Contagion in the Market for Leveraged Loans

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Abstract

Collateralized Loan Obligations (CLOs) spread shocks in the market for leveraged loans. I document that, in order to satisfy constraints based on the par value of their assets, CLOs become forced sellers of high quality securities when hit by negative shocks to otherwise unrelated securities. Loans sold for non fundamental reasons trade at depressed prices for up to nine months after the shock. The effect cannot be explained by selection on ex-ante or ex-post loan characteristics. A large fraction of the dislocation in secondary markets is transmitted to the market of issuance: shocked companies due to refinance their loans substitute away from institutional tranches towards other types of securities. The substitution is imperfect causing an increase in the cost of borrowing.

Keywords: CLOs, Leveraged Loans, Financial Intermediation, Price Pressure.

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1 Introduction

There is ample evidence that the supply of capital from institutional investors is correlated with the price of various securities. It is however particularly challenging to determine whether institutional investors cause or respond to asset prices. This paper provides evidence in favour of the former by analysing the price impact of Collateralized Loan Obligations (CLOs) when they are forced to trade for non-fundamental reasons. CLOs provide an excellent setting to study the causal impact of institutional investors on the price of leveraged loans[1] both in their primary and secondary markets. The compensation of CLO managers is, in fact, tied to the satisfaction of constraints based on the historical value of their assets. In order to avoid fire sales, these so-called *over-collateralization* (OC) constraints have been explicitly designed to be insensitive to the market price and the rating of leveraged loans as long as these securities are not impaired[2]. OC constraints have achieved their goal: CLOs have mostly avoided fire sales during the 2007-09 financial crisis and the market turmoil in March 2020 (Financial Stability Board, 2019; Kothari et al., 2020). However, historical-cost based constraints might have unintended consequences: similarly to *gains trading* in the insurance industry (Ellul et al., 2015), constrained CLOs have an incentive to sell high-quality securities whenever they face binding constraints. Once the quality of some loans of a CLO deteriorates, the management team has an incentive to sell unrelated high quality securities that are trading above par in order to avoid the diversion of cashflows from subordinated to senior notes and leave their compensation unaffected. This behaviour generates contagion in the secondary market for leveraged loans: shocks spread from downgraded to otherwise healthy loans sold by distressed CLOs trying to fix their balance sheets. Consistently

[1]There is no standard definition of leveraged loans. Leveraged loans are usually structured and arranged by a syndicate of investment banks and they satisfy one or more of the following criteria: they are investment grade securities rated at BB+ (Ba1) or below by Standard & Poor's (Moody's); they have a spread of at least 150bps over LIBOR; they are secured by a first or second lien against the issuer's assets (S&P Global, 2020b). The approach of this paper is to consider as leveraged loans those syndicated loans that are traded or held by CLOs.

[2]Leveraged loans are defined as impaired if their market price is below \$85, their rating is at or below Caa (CCC) according to Moody's (Standard & Poor's), or they have defaulted (CreditFlux, 2015).

with the evidence in Loumioti and Vasvari (2019b) and the view of industry practitioners (Morningstar, 2018), I document that CLO managers tend to sell unrelated high quality loans whenever their constraints become binding by providing the following evidence. First, while downgrades to CCC should have a mechanical effect on OC tests, I show that there is no such relationship, hinting at the fact that managers engage in trading aimed at restoring their OC tests after a shock. Second, CLOs are usually allowed to keep on their balance sheet up to 7.5% of CCC rated securities before their OC tests are impaired: I document that there is no bunching in the distribution of CCC securities at this threshold, suggesting that managers do not adjust their OC tests by trading CCC rated loans. Third, I show that CLOs that have just passed their OC tests tend to sell securities that are trading at higher prices compared to CLOs that just missed their tests. This behaviour is particularly pronounced when some of the loans of a CLO have been downgraded to CCC. Fourth, loans sold by distressed CLOs tend to have higher rating compared to those sold by other CLOs.

I then proceed to analyse the impact of this non fundamental trading activity on market prices. I show that loans sold by distressed CLOs looking to restore their OC tests see their price depressed by between 43.6bps and 71.8bps. The effect is robust to the inclusion of various fixed effects which allow me to exclude selection based on ex-ante observable characteristics. These results are robust to the inclusion of issuer-time fixed effects that are meant to compare the price of different loans issued by the same company by capturing any unobservable variables related to the fundamentals of the firm. I further provide evidence that these trades are not motivated by access to private information by showing that the loans sold by distressed CLOs to restore their OC tests are marginally less likely to default, and they are neither more nor less likely to have a change in their rating. I document that the impact on prices is long lasting: loans sold for non fundamental reasons trade at depressed prices for up to nine months after the event. This long lasting effect has two components. First, these loans trade at a discount because of the selling pressure by distressed CLOs. However, CLOs tests are challenged in periods of distress for leveraged loans, implying that both treated and control loans have lower prices in these periods. In the months after a shock, however, securities in the control group recover faster than treated loans, causing a long lasting difference in prices between these two groups.

These results cement the idea that CLOs have a material and long lasting impact on the price of leveraged loans in the secondary market. Moreover, this effect is peculiar because it does not involve distressed securities, but relatively higher quality assets that share the balance sheet of CLOs with downgraded loans. This contagion across loans is reminiscent of what happens in the insurance industry when historical cost accounting is deployed, as Ellul et al. (2015) document.

I finally move to the markets of issuance and study whether shocks to CLOs have an effect there as well. I document that the pricing distortions in the secondary market affect the cost of capital and the financing choices of companies. In order to disentangle demand and supply driven explanations, I fix companies' demand for financing along two dimensions. I first focus on firms who are due to refinance their debt in the following twelve months in the spirit of Almeida et al. (2011). Second, I restrict my attention to the group of companies that eventually do refinance using leveraged loans as a means of revealing and fixing their demand for capital. I then study the choice of firms to finance themselves using institutional or bank tranches, where the former have been affected by a shock in the secondary market while the latter have not. As pointed out by Adrian et al. (2013), Becker and Ivashina (2014) and Fleckenstein et al. (2020), this guarantees that a shift from institutional to non institutional tranches is due to firms facing worse terms of financing. I document that a large fraction of the shock is transmitted to companies via the primary market: firms whose institutional loans have been sold by CLOs have spreads that are up to 55bps higher compared to those that did not experience the shock. Treated companies are between 3.9% and 11.7% less likely to issue an institutional tranche, borrow between 5.5% and 11.3% less by using institutional tranches and, when they do borrow with institutional tranches, the size of these is between 23.5% and 34.2%

smaller. This is consistent and complements the evidence in a contemporaneous paper by Fleckenstein et al. (2020): while Fleckenstein et al. (2020) document the impact of CLOs and other nonbank investors on the cyclicality in the syndicated lending market, I show that the effect is heterogenous across companies. The results in this paper always employ time fixed effects which are meant to partial out any common time varying factor and focus on the differential effect of CLOs in the cross-section of issuing companies.

The rest of the paper proceeds as follows: Section 2 puts the contributions of this paper in the context of the existing literature; Section 3 explains how CLOs work and describes in details the mechanics of OC tests; Section 4 presents and describes the data used in the empirical analysis; Section 5 studies the trading behaviour of CLOs in order to restore their OC tests; Section 6 moves to analyse the price impact that CLOs have on the secondary market for leveraged loans, documenting how loans sold by distressed CLOs trade at depressed prices; Section 7 proceeds to study the impact of CLOs on primary markets, by analysing how the cost of capital and the financing decisions of companies are affected by shocks to distressed CLOs.

2 Contribution to the Literature

The results in the paper add to various strands of literature. First I contribute to the debate on the distortions generated by market based and historical cost based constraints. In these regards, the most similar papers to mine are Ellul et al. (2014) and Ellul et al. (2015) showing how historical cost accounting distorts the trading behaviour of insurers and spreads shocks across unrelated corporate bonds. CLO constraints, where the greatest majority of the assets are considered at their par value, are similar to historical cost accounting. As in Ellul et al. (2015), I show that this type of constraints might have unexpected consequences.

Second, I add on the literature of the propagation and amplification of shocks through financial intermediaries. There is ample literature on the relationship between mutual fund flows and asset returns both in equity and fixed income markets. Among others, Warther (1995), Wermers (1999), Nofsinger and Sias (1999), Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012), Anton and Polk (2014) study the impact of mutual funds on equity markets. Schmidt et al. (2016), Chernenko and Sunderam (2016), Goldstein et al. (2017), Morris et al. (2017), and Zhu (2018), among others, focus on the impact on fixed income securities. Similarly, many have studied the impact of other institutional investors on asset prices: Shleifer and Vishny (2011) provide a comprehensive survey of this literature. In the setting of mutual funds, it is particularly hard to disentangle whether flows cause or predict the subsequent movements in asset prices (Warther, 1995). By focusing on loans sold after the downgrade of otherwise unrelated assets and by exploiting the incentives to trade higher quality securities in constrained CLOs, I am able to establish a clear pattern of causation going from CLOs forced trading decisions to loan prices. On top of that, controlling for ex-ante loan features and showing that traded securities are not different ex-post guarantees that the price impact cannot be justified by changes in fundamentals.

Third, I contribute to the literature on the trading and pricing of loans in the secondary market. Beyhaghi and Ehsani (2017) analyse the cross-sectional properties of loan returns in the secondary market; Gande and Saunders (2012), Allen and Gottesman (2006), Ivashina and Sun (2011b) and Addoum and Murfin (2020) study the relationship between loan prices and equity returns; Fabozzi et al. (2020) document inefficiencies in the secondary market for leveraged loans that are exploited by CLOs. I add on this literature by displaying how prices for leveraged loans are affected by nonfundamental CLO trading and by providing a magnitude of their price impact.

Fourth, this paper adds to the growing recent literature on CLOs. Benmelech et al. (2012) and Nadauld and Weisbach (2012) show that CLOs do not increase adverse selection in corporate loans and often lead to lower loan spreads; Bozanic et al. (2018) show that CLOs contribute to standardize the terms of loans contracts. Loumioti and Vasvari (2019a) and Loumioti and Vasvari (2019b) are the first to study in detail the incentives generated by overcollateralization constraints on CLOs, documenting that tighter OC constraints generate more strategic trading among CLOs and worse performance. I confirm their findings, showing that CLO managers sell high quality and purchase low quality securities in order to meet their constraints and use this feature to study the impact CLO trading has on the price of leveraged loans. Liebscher and Mählmann (2017), Fabozzi et al. (2020) and Cordell et al. (2020) provide evidence in favour of skill in CLO managers collateral selection and trading. In a contemporaneous paper, Elkamhi and Nozawa (2020) analyse the trading behaviour of CLOs after a wave of defaults or downgrades focusing on the effect that portfolio similarity across CLOs has on systematic risk. Compared to their analysis I provide evidence on how price pressure generated by CLOs in the secondary market affects the pricing and the quantity borrowed in primary markets. Finally, Fleckenstein et al. (2020) use CLO origination and repricing to instrument their demand for leveraged loans, showing that they drive issuance and are responsible for the cyclicality in this market. By focusing on the price pressure on individual securities generated by the trading behaviour of CLOs I confirm and add on Fleckenstein et al. (2020)'s findings, showing that the impact of CLOs is heterogeneous across companies. My findings are also consistent with Allen and Gale (1994) who prove that, with endogenous market participation, relatively small idiosyncratic shocks can have large price effects on the underlying securities.

Finally, I add to the ample literature on the interaction between capital supply and firms' financing decisions, such as Faulkender and Petersen (2006), Frank and Goyal (2009), Leary (2009), Sufi (2009), Lemmon and Roberts (2010), among others. Adrian et al. (2013) and Becker and Ivashina (2014) show that firms with access to the bond market have shifted away from bank loans during the 2007-09 financial crisis, hinting at the fact that the credit collapse was due to a contraction in credit supply rather than demand. Ivashina and Sun (2011a) and Fleckenstein et al. (2020) study the substitution between institutional and bank tranches in the syndicated loan market; I expand on their findings by showing how issuer specific shocks in the secondary market force companies to rely on non institutional tranches at the expense of an increase in the cost of borrowing. This complements the literature on firms arbitraging capital market distortions[3]. I show that companies are able to only partially reduce the impact of shocks in the secondary markets by shifting from institutional to non-institutional loans, consistent with the idea of debt specialization (Colla et al., 2013).

3 The Mechanics of CLOs

A collateralized loan obligation (CLO) is a bankruptcy remote[4] investment vehicle whose purpose is to invest in fixed income assets, usually leveraged loans, and whose liabilities are represented by notes with decreasing seniority which is strictly enforced. Similarly to other types of securitizations, the interest and principal payments to noteholders come with a predetermined seniority, with senior notes receiving the first cashflows available to be distributed according to predetermined rules, followed by less senior notes and, eventually, equity holders. To enforce the seniority of the liabilities of a CLO, each tranche is subject to a battery of tests making sure that the priority of repayment is maintained. At each payment date, CLO notes are tested against prespecified thresholds before the CLO is able to determine the distribution of cashflows to the noteholders. We can divide the tests into those that force the management team to divert cashflows from the junior to the senior notes, and the so called *maintain-or-improve* tests. The latter group, which includes tests on the weighted average rating factor (WARF), the weighted average spread (WAS), the industry concentration and the weighted average life (WAL) of

[3]Loughran and Ritter (1995), Baker and Wurgler (2000), Dong et al. (2012) provide evidence on firms arbitraging equity markets misvaluations. Baker et al. (2003), Greenwood and Hanson (2013) and Harford et al. (2014) on firms timing debt markets. Gao and Lou (2013) and Ma (2019) on timing across different markets.

[4]Each party involved in the creation of a CLO, i.e., the originator, the arranger, the trustee and the manager, is separate from the assets which are placed in and legally held by a special purpose vehicle (SPV). The same applies to the CLO's liabilities. This guarantees protection from bankruptcy of the CLO for the parties involved and protection from bankruptcy of the parties involved for the owners of CLO's liabilities. This separation is highly sought after in order to guarantee that the creditworthiness of CLOs' liabilities is fully and uniquely determined by their assets. In order to obtain bankruptcy remoteness, the SPV must be a separate legal and operational entity, the assets must have been transferred via a *true sale*, and the originator cannot exercise control over the SPV (CreditFlux, 2015).

the collateral, are meant to reduce the riskiness of the CLO assets, but have minimal impact on the trading behaviour of the management team (Loumioti and Vasvari, 2019b) because they tend to have ample slack and do not cause any diversion of cashflows from one class of notes to another. The other group, which is comprised of the overcollateralization (OC) and interest coverage (IC) tests, have more serious consequences for noteholders and have material consequences on the trading behaviour of the management team. Among them, OC tests are considered the most onerous tests (CreditFlux, 2015). OC tests are a key tool in enforcing the seniority of the principal value of the notes of a CLO by guaranteeing that the value of the assets under management remains above a certain multiple of the par value of CLO tranches. Starting from the seniormost note, which I will denote with a letter A for ease of exposition, the manager needs to make sure that the following constrain is not violated:

$$\widetilde{OC}^A \equiv \frac{\text{Par value of assets} + \text{Excess cash} + \text{Market value of excess impaired securities}}{\text{Par value of Class A Tranche}} \geq OC^A \tag{1}$$

where OC^A is a tranche specific threshold. It is obvious from equation (1) that, at the numerator of the test, assets under management are counted at par value (usually \$100 for leveraged loans in the United States) unless they have been impaired; in that case they might incur haircuts. The OC tests of CLO 2.0, i.e., the greatest majority of CLOs issued during and after the 2007-09 financial crisis, define as impaired securities all those assets that have defaulted or are at imminent risk of default, that is, those rated at CCC (Caa1 resp.) or below by Standard & Poor's (Moody's). Defaulted securities are counted at the lower between their market value and the assumed recovery rate. The haircut for CCC securities is more complex: each CLO has a CCC bucket with a predetermined threshold, usually 7.5% of the value of the CLO's collateral[5], and the loans above this limit with the lowest market value receive a haircut equal to the difference between their par value and their market price. Given that CCC securities are generally traded at a

[5]Some deals, usually called "enhanced CLOs", are allowed to reach higher limits than 7.5% . They are however rare representing less than 0.3% of the market in 2019 (Goldfarb, 2019; S&P Global, 2019).

significant discount compared to par, this guarantees that the numerator of the OC test is reduced whenever a CLO has more than 7.5% of CCC rated securities.

The same mechanism applies to any other tranche with lower seniority; for instance, for tranches with seniority equal to $k = B, C, etc...$, the OC test can be represented in the following way:

$$\widetilde{OC}^k \equiv \frac{\text{Par value of Loans} + \text{Excess Cash} + \text{Market value of excess impaired securities}}{\sum_{k' \leq k} \text{Par Value of Tranche } k'} \geq OC^k \tag{2}$$

where the denominator sums over the par value of all the tranches k' with higher seniority than k. It is not an accident, but rather a featured design, that OC tests have little sensitivity with respect to swings in loan prices, given that, in their calculation, the greatest majority of assets are treated at their par value. The same holds true for any change in ratings that does not involve the CCC bucket. On the other hand, managers are particularly sensitive to changes in ratings that have a material effect on the CCC bucket, given that breaching the CCC limit of 7.5% forces managers to record loans at their market value. Differently from other CLO tests, violating OC tests has serious consequences for a CLO manager, given that their compensation is directly tied to them. This is because we can split the compensation of managers in three parts, two of which are conditional on the satisfaction of the OC test limit. The managing team first receives a *senior fee* which is a constant fraction of assets under management, usually 0.2%, and does not depend on the performance of the portfolio of loans. This fee is senior to any other payment to the noteholders and it is meant to be used to carry on with the daily management duties of the CLO. Second, we have the *junior fee*, which is earned after all the coupons to noteholders have been paid: this fee is approximately 0.3% of assets under management and it is meant to incentivize the management team to make sure that the CLO's cashflows are sufficient to repay noteholders. Finally, we have the *incentive fee*. The incentive fee is paid after the equity holders of the CLO have achieved a pre-specified hurdle rate and consists of 20% of the cashflows above the prespecified hurdle. Failing any of the OC tests (2) will reduce the compensation of the management team: any interest received must be diverted from paying notes with a lower seniority compared to the one that has failed the test; second, to make sure that the test is satisfied in the future, any principal repayment is diverted into repaying the principal of all the notes with a higher seniority; third, and most importantly, the management team does not receive any junior nor incentive fee, de-facto cutting their income by more than half. It is therefore crucial for a manager to avoid breaching any OC test, and in practice this can be considered as the most important task for the management team. This high powered incentive is indeed designed to make sure that the interests of the management team are aligned with the interest of the liability holders. It is an empirical question whether and how the threat of failing an OC test affect the trading behaviour of CLO managers. This specific issue will be tackled in Section 5. Before delving into this topic, the next section introduces the data I will use in the rest of the paper.

4 Data and Summary Statistics

In order to analyse the trading behaviour of CLO managers and their effect on leveraged loans we need to collect data on the holdings and trading behaviour of CLOs, together with data on the underlying loans. All the data regarding CLOs come from the CreditFlux Clo-i dataset. CLOs are required to provide their investors with a quarterly payment report and a monthly trustee report which have been collected by CreditFlux starting from 2009. More specifically, I will make use of granular data on the universe of CLOs' holdings at their reporting dates, all the transactions that CLOs have completed between reporting dates and all the results of the OC tests which constrain the CLOs in my sample. The focus of the paper will be on US based CLOs in the period between January 2009 and December 2019. Overall I have access to 89,111 unique reports from 2,601 distinct CLO deals, supervised by 218 distinct managers. Summary statistics are provided in Table 1, where Panel A reports the statistics for each individual CLO deal

Table 1 : Summary Statistics - Holdings

The table contains summary statistics for the sample of CLOs in the CLO-i dataset between January 2009 and December 2019. Panel A reports summary statistics at the level of each CLO report, while Panel B aggregates at the level of Management Team - Month. Total Assets refers to the sum of the current balance of securities held measured in $Mlns; Nr. Issuers refers to the distinct number of issuers held; Nr. Securities to the distinct number of securities; % of Assets to the fraction of assets represented by each security in the portfolio; Interest rate to the interest rate of the loan; % CCC to the ratio between the sum of the current balance of securities rated at or below CCC and total assets; % Default to the ratio between the sum of the current balance of securities in default and total assets; Age to the difference between the first time a certain deal or management team appears in sample and the current reporting date; WARF to the weighted-average rating factor computed using Moody's rating factors.

	Panel A: CLO Deals					
	Nr.Obs	Min	Max	Median	Mean	Std.Dev
Total Assets	89,111	0.00	18336.84	408.86	434.73	283.96
Nr. Issuers	89,111	1.00	748.00	157.00	168.20	101.33
Nr. Securities	89,111	1.00	907.00	203.00	213.82	115.27
% of Assets	88,517	0.00	1.00	0.01	0.01	0.05
Interest Rate	88,334	0.00	16.47	4.77	4.87	1.11
% CCC	88,905	0.00	1.00	0.06	0.09	0.12
% Default	88,905	0.00	1.00	0.02	0.05	0.11
Age	89,111	0.00	10.90	2.00	2.57	2.16
WARF	88,421	4.33	10000.00	2737	2923.48	806.63
	Panel B: Management Teams					
	Nr.Obs	Min	Max	Median	Mean	Std.Dev
Deals Managed	15,470	1.00	53.00	3.00	5.57	6.50
Total Assets	15,470	0.00	28504.00	1239.46	2504.18	3328.16
Nr. Issuers	15,470	1.00	1209.00	217.00	257.45	183.73
Nr. Securities	15,470	1.00	4935.00	337.00	565.32	606.29
% of Assets	15,100	0.00	1.00	0.00	0.01	0.04
Interest Rate	15,298	0.00	12.28	4.72	4.88	1.10
% CCC	15,451	0.00	1.00	0.07	0.09	0.10
% Default	15,451	0.00	1.00	0.03	0.05	0.09
Age	15,470	0.00	11.00	4.21	4.70	3.23
WARF	15,080	160.75	10000.00	2753.89	2944.44	818.51

Table 2 : Summary Statistics - Transactions

The table contains summary statistics for the sample of CLOs' transactions in the CLO-i dataset between January 2009 and December 2019. Tot. Transactions refers to the number of transactions completed by a deal between two reporting dates; Purchase Price to the average price at which a loan has been purchased; Nr. Purchases to the total number of securities bought; Amt. Purchased to the amount of securities purchased, measured in $ Mlns; Sale Price to the average price at which a loan has been sold; Nr. Sales to the total number of securities sold; Amt. Sold to the amount of securities sold, measured in $ Mlns. Prices have been capped between $10 and $150. Nr. Obs counts the number of non-zero observations, while Nr. Zeros counts the number of observations equal to zero. Min, Max, Median, Mean and Std. Dev are the minimum, maximum, median, average and standard deviation of the non-zero observations.

	CLO Deals						
	Nr. Obs	Nr. Zeros	Min	Max	Median	Mean	Std.Dev
Tot. Transactions	72,515	16,596	0.00	853.00	19.00	29.73	36.97
Purchase Price	64,919	0	10.00	150.00	98.99	95.31	13.39
Nr. Purchases	65,458	23,653	0.00	736.00	13.00	19.25	26.20
Amt. Purchased	65,458	23,653	0.00	2372.24	15.29	22.44	43.94
Sale Price	64,755	0	10.00	150.00	98.20	91.73	17.53
Nr. Sales	65,239	23,872	0.00	475.00	8.00	13.69	17.55
Amt. Sold	65,239	23,872	0.00	1006.72	6.65	10.84	19.67

at each reporting date, while Panel B presents data aggregated at the management team level. The average (median) CLO deal has $434.73Mln ($408.86Mln) assets under management, comprised by 213.82 (203) unique securities from 168.2 (157) distinct issuers. Each security, on average, represents 1% of the total portfolio. The average age for a CLO is 2.57 years, ranging up to 11.90 years. If we look at the characteristics of the securities held by CLOs, the median fraction of CCC assets is about 6%, with a mean of 9%. On the other hand the median fraction of defaulted assets is equal to 2%, while the median is equal to 5%.[6]. The typical team contemporaneously manages 5.57 CLOs for a total of $2.505Bln of assets. The average number of securities held is 565.32 issued by, on average, 257.45 distinct companies. Management teams are on average 4.70 years in sample.

[6]Some CLOs end up having 100% of assets rated at CCC or below before they are shut down, skewing the mean towards larger values. The same holds true for defaulted securities.

I then proceed to analyse the transactions carried out by CLOs whose summary statistics are reported in Table 2. First of all it should be noted that CLOs do not report a trade in roughly 18% of the months (i.e., they have zero trades for 16,596 reports out of 89,111 total reports). When they do trade, the average number of transactions is equal to 29.73 while the median number of transactions is 19. If we analyse purchases and sales separately, CLOs do not buy any security in 26.5% of the reports, while they do not sell any security in 26.8% of the reports. CLOs tend to purchase securities in the ramping-up period when they are trying to reach the desired amount of assets under management, while sales happen during the whole life of the deal: this implies that the average number of purchases is larger than the average number of sales (19.25 vs 13.69) given that securities are usually bought in bulk at the beginning of the life of a CLO. This can be confirmed by the figures on the total amount of transactions: on average a deal reports purchases for $22.44Mln and sales for $10.84Mln. These figures are highly skewed with the largest amount purchased equal to $2.37Bln and the largest amount of securities sold equal to roughly $1Bln. The typical security is sold at a price of $98.20, while the typical transaction price is $98.99. There are two possible explanations for this divergence: either CLOs tend to sell worse performing and purchase better performing securities, or CLOs tend to purchase securities in periods of relative calm and become forced sellers in periods of distress. I will show in Section 5 that the latter explanation is the more likely: in periods of distress, when downgrades become more prevalent, CLO managers become forced sellers. Even though CLOs tend to sell their best performing securities they do so in times of depressed prices, implying that the average price of a sold security is lower than the average price of a security that has been bought. Further statistics on CLO holdings and transactions are provided in Section B and Section C in the Appendix.

Finally, Section 7 will use data on the primary market of issuance of U.S. syndicated loans in order to test if there are spillovers in this market. The data is collected from Refinitiv's Security Data Company (SDC) Platinum. The dataset includes historical information on more than 315,000 global corporate loan transactions since the early 1980s.

In the paper I will focus on loans issued by companies domiciled in the United States between January 2009 and December 2019. In order to compute the exposure of issuers to loan rollover I will also include all the loans maturing after January 2009, but potentially issued before my sample period starts. The overall sample includes 76,610 unique tranches from 48,757 facilities issued by 19,378 distinct borrowers. No common identifier between the SDC Platinum and the CLO-i dataset exists; for this reason, Section A in the Appendix outlines the matching procedure between the two data sources. The analysis in Section 7 will make use of the number of loans, the tranche size and the All-in Spread Drawn (AISD) obtained from SDC Platinum.

5 Trading Behaviour

In Section 3 I have outlined how the compensation of CLO managers is tied to the satisfaction of OC tests. In this section I will analyse how managers' portfolio choices are affected the incentives generated by OC tests and whether their trading behaviour responds to the deterioration of this metric. Equation (2) clearly shows that OC tests are affected by external shocks only when securities default or when they are downgraded to CCC: in what follows, I will focus on the second type of shock[7]. In particular, in the remaining of this section, I will show the following: managers do actively trade in order to restore their OC constraints when hit by downgrades to CCC; because there is a certain degree of freedom in keeping CCC securities at an inflated value on the balance sheet of CLOs, managers avoid directly trading impaired securities in order to restore OC tests; and CLOs restore their OC tests by building par, namely by selling high quality securities that trade at or above par and buying low quality securities that trade well below par.

To start with, I provide evidence that managers trade in order to restore their OC constraints. When a security is downgraded to CCC, if the CCC bucket is already above the

[7] Table 1 has shown that defaulted securities tend to be a relatively small fraction of CLOs' collateral; moreover, defaulted securities are usually first downgraded to CCC: conditionally on being rated CCC, the probability of default within one year is about 25% (Elton et al., 2001; Fei et al., 2012; S&P Global, 2020a).

Table 3 : The Mechanical Effect of Downgrades to CCC on OC Tests

The table studies the mechanical effect of downgrades to CCC on the slack of OC tests. Columns (1)-(4) report the results of the following regression: $slack^k_{i,t} = \alpha + \beta_1 \text{Shocked}_{i,t} + X_{i,t}\delta + \varepsilon_{i,t}$, where $slack^k_{i,t} = \frac{\widetilde{OC}^k_{i,t} - O^k_i}{O^k_i}$, $\widetilde{OC}^k_{i,t}$ is the realization of the OC test for tranche k and CLO i and O^k_i is the test threshold; $\text{Shocked}_{i,t}$ is an indicator variable that turns on whenever the loans of CLO i have been downgraded to CCC. Column (5) reports the result of the following regression: $slack^k_{i,t} = \alpha + \beta_1 \text{Shocked}_{i,t} + \beta_2 \text{Above 7.5\%}_{i,t} + \beta_3 \text{Shocked}_{i,t} \times \text{Above 7.5\%}_{i,t} + X_{i,t}\delta + \varepsilon_{i,t}$, where Above 7.5%$_{i,t}$ is a dummy variable that turns on whenever the fraction of CCC securities for CLO i is greater than 7.5% at time t. Standard errors are reported in parantheses and are double clustered at the Year × Month & CLO Deal level.

	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.230***				
	(0.069)				
Shocked	0.092	0.090	0.019	0.019	-0.014
	(0.129)	(0.136)	(0.150)	(0.150)	(0.020)
Above 7.5					0.020
					(0.393)
Shocked× Above 7.5%					0.074
					(0.391)
Fixed-Effects					
Year×Month	No	Yes	Yes	Yes	Yes
Deal	No	No	Yes	Yes	Yes
Senior/Junior OC	No	No	No	Yes	Yes
Fit statistics					
Observations	148,851	148,851	148,851	148,851	148,851
R^2	0.000	0.001	0.009	0.009	0.009
Within R^2	–	0.000	0.000	0.000	0.000

Two-way (Year×Month & Deal) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

7.5% threshold, the marginal CCC security receives a haircut which, in turn, impairs the OC test. This implies that, absent any active measure by the manager, OC tests should mechanically deteriorate when a CLO is hit by a downgrade. I therefore measure the slack of an OC test as the percentage distance from the predefined test's threshold, i.e. $\text{slack}^k_{i,t} = \frac{\widetilde{OC}^k_{i,t} - OC^k_i}{OC^k_i}$, where $\widetilde{OC}^k_{i,t}$ is the realization of the OC test for tranche k and CLO i, while OC^k_i is the predetermined test threshold. I then construct two dummy variables:

$\text{Shocked}_{i,t}$ which takes a value of one whenever a CLO has been hit by downgrades to CCC, and Above $7.5\%_{i,t}$ which takes a value of one when the CCC bucket is above the threshold of 7.5%. The results in Table 3 shows that there is no mechanical relationship between tests and shocks. Columns (1)-(4) show that, after having been hit by downgrades to CCC, the slack of OC tests is neither higher nor lower: these results are robust to the inclusion of time, CLO deal, and type of test (Junior vs Senior) fixed effects. When the interaction $\text{Shocked}_{i,t} \times \text{Above } 7.5\%_{i,t}$ is included in column (5), there is still no evidence that the slack of CLOs hit by downgrades to CCC and whose CCC buckets are above 7.5% is somehow lower than those that have not. These results are striking because there should be a mechanical negative relationship between the slack of OC tests and these two conditions. The lack of any relationship is evidence in favour of the fact that managers respond to incentives and actively trade in order to be fully compensated: once hit by downgrades, CLOs managers actively trade in order to restore the numerator of the OC test. As a result, the slack of OC tests is not statistically different from the slack of those CLOs that have not been affected by downgrades. A restored OC test guarantees the manager will be able to receive the junior and incentive fee, at least for the current period.

After having determined that managers respond to incentives and actively trade to restore OC tests, we are left wondering what actions can a manager undertake in order to improve this metric. The mechanics of OC tests seem to suggest that there are only two ways to gain slack on the test: the first way is to directly get rid of CCC securities, the other is to *build par*. Selling CCC securities can help as long as the marginal CCC loan stops receiving the haircut equal to difference between its market price and the par value. This is however a poor strategy for at least two reasons. First there is a purely quantitative consideration: CCC loans trade at depressed prices, hence it takes more securities to gather the same amount of money. Second, selling a CCC security would force the manager to recognize a capital loss that could possibly be avoided. Indeed, distressed loans usually receive a haircut that is in line with their market price if they

Table 4 : Holdings vs. Market Prices

The table compares the discount of loans as they are reported by CLOs with the closest market price in the following year by running the following regression: $\text{discount}_{j,t} = \alpha_i + \alpha_t + \beta_1 \text{Transaction}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, where $\text{discount}_{j,t} = 100 \times \log(100/P_{j,t})$ is the discount at which a loan is recorded or traded compared to par, Transaction_{jt} is an indicator variable equal to one whenever the price comes from an actual sale transaction and zero otherwise, α_i and α_t are issuer and time fixed effects, while X_{jt} includes a set of fixed effects for rating, industry and interest rate of the loan. Panel A consider the universe of loans that have at least one price reported on the balance sheet of CLOs and one market price in the following twelve months, while Panel B focuses on the subset of loans rated CCC. Stanadard errors clustered at the Year $\times$Month and Issuer level are reported in parentheses.

	Panel A: All Loans				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Transaction	0.871***	0.875***	0.875***	0.875***	0.878***
	(0.169)	(0.170)	(0.170)	(0.170)	(0.170)
Fit statistics					
Obs.	2,211,675	2,200,337	2,200,337	2,200,337	2,211,675
R^2	0.578	0.609	0.610	0.610	0.726
Within R^2	0.004	0.005	0.005	0.005	0.006
	Panel B: CCC Loans				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Transaction	3.990***	4.000***	4.000***	4.000***	4.030***
	(0.801)	(0.801)	(0.801)	(0.801)	(0.803)
Fit statistics					
Obs.	195,073	195,073	195,073	195,073	195,073
R^2	0.622	0.644	0.646	0.646	0.728
Within R^2	0.013	0.014	0.014	0.014	0.018
Fixed-Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	No
Issuer	Yes	Yes	Yes	Yes	No
Rating	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Interest	No	No	No	Yes	Yes
Year $\times$ Month$\times$Issuer	No	No	No	No	Yes

Two-way (Year$\times$ Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

have been recently traded; managers, however, can value distressed loans at a theoretical bid price obtained from a dealer in case there is no pricing information(CreditFlux, 2015). This price is then certified by the CLO trustee. Since September 2017, CLO-i reports data on the price at which each loan has been recorded on CLOs' monthly reports. I can therefore directly compare the price at which loans are recorded on the balance sheet of a CLO with their closest market price by running the following regression:

$$\text{discount}_{j,t} = \alpha_j + \alpha_t + \beta_1 \text{Transaction}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{3}$$

where $\text{discount}_{j,t} = 100 \times \log(100/P_{j,t})$ is the discount compared to par[8], Transaction_{jt} is an indicator variable equal to one whenever the price comes from an actual transaction and zero otherwise, α_i and α_t are issuer and time fixed effects, while X_{jt} includes a set of fixed effects for rating, industry and interest rate of the loan. Table 4 reports the results of regression (3), with Panel A focusing on all loans, while Panel B restricting the attention to loans with a rating of CCC and below. The results indicate that managers have a certain freedom in keeping loans at inflated prices on their balance sheet. The average transaction price is at a discount of 87bps compared to the average price at which the loan is recorded on the trustee report, with the result being robust to the inclusion of various fixed effects which are partialling out the impact of confounders. The result is robust to the inclusion of Year×Month×Issuer fixed effects that are meant to partial out any unobservable issuer characteristics. The impact is much larger when we look at CCC loans in Panel B: the average CCC loan is traded at a discount of 400bps compared to the average price recorded on CLO monthly reports. We must therefore conclude that selling a CCC loan represents a very costly measure to improve OC tests. However, CLOs are not required to sell their entire bucket of CCC securities: a management team needs to make sure that the number of CCC securities does not exceed the threshold of 7.5%. If CLOs were actively managing the pool of CCC loans to avoid violations of the OC tests,

[8]For a loan with price $P_{jt} = \$95$ and par value of \$100, the discount is equal to $100 \times \log(\$100/\$95) \approx 5$ percent.

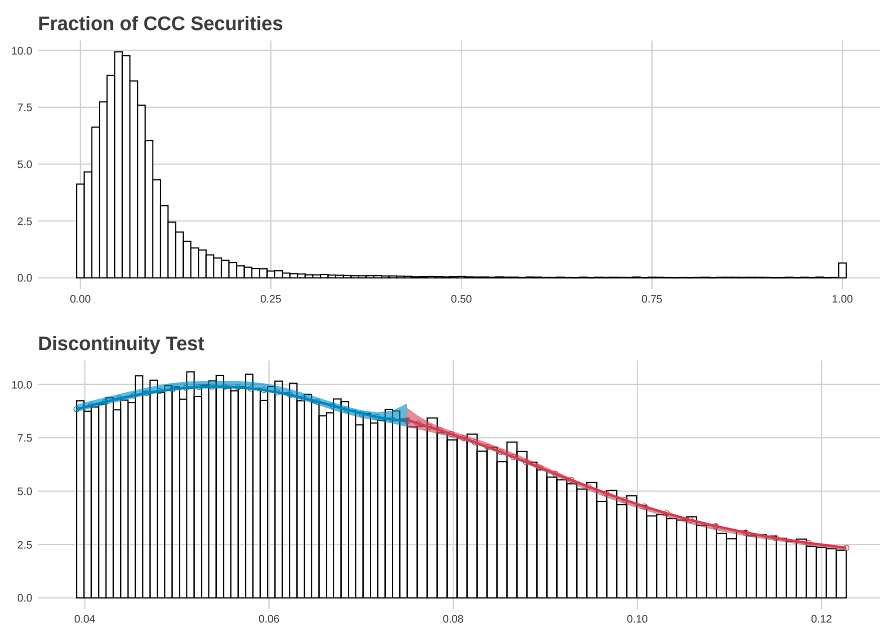
Table 5 : Discontinuity Test

The table reports the result of a discontinuity test where I compare the density of the fraction of CCC or lower rated securities before and after the 7.5% threshold. Number of Obs. reports the total number of observations on the left and right of the 7.5% threshold; Eff. Number of Obs. reports the number of observations used for the test which employs Cattaneo et al. (2020) local polynomial approximation.

Cutoff 0.075	Left	Right
Number of Obs.	53710	35195
Eff. Number of Obs.	8061	8809
Order	2	2
Order Bias	3	3
Bandwith	0.01	0.013
	T	Pr $> \|T\|$
Statistic	-0.7309	0.4648

Figure 1 : Fraction of CCC securities

The upper panel reports a histogram of the fraction of CCC rated securities, while the lower panel superposes a local polynomial approximation of the density with the relative confidence intervals, following Cattaneo et al. (2020).



the optimal behaviour would be to make sure the threshold of 7.5% is never surpassed. I can directly test this hypothesis by examining whether the empirical distribution of the size of the CCC bucket presents any discontinuity at the 7.5% threshold. Figure 1 shows that there is no obvious discontinuity. I can formally test for the absence of a discontinuity using Cattaneo et al. (2020) local polynomial density estimator and test whether there is a jump in the density at the 7.5% threshold. Table 5 provides no evidence in favour of such a discontinuity, suggesting CLO managers do not actively manipulate the pool of CCC securities.

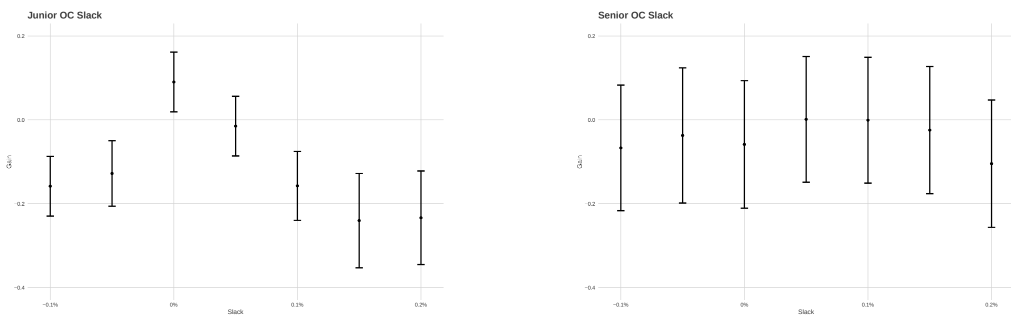
We are left wondering how managers adjust their portfolios in order to improve their OC tests. One common measure is *par building*. Par building involves a trade whereby a manager sells a highly quality security, possibly trading above par, in favour of a lower quality security, trading below par. For instance, a CLO in need of $100 of par value can adopt the following strategy: sell nine loans that are currently trading at $100; the transaction will generate proceeds for $900 which the manager will immediately use to buy ten loans that are currently trading at $90. In market value terms the transaction is neutral, given that the proceeds from the sale can be used to buy the new loans. However the OC test will improve: nine loans trading at par contributed for 9 × $100 = $900 in the OC test, while ten loans trading at $90 will contribute for their full par value in the OC test,i.e., 10 × $100 = $1000 in the numerator of the OC test. The rest of the section will show that, indeed, managers resort to par building in order to improve their OC tests.

First, par building should be more aggressive for those CLOs whose OC constraints are close to be binding. In order to test this hypothesis, I divide CLOs in seven buckets[9] based on the slack of their OC tests. I then measure the amount of par gained with each transaction as: $\text{gain}_{i,j,t} = 100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for purchases and $\text{gain}_{i,j,t} = -100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for sales, where $P_{j,t-1}$ is the last transaction price available for security j before being traded by CLO i. No-

[9]The buckets are the following: [-100%,-5%), [-5%,0%),[0%, 5%), [5%,10%), [10%,15%),[15%,20%),[20%, 100%).

Figure 2 : Par Building and OC Tests Slack

The figure depicts the gain in par as a function of the slack of the over-collateralization test by plotting the estimated coefficients of the following regression: $\text{gain}_{i,t} = \sum_{s=1}^{S} \beta_s \mathbb{1}_s + \varepsilon_{i,t}$, where $\text{gain}_{i,t} = 100 \times \left(\sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{PrincipalBalance_{i,t}} - \sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{PrincipalBalance_{i,t}} \right)$; $\mathbb{1}_s$ is a dummy variable equal to one whenever the Junior (left panel) or Senior (right panel) slack belongs to bucket s of the following $S = 7$ buckets: [-1.00,-0.05), [-0.05,0), [0,0.05), [0.05,0.10), [0.10,0.15), [0.15,0.20), [0.20,1.00). Full results are reported in Table B3 in the Appendix.



tice that the lagged price $P_{j,t-1}$ is not affected by the CLO transaction and captures the price a manager faces when deciding which loans to sell in order to restore their OC tests. I then sum across all the transactions by a CLO in any given reporting period to construct the following variable: $\text{gain}_{i,t} = 100 \times \left(\sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}} - \sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}} \right)$[10]. The left panel of Figure 2 plots the average amount of par gained as a function of the slack of Junior OC tests, while the right panel as a function of the slack of Senior tests. It is clear that CLOs whose Junior OC tests are binding, i.e. those with slack close to 0%, are more likely to engage in par building compared to any other CLOs. The large discontinuity between those CLOs that have just missed an OC test and those that have barely passed it seem to suggest that indeed par building is a key tool used by managers in order to guarantee the satisfaction of their constraint and is consistent with previous evidence by Loumioti and Vasvari (2019a,b).

[10]To understand the construction of the gain, it might be instructive to look at a specific example. If a CLO with assets of \$10,000 sells nine loans trading at \$100 then the gain is equal to $-(\$100 - \$100) \times \frac{9}{\$10{,}000} = 0$, while if the manager buys ten loans trading at \$90 the gain is equal to $(\$100 - \$90) \times \frac{10}{\$10{,}000} = +0.009$. The two transactions have generated an increase in par value equal to $\frac{(\$100-\$100)\times 10+(100-90)\times 9}{\$10{,}000} = +0.009$. If we multiply by 100 we get the figure in percentage terms, i.e. 0.9 percent.

Table 6 : Par Building

Columns (1) and (2) report the results of the following regressions: $\text{gain}_{i,j,t} = \alpha + \beta_1\text{Constrained}_{i,t} + \beta_2\text{Shocked}_{i,t} + \beta_3\text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t}$, where $\text{gain}_{i,j,t} = 100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for purchases and $\text{gain}_{i,j,t} = -100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for sales; $\text{Constrained}_{i,t}$ is a dummy variable equal to one whenever the Junior (column (1)) or Senior (column(2)) slack of CLO i is between 0% and and 5% in period t; $\text{Shocked}_{i,t}$ is a dummy variable equal to one whenever the loans of CLO i have been downgraded. Columns (3) and (4) report the results of the following regressions: $\text{gain}_{i,t} = \alpha + \beta_1\text{Constrained}_{i,t} + \beta_2\text{Shocked}_{i,t} + \beta_3\text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t}$, where $\text{gain}_{i,t} = 100 \times \left(\sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}} - \sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ and the other variables are defined as above. $\text{Constrained}_{i,t}$ refers to Junior tests in column (3) and to Senior tests in column (4). Standard errors are reported in parentheses and they are double clustered at the Year×Month & CLO Deal level.

	Individual Transactions		**Multiple Transactions**	
	(1)	**(2)**	**(3)**	**(4)**
(Intercept)	-0.007***	-0.003***	-0.068***	-0.034***
	(0.001)	(0.000)	(0.006)	(0.002)
Constrained	0.004***	-0.008***	0.035***	-0.052***
	(0.001)	(0.002)	(0.006)	(0.015)
Shocked	0.006***	0.005***	0.050***	0.033***
	(0.001)	(0.000)	(0.006)	(0.003)
Constrained × Shocked	0.005***	0.004	0.069***	0.016
	(0.001)	(0.003)	(0.008)	(0.022)
Fit statistics				
Observations	309,028	303,160	30,156	29,034
R^2	0.002	0.002	0.009	0.005
Adjusted R^2	0.002	0.002	0.009	0.005
OC Test	Junior	Senior	Junior	Senior

Two-way (Year×Month & CLO Deal) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

No such a discontinuity is present in Senior OC tests, signalling that these are less important in determining the trading behaviour of CLO managers. We can then proceed to analyse what happens to those CLOs whose OC constraint is binding whenever they are hit by downgrades to CCC. For this purpose I construct a dummy variable $\text{Shocked}_{i,t}$ that is equal to one whenever the loans of a CLO have been downgraded to CCC and a dummy variable $\text{Constrained}_{i,t}$ that is equal to one whenever the slack of a CLO is between 0% and 5%, i.e. the CLO is in the group that we have shown to be more likely to engage in par building. Columns (1) and (2) in Table 6 report the results of the following regression:

$$\text{gain}_{i,j,t} = \alpha + \beta_1 \text{Constrained}_{i,t} + \beta_2 \text{Shocked}_{i,t} + \beta_3 \text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t} \quad (4)$$

while, columns (3) and (4) report the results of the following regressions, where I sum across all the transactions of a CLO at time t:

$$\text{gain}_{i,t} = \alpha + \beta_1 \text{Constrained}_{i,t} + \beta_2 \text{Shocked}_{i,t} + \beta_3 \text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t} \quad (5)$$

Columns (1) and (3) measure the slack in terms of Junior OC tests, while columns (2) and (4) in terms of Senior tests. From all the regressions we can infer that shocked CLOs are more likely to engage in par building: each transaction of a shocked CLO contributes towards increasing par by between 0.005% and 0.006%, while when we sum across all the transaction carried out by a CLO, we can conclude that shocked deals build between 0.033% and 0.050% more compared to the deals in the control group[11]. When we compare the differential effect of Junior and Senior tests, i.e. we contrast the results in column (1) and (3) with those in columns (2) and (4), we can conclude that only Junior tests matter for par building: deals whose Junior slack is between 0% and 5% build 0.035 more par per period compared to other deals, while being shocked add an extra 0.069 in par. The overall effect for deals that are constrained and have suffered from downgrades is of 15.4bps (i.e., 3.5bps + 5bps + 6.9bps). These results confirm the fact that, in order to improve their OC tests, CLOs tend to sell loans that trade at a higher price compared to the ones they purchase.

It should be pointed out that par building helps a manager in locking-in trading gains

[11]While these figures might seem small, notice that each transaction represents a small fraction the assets of a CLO. Moreover notice that the improvement in OC tests is equal to $\text{gain}_{i,t} \times \frac{\text{Principal Balance}_{i,t}}{\text{Par Value of Note } k_{i,t}}$ where $k =$ Junior, Senior.

Table 7 : Rating Factor

The table shows how to convert Moody's and Standard&Poor's ratings into Moody's Rating Factors. Rating Factors convert the ordinal rating into a cardinal variable.

Moody's	S&P	Rating Factor	Moody's	S&P	Rating Factor
Aaa	AAA	1	Ba1	BB+	940
Aa1	AA+	10	Ba2	BB	1350
Aa2	AA	20	Ba3	BB-	1766
Aa3	AA-	40	B1	B+	2220
A1	A+	70	B2	B	2720
A2	A	120	B3	B-	3490
A3	A-	180	Caa1	CCC+	4770
Baa1	BBB+	260	Caa2	CCC	6500
Baa2	BBB	360	Caa3	CCC-	8070
Baa3	BBB-	610	Ca-C	CC-C	10000

by selling well performing loans and buying loans that are trading at a lower price. However this does not represent a free-lunch: the loans that are sold might be significantly safer compared to the ones that are purchased, resulting in risk-shifting. It is intuitive that constrained and unconstrained CLOs might engage in par building for different reasons: in normal times they do so in order to improve the quality of the CLO's collateral, while - when the constraint is binding - to gain slack on their OC tests. One way to test this hypothesis is to look at the riskiness of the loans that are sold and purchased by constrained and unconstrained CLOs: if indeed the trading behaviour of constrained CLOs is motivated by a desire to restore the soundness of OC tests, then we should expect that they sell safer loans to finance the purchase of riskier ones. In order to carry out this tests, I will measure the riskiness of a loan in terms of its rating factor. CLOs are, in fact, subject to tests on the Weighted-Average Rating Factor (WARF) of their collateral, where each loan is assigned a numeric value on a scale from 1 to 10,000 which is supposed to capture the riskiness of a loan. I will use Moody's rating mapping (reported in Table 7) in order to transform the ordinal ratings into a meaningful cardinal value. The rating factor increases with the riskiness of a security, ranging between 1 (Aaa) and 10,000 (Ca-C). The

Table 8 : WARF Deterioration

The table compares the average rating factor for loans sold, in column (1), and purchased, column (2), by CLOs whose loans have been downgraded to CCC and whose Junior OC tests are binding, by reporting the coefficients of the following regression: $RF_{i,j,t} = \alpha + \beta_1 \text{Shocked}_{i,t} + \beta_2 \text{Constrained}_{i,t} + \beta_3 \text{Shocked}_{i,t} \times \text{Constrained}_{i,t} + \varepsilon_{i,t}$; where $RF_{i,j,t}$ is the rating factor of loan j, sold by CLO i at time t; Shocked$_{i,t}$ is dummy variable equal to one when the loans of CLO i have been downgraded to CCC; Constrained$_{i,t}$ is a dummy variable equal to one when the slack of the Junior OC test is between 0% and 5%. Column (3) aggregates the results by reporting the coefficients of the following regression: $\Delta WARF_{i,t} = \alpha + \beta_1 \text{Shocked}_{i,t} + \beta_2 \text{Constrained}_{i,t} + \beta_3 \text{Shocked}_{i,t} \times \text{Constrained}_{i,t} + \varepsilon_{i,t}$, where $\Delta WARF_{i,t} = \sum_j RF_{i,j,t} \times \frac{\text{Amt. Purchased}_{i,j,t}}{\sum_j \text{Amt. Purchased}_{i,j,t}} - \sum_j RF_{i,j,t} \times \frac{\text{Amt. Sold}_{i,j,t}}{\sum_j \text{Amt. Sold}_{i,j,t}}$. Standard errors clustered by CLO Deal & Year×Month are reported in parentheses.

	Individual Transactions		**Multiple Transactions**
	(1)	**(2)**	**(3)**
(Intercept)	3025***	2641.4***	-441.3***
	(29.5)	(12.3)	(39.6)
Shocked	-151.6***	67.5***	316.2***
	(26.9)	(18.3)	(35.5)
Constrained	73.9**	-6.86	374.5***
	(34.2)	(14)	(43.3)
Shocked × Constrained	-514.2***	105.8***	79.1*
	(40.2)	(23.4)	(41.2)
Fit statistics			
Observations	155,079	162,629	21,043
R^2	0.00847	0.00434	0.04243
Adjusted R^2	0.00845	0.00432	0.0423

Two-way (CLO Deal & Year×Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

typical rating for a loan on the balance sheet of a CLO is B2, commanding a rating factor of 2,720, while the average and median WARF are 2,923.48 and 2,737, respectively. As one should expect, WARFs tend to vary and follow the business cycle, as Figure C8 in the Appendix shows.

Table 8 formally tests whether constrained CLOs tend to sell higher quality securities by regressing the rating factor of loans sold and purchased on the Shocked$_{i,t}$ and Constrained$_{i,t}$ dummies. Unconstrained CLOs tend to sell lower quality loans (average rating factor of 3025) compared the one they buy (average rating factor of 2641), implying that - in normal times - they tend to trade towards the direction of making their portfolio safer. CLOs that are hit by downgrades, however, tend to sell loans of slightly higher quality and purchase loans of lower quality: on average, the loans they sell have a rating factor that is 151.6 points lower, while their purchases have a rating factor that is 67.5 points higher. The coefficient on the Constrained$_{i,t}$ dummy, suggests that, when they have not been hit by downgrades, the quality of the loans they sell is slightly worse (73.9 points), while there is no difference in the loans they purchase. Finally, the coefficient on Shocked$_{i,t}\times$Constrained$_{i,t}$ shows that, after their loans have been downgraded to CCC, CLOs whose OC constraints are binding, sell loans that are significantly safer (-514.2 points), while the purchase riskier loans (105.8 points). These results suggest that the average rating factor of loans sold by distressed CLOs is 591.9 points (i.e., -151.6 + 73.9 - 514.2) lower compared to those in the control group, while the average rating factor of the loans they purchase is 166.44 points higher (i.e., 67.5 - 6.86 + 105.8). It should be pointed out that, so far, we have been able to compare the riskiness of loans sold and purchased across different CLOs. Column (3) in Table 8 allows us to analyse how OC constraints affect the portfolio composition of each individual CLO by aggregating across all the trades executed by a CLO. The variable of interest is now the change in the WARF caused by a CLO trading, namely: $\Delta WARF_{i,t} = \sum_j RF_{i,j,t} \times \frac{\text{Amt. Purchased}_{i,j,t}}{\sum_j \text{Amt. Purchased}_{i,j,t}} - \sum_j RF_{i,j,t} \times \frac{\text{Amt. Sold}_{i,j,t}}{\sum_j \text{Amt. Sold}_{i,j,t}}$. As the previously results suggested, CLOs - when unconstrained - tend to trade in order to make their portfolio safer, as shown by the fact that, on average, their trading behaviour improve their WARF by 441.3 points. CLOs whose loans have been downgraded to CCC, however, deteriorate the quality of their assets by 316.2 point, while those whose Junior slack is between 0% and 5% by 374.5. CLOs whose constraints are binding and whose loans have been downgraded to CCC do even worse by reducing the quality of their portfolio by a further 79.1 points, implying that their portfolios are, on average, 769.9 points riskier compared to CLOs in the control group and 328.6 points compared to the counterfactual where they did not execute any trade.

To conclude, the evidence in this section suggests that whenever loans are downgraded to CCC, CLO managers sell high quality securities in order to restore the par value of their collateral. This is done mainly by selling high quality, highly rated and relatively expensive loans in order to buy lower quality, lower rated and relatively cheaper ones. The trading incentives generated by binding OC constraints suggest we can use downgrades as an exogenous source of variation in the supply of loans held by the CLOs affected by the shock: when the OC constraint of a CLO is binding and some of its loans are downgraded to CCC, they are forced to sell high quality assets in order to avoid failing over-collateralization tests which would have a negative impact on their compensation. To make things clearer, consider the following thought experiment: there are two ex-ante identical loans, L_A and L_B, which are held by CLOs α and β. An otherwise unrelated loan, say L_C, is downgraded to CCC. Imagine, L_C is held by CLO α, not by β. Once α is hit by a downgrade, L_A is more likely to be sold for exogenous reasons; if the market for L_A is not liquid enough to absorb the excess supply, its price might become depressed compared to L_B as long as arbitrageurs are unable to spot the mispricing and bring it back in line with L_B. The usual issue with this type of reasoning is that the management team of CLO α endogenously chose to sell L_A. This is, however, less likely to represent an issue in this case: we have shown in this section that OC tests incentivize managers to sell their best performing loans, implying that, if present, selection is likely to go against finding any price impact, that is, other investors should be willing to buy high quality assets which are sold by distressed CLOs. If, on the other hand, we find that the price of L_A is depressed compared to L_B, we should conclude that this is due to the price impact CLOs have and to the fact that it might take some time for arbitrageurs to direct their capital towards the secondary market for leveraged loans. The next section will analyse and test this hypothesis in greater detail.

6 Impact on Prices

In the previous section I have shown how the presence of binding OC constraints can distort the trading behaviour of CLO managers; in particular I have shown that whenever a loan is downgraded below CCC, managers affected by the downgrade tend to engage in par building by selling higher rated securities, especially so if their junior OC tests are binding. This trading behaviour gives us an instrument to investigate the extent to which the prices of loans are effected by forced sales that are unrelated to fundamentals. I can therefore trace the impact of the sale on the loan's price controlling for ex-ante measurable characteristics to get an estimate of how the secondary market for leveraged loans absorbs supply shocks. The endogenous choice of selling a security will bias the results towards finding no effect, given that loans that are sold by distressed CLOs tend to be of higher quality compared to the ones sold by non-distressed ones. One might still be worried that selection happens through unobservable characteristics that cannot be measured by the econometrician. To alleviate this concern, I will show in Section 6.1 that this is not the case even when we assess the extent of ex-post selection: conditioning on ex-ante observables, loans that are sold by distressed CLOs are not more likely to be downgraded, to default, nor they display worsened liquidity. We can therefore conclude that the results in this section provide a lower bound for the impact of CLOs on the secondary market for leveraged loans. In order to measure the impact of CLOs, I will compare the average discount of loans sold by distressed CLOs with the average discount of a group of control loans. The identification assumption is that, after having controlled for time varying loan characteristics, the average discount of the two groups of loans would be identical if not for the fact they have been sold by distressed CLOs in order to restore their OC tests. The effect should be largest among loans that receive more selling pressure: for this reason I proceed by constructing a dummy variable, $Shocked_{j,t}$, that is equal to one whenever a loan has been sold by an above median number of distressed CLOs, where a CLO is considered distressed if their loans have been downgraded

Table 9 : Price Pressure

The table reports the results of the following regression: $\text{discount}_{j,t} = \beta_1 \text{Shocked}_{i,j,t} + \beta_2 \text{Shocked}_{j,t} \times \text{Post}_{i,j,t} + X_{j,t}\delta + \varepsilon_{i,j,t}$, where $\text{discount}_{j,k,t} = 100 \times \log(100/P_{j,k,t})$, $P_{j,k,t}$ is the price of loan j issued by firm k at time t, $\text{Shocked}_{j,t}$is a dummy variable equal to one when loan j selling volume by shocked CLOs is above median, $\text{Post}_{i,j,t}$ is a dummy equal to one after loan j has received an above median selling volume by shocked CLOs, $X_{j,t}$ is a matrix containing various fixed effects and controls. Column (1) includes year×month fixed effects; column (2) adds year×month×time-to-maturity fixed effects; column (3) adds year×month×rating fixed effects; column (4) adds year×month×industry fixed effects; column (5) adds year×month×interest rate fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. All the regressions include the lagged average discount on the issuer computed as Avg. $\text{discount}_{k,t-1} = \frac{1}{J_k \times (t-1)} \sum_{j=1}^{J_k} \sum_{s=1}^{t-1} \text{discount}_{j,k,s}$, where J_k is the number of loans by issuer k actively traded. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked	-0.395***	-0.093	-0.009	-0.027	-0.011
	(0.116)	(0.094)	(0.068)	(0.063)	(0.067)
Shocked×Post	0.718***	0.494***	0.476***	0.469***	0.436***
	(0.130)	(0.104)	(0.088)	(0.083)	(0.086)
Avg. discount_{t-1}	0.802***	0.798***	0.659***	0.651***	0.660***
	(0.037)	(0.037)	(0.033)	(0.032)	(0.033)
Fixed-Effects					
Year×Month	Yes	No	No	No	No
Year×Month×TTM	No	Yes	Yes	Yes	Yes
Year×Month×Rating	No	No	Yes	Yes	Yes
Year×Month×Industry	No	No	No	Yes	Yes
Year×Month×Interest	No	No	No	No	Yes
Fit statistics					
Observations	738,354	738,354	738,354	738,354	738,354
R^2	0.421	0.432	0.533	0.564	0.540
Within R^2	0.324	0.312	0.224	0.218	0.223

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

to CCC and the Junior OC slack is between 0% and 5%. These two conditions have been proven to be related to non fundamental par-building in the previous section. I then construct a dummy variable $Post_{i,j,t}$ that is equal to one in the twelve months after a loan has been sold by an above median number of distressed CLOs. I then proceed by running the following regression:

$$discount_{j,t} = \beta_1 Shocked_{j,t} + \beta_2 Shocked_{j,t} \times Post_{i,j,t} + X_{j,t}\delta + \varepsilon_{ijt} \tag{6}$$

The matrix $X_{j,t}$ contains various controls that are supposed to partial out the effect of measurable characteristics and exclude selection on ex-ante observables: the regressions include fixed effects for the time-to-maturity (TTM), the rating, the industry and the interest rate of the loan, all interacted with year$\times$month fixed effects, assuring that the discount of treated loans is compared with loans with identical characteristics trading in the same month. I also include the lagged average discount on loans by the same issuer to control for the average discount on loans issued by the same company[12][13]. Column (1) in Table 9 shows that shocked CLOs tend to sell expensive loans to improve their OC tests: loans sold by shocked CLOs trade at 39.5bps premium compared to other loans. This difference, however, becomes insignificant once we add time varying fixed effects for time-to-maturity, rating, industry and interest rate in columns (2)(5), implying that most of the unconditional differences in prices between the treatment and control loans is absorbed by ex-ante measurable characteristics; this points to the fact that fixed effects take care of most of the selection between treatment and control groups. When we look at the impact of sales by shocked CLOs on prices, we notice that treated loans trade at a discount of 71.8bps compared to untreated loans. The result is still statistically significant

[12]Table B5 in the Appendix includes issuer fixed effects instead of the lagged average return per issuer. The key difference between these two specification lies in the fact that the latter control for the average discount on the issuer's loans before and after the treatment date and, hence, might be influenced by the treatment itself. The results are, however, similar to the ones in Table 9

[13]Figure C4 in the Appendix shows the fraction of variation explained by each fixed effect included in the regressions, ranging from year$\times$month rate fixed effects, which explain 15% of the variation, to loan issuer $\times$ year $\times$ month fixed effects, which explain 90% of the variation.

Table 10 : Price Pressure Within Issuers

The table reports the results of the following regression: discount$_{j,k,t} = \alpha_{k,t} + \beta_1$Shocked$_{i,j,t}$ + β_2Shocked$_{j,t} \times$ Post$_{i,j,t} + X_{j,t}\delta + \varepsilon_{j,k,t}$, where discount$_{j,t} = 100 \times \log(100/P_{j,t})$, $P_{j,t}$ is the price of loan j at time t, Shocked$_{j,t}$is a dummy variable equal to one when loan j selling volume by shocked CLOs is above median, Post$_{i,j,t}$ is a dummy equal to one after loan j has received an above median selling volume by shocked CLOs, $X_{j,t}$ is a matrix containing the fixed effects reported in the table. Column (1) includes all the loans that have been traded by CLOs; column (2) restricts the sample to those issuers with at least two actively traded loans; column (3) to those issuers with at least five actively traded loans; column (4) to those issuers with at least 10 actively traded loans. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	(2)	(3)	(4)
Shocked	-0.032	-0.034	-0.053*	-0.042
	(0.026)	(0.026)	(0.032)	(0.040)
Shocked×Post	0.120***	0.126***	0.153***	0.179**
	(0.039)	(0.041)	(0.051)	(0.071)
Fixed-effects				
Year×Month×Issuer	Yes	Yes	Yes	Yes
Year×Month×TTM	Yes	Yes	Yes	Yes
Year×Month×Rating	Yes	Yes	Yes	Yes
Year×Month×Industry	Yes	Yes	Yes	Yes
Year×Month×Interest	Yes	Yes	Yes	Yes
Fit statistics				
Observations	746,956	629,507	402,252	170,122
R^2	0.914	0.884	0.853	0.821
Within R^2	0.000	0.000	0.000	0.000
Nr. Traded Loans	≥ 1	≥ 2	≥ 5	≥ 10

Two-way (mdate & issuer_name) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

and large when we add the other fixed effects in columns (2)-(5), with the coefficients ranging between 43.6 and 49.4bps. I then proceed to analyse whether loans sold by distressed CLOs trade at a significant discount compared to other loans issued by the same company k by including time varying issuer fixed effects which are meant to control for any unobservable time varying firm characteristics. I report in Table 10 the results of the following regression:

$$\text{discount}_{j,k,t} = \alpha_{k,t} + \beta_1 \text{Shocked}_{i,j,t} + \beta_2 \text{Shocked}_{j,t} \times \text{Post}_{i,j,t} + X_{j,t}\delta + \varepsilon_{j,k,t} \quad (7)$$

where $\alpha_{k,t}$ are year×month×issuer fixed effects. Loans sold by distressed CLOs trade at 12bps discount compared to otherwise similar loans issued by the same borrower. Two considerations are in order. First, the median (average) number of loans per issuer actively traded in any given month is 2 (3.1) and 33.6% of the time an issuer has a unique loan traded in a given month, implying that a large fraction of the observations do not have a loan in the control group. If we take into account the fact that companies with fewer traded loans tend to be smaller and less liquid, this might explain the reduction in magnitude of the coefficient. Columns (2)-(4) in Table 10 seem to confirm this hypothesis: when I restrict the sample to issuers having at least 2,5 and 10 actively traded loans the impact of CLOs grows to 12.6bps, 15.3bps and 17.9bps, respectively. Second, loans tend to be priced by comparables (Murfin and Pratt, 2018) and it is very likely that the shock to a specific issue reverberates across all the loans issued by the same company, proof being the fact that the issuer×year×month fixed effects explain a large fraction of the variation in discounts. The spillover from loans sold by shocked CLOs to loans issued by the same company implies that the estimate of β_2 is likely to underestimate the true magnitude of the effect in this specification. On top of that, notice that the $\text{Post}_{i,j,t}$ dummy takes into account the average difference in discounts in the twelve months following the shock: if the impact of the shocks lasts less than one year, we should expect this coefficient to be downward biased, given that it is already incorporating part of the reversal. In order to check whether this is the case and trace the impact of a shock across time I construct a set of dummy variables tracking the discount every month around the forced sale, which allows me to run the following regression:

$$\text{discount}_{j,t} = \gamma \text{Shocked}_{j,t} + \sum_{s=-6}^{12} \beta_s \text{Shocked}_{j,t} \times \mathbb{1}(t+s) + X_{j,t}\delta + \varepsilon_{j,t} \quad (8)$$

Table 11 : The Dynamics of the Shock

The table reports the results of the following regression: $\text{discount}_{j,t} = \gamma\text{Shocked}_{j,t} + \sum_{s=-6}^{12} \beta_s \text{Shocked}_{j,t} \times \mathbb{1}(t+s) + X_{j,t}\delta + \varepsilon_{j,t}$, where $discount_{j,t} = 100 \times \log(100/P_{j,t})$, $P_{j,t}$ is the price of loan j at time t, $\text{Shocked}_{j,t}$is a dummy variable equal to one when loan j selling volume by shocked CLOs is above median, $\mathbb{1}(t+s)$ is a set of dummies that are equal to one $s = -6, -5, ..., 11, 12$ months around the event of the sale at time t, $X_{j,t}$ is a matrix containing various fixed effects. Column (1) includes year×month fixed effects; column (2) adds year×month×time-to-maturity fixed effects; column (3) adds year×month×rating fixed effects; column (4) adds year×month×industry fixed effects; column (5) adds year×month×interest rate fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked×$\mathbb{1}(t-6)$	-0.241*	-0.241*	0.187	0.151	0.162
	(0.136)	(0.136)	(0.124)	(0.111)	(0.109)
Shocked×$\mathbb{1}(t-5)$	-0.076	-0.076	0.145	0.156*	0.161*
	(0.124)	(0.124)	(0.096)	(0.090)	(0.092)
Shocked×$\mathbb{1}(t-4)$	-0.237**	-0.237**	-0.046	-0.028	-0.016
	(0.109)	(0.109)	(0.074)	(0.066)	(0.065)
Shocked×$\mathbb{1}(t-3)$	-0.216*	-0.216*	-0.088	-0.073	-0.047
	(0.126)	(0.126)	(0.094)	(0.090)	(0.084)
Shocked×$\mathbb{1}(t-2)$	-0.081	-0.081	-0.070	-0.028	0.012
	(0.098)	(0.098)	(0.082)	(0.074)	(0.073)
Shocked×$\mathbb{1}(t-1)$	-0.183**	-0.183**	-0.112*	-0.073	-0.052
	(0.081)	(0.081)	(0.060)	(0.057)	(0.055)
Shocked×$\mathbb{1}(t)$	0.259**	0.259**	0.280***	0.221***	0.220***
	(0.107)	(0.107)	(0.085)	(0.068)	(0.068)
Shocked×$\mathbb{1}(t+1)$	0.205*	0.205*	0.191**	0.150**	0.122*
	(0.107)	(0.107)	(0.078)	(0.065)	(0.063)

Continued on next page

Table 11 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)
Shocked $\times \mathbb{1}(t+2)$	0.489***	0.489***	0.402***	0.364***	0.331***
	(0.147)	(0.147)	(0.117)	(0.102)	(0.100)
Shocked $\times \mathbb{1}(t+3)$	0.540***	0.540***	0.368***	0.377***	0.342***
	(0.137)	(0.137)	(0.115)	(0.100)	(0.096)
Shocked $\times \mathbb{1}(t+4)$	0.752***	0.752***	0.554***	0.482***	0.444***
	(0.147)	(0.147)	(0.132)	(0.112)	(0.111)
Shocked $\times \mathbb{1}(t+5)$	0.929***	0.929***	0.648***	0.572***	0.525***
	(0.185)	(0.185)	(0.144)	(0.131)	(0.129)
Shocked $\times \mathbb{1}(t+6)$	1.03***	1.03***	0.587***	0.592***	0.544***
	(0.209)	(0.209)	(0.149)	(0.135)	(0.124)
Shocked $\times \mathbb{1}(t+7)$	0.872***	0.872***	0.408**	0.378***	0.346***
	(0.196)	(0.196)	(0.171)	(0.139)	(0.130)
Shocked $\times \mathbb{1}(t+8)$	0.760***	0.760***	0.266	0.260*	0.250*
	(0.200)	(0.200)	(0.172)	(0.152)	(0.144)
Shocked $\times \mathbb{1}(t+9)$	0.467***	0.467***	0.037	0.158	0.126
	(0.166)	(0.166)	(0.139)	(0.123)	(0.119)
Shocked $\times \mathbb{1}(t+10)$	0.683***	0.683***	0.273*	0.309**	0.239*
	(0.176)	(0.176)	(0.150)	(0.144)	(0.132)
Shocked $\times \mathbb{1}(t+11)$	-0.130	-0.130	-0.033	0.030	0.034
	(0.149)	(0.149)	(0.132)	(0.122)	(0.120)
Shocked $\times \mathbb{1}(t+12)$	-0.294***	-0.294***	0.068	0.080	0.088
	(0.111)	(0.111)	(0.095)	(0.089)	(0.087)
Fixed-Effects					
Year$\times$Month	Yes	No	No	No	No

Continued on next page

Table 11 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)
Year×Month×TTM	No	Yes	Yes	Yes	Yes
Year×Month×Rating	No	No	Yes	Yes	Yes
Year×Month×Industry	No	No	No	Yes	Yes
Year×Month×Interest	No	No	No	No	Yes
Fit statistics					
Observations	746,956	746,956	746,956	746,956	746,956
R^2	0.48414	0.48414	0.58706	0.61761	0.62407
Within R^2	0.00153	0.00153	0.00107	0.00091	0.00072

Two-way (Year×Month & Issuer) standard-errors in parentheses

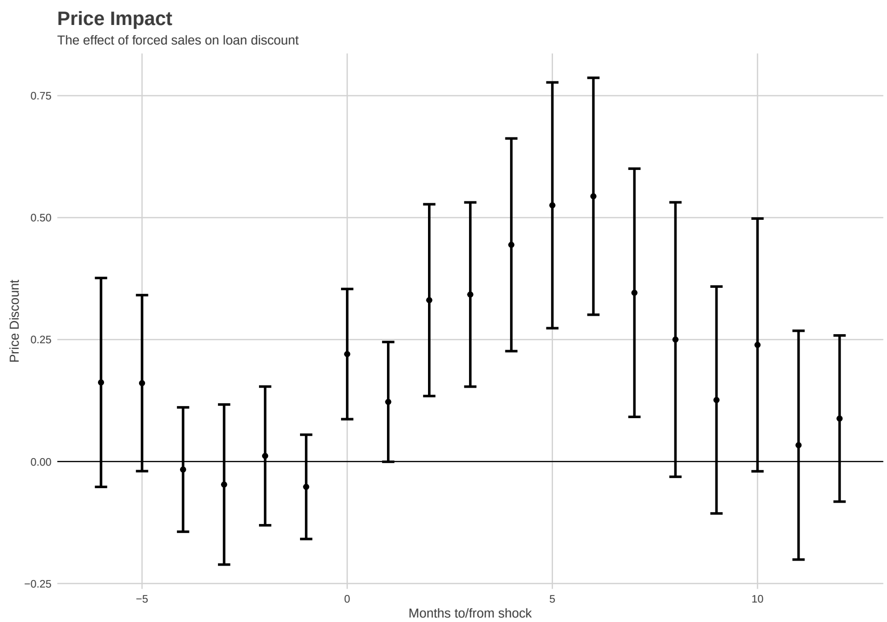
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

where $\text{Shocked}_{j,t}$ is defined as above and $\mathbb{1}(t+s)$ is a set of dummies that are equal to one $s = -6, -5, ..., 11, 12$ months around the event of the sale at time t. The results are provided in Table 11 and plotted in Figure 3[14]. The results in Table 11 show that the direct impact of CLOs is between 22bps and 25.9bps in the month when loans are sold. The gap between the treatment and control group starts widening in the months after the sale with the difference reaching its maximum around six months after the sale when treated loans trade at between 54.4bps and 103bps discount compared to loans in the control group. Shocked loans need between ten and twelve months before their discount is not statistically different from the discount of the control group. Figure C12 in the Appendix plots the average discount of loans in the treated group showing that their discount jumps immediately on impact; however, CLOs are more likely to be distressed in months when the market for leveraged loans is in distress as well. In the months

[14]Figure 3 plots the results for model (4) in Table 11, including year×month×time-to-maturity, year×month×rating and year×month×industry fixed effects. The other results are plotted in Figure C11 in the Appendix.

Figure 3 : Price Pressure

The figure plots the results of the following regression: $\text{discount}_{j,t} = \gamma\text{Shocked}_{j,t} + \sum_{s=-6}^{12} \beta_s \text{Shocked}_{j,t} \times \mathbb{1}(t+s) + X_{j,t}\delta + \varepsilon_{j,t}$, where $discount_{j,t} = 100 \times \log(100/P_{j,t})$, $P_{j,t}$ is the price of loan j at time t, $\text{Shocked}_{j,t}$is a dummy variable equal to one when loan j selling volume by shocked CLOs is above median, $\mathbb{1}(t+s)$ is a set of dummies that are equal to one $s = -6, -5, ..., 11, 12$ months around the event of the sale at time t, $X_{j,t}$ is a matrix containing the following fixed effects: year×yonth×time-to-maturity, year×month×rating, year×month×industry. Time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. Standard errors are two-way clustered at the year×month and issuer level.



after the shock, treated loans tend to recover at a slower pace compared to those in the control group, widening the gap in average discounts up to seven/nine months when the treated loans slowly converge back to the control group. The presence of significant price reversal towards the control group is suggestive of the fact that the increase in discounts is more likely due to price pressure rather than changes in the fundamental value of the assets (Coval and Stafford, 2007), consistently with the idea that loans sold by distressed CLOs tend to be of higher quality; the fact that the market for leveraged loans tend to be dislocated between seven and nine months after the fire sale is consistent with the evidence in Elkamhi and Nozawa (2020) who find a price impact of 35-40 weeks for loans sold by CLOs.

Finally, I turn to loans that distressed CLOs have purchased to build par. We can expect an asymmetry between sales and purchases in times of distress: distressed CLOs have a hard time finding investors willing to buy their assets, while it might be easier to meet with an investor willing to sell in periods of distress. I proceed to analyse the effect on loans purchased by distressed CLOs by running a difference-in-differences regression similar to the one in equation (6). If we look at the coefficient on $\text{Shocked}_{j,t} \times \text{Post}_{i,j,t}$ in Table 12 we can infer that there is no evidence of upward price pressure on loans purchased by shocked CLOs. The coefficient is never statistically significant, with the exception of column (2) which includes only year×month×time-to-maturity fixed effects, suggesting that the discount on loans purchased by shocked CLOs is not different from other loans purchased in the twelve months after the event. The dynamic response of discounts to forced purchases by shocked CLOs are reported in Table B7 and Figure C13 in the Appendix.

Overall, the evidence in this section is conclusive of the fact that CLOs exercise a statistically and economically significant price pressure on the loans they are forced to sell whenever their OC tests bind because of a shock to their CCC bucket. I have previously argued that any selection in the treated loans is likely to generate downward bias in the magnitude of the price pressure. The addition of fixed effects based on loan characteristics has made sure that, conditional on ex-ante observables, there is indeed no selection between treated and control groups. However, the following section will test whether there is any selection ex-post by analysing whether shocked loans are more likely to default or be downgraded.

6.1 Absence of Selection

By controlling for time, time-to-maturity, rating, industry and borrower fixed effects we can be confident that the effect on loans' discounts documented in Section 6 is not motivated by ex-ante observable characteristics. In the specification where I have included year×month×issuer fixed effect, we can be confident that all the borrower time varying

Table 12 : Price Pressure - Purchases

The table reports the results of the following regression: $\text{discount}_{j,t} = \beta_1 \text{Shocked}_{i,j,t} + \beta_2 \text{Shocked}_{j,t} \times \text{Post}_{i,j,t} + X_{j,t}\delta + \varepsilon_{i,j,t}$, where $\text{discount}_{j,k,t} = 100 \times \log(100/P_{j,k,t})$, $P_{j,k,t}$ is the price of loan j issued by firm k at time t, $\text{Shocked}_{j,t}$is a dummy variable equal to one when loan j purchasing volume by shocked CLOs is above median, $\text{Post}_{i,j,t}$ is a dummy equal to one after loan j has received an above median purchasing volume by shocked CLOs, $X_{j,t}$ is a matrix containing various fixed effects and controls. Column (1) includes year×month fixed effects; column (2) adds year×month×time-to-maturity fixed effects; column (3) adds year×month×rating fixed effects; column (4) adds year×month×industry fixed effects; column (5) adds year×month×interest rate fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. All the regressions include the lagged average discount on the issuer computed as Avg. $\text{discount}_{k,t-1} = \frac{1}{J_k \times (t-1)} \sum_{j=1}^{J_k} \sum_{s=1}^{t-1} \text{discount}_{j,k,s}$, where J_k is the number of loans by issuer k actively traded. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked	-1.16***	-0.923***	-0.612***	-0.634***	-0.603***
	(0.130)	(0.109)	(0.084)	(0.086)	(0.084)
Shocked×Post	-0.108	-0.281**	0.014	0.004	-0.054
	(0.149)	(0.142)	(0.139)	(0.135)	(0.133)
Avg. discount_{t-1}	0.795***	0.790***	0.611***	0.609***	0.607***
	(0.036)	(0.037)	(0.039)	(0.038)	(0.038)
Fixed-Effects					
Year×Month	Yes	No	No	No	No
Year×Month×TTM	No	Yes	Yes	Yes	Yes
Year×Month×Rating	No	No	Yes	Yes	Yes
Year×Month×Industry	No	No	No	Yes	Yes
Year×Month×Interest	No	No	No	No	Yes
Fit statistics					
Observations	738,354	738,354	597,976	597,976	596,807
R^2	0.42337	0.42419	0.48533	0.4922	0.4915
Within R^2	0.32595	0.31629	0.19398	0.18928	0.18685

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

characteristics have been partialled out in the analysis, hence showing that at least a fraction of the effect is security specific. However, we can still argue that CLOs might trade on ex-ante unobservable information which is not captured by the previously used controls. There is indeed evidence that trades in the secondary market for leveraged loans predict equity returns (Addoum and Murfin, 2020), suggesting that active investors in this market have access to private and valuable information; moreover Fabozzi et al. (2020) and Cordell et al. (2020) show that CLO managers tend to profit by actively trading loans, further suggesting that they might have access to information that is not available to other investors in real time. In order to be able to differentiate between the hypothesis suggested in Section 6, i.e. the fact that trades by distressed CLOs cause price pressure, and an alternative hypothesis where distressed CLOs simply have access to superior information and forecast a drop in the price of the loans they sell, we need to look at whether their trades are indeed able to predict outcomes that can be measured ex-post by the econometrician. In particular, in the rest of this section, I will show that trades by distressed CLOs are not able to predict defaults or rating downgrades, therefore suggesting that these trades are indeed purely caused by concerns related to their OC tests.

The first test I conduct regards defaults. The results in Table 11 and Figure 3 suggest that the price impact of CLO trades lasts up to twelve months, therefore I proceed by constructing a dummy variable that is equal to one whenever a loan defaults in the following twelve months and check if loans sold by distressed CLOs are more likely to default compared to other loans held by CLOs. In order to control for loan characteristics by employing fixed effects and avoid the *incidental parameter problem* (Neyman and Scott, 1948), I will use the following linear probability model:

$$\text{default}_{j,t\to t+12} = \beta_1 \text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{9}$$

where $\text{default}_{j,t\to t+12}$ is a dummy variable equal to one when loan j defaults in the period between t and $t+12$, $\text{Shocked}_{j,t}$ is a dummy equal to one when the loan has been

Table 13 : Defaults

The table reports the results of the following regression: $\text{default}_{j,t\to t+12} = \beta\text{Shocked}_{jt} + X_{jt}\delta + \varepsilon_{ijt}$, where $\text{default}_{j,t\to t+12}$ is a dummy variable equal to one when loan j defaults in the period between t and $t+12$, $\text{Shocked}_{j,t}$ is a dummy equal to one when the loan has been sold by distressed CLOs and $X_{j,t}$ is a matrix of fixed effects to control for loan characteristics. Column (1) includes year×month fixed effects; column (2) includes year×month×time-to-maturity fixed effects; column (3) adds year×month×rating fixed effects; column (4) adds year×month×industry fixed effects; column (5) adds year×month×interest fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked	-0.023***	-0.009***	-0.000	-0.000	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed-effects					
Year×Month	Yes	No	No	No	No
Year×Month×TTM	No	Yes	Yes	Yes	Yes
Year×Month×Rating	No	No	Yes	Yes	Yes
Year×Month×Industry	No	No	No	Yes	Yes
Year×Month×Interest	No	No	No	No	Yes
Fit statistics					
Observations	141,564	141,564	141,564	141,564	141,564
R^2	0.052	0.129	0.408	0.471	0.483
Within R^2	0.00	0.000	0.000	0.000	0.000

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

sold by distressed CLOs and $X_{j,t}$ is a matrix of fixed effects to control for loan characteristics. The results are reported in Table 13. The baseline average probability of defaulting in the following twelve months for a loan that is sold by a CLO is equal to 4.79%; column (1) shows that this probability is reduced by 2.3% for the loans that are sold by distressed CLOs, confirming the hypothesis that shocked CLOs tend to sell higher quality securities to meet their OC test constraints. The effect is large compared to the baseline and significant even when we include time-to-maturity fixed effects at 0.9%. When we include rating fixed effects in columns (3)-(5) the coefficient becomes insignificant, suggesting that ratings capture the difference in risk between treatment and control group. Overall, the evidence in Table 13 is consistent with the hypothesis that sales by shocked CLOs have no informational motives and are executed to meet OC tests constrains, adding to the evidence that shocked CLOs are more aggressive in building par, they sell loans with lower rating factors, and they cause price pressure on the loans they sell which dissipates within seven/nine months.

I can further develop this hypothesis by testing whether loans sold by distressed CLOs are more or less likely to be downgraded or upgraded in the twelve months following the sale. In order to do so, I run the following regression:

$$\text{downgrade}_{j,t\rightarrow t+12} = \beta_1 \text{Shocked}_{jt} + X_{jt}\delta + \varepsilon_{ijt} \tag{10}$$

where $\text{downgrade}_{j,t\rightarrow t+12}$ is a dummy variable equal to one when loan j is downgraded in the period between t and $t+12$. Similarly I run a regression where the outcome variable is $\text{upgrade}_{j,t\rightarrow t+12}$, a dummy variable equal to one when a loan is upgraded in the period between t and $t+12$. The results of the regressions are reported in Table 14. The three leftmost columns show that loans sold by shocked CLOs are not more likely to be downgraded compared to loans sold by other CLOs after we control for ex-ante observable loan characteristics: in none of the specifications the coefficient is statistically different from zero. The same conclusion can be drawn by looking at upgrades: none of the specifications makes us conclude that loans sold by CLOs are more likely to be upgraded in the following twelve months, compared to loans sold by other CLOs. Ex-ante observable characteristics seem to absorb ex-post observable outcomes, suggesting that the former prevent any selection between treatment and control group based on the latter.

Finally, one might wonder whether loans sold by distressed CLOs differ from loans sold by other CLOs in terms of their liquidity. If loans sold by CLOs under stress become less liquid after the sale, and if liquidity commands a premium, the difference in

Table 14 : Rating Changes

The table reports the results of the following regression: $y = \beta \text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, where the outcome variable is either $y = \text{downgrade}_{j,t\to t+12}$ or $y = \text{upgrade}_{j,t\to t+12}$. $\text{downgrade}_{j,t\to t+12}$ is a dummy variable equal to one if loan j is downgraded between time t and $t+12$; $\text{upgrade}_{j,t\to t+12}$ is a dummy variable equal to one if loan j is upgraded between time t and $t+12$. $\text{Shocked}_{j,t}$ is a dummy equal to one when the loan has been sold by shocked CLOs and $X_{j,t}$ is a matrix of fixed effects to control for loan characteristics. Column (1) includes year×month fixed effects; column (2) adds year×month×time-to-maturity and year×month×rating fixed effects; column (3) adds year×month×industry and year×month×interest rate fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	$\mathbf{downgrade_{j,t\to t+12}}$			$\mathbf{upgrade_{j,t\to t+12}}$		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Shocked	0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed-effects						
Year×Month	Yes	Yes	Yes	Yes	Yes	Yes
Year×Month×TTM	No	Yes	Yes	No	Yes	Yes
Year×Month×Rating	No	Yes	Yes	No	Yes	Yes
Year×Month×Industry	No	No	Yes	No	No	Yes
Year×Month×Interest	No	No	Yes	No	No	Yes
Fit statistics						
Observations	75,489	75,484	75,405	75,489	75,484	75,405
R^2	0.222	0.270	0.278	0.171	0.262	0.268
Within R^2	0	0	0	0	0	0

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

discounts documented in Section 6 might be simply due to compensation for liquidity risk. In order to test this hypothesis, we need to construct a proxy for the liquidity of the loan. I will employ two commonly used proxies for liquidity in the literature on corporate bonds. First I will employ Roll (1984)'s measure computed as the the negative of the autocovariance in price changes, i.e. $\gamma = -Cov(\Delta p_t, \Delta p_{t-1})$. Second I will use the (log) number of trades per loan per month. The average value of γ is equal to 0.487, in line

Table 15 : Liquidity

The table reports the results of the following regression: $y = \beta_1 \text{Shocked}_{jt} + \beta_2 \text{Shocked}_{jt} \times \text{Post}_{jt} X_{jt} \delta + \varepsilon_{ijt}$, where the outcome variable is either $y = \gamma_{j,t}$ or $y = \log(\text{Nr.Trades})$. $\gamma_{j,t}$ measures the liquidity of loans by using the covariance in price changes (Roll, 1984), while log(Nr.Trades) is the natural logarithm of the number of times a given loan has been traded by CLOs. $\text{Shocked}_{j,t}$ is a dummy equal to one when the loan has been sold by distressed CLOs and Post_{jt} is a dummy that is equal to one after a loan has been sold by a shocked CLO. $X_{j,t}$ is a matrix of fixed effects to control for loan characteristics.

	γ			**log(Nr.Trades)**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Shocked	0.561	0.446	0.387	-0.048***	0.054***	0.051***
	(0.399)	(0.349)	(0.333)	(0.014)	(0.012)	(0.013)
Shocked× Post	-0.293	-0.301	-0.290	0.039***	-0.015	-0.015
	(0.328)	(0.362)	(0.363)	(0.012)	(0.014)	(0.014)
Fixed-effects						
Year×Month	Yes	Yes	Yes	Yes	Yes	Yes
Year×Month×TTM	No	Yes	Yes	No	Yes	Yes
Year×Month×Rating	No	Yes	Yes	No	Yes	Yes
Year×Month×Industry	No	No	Yes	No	No	Yes
Year×Month×Interest	No	No	Yes	No	No	Yes
Fit statistics						
Observations	137,866	123,273	123,165	137,866	123,273	123,165
R^2	0.121	0.155	0.156	0.154	0.198	0.200
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

with measures for the corporate bond market (Bao et al., 2011), while the average number of trades per month is equal to 8.98, but heavily skewed towards few liquid loans, with the median number equal to 5 and way lower than the average number of trades in the corporate bond market. In Table 15 I report the results of the following regression:

$$\text{liquidity}_{j,t} = \beta_1 \text{Shocked}_{j,t} + \beta_2 \text{Shocked}_{j,t} \times \text{Post}_{i,j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{11}$$

where $liquidity_{jt}$ is either γ or $\log(Nr.Trades)$. In general we can conclude that there is no clear difference in liquidity after a loan has been sold by a shocked CLO. When we look at γ, the difference is significant in none of the specifications; moreover, a higher value of γ signals higher illiquidity, implying that - if something - loans sold by shocked CLOs tend to be more liquid ex-post, even though this is not statistically significant. When we look at the number of trades, we cannot draw a firm conclusion: column (1) seems to suggest that loans sold by shocked CLOs tend to trade 3.9% more often after the sale, however the coefficient switches sign and becomes insignificant in columns (2) and (3) once we add further fixed effects, suggesting that there is no statistical difference in liquidity.

We can conclude this section by summarizing its main findings. While we have controlled for selection on ex-ante observables in Section 6, one might be worried that treatment and control groups could select on unobservables. In this section we have shown that, on the contrary, loans sold by shocked CLOs tend to be less likely to default after the sale, there is no statistical difference in the likelihood of being downgraded or in the liquidity of the loan ex-post. This confirms that selection on unobservable characteristics is unlikely to explain the findings in Section 6.

6.2 Placebo Tests

In order to make sure the results in Sections 5 and 6 are not spurious I will conduct some placebo tests. The previous analysis is based on the premise that shocks to the CCC bucket have potentially a material effect on OC tests and managers are forced to trade in order to make sure their tests are not violated. In order to test whether these distortions are really caused by the downgrades to CCC I will conduct the following placebo test: I will construct a dummy variable that turns on when a CLO receives a shock to the bucket of securities rated B3 (B-) by Moody's (Standard & Poor's) and test whether these shocks have any effect on the trading behaviour of CLOs. Given that the OC tests are unaffected by the downgrade, the behaviour of management teams should not be distorted by these shocks. First I will study whether CLOs whose loans have been downgraded to B3 tend

Table 16 : Par Building - Placebo Test

The table reports the difference in par built between CLOs that have received a shock to the bucket of securities rated B3. Columns (1) and (2) report the results of the following regressions: $\text{gain}_{i,j,t} = \alpha + \beta_1 \text{Constrained}_{i,t} + \beta_2 \text{Shocked}_{i,t} + \beta_3 \text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t}$, where $\text{gain}_{i,j,t} = 100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for purchases and $\text{gain}_{i,j,t} = -100 \times \left((100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ for sales; $\text{Constrained}_{i,t}$ is a dummy variable equal to one whenever the Junior (column (1)) or Senior (column(2)) slack of CLO i is between 0% and and 5% in period t; $\text{Shocked}_{i,t}$ is a dummy variable equal to one whenever the loans of CLO i have been downgraded to B3. Columns (3) and (4) report the results of the following regressions: $\text{gain}_{i,t} = \alpha + \beta_1 \text{Constrained}_{i,t} + \beta_2 \text{Shocked}_{i,t} + \beta_3 \text{Constrained}_{i,t} \times \text{Shocked}_{i,t} + \varepsilon_{i,t}$, where $\text{gain}_{i,t} = 100 \times \left(\sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans bought}_{i,j,t}}{\text{Principal Balance}_{i,t}} - \sum_j (100 - P_{j,t-1}) \times \frac{\text{Nr. loans sold}_{i,j,t}}{\text{Principal Balance}_{i,t}}\right)$ and the other variables are defined as above. $\text{Constrained}_{i,t}$ refers to Junior tests in column (3) and to Senior tests in column (4). Standard errors are reported in parentheses and they are double clustered at the Year×Month & CLO Deal level.

	Individual Transactions		**Multiple Transactions**	
	(1)	**(2)**	**(3)**	**(4)**
(Intercept)	-0.004***	-0.002***	-0.078***	-0.051***
	(0.0004)	(0.0002)	(0.006)	(0.003)
Shocked	0.0005	0.0003*	0.005	0.004
	(0.0004)	(0.0002)	(0.009)	(0.003)
Constrained	0.002***	-0.008***	0.030***	-0.079***
	(0.0004)	(0.002)	(0.007)	(0.024)
Shocked × Constrained	-0.0003	0.002	-0.003	0.026
	(0.0005)	(0.002)	(0.010)	(0.028)
Fit statistics				
Observations	309,028	303,160	30,156	29,034
R^2	0.000	0.000	0.001	0.001
Adjusted R^2	0.000	0.000	0.000	0.001
OC Test	Junior	Senior	Junior	Senior

Two-way (Year×Month & CLO Deal) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

to build par by regressing the amount of par gained in each transaction on this dummy variable and another indicator that is equal to one whenever the slack of the CLO is between 0% and 5%. The results are presented in Table 16, from which it is clear that, as expected, CLOs hit by downgrades to B3 are neither more likely nor less likely to build par compared to deals in the control group: none of the coefficients is statistically significant and their magnitudes tend to be puny. This is indeed consistent with the idea that OC tests are insensitive to rating downgrades, as long as these downgrades do not affect CCC buckets, implying that treated CLOs do not have any incentives to engage in par building more than they usually do. A similar placebo test where I consider as shocked those CLOs whose loans have been downgraded to a rating of B2 (B) according to Moody's (Standard & Poor's) is presented in Table B9 in the Appendix, displaying similar results.

I then proceed with the final placebo test which is constructed similarly and tests whether sales completed by CLOs that have suffered a downgrade to B3 cause price pressure. As Table 16 has shown, the trading bahaviour of these CLOs is not significantly different from the trading behaviour of CLOs in the control group, hence there is no reason to expect their trades will be forced to happen at depressed prices. Moreover, downgrades to B3 do not generate significant pressure across CLOs, implying that there will likely be other deals willing to buy the loans that have just been sold by CLOs that have received downgrades to B3. I construct a dummy variable, $\text{Shocked}_{j,t}$, that is equal to one if a loan has been sold by an above median number of distressed CLOs that have received downgrades to B3 and a dummy variable Post_{jt} that is equal to one after the loan has been sold by shocked CLOs. Table 17 reports the results of the following regression:

$$\text{discount}_{j,t} = \beta_1 \text{Shocked}_{j,t} + \beta_2 \text{Shocked}_{j,t} \times Post_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{12}$$

where the variables are constructed as previously mentioned. The results in Table 17 confirm that loans sold by CLOs affected by downgrades to B3 do not trade at a significant discount compared to loans in the control group. A similar result for loans which have been mainly sold by CLOs that suffered downgrades to B2 is reported in Table B10 in the Appendix, confirming that loans in the treated group do not suffer significant price

Table 17 : Price Pressure - Placebo Test

The table reports the results of the following regression: $\text{discount}_{j,k,t} = \beta_1 \text{Shocked}_{j,t} + \beta_2 \text{Shocked}_{j,t} \times Post_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, where $\text{discount}_{j,k,t} = 100 \times \log(100/P_{j,k,t})$, $P_{j,k,t}$ is the price of loan j issued by firm k at time t, $\text{Shocked}_{j,t}$is a dummy variable equal to one when loan j selling volume by CLOs that experienced downgrades to B3 is above median and their slack is between 0% and 5%, $\text{Post}_{j,t}$ is a dummy equal to one after loan j has received an above median selling volume by CLOs with downgrades to B3, $X_{j,t}$ is a matrix containing various fixed effects and controls. Column (1) includes year×month fixed effects; column (2) adds year×month×time-to-maturity fixed effects; column (3) adds year×month×rating fixed effects; column (4) adds year×month×industry fixed effects; column (5) adds year×month×interest rate fixed effects. Interest and time-to-maturity fixed effects are constructed after bucketing the continuous variable in ten groups. All the regressions include the lagged average discount on the issuer computed as $\text{Avg. discount}_{k,t-1} = \frac{1}{J_k \times (t-1)} \sum_{j=1}^{J_k} \sum_{s=1}^{t-1} \text{discount}_{j,k,s}$, where J_k is the number of loans by issuer k actively traded. Two-way clustered standard errors at the year×month and issuer level are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked	0.738***	0.597***	0.538***	0.427***	0.377***
	(0.176)	(0.151)	(0.122)	(0.111)	(0.107)
Shocked×Post	-0.204	-0.001	0.059	0.066	0.075
	(0.147)	(0.132)	(0.111)	(0.104)	(0.103)
Avg. Discount_{t-1}	0.853***	0.838***	0.709***	0.693***	0.690***
	(0.033)	(0.034)	(0.032)	(0.031)	(0.031)
Fixed-Effects					
Year×Month	Yes	No	No	No	No
Year×Month×TTM	No	Yes	Yes	Yes	Yes
Year×Month×Rating	No	No	Yes	Yes	Yes
Year×Month×Industry	No	No	No	Yes	Yes
Year×Month×Interest	No	No	No	No	Yes
Fit statistics					
Observations	332,118	332,118	332,118	332,118	332,118
R^2	0.489	0.504	0.597	0.636	0.644
Within R^2	0.406	0.388	0.290	0.276	0.274

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

pressure compared to loans sold by other CLOs.

7 Impact on Primary Markets

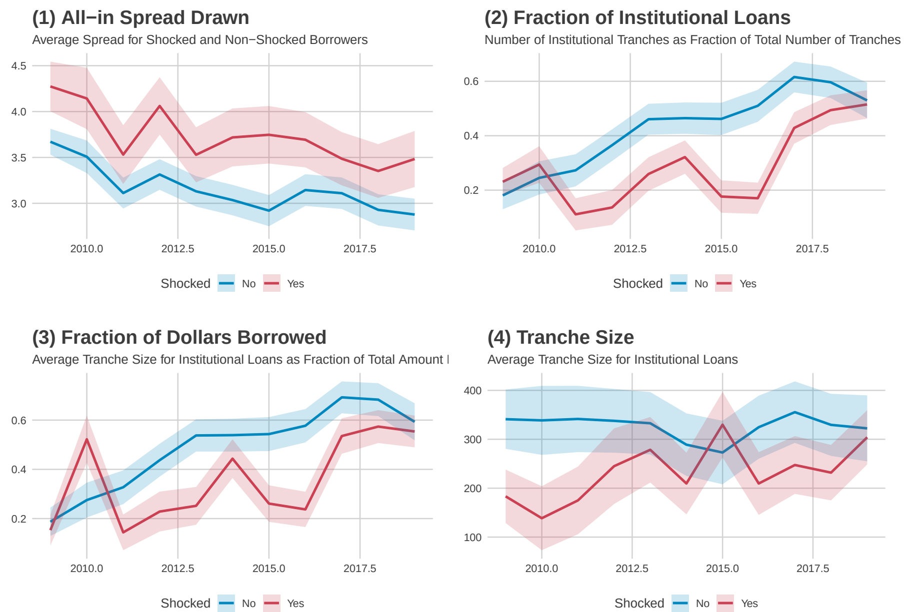
Section 6 has documented that CLOs whose loans have been downgraded to CCC, and whose OC constraints are binding, tend to sell high quality securities in order to restore the value of their tests. These sales depress the price of loans for up to seven to nine months. Section 6.1 has shown that the trading behaviour of distressed CLOs is not likely motivated by access to superior information. Finally, Section 6.2 has provided evidence that these results are specific to downgrades to CCC, hinting at the fact that these trades are indeed carried out in order to gain slack on OC tests. Overall, these results can be interpreted as evidence in favour of dislocations in the secondary market for loans unrelated to issuing companies' fundamentals and purely motivated by the mechanics of OC tests. However distortions in the secondary market might simply result in zero-sum transfers between distressed CLOs and unconstrained investors who are able to purchase high quality securities at depressed prices and, hence, have limited economic implications. That might not be the case whenever companies are forced to access dislocated markets and accept worse terms of financing compared to what they would have been able to otherwise. Testing this hypothesis is particularly challenging: firms can endogenously reduce their demand for funds or divert it towards different markets, for instance, by trying to finance themselves using corporate bonds, equities or even other types of leveraged loans that are not affected by the previously documented shocks. In this section I will provide evidence in favour of the hypothesis that companies whose loans have been sold for non-fundamental reasons face worse terms of financing in primary markets. Testing this hypothesis is particularly challenging because the demand for credit is an endogenous choice and if, as hinted above, companies whose loans have been sold by distressed CLOs tend to be of higher quality, they might endogenously demand less capital. I will attempt to tackle the issue of endogenous credit demand by adopting the two following strategies. First, I will focus on companies whose previously issued loans are due to mature in the following twelve months. As in Almeida et al. (2011), the fact that a firm is scheduled to refinance its debt in the following twelve months is the result of previous financing decisions and is, therefore, plausibly exogenous with respect to the downgrades to CCC that have affected CLOs. By focusing on this subset of firms for the treatment and control group, I will make sure that the two have roughly the same likelihood of requiring funds. Second, and more importantly, I will look at firms that do eventually refinance themselves using leveraged loans and study the composition of newly issued securities between institutional and non-institutional loans. This strategy is reminiscent of the one used by papers analysing the substitution between corporate bonds and loans in periods of distress (Adrian et al., 2013; Becker and Ivashina, 2014) and by those on the substitution between institutional and bank tranches in the syndicated loan market (Ivashina and Sun, 2011a; Fleckenstein et al., 2020). This strategy guarantees that any variation in the terms of the loan cannot be explained by company-specific factors, given that institutional and bank tranches are claims on the same assets and have identical seniority. I will document four facts: first, companies whose loans have been sold by distressed CLOs face a higher cost of capital; second, these companies are less likely to issue institutional tranches which are usually held by CLOs; third, these companies borrow less money through institutional tranches; fourth, conditional on issuing an institutional tranche, these tend to be smaller. Figure 4 provides suggestive evidence in this regards, which I will discuss in greater detail in the following paragraphs.

First I study whether the price impact in the secondary market translates into higher cost of funding in primary markets. Panel (1) of Figure 4 plots the yearly average all-in spread drawn (AISD)[15] for companies that have been affected by fire sales from distressed CLOs (in red) against other companies (in blue); both groups are in the CLO-i/SDC Platinum matched sample, guaranteeing that, at least once, their loans have been

[15]The all-in spread drawn is measured as the total annual spread including fees paid over the reference rate (usually LIBOR) for each dollar drawn from the loan. It therefore includes any fee or commission associated with the syndication process.

Figure 4 : The Outcome in the Primary Market

The figure is composed of fours panels. (1) reports the yearly average all-in spread drawn in basis points; (2) reports the fraction of institutional loans per year as the total number of institutional tranches as a fraction of the total number of tranches; (3) reports the total amount of funds raised via institutional tranches as a fraction of total amount of funds raised; (4) reports the yearly average tranche size for institutional loans. All the panels reports the statistics for shocked firms in red and for the control group in blue.



held by CLOs. In each year in the sample the cost of capital for firms whose loans have been sold in the secondary market by distressed CLOs is higher by almost 100bps. This is not surprising given the evidence in Section 6: leveraged loans are usually priced by looking at the price of comparables (Murfin and Pratt, 2018) and the price of leveraged loans of the same company traded in the secondary market represents a clear benchmark for the cost of new issues (S&P Global, 2020b). Once previous loans trade in the secondary market at a discount, it is realistic to expect that new issued loans will likely be priced taking this extra spread into account. This is even less surprising once we recall that most of the discount suffered by these loans is due to a lack of convergence towards the control group: after an initial negative shock, the discount on treated loans reduces but in a slower fashion compared to their control group, making the mispricing particularly hard to detect to an investor that is simply looking at the treated loan in isolation. The results in Figure 4 do not control for firm characteristics, which might drive the difference in AISD between the two groups. For this reason, I investigate the effect on spreads by running the following regression whose results are reported in Table 18:

$$\text{AISD}_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{13}$$

where $\text{AISD}_{j,t}$ is the all-in drawn spread for issuer j at time t and $\text{Shocked}_{j,t}$ is a dummy variable that is equal to one when firm j has been sold by distressed CLOs in the previous twelve months. Column (1) shows that the spread for shocked firms is 55bps higher compared to the control group once we include time fixed effects which help in partialling out any macroeconomic source of variation in loan spreads. Columns (2)-(4) show that the effect is robust to the inclusion of time-to-maturity, industry, rating and issuer fixed effects even though the magnitude is reduced. The effect ranges between 23.2 and 34.7 basis points when we consider time-to-maturity, industry and rating fixed effects. When we add issuer fixed effects in column (5), the magnitude is reduced to 8bps, however it should be noted that the effect is now identified from the subset of firms that have issued loans twelve months after being sold by CLOs and have been at least once in the control and at least once in the treated group, representing a small subset of the whole sample. A significant fraction of the shock documented in Section 6 is transmitted to the primary market of issuance, implying that the ex-post cost of borrowing for treated firms is higher than for firms in the control group. This can be reconciled with the idea that those firms are now facing a shock to the supply of institutional loans and are forced to resort to the next best source of funds. The rest of the section tests this hypothesis by looking at differences in the composition of borrowed funds between these two groups of companies. Panel (2) in Figure 4 compares the number of institutional tranches as a fraction of the total number of tranches issued by the two groups every year. With the exception of 2009 and 2010, the fraction of institutional tranches for shocked issuers has

Table 18 : All-in Spread Drawn

The table reports the results of the following regression: $\text{AISD}_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, $\text{AISD}_{j,t}$ is the all-in drawn spread for issuer j at time t, $\text{Shocked}_{j,t}$ is a dummy variable that is equal to one when firm j has been sold by shocked CLOs in the previous twelve months. Column (1) includes Year×Month fixed effects; column (2) adds time-to-maturity fixed effects constructed by grouping the variable in ten buckets; column (3) adds industry fixed effects; column (4) adds rating fixed effects; column (5) adds issuer fixed effects. Rating is constructed from the closest rating available for the firm. Standard errors are reported in paretheses and double clustered by Year×Month and Issuer.

	(1)	(2)	(3)	(4)	(5)
Shocked	0.550***	0.347***	0.232***	0.232***	0.084**
	(0.037)	(0.042)	(0.041)	(0.041)	(0.039)
Fixed-effects					
Year × Month	Yes	Yes	Yes	Yes	Yes
TTM	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Rating	No	No	No	Yes	Yes
Issuer	No	No	No	No	Yes
Fit statistics					
Observations	13,468	13,365	13,365	13,365	13,365
R^2	0.04806	0.06598	0.09166	0.09166	0.60933
Within R^2	0.00304	0.00121	0.00055	0.00055	7e-05

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

always been lower compared to firms in the control group, corroborating the hypothesis that companies indeed move away from institutional loans whenever they face a supply shock in favour of other types of loans. Notice that, by focusing only on firms that do eventually issue leveraged loans, we are able to fix the demand for funds and make sure that indeed the effect is driven by the supply of credit. Panel (3) provides similar evidence if we look at the total amount of funds borrowed using institutional tranches as a fraction of the total amount borrowed: after 2010 shocked firms have borrowed less capital compared to firms in the control group via institutional loans. I then proceed to test whether the fraction of institutional tranches and the amount of dollars borrowed

Table 19 : Fraction of Institutional Loans

The table reports the results of the following regression: Fraction $\text{Inst.}_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, Fraction $\text{Inst.}_{j,t}$ measures the number of institutional tranches as a fraction of the total number of tranches issued by issuer j at time t, $\text{Shocked}_{j,t}$ is a dummy variable that is equal to one when firm j has been sold by distressed CLOs in the previous twelve months. Column (1) includes Year×Month fixed effects; column (2) adds time-to-maturity fixed effects constructed by grouping the variable in ten buckets; column (3) adds industry fixed effects; column (4) adds rating fixed effects; column (5) adds issuer fixed effects. Rating is constructed from the closest rating available for the firm. Standard errors are reported in paretheses and double clustered by Year×Month and Issuer.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Shocked	-0.117***	-0.082***	-0.080***	-0.055**	-0.039*
	(0.024)	(0.024)	(0.024)	(0.022)	(0.022)
Fixed-effects					
Year×Month	Yes	Yes	Yes	Yes	Yes
TTM	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Rating	No	No	No	Yes	Yes
Issuer	No	No	No	No	Yes
Fit statistics					
Observations	13,468	13,365	13,365	13,365	13,365
R^2	0.11799	0.20027	0.20301	0.23609	0.34322
Within R^2	0.00183	0.001	0.00095	0.00047	2e-04

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

are significantly lower for treated firms by running the following regressions:

$$\text{Fraction Inst.}_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{14}$$

$$\text{Fraction Inst. }\$_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t} \tag{15}$$

where Fraction $\text{Inst.}_{j,t}$ measures the number of institutional tranches as a fraction of the total number of tranches issued by issuer j at time t and Fraction Inst. $\$_{j,t}$ measures the total amount of dollars borrowed using institutional tranches as a fraction of the total

Table 20 : Fraction of Dollars Borrowed

The table reports the results of the following regression: Fraction Inst. $\$_{j,t} = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, Fraction Inst. $\$_{j,t}$ measures the total amount of dollars borrowed using institutional tranches as a fraction of the total amount borrowed by issuer j at time t, $\text{Shocked}_{j,t}$ is a dummy variable that is equal to one when firm j has been sold by shocked CLOs in the previous twelve months. Column (1) includes Year×Month fixed effects; column (2) adds time-to-maturity fixed effects constructed by grouping the variable in ten buckets; column (3) adds industry fixed effects; column (4) adds rating fixed effects; column (5) adds issuer fixed effects. Rating is constructed from the closest rating available for the firm. Standard errors are reported in paretheses and double clustered by Year×Month and Issuer.

	(1)	(2)	(3)	(4)	(5)
Shocked	-0.113***	-0.099***	-0.092***	-0.059**	-0.055**
	(0.029)	(0.030)	(0.030)	(0.027)	(0.027)
Fixed-effects					
Year×Month	Yes	Yes	Yes	Yes	Yes
TTM	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Rating	No	No	No	Yes	Yes
Issuer	No	No	No	No	Yes
Fit statistics					
Observations	8,969	8,667	8,667	8,667	8,667
R^2	0.2085	0.23172	0.24261	0.31183	0.54704
Within R^2	0.00245	0.00195	0.00169	0.00077	0.00073

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

amount borrowed by issuer j at time t. The results reported in Table 19 and Table 20 show that shocked borrowers issue between 3.9% and 11.7% less institutional tranches, while the amount borrowed is between 5.5% and 11.3% lower after we have controlled for firm characteristics, suggesting that affected borrowers are substituting between institutional and non-institutional loans. How can we interpret this evidence? If companies finance themselves with the cheapest source of financing trying to arbitrage across different types of securities (Ma, 2019), when the supply of institutional loans shifts they might move to the next best source of funds, namely non-institutional leveraged loans. In equilibrium we should expect the cost of capital to increase, as documented in Table 18, and the quantities borrowed to decrease.

As a final test, Panel (4) in Figure 4 and Table 21 study whether companies are affected at the intensive margin on top of at the extensive, by looking at the size of institutional tranches in terms of dollars borrowed: even when they maintain access to institutional loans, treated companies tend to draw less money through CLOs. The institutional tranches of companies affected by dislocations in the secondary market are between 23.5% and 34.2% smaller compared to those in the control group. This is true even when we include issuer fixed effect, which control for the average size of loans issued by that specific borrower.

8 Conclusions

The evidence in this paper has documented that, in order to satisfy their OC tests, CLO managers engage in par building when their constraints are binding some of their loans have been downgraded to CCC. Distressed CLOs tend to purchase discounted securities and sell expensive ones. This comes at the expense of the quality of their collateral: the securities sold by distressed CLOs are safer, in terms of their rating, compared to the ones that are bought. This behaviour documented in Section 5 allows me to study the impact of the trading action of distressed CLOs. Securities sold by distressed CLOs trade at roughly 40bps discount: I show that this effect is likely causal and cannot be explained by selection on ex-ante or ex-post loan characteristics. The effect is long lasting (up to nine months) and mostly due to the failure of loans sold by distressed CLOs to recover from depressed prices. I have then provided evidence that shocks in the secondary market transmit to the primary market: companies that are due to refinance their loans are less likely to employ institutional tranches when hit by the selling pressure of CLOs in the primary market. Switching from institutional to bank tranches increases the cost of capital for these firms.

The results in the paper might inform regulators when designing constraints for in-

Table 21 : Institutional Tranches Size

The table reports the results of the following regression: $\log(\text{Inst. Tranche Size}_{j,t}) = \alpha_t + \alpha_j + \beta\text{Shocked}_{j,t} + X_{j,t}\delta + \varepsilon_{j,t}$, where $\log(\text{Inst. Tranche Size}_{j,t})$ is the logarithm of the tranche size for institutional loans measured in dollars, $\text{Shocked}_{j,t}$ is a dummy variable that is equal to one when firm j has been sold by shocked CLOs in the previous twelve months. Column (1) includes Year×Month fixed effects; column (2) adds time-to-maturity fixed effects constructed by grouping the variable in ten buckets; column (3) adds industry fixed effects; column (4) adds rating fixed effects; column (5) adds issuer fixed effects. Rating is constructed from the closest rating available for the firm. Standard errors are reported in paretheses and double clustered by Year×Month and Issuer.

	(1)	(2)	(3)	(4)	(5)
Shocked	-0.342***	-0.326***	-0.334***	-0.270***	-0.235***
	(0.111)	(0.109)	(0.106)	(0.096)	(0.077)
Fixed-effects					
Year×Month	Yes	Yes	Yes	Yes	Yes
TTM	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes
Rating	No	No	No	Yes	Yes
Issuer	No	No	No	No	Yes
Fit statistics					
Observations	5,723	5,623	5,623	5,623	5,623
R^2	0.08508	0.12548	0.15397	0.24187	0.59158
Within R^2	0.0033	0.00318	0.00341	0.00247	0.00204

Two-way (Year×Month & Issuer) standard-errors in parentheses
*Signif Codes: ***: 0.01, **: 0.05, *: 0.1*

stitutional investors: constraints based on the par value of assets might prevent investors from causing selling spirals where shocked assets are sold by distressed investors, further exacerbating the initial shock. They might, however, lead to spillovers where shocks are transmitted from troubled securities to otherwise unrelated ones through the balance sheet of institutional investors. Finding the optimal balance between the two concerns is crucial and should be the topic of further research.

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