 0.28 | -0.72 | $\log Mgrsize$ | -4.54 | -13.82 | 5.37 |
| | (-0.44) | (0.90) | (-2.79) | | (-0.68) | (-1.41) | (0.60) |
| $CCCRatio$ | -0.14 | -0.14 | 0.00 | $CCCRatio$ | 3.86 | 3.02 | 4.74 |
| | (-1.86) | (-1.54) | (0.00) | | (4.18) | (2.52) | (3.66) |
| Time FE | Yes | Yes | Yes | Time FE | Yes | Yes | Yes |
| $\bar{R}^2$ | 0.12 | 0.09 | 0.38 | $\bar{R}^2$ | 0.30 | 0.08 | 0.31 |
| $N$ | 15,335 | 11,397 | 3,938 | $N$ | 11,311 | 8,463 | 2,848 |

This table reports the estimates for the slope coefficients of OLS regressions of equity yield, and the slope coefficients (times 100) of logit regressions of downgrading of CLO $i$'s tranche in quarter $t+1$:

$$y_{i,t+1} = bSlack(J)_{it} + \gamma_1 Y_{it} + \gamma_2 FE_t + \varepsilon_{it}$$
$$D^{Downgrade}_{i,t+1} = f\left(b\Delta Slack(J)_{i,t-4\to t} + \gamma_1 Y_{it} + \gamma_2 FE_t + \varepsilon_{it}\right)$$

where $Slack(J)_{it}$ is the slack on junior OC rate in percent, $Y_{it}$ 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, $CCCRatio$ is the ratio of CCC loans to assets under management), $FE$ is year-quarter fixed effects, $f(\cdot)$ is a logit function. Values in parentheses are $t$-statistics robust to model misspecification (for logit regressions). For OLS regressions, standard errors are clustered at the CLO level. $R^2$ for the OLS regression is adjusted R-squared, while $R^2$ for the logit regression is pseudo R-squared. $N$ is the number of observations.

**Table A3: Logit Regression of Launching a New CLO at the Manager-Quarter Level**

| | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ |
|---|---|---|---|---|---|---|
| $Downgrade$ | -0.39 | -4.38 | | | -0.42 | -4.64 |
| | (-2.87) | (-2.89) | | | (-3.02) | (-3.03) |
| $\log y$ | | | 0.24 | 2.66 | 0.23 | 2.55 |
| | | | (2.81) | (2.83) | (2.64) | (2.66) |
| $\log Mgrsize$ | 0.94 | 10.59 | 0.93 | 10.51 | 0.99 | 11.09 |
| | (13.48) | (16.69) | (13.23) | (16.45) | (15.54) | (19.18) |
| $MgrAge$ | -0.05 | -0.55 | -0.04 | -0.40 | -0.04 | -0.44 |
| | (-3.25) | (-3.35) | (-2.36) | (-2.40) | (-2.65) | (-2.69) |
| Time FE | Yes | | Yes | | Yes | |
| $\bar{R}^2$ | 0.22 | | 0.23 | | 0.23 | |
| $N$ | 4,890 | | 4,803 | | 4,632 | |

The table presents a logit regression of a dummy variable which equals one if a CLO manager $m$ launches at least one CLO in a quarter $t+1$ and zero otherwise,

$$D_{m,t+1}^{Launch} = f\left(b_1 D_{m,t}^{Downgrade} + b_2 \log y_{m,t} + \gamma_1 Y_{m,t} + \gamma_2 FE_t + \varepsilon_{it}\right),$$

where $D_{m,t}^{Downgrade}$ is a dummy variable that equals one if at least one CLO of manager $m$ is downgraded in quarter $t$, $y_{m,t}$ is the average equity yield for manager $m$, $Y_{m,t}$ is the CLO manager-level control variables including $MgrAge$ is the age of the CLO manager and $Mgrsize$ is total assets under management for the manager, $FE$ is year-quarter fixed effects, $f(\cdot)$ is a logit function. $b$ is estimated slope coefficients multiplied by 100, and $m(b)$ is marginal effect in percent, and values in parentheses are $t$-statistics robust to model misspecification. $\bar{R}^2$ is pseudo R-squared, and $N$ is the number of observations.

## Table A4: Determinants of Sales Across Different CLO Cohorts

| | CLO 1.0 | | CLO 2.0 | | CLO 3.0 | |
|---|---|---|---|---|---|---|
| | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ |
| Dummy: | 28.65 | 1.41 | 88.04 | 9.16 | 25.45 | 3.13 |
| $Slack(J)$ <33rd pct | (1.83) | (1.83) | (4.93) | (5.07) | (4.10) | (4.11) |
| Dummy: 33rd pct≤ | 28.22 | 1.39 | 52.71 | 5.48 | 24.01 | 2.95 |
| $Slack(J)$ <67th pct | (1.40) | (1.41) | (2.88) | (2.92) | (4.56) | (4.58) |
| $Rtg$ | -1.02 | -0.05 | -3.46 | -0.36 | -2.72 | -0.33 |
| | (-0.28) | (-0.28) | (-1.16) | (-1.16) | (-2.20) | (-2.20) |
| $LoanMat$ | -5.97 | -0.29 | -5.30 | -0.55 | -1.33 | -0.16 |
| | (-1.13) | (-1.13) | (-0.67) | (-0.67) | (-0.39) | (-0.39) |
| $CLOMat$ | 8.79 | 0.43 | -1.07 | -0.11 | 3.66 | 0.45 |
| | (2.18) | (2.20) | (-0.35) | (-0.35) | (2.56) | (2.56) |
| $\log CLOSize$ | -13.48 | -0.67 | -20.06 | -2.09 | 6.04 | 0.74 |
| | (-1.38) | (-1.38) | (-1.79) | (-1.79) | (0.75) | (0.75) |
| $MgrAge$ | -3.87 | -0.19 | -2.60 | -0.27 | -4.21 | -0.52 |
| | (-1.48) | (-1.49) | (-1.98) | (-1.98) | (-8.55) | (-8.61) |
| $\log MgrSize$ | 16.08 | 0.79 | 11.70 | 1.22 | 16.53 | 2.03 |
| | (2.34) | (2.34) | (1.41) | (1.41) | (5.48) | (5.50) |
| $CCCRatio$ | -2.94 | -0.15 | -0.19 | -0.02 | -2.14 | -0.26 |
| | (-2.15) | (-2.17) | (-0.12) | (-0.12) | (-3.31) | (-3.32) |
| Time FE | Yes | | Yes | | Yes | |
| $\bar{R}^2$ | 3.65 | | 5.60 | | 2.43 | |
| $N$ | 7,445 | | 4,579 | | 24,068 | |

This table reports the coefficient estimates and marginal effects of logit regressions of loan sale dummies on junior OC ratio slack and other control variables. We run regressions separately for CLO1.0 (whose closing date is in or before 2008), CLO2.0 (whose closing date is in between 2009 and 2013), and CLO3.0 (whose closing date is after 2013) over the event window [0,2]. For the regression specification and control variables, see notes to Table 4. 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 the reinvestment date, and the CCC-ratio above 5%.

**Table A5: 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 | $OC(J)$ | -0.1 | -4.1 | -1.5 | -0.1 | 1.1 | 4.1 | 52.2 |
| holdings | $OC(S)$ | 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 | $OC(J)$ | -0.2 | -3.1 | -1.1 | -0.3 | 0.4 | 3.8 | 61.2 |
| difersi- | $OC(S)$ | 5.2 | 0.4 | 2.2 | 2.9 | 4.7 | 20.6 | 3.0 |
| fied | $Def$ | 17.4 | 10.3 | 14.8 | 16.7 | 18.2 | 28.4 | 0.0 |
| Not | $OC(J)$ | 0.1 | -3.0 | 2.0 | 3.1 | 3.8 | 7.2 | 8.0 |
| difersi- | $OC(S)$ | 5.5 | 1.3 | 5.5 | 6.3 | 8.1 | 23.6 | 4.2 |
| fied | $Def$ | 17.6 | 9.4 | 17.8 | 20.0 | 21.6 | 31.5 | 3.8 |
| Panel C. VaR95% shock | | | | | | | | |
| Actual | $OC(J)$ | -1.8 | -6.1 | -3.2 | -1.8 | -0.4 | 2.9 | 80.0 |
| holdings | $OC(S)$ | 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 | $OC(J)$ | -5.3 | -10.3 | -7.2 | -5.5 | -3.5 | 0.2 | 94.5 |
| holdings | $OC(S)$ | -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 we 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 we assign defaulted loans randomly across CLOs. The number of observations is 53,960 CLO-months.

**Table A6: List of Top 10 Borrowers**

| Firm name | Amount ($ mil) | Firm name | Amount ($ mil) |
|---|---|---|---|
| 2007 | | 2010 | |
| Community Health Systems | 114 | Community Health Systems | 1,625 |
| IDEARC INC | 96 | Univision | 1,545 |
| Venetian Macau Management Ltd | 94 | HCA | 1,494 |
| Freescale Semiconductor | 86 | Charter Communications | 1,447 |
| Vistra Operations | 85 | First Data | 1,260 |
| MGM Growth Properties | 83 | Nielsen Finance | 1,257 |
| HCA | 82 | Las Vegas Sands | 1,199 |
| Univision | 72 | Fidelity National Info Srvc | 1,171 |
| Tribune | 71 | Liberty Global | 1,129 |
| Sungard | 69 | Aramark | 996 |
| 2008 | | 2011 | |
| HCA | 909 | Univision | 1,744 |
| Liberty Global | 674 | HCA | 1,521 |
| Calpine | 637 | First Data | 1,498 |
| Freescale Semiconductor | 586 | Vistra Operations | 1,339 |
| Univision | 521 | Nielsen Finance | 1,238 |
| Community Health Systems | 516 | Charter Communications | 1,210 |
| Health Management Associates Inc | 511 | Community Health Systems | 1,176 |
| MGM Growth Properties | 508 | Fidelity National Info Srvc | 1,148 |
| Las Vegas Sands | 501 | Aramark | 1,069 |
| Aramark | 474 | Mediacom | 993 |
| 2009 | | 2012 | |
| HCA | 1,133 | Univision | 1,466 |
| Community Health Systems | 1,097 | HCA | 1,447 |
| Calpine | 1,056 | First Data | 1,265 |
| Liberty Global | 940 | Nielsen Finance | 1,089 |
| Vistra Operations | 790 | Aramark | 1,061 |
| Nielsen Finance | 787 | Charter Communications | 1,049 |
| Health Management Associates Inc | 696 | Community Health Systems | 1,015 |
| Aramark | 668 | Mediacom | 1,013 |
| Georgia-Pacific Corp | 665 | Vistra Operations | 999 |
| Univision | 660 | Altice | 964 |

**Table A6, Continued**

| Firm name | Amount ($ mil) | Firm name | Amount ($ mil) |
|---|---|---|---|
| 2013 | | 2016 | |
| First Data | 1,655 | Liberty Global | 1,964 |
| HCA | 1,566 | Altice | 1,756 |
| Nielsen Finance | 1,210 | Bausch Health Companies | 1,743 |
| Mediacom | 1,031 | Asurion | 1,632 |
| Community Health Systems | 1,021 | Dell International | 1,528 |
| Aramark | 974 | First Data | 1,514 |
| Sabre | 950 | Albertsons | 1,351 |
| Delta Air Lines | 927 | American Airlines | 1,296 |
| Bausch Health Companies | 909 | Charter Communications | 1,210 |
| DaVita | 876 | Calpine | 1,177 |
| 2014 | | 2017 | |
| First Data | 2,006 | Liberty Global | 3,417 |
| HCA | 1,580 | Altice | 2,934 |
| Community Health Systems | 1,443 | Asurion | 2,175 |
| Asurion | 1,371 | Dell International | 2,086 |
| Calpine | 1,297 | Caesars Entertainment | 1,992 |
| Chrysler | 1,236 | First Data | 1,843 |
| Delta Air Lines | 1,216 | Transdigm | 1,677 |
| American Airlines | 1,212 | American Airlines | 1,669 |
| Liberty Global | 1,109 | Avolon (US) LLC | 1,499 |
| Bausch Health Companies | 1,095 | Calpine | 1,344 |
| 2015 | | 2018 | |
| Bausch Health Companies | 2,125 | Altice | 4,329 |
| Altice | 2,064 | Liberty Global | 3,839 |
| First Data | 1,984 | Asurion | 2,915 |
| Asurion | 1,741 | CenturyLink | 2,732 |
| Avago | 1,524 | Transdigm | 2,438 |
| Community Health Systems | 1,502 | Caesars Entertainment | 2,346 |
| American Airlines | 1,498 | Dell International | 2,096 |
| Albertsons | 1,456 | SS&C | 1,936 |
| Calpine | 1,254 | American Airlines | 1,810 |
| Ineos | 1,232 | Vistra Operations | 1,597 |

**Table A6, Continued**

| Firm name | Amount ($ mil) |
|---|---|
| 2019 | |
| Altice | 5,153 |
| Asurion | 3,072 |
| Liberty Global | 2,937 |
| CenturyLink | 2,485 |
| TransDigm Group Incorporated | 2,213 |
| Caesars Entertainment | 2,085 |
| Berry Global Group | 1,953 |
| SoftBank Corp | 1,914 |
| American Airlines | 1,887 |
| Dell International | 1,806 |
| 2020 | |
| Altice | 5,425 |
| Liberty Global | 3,257 |
| TransDigm Group Incorporated | 2,934 |
| Asurion | 2,898 |
| Lumen Technologies Inc | 2,469 |
| Sinclair | 2,087 |
| Caesars Entertainment | 2,050 |
| American Airlines | 1,895 |
| Berry Global Group | 1,885 |
| Calpine | 1,835 |

**Table A7: VaR Estimates on OC Ratio Slack for Different Values of Correlation**

| | | $\rho$ | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.1 | 0.2 | 0.24 | 0.3 | 0.4 | 0.5 |
| Panel A. Averge OC Ratio Slack After Shocks | | | | | | | |
| VaR95% | $OC(J)$ | -0.5 | -1.7 | -1.8 | -2.7 | -3.7 | -3.6 |
| | $OC(S)$ | 4.2 | 3.1 | 3.2 | 2.0 | 1.0 | 1.6 |
| | $Def$ | 17.3 | 16.1 | 15.5 | 15.1 | 14.1 | 13.7 |
| VaR99% | $OC(J)$ | -2.3 | -5.0 | -5.3 | -7.7 | -10.5 | -11.3 |
| | $OC(S)$ | 2.4 | -0.3 | -0.3 | -3.0 | -5.7 | -6.2 |
| | $Def$ | 15.5 | 12.7 | 12.0 | 10.0 | 7.3 | 5.9 |
| Panel B. Fraction (%) of CLOs with Negative Slack After Shocks | | | | | | | |
| VaR95% | $OC(J)$ | 55.2 | 69.8 | 80.0 | 78.1 | 83.0 | 90.3 |
| | $OC(S)$ | 10.9 | 22.4 | 24.4 | 34.9 | 46.2 | 53.3 |
| | $Def$ | 0.0 | 0.0 | 0.0 | 1.1 | 1.6 | 0.0 |
| VaR99% | $OC(J)$ | 75.7 | 87.3 | 94.5 | 91.7 | 93.8 | 98.4 |
| | $OC(S)$ | 29.9 | 58.5 | 68.5 | 73.3 | 80.8 | 86.7 |
| | $Def$ | 0.0 | 3.0 | 1.2 | 7.5 | 14.5 | 10.5 |

This table reports the results of stress tests using VaR with different values of parameter $\rho$. Panel A reports the OC ratio slack for the average CLO in the sample, while Panel B reports the percentage of CLOs with negative slack.

## Table A8: Sales of CCC Loans That Are Not Recently Downgraded

| | Months 0 to 2 | | Months -3 to -1 | | Months 3 to 5 | |
|---|---|---|---|---|---|---|
| | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ |
| Panel A. Regression on Exposure Dummies | | | | | | |
| $Dummy: 67th\text{pct} < Exposure$ | 12.77 | 0.81 | 0.76 | 0.03 | 7.62 | 0.40 |
| | (6.48) | (6.49) | (0.36) | (0.36) | (3.47) | (3.47) |
| $Dummy: 33rd < Exposure < 67th\text{pct}$ | 6.57 | 0.42 | -4.03 | -0.17 | 4.50 | 0.23 |
| | (3.62) | (3.62) | (-2.09) | (-2.09) | (2.32) | (2.33) |
| Loan and CLO Controls | Yes | | Yes | | Yes | |
| Time FE | No | | No | | No | |
| $\bar{R}^2$ | 0.95 | | 1.41 | | 0.66 | |
| $N$ | 672,713 | | 672,713 | | 672,713 | |
| Panel B. Regression on Exposure Dummies and Interactions with Constrained CLO Dummies | | | | | | |
| $Dummy: 67th\text{pct} < Exposure$ | 10.09 | 0.65 | -3.73 | -0.16 | 11.06 | 0.58 |
| | (3.94) | (3.94) | (-1.33) | (-1.33) | (3.41) | (3.41) |
| $Dummy: 67th\text{pct} < Exposure$ | 5.53 | 0.36 | 8.95 | 0.38 | 2.39 | 0.13 |
| $\times Constrained$ | (1.63) | (1.63) | (2.42) | (2.42) | (0.86) | (0.86) |
| $Dummy: 33rd < Exposure < 67th\text{pct}$ | -0.04 | 0.00 | -8.96 | -0.38 | -1.18 | -0.06 |
| | (-0.02) | (-0.02) | (-3.70) | (-3.70) | (-4.81) | (-4.85) |
| $Dummy: 33rd < Exposure < 67th\text{pct}$ | 11.97 | 0.77 | 5.72 | 0.24 | 0.00 | 0.00 |
| $\times Constrained$ | (3.88) | (3.88) | (1.78) | (1.78) | (0.00) | (-0.00) |
| Loan and CLO Controls | Yes | | Yes | | Yes | |
| Time FE | No | | No | | No | |
| $\bar{R}^2$ | 1.11 | | 1.66 | | 0.75 | |
| $N$ | 572,357 | | 572,357 | | 572,357 | |

This table reports the estimates for logit regressions of a dummy variable for sales of CCC loans that are not recently downgraded on the dummy for a large exposure to downgraded loans, and an interaction with the dummy for constrained CLOs which equals one if a CLO has the CCC ratio above 5% and the OC ratio below median,

$$D^{SELL}_{i,j,m_0\to m_1} = f\left(b_0 D^{Exp}_{i,m_0-1} + b_1 D^{Exp}_{i,m_0-1} D^{Constrained}_{i,m_0-1} + \gamma_0 X_{j,m_0-1} + \gamma_1 Y_{i,m_0-1} + \varepsilon_{i,j,m_0\to m_1}\right),$$

where $D^{Exp}_{i,t-1}$ is a vector which comprises of two dummies, one which equals 1 if CLO $i$'s exposure to downgraded loans is between the 33rd and 67th percentile and zero otherwise, and the other corresponding to exposure above 67th percentiles; $X_{j,m_0-1}$ is loan-level control variables ($Rtg$ is a numerical rating variable, $LoanMat$ 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, $CCCRatio$ is the ratio of CCC loans to assets under management); $f(\cdot)$ is a logit function. Standard errors are clustered at the CLO-month level, and values in parentheses are $t$-statistics.

**Table A9: Gains Trade: Regression of a Sell Dummy on Book Values for Loans Above CCC Rating**

| | Above CCC | | IG | | BB | | B | | Above CCC | |
|---|---|---|---|---|---|---|---|---|---|---|
| Parameter | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ | $b$ | $m(b)$ |
| $Dummy : BP < 33rdpct$ | 12.50 | 0.36 | 46.64 | 0.82 | 42.42 | 1.09 | 4.60 | 0.13 | 14.83 | 0.40 |
| | (9.21) | (8.57) | (5.16) | (4.74) | (16.61) | (14.76) | (3.30) | (3.24) | (7.38) | (6.95) |
| $Dummy : BP < 33rdpct$ | | | | | | | | | -5.79 | -0.15 |
| $\times Dummy : \Delta OC > 50thpct$ | | | | | | | | | (-2.36) | (-2.35) |
| $Dummy : 33rdpct < BP < 67thpct$ | 3.55 | 0.10 | 12.86 | 0.23 | 16.01 | 0.41 | -0.67 | -0.02 | 3.97 | 0.11 |
| | (3.33) | (3.27) | (1.22) | (1.20) | (8.34) | (8.02) | (-0.55) | (-0.55) | (2.67) | (2.64) |
| $Dummy : 33rdpct < BP < 67thpct$ | | | | | | | | | -1.78 | -0.05 |
| $\times Dummy : \Delta OC > 50thpct$ | | | | | | | | | (-0.91) | (-0.91) |
| $Dummy : \Delta OC > 50thpct$ | | | | | | | | | 7.95 | 0.21 |
| | | | | | | | | | (2.39) | (2.40) |
| Loan and CLO Controls | Yes | | Yes | | Yes | | Yes | | Yes | |
| Time FE | Yes | | Yes | | Yes | | Yes | | Yes | |
| $\bar{R}^2$ | 1.54 | | 4.53 | | 2.51 | | 1.48 | | 1.71 | |
| $N$ | 5,068,427 | | 41,140 | | 1,043,820 | | 3,983,467 | | 3,466,810 | |

We regress a dummy variable for selling loans on book values of loans.

$$D^{SELL}_{i,j,t} = f\left(b_0 D^{BP}_{i,j,t-1} + b_1 D^{\Delta Slack}_{i,j,t-1} + b_2 D^{BP}_{i,j,t-1} D^{\Delta Slack}_{i,j,t-1} + \gamma_0 X_{j,t-1} + \gamma_1 Y_{i,t-1} + \gamma_2 FE_{q(t)} + \varepsilon_{i,j,t}\right),$$

where $D^{BP}_{i,j,t-1}$ is a vector of dummy variables which comprises of two dummies, one which equals 1 if CLO $i$'s book value of loan $j$ is less than the 33rd percentile of the loans held by the CLO in month $t$ and zero otherwise, and the other corresponding to the book value between the 33rd and 67th percentiles; $D^{\Delta Slack}_{i,j,t-1}$ is a dummy variable which equals one if a 12-month change in junior OC ratio slack for CLO $i$ is above median and zero otherwise; $X_{j,m_0-1}$ is loan-level control variables ($Rtg$ is a numerical rating variable, $LoanMat$ 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, $CCCRatio$ is the ratio of CCC loans to assets under management); Time FE is year-quarter fixed effects, $f(\cdot)$ 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 clustered at the CLO level, $\bar{R}^2$ is pseudo R-squared, and $N$ is the number of observations.

## Table A10: Mutual Fund Flows and Past Returns on Funds

| | Loan Participation | | Corporate Bond | | High Current Yield | |
|---|---|---|---|---|---|---|
| | $b$ | $t(b)$ | $b$ | $t(b)$ | $b$ | $t(b)$ |
| Panel A. On the Previous Quarter | | | | | | |
| $Flow_{q-1}$ | 0.08 | (4.55) | 0.03 | (4.07) | 0.02 | (3.76) |
| $R_{q-1}$ | 2.31 | (2.15) | 0.77 | (4.71) | 0.92 | (4.59) |
| Intercept | 0.07 | (3.27) | 0.02 | (4.39) | 0.02 | (3.68) |
| N(funds) | 159 | | 533 | | 657 | |
| $N$ | 70 | | 70 | | 70 | |
| $\hat{R}^2$ | 0.12 | | 0.03 | | 0.02 | |
| Panel B. On the Previous Four Quarters | | | | | | |
| $Flow_{q-1}$ | 0.16 | (5.93) | 0.06 | (6.11) | 0.05 | (6.06) |
| $Flow_{q-2}$ | 0.05 | (2.09) | 0.03 | (6.02) | 0.05 | (5.50) |
| $Flow_{q-3}$ | 0.05 | (3.25) | 0.03 | (3.66) | 0.03 | (4.70) |
| $Flow_{q-4}$ | 0.02 | (1.86) | 0.01 | (3.35) | 0.01 | (2.70) |
| $R_{q-1}$ | 3.19 | (1.78) | 0.71 | (2.84) | 1.08 | (6.92) |
| $R_{q-2}$ | 1.64 | (1.25) | 1.17 | (3.29) | 0.71 | (3.45) |
| $R_{q-3}$ | 2.88 | (2.05) | 0.83 | (2.99) | 0.69 | (3.98) |
| $R_{q-4}$ | 2.19 | (1.44) | 0.94 | (3.75) | 0.50 | (3.53) |
| Intercept | -0.01 | (-0.34) | -0.01 | (-1.93) | 0.00 | (-0.34) |
| N(funds) | 147 | | 507 | | 618 | |
| $N$ | 70 | | 70 | | 70 | |
| $\hat{R}^2$ | 0.24 | | 0.08 | | 0.09 | |

The table shows the estimates for the regression of quarterly mutual fund flow on lagged fund flow and returns for different fund types. We run cross-sectional regressions every quarter from 2004 to 2020, and report the average of the coefficients over time. N(funds) is the time-series average of the number of mutual funds, while $N$ is the number of time-series observations. $\hat{R}^2$ is the average of the cross-sectional R-squared.

**Table A11: Hedge Fund Flows and Past Returns on Funds**

| | Distressed | | Multi-Strategy | | Activist/Merger | | Special Situation | |
|---|---|---|---|---|---|---|---|---|
| | $b$ | $t(b)$ | $b$ | $t(b)$ | $b$ | $t(b)$ | $b$ | $t(b)$ |
| Panel A. Regression on the Returns and Flows in the Previous Quarter | | | | | | | | |
| $Flow_{q-1}$ | 0.15 | (11.54) | 0.15 | (20.63) | 0.21 | (7.64) | 0.25 | (8.05) |
| $R_{q-1}$ | 0.37 | (9.56) | 0.32 | (8.89) | 0.41 | (5.70) | 0.32 | (5.19) |
| Intercept | -1.08 | (-3.35) | -0.30 | (-1.01) | -0.51 | (-1.16) | 0.38 | (1.19) |
| N(funds) | 311 | | 679 | | 84 | | 91 | |
| $N$ | 66 | | 66 | | 66 | | 66 | |
| $\hat{R}^2$ | 0.06 | | 0.06 | | 0.11 | | 0.11 | |
| Panel B. Regression on the Returns and Flows in the Previous Four Quarters | | | | | | | | |
| $Flow_{q-1}$ | 0.11 | (9.09) | 0.10 | (12.50) | 0.13 | (4.55) | 0.15 | (5.63) |
| $Flow_{q-2}$ | 0.11 | (9.34) | 0.09 | (10.89) | 0.09 | (4.55) | 0.13 | (4.58) |
| $Flow_{q-3}$ | 0.04 | (2.58) | 0.04 | (5.88) | 0.04 | (1.38) | 0.09 | (4.67) |
| $Flow_{q-4}$ | 0.06 | (5.40) | 0.04 | (6.39) | 0.01 | (0.38) | 0.07 | (3.31) |
| $R_{q-1}$ | 0.29 | (6.93) | 0.26 | (7.20) | 0.34 | (4.98) | 0.18 | (2.78) |
| $R_{q-2}$ | 0.27 | (6.69) | 0.16 | (5.70) | 0.40 | (5.22) | 0.09 | (1.78) |
| $R_{q-3}$ | 0.09 | (2.25) | 0.13 | (5.32) | 0.17 | (2.92) | 0.14 | (2.42) |
| $R_{q-4}$ | 0.13 | (2.96) | 0.13 | (5.87) | 0.10 | (1.33) | 0.03 | (0.42) |
| Intercept | -1.97 | (-7.01) | -1.39 | (-6.10) | -1.55 | (-3.14) | -0.68 | (-1.70) |
| N(funds) | 258 | | 554 | | 70 | | 77 | |
| $N$ | 63 | | 63 | | 63 | | 63 | |
| $\hat{R}^2$ | 0.11 | | 0.09 | | 0.17 | | 0.18 | |

The table shows the estimates for the regression of quarterly hedge fund flow on lagged fund flow and returns for different fund types. We run cross-sectional regressions every quarter from January 2004 to December 2020, and report the average of the coefficients over time. N(funds) is the time-series average of the number of hedge funds, while $N$ is the number of time-series observations. $\hat{R}^2$ is the average of the cross-sectional R-squared.

**Table A12: Regression of Borrower's Growth on Lending CLOs' OC-Ratio Slack**

| | $b$ | $t(b)$ | $b$ | $t(b)$ | $b$ | $t(b)$ |
|---|---|---|---|---|---|---|
| Panel A. Asset Growth | | | | | | |
| $OC(J)$ | 0.30 | (4.03) | 0.18 | (1.67) | 0.21 | (1.96) |
| $\log BEME$ | | | | | -0.04 | (-7.88) |
| $MissBEME$ | | | | | -0.01 | (-1.12) |
| $D_{Age,1}$ | | | | | 0.00 | (0.01) |
| $D_{Age,2}$ | | | | | -0.01 | (-0.27) |
| $D_{Age,3}$ | | | | | -0.02 | (-0.63) |
| $D_{Asset,1}$ | | | | | 0.02 | (2.49) |
| $D_{Asset,2}$ | | | | | 0.00 | (0.60) |
| Lagged LHV | 0.09 | (6.92) | 0.09 | (6.75) | 0.08 | (6.34) |
| Industry FE | No | | Yes | | Yes | |
| Year FE | No | | Yes | | Yes | |
| $R^2$ | 0.03 | | 0.06 | | 0.09 | |
| $N$ | 4,389 | | 4,389 | | 4,389 | |
| Panel B. Sales Growth | | | | | | |
| $OC(J)$ | 0.32 | (3.31) | 0.30 | (2.24) | 0.32 | (2.40) |
| $\log BEME$ | | | | | -0.02 | (-4.47) |
| $MissBEME$ | | | | | -0.01 | (-1.68) |
| $D_{Age,1}$ | | | | | -0.06 | (-1.41) |
| $D_{Age,2}$ | | | | | -0.07 | (-1.61) |
| $D_{Age,3}$ | | | | | -0.09 | (-2.04) |
| $D_{Asset,1}$ | | | | | 0.01 | (1.06) |
| $D_{Asset,2}$ | | | | | 0.00 | (-0.23) |
| Lagged LHV | 0.21 | (5.31) | 0.22 | (6.06) | 0.21 | (5.83) |
| Industry FE | No | | Yes | | Yes | |
| Year FE | No | | Yes | | Yes | |
| $R^2$ | 0.07 | | 0.17 | | 0.18 | |
| $N$ | 4,232 | | 4,232 | | 4,232 | |

This table reports the regression of asset growth and sales growth of firm $c$ in year $y$+1 on the loan-amount-weighted average slack of CLO managers that have outstanding loans in year $y$. $BEME$ is the book-to-market ratio of the borrower which is set to 0 if it is missing, $MissBEME$ is the indicator variable which equals 1 if BEME is missing, and 0 otherwise. $D_{Age,n}$ is a dummy variable which is 1 if the borrower's age is in the n-th tercile of the distribution. $D_{Asset,n}$ is a dummy variable which is 1 if the borrower's total asset is in the n-th tercile of the distribution. Lagged LHV is asset growth or sales growth in year $y$. Industry fixed effects are defined based on Moody's 35 industry classification. $N$ is the number of observations in firm-years. Values in parentheses are $t$-statistics in which standard errors are clustered at the year-industry level. The sample is limited to non-financial private firms, which removes 'Banking', 'Finance', 'Insurance' and 'Sovereign' in Moody's classification.