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Active Loan Trading*

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Abstract

Using a novel dataset of leveraged loan trades executed by managers of collateralized loan obligations (CLOs), we document the importance of "active loan trades" – trades executed at a manager's discretion. More active trading increases the returns to CLO equity investors, lowers collateral portfolio default rates, and increases the manager's chances of closing a new deal. Examining the observed loan trades, we find that more active CLOs trade at better prices than less active CLOs, selling leveraged loans earlier and before they get downgraded. Our findings suggest that more active CLOs are better at anticipating deteriorations in loan credit quality.

Keywords: Active management, Collateralized loan obligations (CLOs), Market efficiency, Structured finance, Syndicated loans

JEL: G11, G12, G23, G24

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1 Introduction

Does active trading improve an asset manager's performance? We investigate this question by examining a novel dataset of leveraged loan transactions, executed by the managers of collateralized loan obligations (CLOs).

CLOs are structured investment vehicles, created by repackaging the cash flows from a pool of leveraged loans (loans in which a lead bank arranges a syndicate of lenders) into tranches with varying risk-return profiles and selling these tranches to investors. In 2018, new CLO issuance in the U.S. reached an all-time high of $125 billion, with $600 billion outstanding (Standard & Poor's, 2018). The CLO collateral manager is responsible for ensuring the quality of the pool of leveraged loans and can pursue a strategy of actively trading the leveraged loans to enhance CLO performance. This *active loan trading* is the focus of this paper.

To investigate the role of more active trading by CLO managers, we use a novel data set of transaction prices of leveraged loans reported by CLO managers. We show that the level of a CLO manager's trading activities is a strong predictor of CLO performance. More specifically, we find that more active CLO managers deliver higher returns to their equity investors than less active managers. Examining the source of this difference in performance, we find that more active managers trade at better prices and reduce losses on their loan portfolio by better anticipating rating downgrades. Our findings suggest that an important skill of more active CLO managers is to better anticipate deteriorations in the credit quality of their loan portfolio.

Despite the fact that investors who trade more incur more transaction costs (see, for example Barber and Odean, 2000), Busse, Tong, Tong, and Zhang (2018) show that more trading of professional investors in the stock market enhances their return performance. Moreover, Pastor, Stambaugh, and Taylor (2017) find that in the presence of time-varying investment opportunities in the stock market, more trading is similarly associated with higher returns, and particularly so for trading in less liquid stocks. We examine if these results carry over to the performance of CLO managers. On the one hand, the leveraged loan market is an opaque over-the-counter (OTC) market, making it difficult to identify profitable trading opportunities and to replicate the investment strategies of more successful CLO managers. Hence, it is plausible that more active CLO managers can outperform less active managers. On the other hand, investments in leveraged loans differ from stock investments because of the different risk-return profile – there is a limited upside to loan investments but a large downside risk if the credit quality of the loan deteriorates. Hence, while stock picking is a major skill of stock market investors, managing leveraged loan portfolios requires different skills.

Based on our transactions sample, we categorize a loan sale as "active" if the CLO simultaneously purchases a new loan, that is, if the loan sale is for the purpose of portfolio rebalancing. We then obtain our active turnover measure by aggregating the notional of all active sales within a quarter and dividing it by the total CLO balance in that quarter.

In a first test, we compare the performance of the most active and least active CLOs by forming portfolios based on the CLOs' active trading in the previous quarter (henceforth, we refer to a CLO's trading activity in the previous quarter as "lagged active turnover"). More active CLOs do not only generate higher returns to their equity investors but also have lower collateral default rates, suggesting that the most active CLOs are better in avoiding defaults in their loan portfolios.[1] We next use the CLO portfolios to examine other differences between more active and less active CLOs and find that more and less active CLOs differ across three dimensions. First, more active CLOs tend to have a lower equity share, suggesting that they use more leverage than less active CLOs. Second, measuring the quality of the initial loan portfolio as the fraction of loans which get downgraded within their first year, we find that more active CLOs also tend to pick better initial portfolios than less active CLOs. Finally, more active CLOs are, on average, younger than less active CLOs.

The difference in CLO age raises the potential concern that active turnover reflects the stage of the CLO lifecycle instead of managerial skill. Examining the properties of our active turnover measure, we do find that CLO trading activity decreases with CLO age and drops sharply after the CLO exits its reinvestment period. However, we also find that the variation in trading activity is higher across CLOs than over time. To distinguish our finding that more active CLOs generate higher equity payments from the impact of the CLO lifecycle or other explanations, such as performance persistence, we run panel regressions of CLO equity payments on lagged active turnover. In doing so, we control for various proxies of the CLO lifecycle, past performance, and a variety of other CLO characteristics. Even after controlling for 12 other potential drivers of CLO equity payments as well as year-quarter and closing-year fixed effects, lagged active turnover remains a significant explanatory variable for equity payments. However, active turnover becomes insignificant after controlling for manager-fixed effects, suggesting that active turnover persists across CLOs under the same manager. Examining the role of the CLO manager more closely, we show that CLOs closed

[1] Our main focus is on the CLO's returns to equity investors because tranche defaults are rare (see, for instance, Standard and Poor's, 2013), making differences in equity payments a key performance measure.

by managers whose past CLOs have higher active turnover generate better returns to equity investors. Hence, equity investors can profit from observing a manager's past active turnover to predict equity returns of a newly-closed CLO.

The robust link between trading activity and equity payments raises another question: Is a more active CLO manager more likely to close a new CLO deal? To investigate this question, we examine if a manager's probability of closing a new deal increases when the manager is more active. Running logistic regressions of new deal assignments on the manager's lagged active turnover (measured as the weighted average active trading across all CLOs under the same manager), we find that more active managers are more likely to close a new deal. This link is robust to controlling for past equity payments, default rates, and a variety of manager characteristics.

To investigate why more active CLO managers outperform, we again form three CLO portfolios, this time based on active turnover within the same quarter. Comparing the average transaction prices of the most active and least active CLOs, we find that more active CLOs earn \$5.47 (on an average transaction of \$88.60) more than less active CLOs when they sell loans and also purchase cheaper loans, although the difference of 37 cents (on a \$96.93 transaction) is small compared to the difference in sale prices. Next, comparing transaction prices of the same loan, for trades executed within the same month, we find that high turnover CLOs earn 9 cents (on a \$94 transaction) more when selling the same loan in the same month as low turnover CLOs, and pay 5 cents less (on a \$98 transaction) when purchasing the same loan in the same month. While these differences in sales and purchase prices of the same loan within the same month seem small, we estimate that they could explain up to 10% of the annual difference of \$2.2 million in equity payments between high and low turnover CLOs.

The large difference of \$5.47 for average sales prices, compared to the small difference of 9 cents for the loan-month-matched transactions, leads us to investigate if more active CLOs are better in timing the leveraged loan market by selling non-performing loans earlier. To that end, we compare transaction prices for loans traded by both high turnover and low turnover CLOs, without controlling for the timing of the transaction. We find that high turnover CLOs earn 95 cents more (on a \$94.59 transaction) on these transactions compared to low turnover CLOs. Investigating our timing hypothesis, we find that high turnover CLOs sell 111 days earlier than low turnover CLOs. In addition, when high turnover CLOs sell a loan, the loan rating is significantly higher than when low turnover CLOs sell the same loan, suggesting that more active CLOs are better at anticipating deteriorating loan conditions.

Using a panel regression, we next confirm the robustness of our finding that more active CLOs trade at better prices than less active CLOs after controlling for other factors, such as loan type, transaction size, and various CLO characteristics. We conclude by exploring the predictive power of active loan trades for credit ratings. In line with our finding that more active CLOs sell loans before they get downgraded, we show that a rating downgrade is more likely after an active loan sale, compared to a non-active loan sale.

Related Literature

Our findings suggest an inefficiency in the leveraged loan market that enables more active CLOs to outperform less active CLOs by selling loans with deteriorating credit quality early. Hence, our results contribute to an ongoing debate about whether asset managers can improve their performance by trading more. In line with Busse et al. (2018) and Pastor et al. (2017), we find a positive link between more active trading and better performance of collateral managers in the leveraged loan market. However, while "skill" for equity portfolio managers is mostly about stock picking in non-recession times (see, for example, Kacperczyk, Nieuwerburgh, and Veldkamp, 2014), we show that an even more important skill of CLO managers is to anticipate deteriorations in the credit quality of their underlying assets.

We contribute to the growing literature on CLOs (Benmelech and Dlugosz, 2009, Benmelech, Dlugosz, and Ivashina, 2012, Bord and Santos, 2015, Liebscher and Mählmann, 2017, and Peristiani and Santos, 2019) by linking the performance of CLO managers to detailed information about their leveraged loan trading. The two papers closest to our analysis are Liebscher and Mählmann (2017), who analyze the performance persistence of CLO managers, and Peristiani and Santos (2019), who find that bank-affiliated CLO managers tend to sell leveraged loans before defaults. We contribute to their findings by showing that more active trading helps predict future equity payments, even after controlling for the CLOs' past performance or the managers' bank affiliation. To the best of our knowledge, our paper is the first one to examine the impact of more active loan trading on CLO performance.

Our analysis also helps shed more light on trading in OTC markets and leveraged loans in particular. For corporate bonds, Feldhütter (2012) and O'Hara, Wang, and Zhou (2018) show that different agents trading the same bond might trade at significantly different prices. We confirm this finding in the leveraged loan market, where more active CLOs trade at significantly better prices than less active CLOs. The effects of securitization on leveraged loan prices are studied by, among others, Ivashina and Sun (2011), Nadauld and Weisbach (2012), and Shivdasani and Wang (2011). Ivashina and Sun (2011) show that institutional demand for buying leveraged loans by CLOs can increase loan prices. Nadauld and Weisbach

(2012) and Shivdasani and Wang (2011) study the influence of securitization on corporate debt and leveraged buyouts, respectively. Loan sales have been studied by Gatev and Strahan (2009) who find that banks are a primary investor in illiquid loans and by Drucker and Puri (2008) who study the link between loans' characteristics and their propensity to be sold. By examining trade-level data of leveraged loan transactions, our paper sheds more light on the secondary market for leveraged loans.

The remainder of the paper is organized as follows. We provide an overview of CLOs and leveraged loans in Section 2 and describe our data set and variable construction in Section 3. In Section 4 we study the link between CLO trading activity and CLO performance and show in Section 5 that more active CLOs trade at better prices than less active CLOs. Section 6 concludes.

2 Institutional Background

This section provides the institutional background for our analysis. After an overview of CLOs and leveraged loans, we discuss CLO managers' incentives and constraints, and the secondary market for leveraged loans.

2.1 CLOs and Leveraged Loans

Like other structured finance products, the securities issued by a CLO have a strict seniority ranking. The equity tranche takes the first losses of the underlying portfolio and the senior tranche only suffers losses if all other tranches have realized all of their losses. In the case of a CLO, the securities issued are backed by an asset portfolio comprising leveraged loans. These loans are tradable on a secondary market and allow for a manager who, besides the initial selection and purchase of the loan portfolio, purchases and sells leveraged loans throughout the CLO's lifetime. These leveraged loan transactions and their impact on CLO performance are the focus of this paper.

A leveraged loan is defined as "a syndicated loan given to a non-investment-grade company or a loan that exceeds a certain interest threshold, for instance, LIBOR + 125 basis points" (LSTA, 2013). As we can see from the definition, leveraged loans are loans to credit risky corporations.[2] In addition, leveraged loans are syndicated, meaning that a lead bank, called the arranger, organizes the loan issuance with several counterparties to raise the required volume. At issuance, the arranger searches for investors to co-finance the loan, which makes it relatively easy for CLOs to purchase leveraged loans. By contrast, selling a leveraged loan is more difficult – while the notional amount of leveraged loans outstanding is huge, there is a small secondary market for leveraged loans. Before explaining the secondary market for leveraged loans in more detail, we note that a typical CLO only invests in a small fraction of a leveraged loan: The average leveraged loan notional is approximately \$523 million (e.g. Benmelech et al., 2012) while, in our sample described in the data section, the average number of leveraged loans in a CLO portfolio is 352 and the average CLO balance of USD-denominated CLOs is approximately \$510 million.

2.2 The Manager's Incentives and Constraints

The CLO manager receives compensation from three different fees. First, a senior fee, which is around 15 basis points of the CLO balance. Usually, this fee has the highest priority in the

[2]Lower-rated corporations who need to raise large amounts of debt that exceed normal loan volumes have two financing options, issuing bonds or syndicated loans. See Denis and Mihov (2003) and Altunbas, Kara, and Marques-Ibanez (2010) for more details on this trade-off.

cash flow waterfall and is paid to the manager before interest is paid to the senior tranches. Second, a junior fee of approximately 30 basis points, which is paid if all cash flows to senior and mezzanine tranches are made and the collateral tests (described below) are met. Finally, the manager receives an incentive fee if the CLO fulfills all the criteria for the junior fees and the equity payments exceed a pre-specified threshold. The incentive fee is approximately 20% of the payment to the equity investors but can vary across CLOs. Despite this complex compensation structure, our conversations with market participants suggest that the major source of income for a CLO manager is the incentive fee.

More important than the complex compensation structure are the constraints faced by the CLO manager. As discussed before, a typical CLO invests in a large number of leveraged loans. This is because the CLO collateral portfolio must fulfill a pre-specified diversity score, avoiding concentration in specific issuers or industries and credit rating categories. Moreover, CLO managers can only invest in "eligible" assets, which are assets that are consistent with the structure of the CLO. For example, a manager of a U.S. CLO must allocate most of the collateral portfolio to USD denominated assets. In addition, a CLO manager faces a variety of dynamic constraints that can even lead to forced sales of part of the loan portfolio. We label such forced trades as "non-active trading" and discuss the dynamic constraints that can lead to non-active trading next.

Reasons for Non-Active Trading

We start by explaining three reasons for non-active trading. First, the fraction of the CLO collateral portfolio invested in loans rated CCC or below may not exceed a pre-specified threshold. Hence, if the credit quality of a CLO collateral portfolio deteriorates, the CLO manager is forced to sell some CCC rated loans. Second, the CLO's performance is monitored through a variety of collateral tests, which ensure the safety of the senior debt tranches. The most common collateral test is the over-collateralization (OC) test which measures the cushion of the par value of the CLO assets relative to the par value of the senior CLO tranche(s):

$$\frac{Asset\ Par}{CLO\ Tranche\ Par} \geq Limit, \tag{1}$$

where *CLO Tranche Par* is either the notional value of the most senior debt tranche (for senior OC tests) or the sum of notional values for several debt tranches, depending on their seniority (junior OC tests). If the test result (1) is below the limit, the OC test is breached, which forces the CLO manager to sell part of the loan portfolio and repay a fraction of the debt tranches to comply with the test limit again. Third, the simplest reason for a non-active trade occurs when a loan in the collateral portfolio matures. In that case, the manager uses the proceeds from the matured loan to invest in new loan(s).

Hence, a large amount of loan purchase could simply occur if several loans in a CLO collateral portfolio mature, while a large amount of loan sales could be an indicator of poor collateral management skill, if they are non-active sales. To ensure that a loan sale reflects a manager's view instead of being enforced to repay debt tranches, we construct a measure of *active* trading by focusing on loan sales and loan purchases that occur within a small time window. As explained in more detail later, this approach of matching a loan sale with a loan purchase ensures that a loan sale is conducted to purchase new loans instead of selling the loan to repay tranche holders.[3]

[3]While a simultaneous sale and purchase of different leveraged loans is more likely to positively influence

Finally, the CLO managers' constraints vary over the CLO lifecycle, which comprises three stages. First, during the ramp-up period (typically the first 3–6 months after issuance), the CLO manager still needs to purchase parts of the loan portfolio in this period. During this period, we expect less loan sales and therefore less active trading. Second, during the reinvestment period (which follows the ramp-up period and lasts for 3–6 years) the CLO manager can reinvest the proceeds from maturing loans and loan sales in new loans. In this period, the CLO manager faces the lowest constraints for active trading. Finally, in the amortization period (which starts after the reinvestment period), the CLO manager must dedicate most cash flows from maturing loans and loan sales to debt repayments. In this period, we expect active loan trading to be significantly lower than during the reinvestment period.

2.3 The Secondary Market for Loan Transactions

While loan purchases can be conducted in the primary market, where the CLO manager purchases part of a loan from the arranging bank, selling a loan requires finding a buyer. We next describe the process of finding a leveraged loan buyer and discuss whether a CLO manager with a reputation of anticipating deteriorations in its collateral portfolio might have informational advantages over the buyer.[4]

To get a better understanding of the secondary market for leveraged loans, we talked to

CLO performance, the CLO manager might simply sell loans with a high market value and buy loans with a lower market value but a higher principal value instead. This transaction is called "par building" and can help a CLO to avoid an OC test breach because the transaction increases the par value of the asset portfolio. In contrast to active trading based on managerial insights, it is not obvious that par building affects collateral default rates or CLO equity payments.

[4] One potential counterparty to a loan sale by a CLO would be another CLO. However, only an insignificant fraction of all loan sales in our sample can be matched to subsequent purchases by other CLOs. Hence, we need to rely on anecdotal evidence by CLO managers to understand the secondary market for leveraged loans.

several market participants and CLO managers in the U.S. and Europe. All CLO managers and market participants confirmed that dealer-banks are the main counterparty to loan sales by CLOs. The process of finding a counterparty depends on both the liquidity of the loan in question and the experience of the CLO manager. An experienced CLO manager might find an interested buy-side dealer on the phone while a less-experienced manager either needs to place a sell order with a broker (who then searches for a buyer on behalf of the CLO manager) or place a so-called BWIC (bids wanted in competition), asking many dealers for a bid. In the context of selling a leveraged loan, market participants emphasized that many loan sales by CLOs are effectively loan swaps, where a CLO immediately purchases a new loan to ensure high yields on their investments.

Given this market structure, it is not obvious if an active CLO manager has informational advantages over the broker-dealer purchasing the loan. In addition, if an active CLO manager can anticipate deteriorations in the credit quality of its loans, a dealer with the same information can have three reasons for purchasing the loans. First, the dealer might work for a buy-side client, helping the client to purchase a list of loans and not taking the loan in its own inventory. Second, the dealer might want to swap part of its own loan portfolio with the loans sold by the CLO. The dealer's reason for taking the CLO's loans (even if they are about to be downgraded) could be that the loans add some diversification benefit to the dealer's portfolio. Furthermore, it is likely that the dealer is better equipped to hold the loans, while CLOs face high penalties for holding low-rated or defaulted loans, dealers might be able to hold defaulted loans and speculate on a high recovery rate. Finally, the trading relationship with the CLO can be valuable if, for example, the dealer also acts as loan arranger and needs to find loan investors.

3 Data and Variable Construction

Our data set contains information on leveraged loan transactions conducted by CLO managers as well as the CLO structure, performance, and collateral portfolios. The data source is the Creditflux CLO-i database and we focus our analysis on the U.S. market for the period from January 2009 to December 2016, including both CLOs closed before the financial crisis (closing years 2001-2008) and after the financial crisis (closing years 2010-2016). We first describe the sample of CLOs and loan transactions used in our analysis. Afterwards, we construct our active turnover measure and examine its basic properties.

3.1 CLO Data

We apply the following four filters to the CLO-i database. First, to be included in our sample, the CLO must have both tranche information and equity payments reported in the CLO-i database. This is the minimum information necessary to understand the CLO structure and leaves us with information for 1,007 CLOs. Second, we drop 79 CLOs where we are unable to identify the equity tranche, which is important to compute the CLO's leverage ratio and annualized equity payment. Third, we remove observations where the CLO's original tranche balance deviates from the median original balance of the CLO.[5] If over 20% of the original balance observations deviate from the median, we are unable to determine the true original balance of the CLO and remove the CLO from the sample (which happened for 19 of the CLOs). In addition, because changes in the original balance are a clear mistake (they occur, for example, due to missing tranche information in a quarter), we also drop 186 year-quarter

[5] The original tranche balance is reported every quarter. A change in the original tranche balance is a reporting error that can occur due to some missing tranche information in a quarter.

observations where the original balance changes. Finally, to avoid strong outliers driving our results, we remove observations where the CLO repaid over 50% of the original balance. CLOs that have repaid more than half of their original balance, tend to report extremely high default rates and/or high equity payments. Our final sample comprises 892 CLOs.[6]

To study the impact of active loan trading on CLO performance, we focus on the payments to the most junior tranche holders, called equity payments. Panel A of Table 1 reports summary statistics of the different CLO characteristics and performance measures in our filtered database. As we can see from the table, the average annualized equity payment is 19.72% with a standard deviation of 8.30%. Because equity payments are a combination of principal repayments and returns to equity investors, these numbers are only an indirect proxy of equity tranche returns. As an alternative performance measure, we also compute each CLO's internal rate of return (IRR) by using all cashflows to equity investors and estimating the final value of the equity tranche for non-closed deals using the junior OC test (see Appendix A.2 for a detailed description of our IRR computation). As shown in Table 1, the average IRR across CLOs is 11.37% with a large standard deviation of 23.76%.

[Table 1 about here]

Despite the higher variation of IRR, the correlation between IRR and average equity payments is 39% and a regression of IRR on average equity payments reveals a beta coefficient of 1.06, suggesting an almost one-to-one link between the two numbers (Figure A.1 in the Appendix shows a scatter plot of IRR and average equity payments). Because of the strong

[6] To examine if our filtering process introduces any systematic biases, we compute median CLO characteristics after applying of the filters. As shown in Table A.1 in the appendix, none of the medians change substantially, suggesting that the filtered sample is representative of the full sample.

link between equity payments and IRRs, we follow the market convention and use the terms equity payment and equity return interchangeably.

Panel A also shows collateral default rates, which measure the percentage of defaulted loans in each CLO's collateral portfolio. The average collateral default rate in our CLO sample is 1.65%, with a high standard deviation of 4.59%. The average CLO size is $510 million and the average equity share in a CLO is 10.53%. On average, a CLO in our sample is 41.94 months old and its underlying collateral portfolio comprises 5.95% of loans rated CCC or below. Family size shows that the number of CLOs under the same manager is 12.62, on average, with a large cross-sectional variation ranging from a 10% quantile of 2.54 to a 90% quantile of 24.88. Moreover, CLOs hold, on average, 352 different leveraged loans in their portfolio and the average experience of a CLO manager, defined as the age of the manager's oldest CLO, is 101.34 months.

For a subset of CLOs, we were also able to collect information on the fee structure. Consistent with the discussion in Section 2, the median senior and junior fees are 15 basis points and 30 basis points, respectively. On average, 25% of the CLOs in our sample are under a manager who is affiliated with an investment bank (which becomes relevant when we discuss the link between our results and the findings of Peristiani and Santos (2019) in Section 4).

Finally, using information on the CLO holdings, we construct a variable that proxies the quality of the initial collateral portfolio, proceeding in three steps. First, because the typical ramp-up period lasts for three to six months, we focus on the first available holdings data six months after closing. If we do not obtain holdings within the first two years after the closing date or if the CLO closed after December 2015, we do not calculate this measure.

Second, we match the data with rating information four quarters after the reporting date of the holdings, thereby capturing rating changes for approximately 75% of the collateral portfolios. Third and finally, we compute the variable "Initial downgraded (%)" based on the CLO holdings data as the percentage of loans in the initial collateral portfolio that gets subsequently downgraded four quarters after the holding observation. As we can see from the last row of Panel A, this variable is available for a subsample of 487 CLOs and is on average 22.6%.

3.2 Transaction Data

To obtain insights into the leveraged loan trading, we also collect information on CLO collateral transactions. We observe information on the transaction type and price, the loan in question, the transaction volume, and the transaction date. The data set comprises purchases and sales made by CLOs in our filtered sample and we focus on term loans, denominated in U.S. dollars, which comprise over 90% of the transaction data sample. We remove observations with obvious reporting errors in the price (above \$120 or below \$15) or the size of the transaction (zero or negative), which predominantly occur in the early part of the sample period. Finally, 14% of the transactions have a price equal to \$100, which, according to conversations with CLO-i, is likely a default value used when the actual transaction price is not observed. We remove these observations from our sample but note that the results are robust to including transactions with a price equal to \$100.

We report summary statistics of transaction prices, trade size, loan rating, and loan maturity in Panel B of Table 1. The sample comprises almost half a million transactions with 196,312 sales and 280,612 purchases, indicating that approximately one third of the purchased loans are held until the loan either matures, gets called, or defaults. The average transaction size is \$1.06 million, ranging from a 10% quantile of \$0.13 million to a 90% quantile of \$2.45 million. Splitting these numbers into loan purchases and sales, the average transaction size is \$1.2 million and \$0.8 million, respectively (we do not report these separate numbers in the table to conserve space). The credit rating and loan maturity are available for a subsample of 245,179 and 343,870 of the traded loans respectively. The average traded loan has a rating of B+ and a time to maturity of 4.98 years. Again, splitting these numbers into purchases and sales, the loans in our sample have, on average, 5.2 years to maturity and B+ rating when purchased, and 4.5 years to maturity and a B rating when sold.

3.3 The Active Turnover Measure

In this section, we explain how we distinguish active loan trading from non-active trading, which can occur after a collateral test breach or when part of the collateral portfolio matures (see Section 2.2). First, to distinguish active from non-active trades, we identify active sales by matching the cash flows from loan sales at day τ (CF_{τ}^{Sales}) to the cash flows of loan purchases (CF_{τ}^{Purch}) executed within a 3-day window:

$$\text{ActiveSale}_{\tau,3} := \min\left(CF_{\tau}^{Sales}, CF_{\theta\in[\tau-3,\tau+3]}^{Purch}\right). \tag{2}$$

Equation 2 identifies transactions where the manager has sold part of the loan portfolio to purchase new loans. Second, we on each trading day, we compute $\text{ActiveSale}_{\tau,3}$, where we remove any previously matched purchases to avoid double-counting of loan purchases. Finally, we aggregate all active sales within quarter t and divide this figure by the total size of CLO tranches in quarter t. In summary, our measure of active turnover for a given CLO is defined as:

$$\text{ActiveTurnover}_t := \sum_{\tau \in t} \frac{\text{ActiveSale}_{\tau,3}}{CLO\ Tranche\ Par_t}. \tag{3}$$

Basic Properties of the Active Turnover Measure

Panel C of Table 1 provides summary statistics of the active turnover measure. As we can see from the table, active turnover is on average 2.44% and it varies from a 10% quantile of 0.25% to a 90% quantile of 5.21%, illustrating that there is a large variation in trading activity across CLOs. To understand whether active turnover varies mainly over the CLO lifecycle or across CLOs, we compute the average standard deviation of active turnover for each CLO (over time) and compare it to the average standard deviation of active turnover in the cross-section of CLOs. The average cross-sectional standard deviation is 2.94% and more than one percentage point higher than the average time-series standard deviation of 1.93%, suggesting that a substantial part of the variation in active turnover is driven by differences across managers.

To get a better understanding of how active turnover varies over the CLO lifecycle, Panel (a) of Figure 1 shows the median active turnover, as well as the 25% and 75% quantiles, across CLOs as a function of the CLO age, measured as the distance from the closing date. As we can see from the figure, median CLO turnover increases sharply one quarter after the closing date (when the CLOs start to exit their ramp-up period) and tends to decrease with CLO age afterwards.

[**Figure 1 about here**]

Recall from Section 2.2 that active turnover can vary over the CLO lifecycle and is likely to drop after the reinvestment period, when the CLO needs to start repaying principal on its debt tranches. Because the time between closing date and reinvestment date can vary across CLOs, the impact of exiting the reinvestment period on active turnover is not obvious from Panel (a). Hence, we next plot the median active turnover as a function of the distance from the reinvestment date instead of CLO age. As we can see from Panel (b), the median level of active turnover is stable during the CLOs' reinvestment period but drops sharply afterwards, suggesting that the level of active turnover depends on whether a CLO is in its reinvestment period or not. Hence, we will control for CLO reinvestment period in our empirical tests.

We conclude this section by examining if the level of active turnover is similar across CLOs under the same manager. To that end, we first compute the average active turnover of each CLO in our sample. Guided by Figure 1, we compute the average active turnover using only observations during the reinvestment period (i.e., removing all observations after the reinvestment date), which lowers the risk that the CLO lifecycle clouds our analysis. We then examine the link between the average active turnover of two consecutively closed CLOs by the same manager. Figure 2 shows the average active turnover of a given CLO on the y-axis (current CLO) and the average active turnover of the last CLO closed by the same manager (previous CLO) on the x-axis. The figure suggests a strong persistence in active turnover across CLOs under the same collateral manager. A new CLO by an active collateral manager is likely to exhibit a higher active turnover than a CLO closed by a less active manager.

[**Figure 2 about here**]

4 Active CLOs Perform Better

We now test the implications of more active trading on CLO performance proceeding in three steps. First, to motivate our analysis, we investigate how active turnover relates to equity payments on a quarter-by-quarter basis. Second, we test the link between active turnover and CLO equity payments in a regression setting. Finally, we examine the link between active turnover and CLO performance at the manager level, testing if a manager's past turnover predicts future performance and management assignments.

4.1 Motivating Evidence

To investigate the differences between high and low turnover CLOs, we split our CLO sample into three equally-sized portfolios, based on the quarterly active turnover measure described in Section 3.3: High turnover, where lagged active turnover is above the 66% quantile; medium turnover, where lagged active turnover is between the 66% and 33% quantile; and low turnover, where lagged active turnover is below the 33% quantile. The portfolio formation is based on the active trading measure in quarter $t-1$ and we rebalance the portfolios every quarter.

As we can see from Panel A of Table 2, there is a significant difference between active turnover in quarter t for CLOs with a high turnover in quarter $t-1$ and CLOs with a low turnover in quarter $t-1$. Moreover, annualized equity payments decrease monotonically from CLOs with high turnover to CLOs with low turnover and there is a difference of 2.20 percentage points ($t = 2.27$) between the high and low turnover groups, suggesting that high turnover CLOs outperform low turnover CLOs. To investigate whether more active

CLOs simply take on more default risk, we use the percentage of defaulted loans in the CLO collateral portfolio as a measure of the CLO's riskiness. Similarly to equity payments, default rates increase monotonically from high turnover to low turnover CLOs and the difference between the high and low turnover groups is -0.76 percentage points ($t = -5.93$), suggesting that more active CLOs are actually less risky because they are better at avoiding collateral defaults.

[**Table 2 about here**]

4.1.1 The Characteristics of More Active Managers

In Panel B of Table 2, we compare average CLO characteristics for high and low active turnover CLOs. As we can see from the table, the most active and least active CLOs are comparable across most dimensions. In particular, there is no significant difference in their original size, CCC bucket, family size, number of loans held in their collateral portfolios, managerial experience, or bank affiliation. Interestingly, there is also no significant difference in senior or junior fee between high and low turnover CLOs. One possible explanation for this insignificant difference in fees is that the major source of income for CLO managers is the incentive fee, which is proportional to equity payments, while junior and senior fees make up a very small proportion of the managers' compensation. In line with this conjecture, we observe that more active CLOs tend to have a smaller equity share, indicating that they use more leverage, thereby possibly increasing their compensation.

More active and less active CLOs differ across two additional dimenstions. First, more active CLOs are, on average, 14 months younger than less active CLOs, suggesting a potential link between active turnover and the stage of the CLO lifecycle. Because active turnover drops after the reinvestment period (see Figure 1), we examine the impact of CLO age and various stages of the CLO lifecycle in more detail in the following section.

Second, to examine if more active CLOs also pick better initial collateral portfolios, we use the variable "Initial downgraded (%)" that we constructed in Section 3 and investigate if it differs between more and less active CLOs. As we can see from the last row of Table 2, the difference in "Initial downgraded (%)" is statistically significant with high turnover CLOs having a 3.46 percentage point lower fraction of loans in their initial portfolio that subsequently get downgraded.

4.2 Regression Analysis

In this section we further investigate the relationship between lagged active turnover and CLO performance. Because equity payments are the main source of managerial compensation and the focus of most investors, we focus our analysis on equity payments and relegate tests of collateral portfolio default rates to the appendix.[7] In contrast to Section 4.1, we now estimate the impact of active turnover on equity payments using panel regressions of the following form:

$$Ret_{i,t} = \alpha_t + \beta Turnover^{Active}_{i,t-1} + \gamma_1 Ret_{i,t-1} + \gamma_2 D_i^{ClosingYear} + \gamma^{Add} Controls_{i,t} + \varepsilon_{i,t}. \quad (4)$$

[7] Recall that the cash flows of the CLO debt tranches are fixed. Moreover, Standard and Poor's (2013) notes that "since we began rating it, the CLO asset class has performed strongly, with few negative rating actions on senior notes due to underlying collateral deteriorations, few defaults, and minimal loss rates." Hence, higher returns to equity investors are the predominant way of distinguishing good CLO managers from poor CLO managers.

$Ret_{i,t}$ is the equity return of CLO i in quarter t and the main coefficient of interest is β, which captures the impact of lagged active turnover ($Turnover^{Active}_{i,t-1}$) on equity payments. To ensure that our results are not driven by performance persistence, we add lagged equity payments ($Ret_{i,t-1}$) to all specifications and confirm the robustness of our results to adding more lags in Table A.3 in the appendix. In addition, to ensure that our results are not affected by changing market conditions or CLO vintage years, we add year-quarter fixed effects (α_t) and closing-year dummies ($D_i^{ClosingYear}$) to all specifications.

As we can see from specification (1) of Table 3, the link between $Ret_{i,t}$ and $Turnover^{Active}_{i,t-1}$ is statistically significant at a 1% level, when controlling for lagged equity payments, year-quarter fixed effects, and closing-year dummies. Turning to the economic significance, a one standard deviation increase in active turnover predicts an increase of 0.5% (16.58% $\times$ 3.03%) in equity payments.

[**Table 3 about here**]

To examine the robustness of our findings, we next add a variety of controls. In specification (2), we add controls capturing the CLO lifecycle and collateral performance. More precisely, to capture the collateral performance, we control for a dummy variable, which equals one if a senior OC test breach occurred (Senior test breach dummy$_{i,t}$), and the percentage difference between the current OC test result and the level at which the OC test is breached (Senior cushion (%)$_{i,t}$). To capture CLO lifecycle effects, we control for a dummy variable which equals one if the CLO is still in its reinvestment period (Reinvest dummy$_{i,t}$), CLO age (Age$_{i,t}$), and an interaction between age and reinvestment dummy (Age$_{i,t}\times$ Reinvest dummy$_{i,t}$). Our results are robust to adding these control variables. In addition, to rule out that our results are driven by the CLO lifecycle, we confirm the robustness of our results using different subsamples, dropping the first year of observations, and using only observations before or after the reinvestment date, in column (2)–(4) in Table A.4 in the appendix.

In specification (3) of Table 3, we next control for the size of the CLO ($\log(\text{Size})_{i,t}$), the number of CLOs under the same manager (Family $\text{size}_{i,t}$), and the equity share (Equity $\text{share}_{i,t.}$). In addition, to distinguish our results from Peristiani and Santos (2019), who find that bank-affiliated CLO managers are more likely to sell prior to loan defaults, we add a dummy variable which equals one if the CLO manager is affiliated with a bank (Bankaffil. dummy_i).[8] In specification (4), we add two portfolio characteristics, the average time to maturity of the loan portfolio (Average portfolio $\text{TTM}_{i,t}$) and a measure of portfolio diversification (Portfolio $\text{diversification}_{i,t}$) as controls.[9] Again, specification (3) and (4) confirm the robustness of our finding, that is, none of the additional controls decreases the statistical or economic significance of lagged active turnover substantially.

Finally, because Figure 2 suggests that active turnover is persistent across CLOs under the same manager, we next examine if the link between CLO performance and active turnover can be attributed to the CLO manager by adding manager-fixed effects to our analysis. Column (5) of Table 3 shows that, while the impact of test breach, equity share, and portfolio diversification remains statistically significant, $Turnover^{Active}_{i,t-1}$ becomes insignifi-

[8]As an additional robustness test, we also drop all bank-affiliated collateral managers from our sample. Again, our results are robust to this additional test and can be found in column (1) of Table A.4 in the appendix.

[9]The measure of portfolio diversification is constructed as follows: First, we compute the percentage of loans within a certain industry held by the CLO. Second, we compute an Herfindahl-Hirschman Index (HHI) of the portfolio holdings (i.e. we compute the sum of squared industry percentages). Finally, we use $1 - \frac{HHI}{10{,}000}$ as our proxy for portfolio diversification, where we divide by the highest possible HHI, which is $10,000$.

cant. Phrased differently, the link between lagged active turnover and CLO equity payments breaks down after controlling for manager-fixed effects, suggesting that the variation in active turnover across managers is the predominant driver of CLO equity payments.

4.3 Future Performance and New Management Assignments

Having established that active CLOs outperform less active CLOs and that trading activity persists at the manager level, we next test if investors can profit from from investing in more active CLOs by tracking CLO managers' past activity. First, we test if the trading activity of a manager's past CLO(s) predicts the performance of its future CLOs. Second, we examine if more active CLO managers are also more likely to close a new CLO.

4.3.1 Past Active Turnover and Future CLO Performance

We start by computing the average active turnover and average equity returns for each CLO using only observations from the CLO's reinvestment period. We then regress the average equity return of a CLO (the current CLO) on the average active turnover of the last CLO closed by the same manager (the previous CLO). That is, the two CLOs are consecutively closed by the same manager. As we can see from column (1) of Table 4, there is a strong positive link between the average equity payments of a manager's current CLO and the active turnover of its previous CLO, even after controlling for the current CLO's equity share, family size, and bank affiliation, as well as the average equity payments of the previous CLO.

[Table 4 about here]

While column (1) illustrates the persistence of active turnover and performance across CLOs under the same manager, it is not a predictive analysis as the reinvestment period of the current and the previous CLO overlaps in most cases. Hence, most of the turnover observations of the previous CLO are not available at the closing date of the current CLO. To run a predictive regression from the perspective of a CLO equity investor, we repeat the analysis, replacing the average turnover and average equity payment of the previous CLO with a size-weighted average past turnover and average past equity payment, using all observations for a given manager that are available before the closing date of the current CLO. As we can see from Panel (2), past active turnover remains a significant predictor for future equity payments while average past equity returns become insignificant.[10]

Because CLO equity investors might care about other performance measures besides average equity return, we repeat the predictive analysis replacing average equity payments with two alternative performance measures – the IRR and the average *excess* equity payment, computed as the time series average of the difference between the equity payment of a given CLO in quarter t and the average equity payments of all CLOs in our sample in the same quarter. While the IRR proxies the actual return on investment, it suffers from the fact that there are some missing equity payments in our data sample. To mitigate this problem, we add the percentage of unobserved equity payments for each CLO as a control variable. The excess equity payment has the advantage that it captures the performance of an individual CLO relative to the overall market. As we can see from column (3) and (4), there is a strong positive link between past active turnover and both IRR and excess equity payments, confirming that CLO equity investors can benefit from using past trading activity as investment criterion.

[10]Using only observations that are available before the closing date of the current CLO also leads to a drop in the number of available observations. This drop in observations is partly driven by the cut-off in our sample, where we do not observe active turnover before January 2009.

4.3.2 New Management Assignments

Because more active CLO managers generate higher returns on future CLOs, we now examine if a manager with higher active turnover is also more likely to close a new deal. To that end, we define a dummy variable which equals one for manager j in quarter t if the manager gets assigned to a new deal and zero otherwise, referring to this dummy variable as "NewAssignment". Next, we construct active turnover for manager j in quarter $t-1$ ($Turnover^{Active}_{j,t-1}$) as the sum of all active sales conducted by all CLOs under manager j in quarter t, divided by the CLO tranche par value of all CLOs under manager j in quarter t.[11] We then examine the predictive power of active turnover for new assignments in a logistic regression of the following form:

$$\text{logit}(NewAssignment_{j,t}) = \alpha_t + \beta Turnover^{Active}_{j,t-1} + \gamma Controls_{j,t-1} + \varepsilon_{j,t}. \quad (5)$$

As before, we control for year-quarter fixed effects (α_t) and focus on the coefficient β, which captures the impact of active turnover on new assignments. As we can see from column (1) of Table 5, lagged active turnover does predict new assignments. A one percentage point increase in the active turnover measure increases the odds of getting a new assignment by 5.97% ($e^{0.058}-1$).

[Table 5 about here]

Next, to test the predictive power of active turnover above past equity payments or

[11] An alternative way of using a manager's active turnover to predict future assignments is to compute the average turnover using all past observations up to quarter $t-1$ instead of the most recent observation. However, the correlation between average active turnover using all past observations and using only quarter $t-1$ is 68% and using all past observations leads to virtually unchanged results.

default rates, we construct size-weighted averages (using the size of the equity tranches for equity payments and the total CLO size for default rates) on the manager level in quarter $t-1$ and add them as controls. Column (2) and (3) show that both equity payments and default rates help predict new assignments with the expected signs. However, the effect of active turnover remains almost unchanged after controlling for these variables. Finally, controlling for CLO family size, managerial experience, and the size-weighted average equity share for a given manager, column (4) confirms that the impact of active turnover on new assignments is robust to controlling for these manager characteristics.

5 The Trading Pattern of Active CLOs

In this section, we compare the transactions of more and less active CLOs and examine if differences in transaction prices can explain differences in equity payments. As in Section 4.1, we first split the overall sample of CLOs into three buckets (high active turnover, medium active turnover, and low active turnover) and use regression analyses to confirm our results afterwards.

5.1 More Active CLOs Trade at Better Prices

We first compare loan transactions by high and low turnover CLOs. As before, to get CLO portfolios with significantly different active turnover, we use the quarterly active turnover measure described in Section 3.3 and form three portfolios: High turnover, medium turnover, and low turnover. In contrast to the analysis in Section 4.1, the portfolio formation is based on the active trading measure within the same quarter. Our rationale for using the contemporaneous turnover measure in this analysis is that transactions in quarter t will affect returns in quarter $t+1$ and understanding why more active CLOs generate higher equity payments in quarter $t+1$ is the goal of this analysis.

Figure 3 illustrates that the transaction prices of high turnover CLOs differ substantially from those of low turnover CLOs. As we can see from Panel (a), more active CLOs sell more leveraged loans at or above par value while less active CLOs sell more loans with a market value of 60% and below. Panel (b) shows that the pattern is reversed for purchases, although at a smaller magnitude. Panel A of Table 6 shows the average sales and purchase prices for the three CLO categories, as well as the difference between transaction prices for the most and least active CLOs. As we can see from the table, more active CLOs, on average, sell loans at \$5.47 higher prices ($t = 5.15$) and purchase loans \$0.37 cheaper ($t = -2.54$).

[**Figure 3 about here**]

To put these differences in perspective, recall that the average sales and purchase prices are \$88.60 and \$96.93, respectively. Moreover, given the discussion in Section 2, it is not surprising that there is a larger price difference for loan sales (which are always conducted in the secondary market) than for loan purchases (which might be conducted in the primary market).

[**Table 6 about here**]

5.1.1 Conditional Tests

We next examine if loan prices for transactions of the same loan, executed within the same month, differ between more and less active CLOs. To that end, Panel B of Table 6 compares the average transaction prices for high turnover, medium turnover, and low turnover CLOs conditional on transactions of the same loan within the same month. For each loan and each month, we compute the median sale and purchase price for high, medium, and low turnover CLOs. We then use the subset of loan-months where both high and low turnover CLOs sell the same loan in the same month and report the average sale price of high turnover, medium turnover, and low turnover CLOs. We find that high turnover CLOs, on average, get 9 cents more, when selling the same loan in the same month as low turnover CLOs. For loan purchases, we find that high turnover CLOs, on average, pay 5 cents less when purchasing the same loan in the same month as low turnover CLOs. Both differences are statistically significant at a 1% level. This finding resonates with O'Hara et al. (2018), who find that less-active insurance companies sell corporate bonds at lower prices than more-active insurance companies and purchase loans at higher prices. In line with their results, our findings suggest that the effect is more pronounced for sales.

While the price differences of 9 and 5 cents (on a \$100 notional transaction) might seem small, they can have a large impact on CLO equity returns. To illustrate the potential impact on CLO equity payments, we first approximate the average difference in annual equity payments between high and low turnover CLOs as \$1.17 million ($2.2\% \times \$53$ million), using the equity return difference estimated in Table 2 and approximating the average equity share in all CLOs as \$53 million. Next, we estimate the average annual sale and purchase volumes for each CLO as \$93 million and \$195 million, respectively. Hence, assuming that the active CLOs' price advantage holds for all trades, more active CLOs earn approximately \$0.18 ($\frac{0.09}{100} \times 93 + \frac{0.05}{100} \times 195$) million more than a less active CLOs every year. This figure suggest that approximately 10% of the performance difference between more and less active CLOs can be traced back to active CLOs being able to negotiate better transaction prices.

Only a small part of the unconditional difference of \$5.47 in sales prices is linked to price differences when more and less active CLOs trade the same loans simultaneously. Hence, it is plausible that more active CLOs are also better in timing the leveraged loan market than less active CLOs by selling underperforming loans early. To test this hypothesis, we compute the median sale price, sale date, and credit rating at the median sale date for each loan sold by both more and less active CLOs. The last three rows in Panel B of Table 6 exhibit the averages of these values across loans for each turnover group.[12]

We find a price difference of \$0.95 (on a \$100 transaction) when a high turnover CLO sells the same loan as a low turnover CLO. Moreover, a high turnover CLO sells 111 days earlier than a low turnover CLO and the average numerical rating of the loans at the time they are sold is 7.4 for high turnover CLOs and 7.31 for low turnover CLOs. Though both numerical ratings correspond to a credit rating of B, there is a statistically significant difference in credit ratings for the two groups, suggesting that high turnover CLOs tend to sell loans with better ratings than low turnover CLOs. To put these numbers into perspective, recall that the average annual sale volume is \$93 million, suggesting that more active CLOs earn \$0.88 million more than less active CLOs by being better at timing sales. This difference can explain 75% of the difference in equity payments between high and low turnover CLOs.

5.1.2 Analysis on the Manager Level

As we have seen in Table 1, the average CLO manager is responsible for 12 different CLOs, which raises two potential concerns. First, industry practitioners indicated to us that several of the trades executed by individual CLOs could occur within the same family, for example,

[12]To compute the median credit rating, we convert the letter rating into numbers, where AAA corresponds to the number 23; AA- to 22; and so forth. We henceforth refer to these numbers as "numerical ratings."

when a CLO manager wants to sell the same loan in various CLOs he would first transfer the loans to one CLO to sell them as one bundle. We alleviate this concern by excluding transactions executed at a price of \$100, which is the most common price for these transactions. Second, Eisele, Nefedova, and Parise (2016) report that, for mutual funds, trades within the same fund family are more likely executed at a different price than the market price. They hypothesize that mutual fund managers use transactions within the same family to improve the performance of the family's "star fund." Hence, we next analyze whether our results remain intact if we compare CLO families instead of individual CLOs.

As for the new assignment tests in Section 4.3.2, we aggregate CLO turnover at the manager level and afterwards sort CLO managers into high turnover, medium turnover, and low turnover buckets. Panel C of Table 6 reports the results for the manager-level tests. As before, for each loan in the sample, we determine the median sale price, median sale date, and numerical credit rating at the median sale date. We find that, on average, the high turnover managers earn \$0.59 more (on a \$100 notional transaction) when they sell the same loan as a low turnover manager. Moreover, active managers sell, on average, 73 days earlier than the passive managers and tend to sell loans with a better rating. Overall, the manager level results are consistent with the individual CLO level tests: Compared to less active managers, more active managers trade earlier, at better prices, and while the loans have a higher credit rating. Hence, we can rule out that the better transaction prices are only driven by a spurious manager effect, arising, for example from managers shifting loans across CLOs.

5.1.3 The Impact of Trade Size

Because of a potential link between transaction price and transaction size,[13] we now repeat our analysis for transactions of similar size. Although CLOs execute sales at a wide range of transaction sizes, a large transaction cluster is around \$1 million. To control for transaction size, we therefore use a subset of transactions and compute the median sale price, the median transaction date, and the numerical loan rating at the median date, only including transactions with a size between \$0.9 million and \$1.1 million.

Panel D of Table 6 reports the averages numbers and suggests that the positive relation between high trading activity and favorable prices is even stronger when focusing on large transactions with a similar volume. High turnover CLOs realize \$1.19 more when selling the same loan as low turnover CLOs and sell, on average, 139 days earlier and when the loans are 0.19 notches higher rated. One possible explanation for the stronger findings is that the average transaction size for loan sales is only \$0.8 million and therefore the benefit of being more active is stronger when CLOs conduct larger transactions.

5.1.4 Controlling for CLO Characteristics

To confirm the robustness of our results, we next run panel regressions of transaction prices – separately for sales and purchases – on the active turnover measure and a number of different

[13]In the stock market, larger transactions have a higher price impact and therefore a large sale drives the price down. The opposite is true in corporate bond markets where large participants, who are typically behind the large transactions, are better negotiators and therefore capable of obtaining tighter bid-ask spreads (see, for example, Feldhütter, 2012) and higher sale prices. Hence, the transaction volume can influence the sale price, although it is not obvious in which direction.

controls:

$$Price_{k,t} = \alpha_t + \alpha_l + \beta^{Active} Turnover_{i,t}^{Active} + \beta^{TTM} TTM_{k,t}$$
$$+\beta^{Principal} \log(Principal)_{k,t} + \beta^{Rating} Rating_{k,t} + \gamma Controls_{i,t} + \varepsilon_{k,t}. \quad (6)$$

As before, we use the subscript i to indicate CLO-level variables and now use the subscript k for transaction-level variables. The three main controls in this specification are the time to maturity of the loan ($TTM_{k,t}$), the loan principal ($\log(Principal)_{k,t}$), and the current loan rating ($Rating_{k,t}$), as well as year-month fixed effects (α_t) and loan-type fixed effects (α_l). In a second specification, we control for 11 CLO characteristics discussed in Section 4.2.

[Table 7 about here]

As we can see from Table 7, active turnover is a significant explanatory variable for both sales and purchases. To interpret the coefficient on $Turnover_{i,t}^{Active}$ we note that the standard deviation of active turnover is 3.03% and, hence, a one standard deviation increase in active turnover corresponds to a \$0.35 (\$11.592 × 3.03%) increase in sale price on a \$100 notional transaction, after controlling for loan characteristics. Similarly, a one standard deviation increase in $Turnover_{i,t}^{Active}$ corresponds to a \$0.19 drop in the purchase price.

5.2 Active Trades and Rating Downgrades

Because the the results in Section 5.1 suggest that more active CLOs sell loans earlier than less active CLOs and while the loans have a higher credit rating, we now examine if active loan sales are more likely to precede rating downgrades than non-active loan sales. To that end, for each loan k and each year-quarter t, we aggregate the total sales volume and construct the variable $Active^{Frac}_{k,t}$ as the ratio between the notional of all *active* sales of loan k in quarter t and the total notional of both active and non-active sales of loan k in quarter t. We further introduce a dummy variable $Downgrade_{k,t}$ that equals one if the loan is downgraded between quarter $t-1$ and t and zero otherwise. Using these two variables, we investigate if higher $Active^{Frac}_{k,t}$ predicts rating downgrades using a logistic regression of the following form:

$$\text{logit}(Downgrade_{k,t}) = \alpha + \beta Active^{Frac}_{k,t-1} + \gamma Controls_{k,t-1} + \varepsilon_{k,t} \quad (7)$$

Column (1) of Table 8 shows the results of Regression (7) without adding controls. In this specification, increasing $Active^{Frac}_{m,t}$ from 0 to 1 (which corresponds to comparing a non-active transaction with an active transaction) implies an increase in the odds of the loan getting downgraded in the following quarter with 6.82%. We repeat the analysis adding year-quarter fixed effects, the past rating of loan k and a dummy variable that equals one if the loan has been downgraded between quarter $t-2$ and $t-1$. While the number of observations decreases due to missing rating observations in quarter $t-2$, the statistical and economic significance of $Active^{Frac}_{k,t}$ increases, now implying a 8.33% increase in the odds of a downgrade.

[Table 8 about here]

The variable $Active^{Frac}_{k,t}$ is a number between 0 and 1 and does not take the notional amount traded into account. Hence, column (1) and (2) have the shortcoming that a small active sale can lead to a $Active^{Frac}$ of one if no other trades took place, while a large amount of active sales in another quarter could lead to lower values of $Active^{Frac}_{k,t}$. Hence, we next compare the impact of aggregate sale volumes and active sale volumes on downgrade probabilities. As we can see from column (3) and (4), aggregate sale volume has no predictive power for future rating changes while the notional amount of active sales is highly significant. Taken together, Table 8 suggests that active sales are more likely to precede rating downgrades than non-active sales, suggesting that active CLO managers anticipate rating downgrades and sell before the loans are downgraded.

6 Conclusion

In this paper, we analyze the impact of active trading on the performance of collateral managers in the leveraged loan market. After constructing a measure for active portfolio turnover of CLOs, we examine the performance of CLOs with different active turnover and find that higher active turnover predicts higher equity payments and lower CLO portfolio default rates. This finding is in line with previous research on active versus passive management in the case of equities, showing that more active managers are capable of outperforming the market. However, because of the different risk-return profile of leveraged loans compared to stocks, we hypothesize that CLO managerial skill is related to anticipating the deteriorating credit quality of an underlying loan rather than picking well-performing loans. In line with this hypothesis, we show that more active CLOs trade at better prices and earlier than less active CLOs. In addition, active loan sales are more likely to precede rating downgrades than non-active loan sales.

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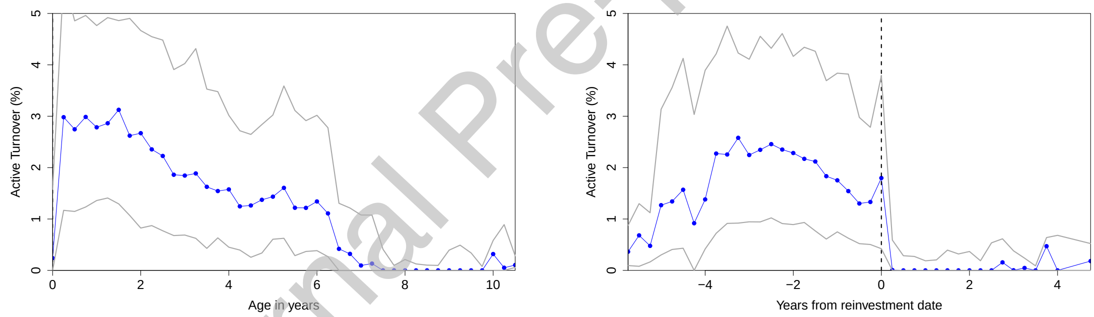
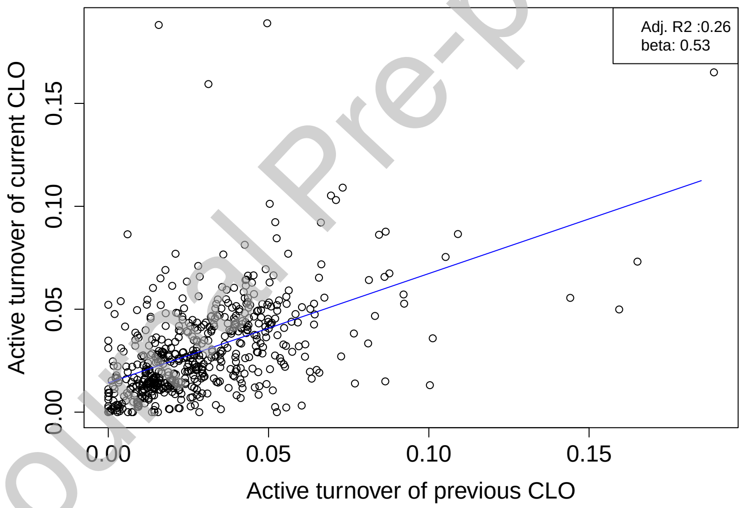
Figure 1: **Link between active turnover and CLO age.** This figure shows the median active turnover (blue line) as well as the 25% and 75% quantiles (grey lines) relative to the CLO age. In Panel (a), age is measured as years after the CLOs' closing date. In Panel (b), age is computed as the distance between the current date and the CLOs' reinvestment date.

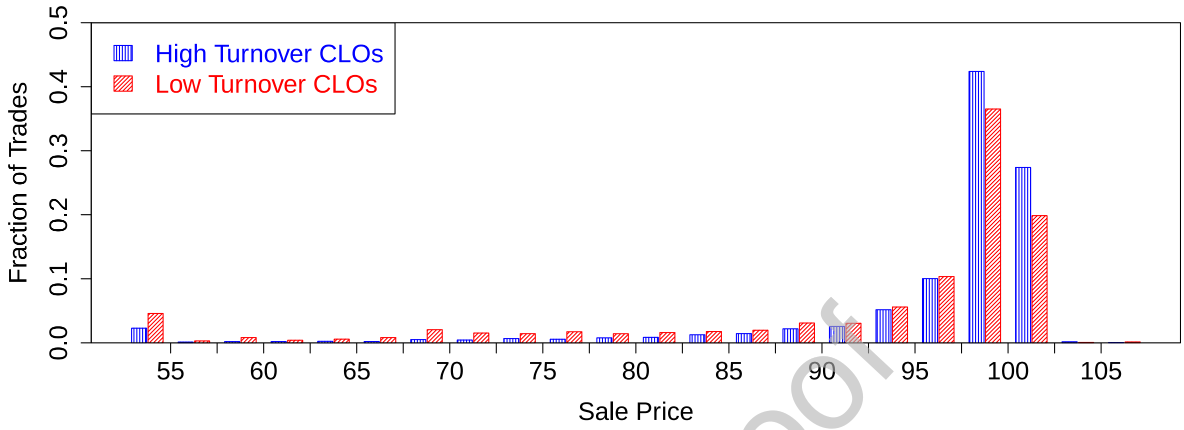


(a) Age measured in years after closing date

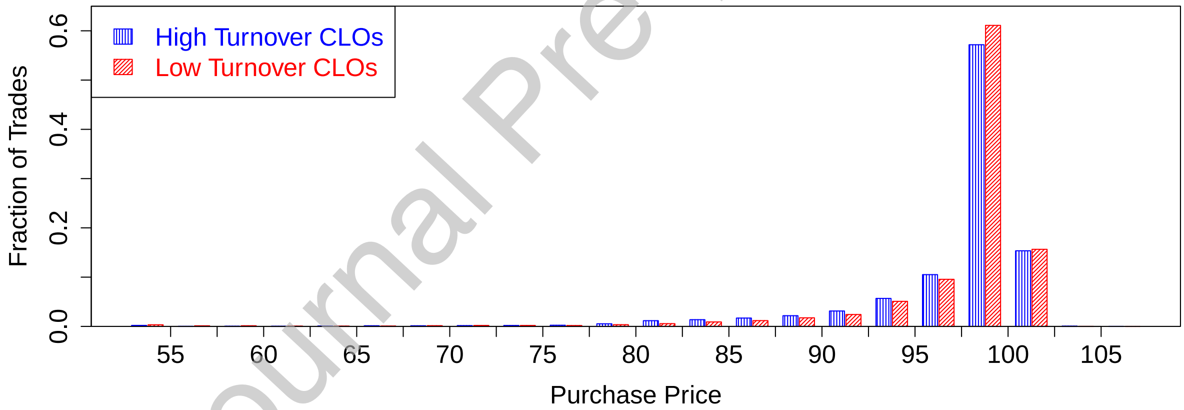
(b) Years from reinvestment date

Figure 2: **Active turnover persistence on manager level.** This figure illustrates the link between the average active turnover of a CLO (current CLO) and the last CLO (previous CLO) closed by the same manager. The average active turnover is computed using only observations during the reinvestment period of the CLO.





(a) Distribution of sale prices



(b) Distribution of purchase prices

Figure 3: **CLOs with high active turnover trade at better prices.** The figure shows the empirical distribution of the median sale price (panel (a)) and median purchase price (panel (b)), respectively. Transactions are categorized as high turnover, medium turnover, and low turnover based on the active turnover of the CLO executing the transaction, using the measure for active turnover defined in Section 3.3. For each loan we find the median high turnover and low turnover sale and purchase price over the full sample period of transactions. The sample period is January 2009 to December 2016. The sample of transactions consists of loans that are sold by both high and low turnover CLOs in this period.

Table 1: **Summary Statistics.** This table reports summary statistics of our filtered CLO and loan trade sample. Panel A reports CLO performance measures and other characteristics. Panel B reports summary statistics for loan transactions executed by CLOs in our sample. To compute the standard deviation of the loan rating, we convert the letter rating into numbers, where AAA corresponds to the number 23, AA- to 22, and so forth. Panel C reports summary statistics of the active turnover measure. We report mean, standard deviation (std), 10% quantile (10%), median, 90% quantile (90%), and the number of observations (N). In Panels A and C, we first compute CLO lifetime averages of all variables and then use these averages to compute the cross-sectional summary statistics. The number of observations in Panels A and C refer to the number of CLOs with available data. The sample period for all data is January 2009 to December 2016.

	Mean	std	10%	Median	90%	N
Panel A: CLO characteristics						
Equity return (%)	19.72	8.30	10.39	19.67	27.58	845
IRR (%)	11.37	23.76	−12.44	12.38	34.87	751
Default rate (%)	1.65	4.59	0.00	0.65	4.00	854
Original size (mill USD)	509.48	201.78	333.79	499.45	712.19	892
Equity share (%)	10.53	5.11	7.90	9.45	13.17	892
Age (months)	41.94	29.74	8.26	32.05	80.89	892
CCC bucket (%)	5.95	3.29	2.68	5.40	9.62	855
Family size	12.62	10.04	2.54	10.19	24.88	892
# Loans	352.24	187.11	158.65	318.93	602.47	854
Experience (months)	101.34	27.66	47.43	109.40	124.33	892
Senior fee (bps)	17.23	5.53	12.50	15.00	20.00	499
Junior fee (bps)	31.43	9.91	20.00	30.00	40.00	499
Bank affiliation	0.25	0.43	0.00	0.00	1.00	892
Initial downgraded (%)	22.60	9.81	13.22	19.86	38.47	487
Panel B: Loan transactions						
Sale price	94.57	12.16	83.12	99.01	100.50	196,312
Purchase price	97.36	5.48	92.50	99.00	100.25	280,612
Transaction size (mill USD)	1.06	1.41	0.13	0.69	2.45	476,924
Rating	B+	1.67	B-	B	BB	245,179
Maturity (years)	4.98	1.60	2.70	5.12	7.00	343,870
Panel C: Active turnover measure						
Turnover^{Active} (%)	2.44	2.24	0.25	1.76	5.21	848

Table 2: **Analysis of different CLO subsamples split by active turnover.** This table shows average active turnover, CLO performance, collateral default rates, and other CLO characteristics for different subsamples of the entire CLO sample. At the beginning of quarter t, the entire CLO sample is split into three portfolios based on their active turnover in quarter $t-1$. Panel A reports average turnover, equity payments and collateral default rates for the different portfolios. Panel B reports average CLO characteristics for the three portfolios. High - Low tests if there is a significant difference between high and low turnover portfolios. Newey-West t-statistics are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016.

	High Turnover	Medium Turnover	Low Turnover	High − Low	[t-stat]
Panel A: Active turnover and CLO performance					
Turnover^{Active}	0.06	0.02	0.01	0.05***	[24.52]
Equity return	23.20	22.26	21.00	2.20**	[2.27]
Default rate	1.34	1.61	2.10	-0.76***	[-5.93]
Panel B: Portfolio characteristics					
Original size	540.23	536.48	520.72	19.51	[1.44]
Equity share	9.48	9.16	9.70	-0.22*	[-2.02]
Age	44.31	50.26	59.10	-14.79***	[-2.99]
CCC bucket	6.76	6.52	6.51	0.25	[0.87]
CLO family	12.35	12.63	12.60	-0.25	[-0.56]
# Loans	385.06	408.91	376.23	8.83	[0.51]
Experience	0.55	0.50	0.71	-0.16	[-1.32]
Senior fee	17.43	17.40	17.84	-0.41	[-1.16]
Junior fee	34.33	32.52	33.60	0.72	[1.24]
Bank affiliation	0.27	0.28	0.30	-0.02	[-0.67]
Initial downgraded	29.21	30.98	32.66	-3.46**	[-2.31]

Table 3: **Higher active turnover predicts higher CLO equity returns.** This table shows regressions of annualized equity payments on the lagged active turnover measure constructed in Section 3.3 and controlling for the following CLO and CLO collateral characteristics. Reinvest dummy is a dummy variable that equals one if the CLO is still in its reinvestment period. Age measures the years since closing of the CLO. Senior test breach dummy is a dummy variable that equals one if the senior collateral test has been breached. Senior cushion measures the percentage distance between the current senior test from breaching the test. $\log(Size)$ measures the size of the collateral portfolio. Family size is the number of CLOs under the same manager. Equity share is the percentage share of the equity tranche in the overall CLO balance. Dummy Bankaffil. dummy is a dummy variable that equals one if the CLO manager is affiliated with a bank. Average portfolio TTM is average time to maturity of the loans in the CLO collateral portfolio. Portfolio diversification is the HHI index of the collateral portfolio. Newey-West standard errors, clustered at the CLO level are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016, including all CLOs from our filtered sample.

	(1)	(2)	(3)	(4)	(5)
$\text{Turnover}^{Active}_{i,t-1}$	16.59***	15.54***	14.73***	13.80***	8.14
	(3.17)	(3.38)	(3.52)	(3.59)	(5.12)
Reinvest $\text{dummy}_{i,t}$		2.12**	1.75*	1.16	1.24
		(0.91)	(0.92)	(0.85)	(0.90)
$\text{Age}_{i,t}$		0.40	0.60	0.03	0.38
		(1.00)	(0.99)	(0.86)	(0.94)
$\text{Age}_{i,t}$ × Reinvest $\text{dummy}_{i,t}$		−0.61	−0.80	−0.19	−0.43
		(1.10)	(1.09)	(0.96)	(1.00)
Senior test breach $\text{dummy}_{i,t}$		−4.49***	−4.24***	−5.17***	−2.63***
		(1.04)	(1.07)	(1.32)	(0.98)
Senior $\text{cushion}_{i,t}$		−0.09	0.12	0.12	0.21**
		(0.06)	(0.09)	(0.09)	(0.09)
$\log(\text{Size})_{i,t}$			0.96***	0.78**	0.37
			(0.31)	(0.35)	(0.45)
Family $\text{size}_{i,t}$			−1.88*	−2.42**	8.42
			(1.02)	(1.03)	(5.82)
Equity share_i			−0.18***	−0.18***	−0.21***
			(0.04)	(0.04)	(0.05)
Bankaffil. dummy_i			0.08	0.19	
			(0.29)	(0.28)	
Average portfolio $\text{TTM}_{i,t}$				0.44	1.84**
				(0.35)	(0.92)
Portfolio $\text{diversification}_{i,t}$				−3.28**	−3.95**
				(1.64)	(1.60)
Equity $\text{return}_{i,t-1}$	0.67***	0.66***	0.64***	0.63***	0.55***
	(0.07)	(0.08)	(0.08)	(0.08)	(0.09)
Year-quarter FE	√	√	√	√	√
Closing year FE	√	√	√	√	√
Manager FE	–	–	–	–	√
Adj. R^2	0.42	0.43	0.43	0.45	0.46
Num. obs.	8,032	7,497	7,497	7,412	7,412

Table 4: **Active turnover and future CLO performance.** Column (1) shows a regression of the average equity return of the current CLO on the average active turnover and average equity return of the previously closed CLO of the same manager. Column (2) – (4) show the current CLO's average equity return, internal rate of return (IRR), and average excess equity return (relative to the cross-sectional average CLO return), respectively, regressed on the average past active turnover and average past equity return of CLOs of the same manager, using only observations before the closing date of the current CLO. All specifications include the following controls for the current CLO: Equity share, Family size, Bank affiliation dummy, and closing-year fixed effects. For IRR, we also control for the amount of missing equity payments, which can lower the IRR. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016 and only includes observations before the end of the CLOs' reinvestment period.

	Equity pmt		IRR	Excess equity pmt
	(1)	(2)	(3)	(4)
$\text{Turnover}^{Active}_{previous\ CLO}$	37.70^{**}			
	(15.57)			
$\text{Turnover}^{Active}_{past}$		21.14^{**}	90.76^{**}	19.64^{**}
		(10.37)	(40.06)	(9.61)
$\text{Equity share}_{current\ CLO}$	-0.27^{***}	-0.16	-0.90	-0.21^{*}
	(0.11)	(0.11)	(0.59)	(0.11)
$\text{Family size}_{current\ CLO}$	-1.22	3.06	3.70	3.67
	(2.66)	(2.44)	(10.18)	(2.50)
$\text{Bankaffil. dummy}_{current\ CLO}$	1.52^{**}	0.17	-1.46	-0.04
	(0.66)	(0.56)	(2.18)	(0.54)
$\text{Average equity return}_{previous\ CLO}$	0.18^{***}			
	(0.05)			
$\text{Average equity return}_{past}$		0.01	0.12	-0.00
		(0.04)	(0.11)	(0.03)
Closing year FE	√	√	√	√
Additional controls	–	–	Missing pmt	–
Adj. R^2	0.28	0.09	0.14	0.13
Num. obs.	589	380	349	380

Table 5: **Higher active turnover predicts future assignments.** This table shows the results of a logit model for a CLO manager closing a new deal. The dependent variable equals one if the manager gets assigned to a new deal in quarter t and zero otherwise. All explanatory variables are calculated on the manager level and lagged by one quarter. Experience is the age of the oldest CLO managed by the same manager. See the caption of Table 3 for a description of the other variables. Standard errors are clustered at the manager level. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016, including all CLOs from our filtered sample.

	(1)	(2)	(3)	(4)
$\text{Turnover}^{Active}_{j,t-1}$	0.058^{**}	0.053^{**}	0.048^{**}	0.045^{*}
	(0.023)	(0.023)	(0.023)	(0.025)
$\text{Equity return}_{j,t-1}$		0.017^{***}	0.014^{**}	0.012^{*}
		(0.006)	(0.006)	(0.006)
$\text{Default rate}_{j,t-1}$			-0.081^{**}	-0.052
			(0.033)	(0.036)
$\text{Family size}_{j,t-1}$				0.056^{***}
				(0.008)
$\text{Experience}_{j,t-1}$				-0.028
				(0.036)
$\text{Equity share}_{j,t-1}$				-0.029
				(0.022)
Year-quarter FE	$\surd$	$\surd$	$\surd$	$\surd$
Num. obs.	2,579	2,578	2,578	2,552

Table 6: **CLOs with high active turnover trade at better prices.** We categorize transactions as high turnover, medium turnover, and low turnover based on the active turnover of the CLO which executed the transaction in Panels A, B and D, or based on the aggregate active turnover of the CLO manager in Panel C. Panel A shows the average transaction prices without matching the same loans. In Panels B–D we start with the sample of loans that are traded by both high turnover and low turnover CLOs. For each loan and for each turnover group we compute the median sale price over the full sample length, the median sale date, and numerical rating (defined in Section 5) at the median sale date. We then report averages of the median values across loans and test if high and low turnover values are significantly different. The addition (same month) indicates that we match transactions by high turnover and low turnover CLOs of the same loan executed in the same month. Panel D shows the results for a subset of transactions with a transaction size between USD 900,000 and USD 1,100,000. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016.

	High Turnover	Medium Turnover	Low Turnover	High - Low	[t-stat]
Panel A: Results without matching loans					
Sale price	94.07	91.57	88.60	5.47***	[5.15]
Purchase price	96.56	96.73	96.93	−0.37**	[-2.54]
Panel B: Results for individual CLOs					
Sale price (same month)	94.26	94.14	94.17	0.09***	[3.71]
Purchase price (same month)	97.80	97.78	97.85	−0.05***	[-6.47]
Sale price (anytime)	95.55	95.09	94.59	0.95***	[7.68]
Sale date	Jan 4, 2014	Apr 15, 2014	Apr 25, 2014	-111***	[-13.29]
Loan rating at sale date	7.40	7.34	7.31	0.09***	[4.60]
Panel C: Results at manager level					
Sale price (anytime)	95.64	95.28	95.05	0.59***	[4.39]
Sale date	Feb 6, 2014	May 9, 2014	Apr 20, 2014	-73***	[-8.18]
Loan rating at sale date	7.44	7.42	7.33	0.11***	[5.23]
Panel D: Transaction size between \$900,000 and \$1,100,000					
Sale price (anytime)	95.87	95.32	94.67	1.19***	[4.74]
Sale date	Dec 25, 2013	Jun 1, 2014	May 13, 2014	-139***	[-6.69]
Loan rating at sale date	7.59	7.56	7.40	0.19***	[3.78]

Table 7: **More active CLOs obtain better transaction prices.** This table shows regressions of sale prices (first two columns) and purchase prices (last two columns) on the active turnover measure constructed in Section 3.3, controlling for the time to maturity ($\text{TTM}_{k,t}$) of the traded loan, the loan principal ($\log(\text{Principal}_{k,t})$), and the credit rating of the loan at the transaction date ($Rating_{k,t}$), as well as several CLO and CLO collateral controls that are described in the caption of Table 3. Heteroskedasticity robust standard errors, clustered at the issuer level, are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016, including all USD leveraged loan transactions executed by the CLOs from our filtered sample.

	Sale price		Purchase price	
$\text{Turnover}_{i,t}^{Active}$	11.592***	7.578***	−6.298***	−5.611***
	(2.362)	(2.552)	(0.911)	(0.836)
$\text{TTM}_{k,t}$	0.532***	0.446***	0.273***	0.310***
	(0.163)	(0.166)	(0.046)	(0.049)
$\log(\text{Principal})_{k,t}$	0.357***	0.338***	0.344***	0.338***
	(0.119)	(0.129)	(0.052)	(0.053)
$\text{Rating}_{k,t}$	3.205***	3.219***	0.815***	0.815***
	(0.243)	(0.242)	(0.080)	(0.076)
Reinvest $\text{dummy}_{i,t}$		0.991***		−0.154*
		(0.515)		(0.103)
$\text{Age}_{i,t}$		−0.169		0.250***
		(0.280)		(0.057)
Age × Reinvest $\text{dummy}_{i,t}$		0.073		−0.222***
		(0.291)		(0.060)
Senior test breach $\text{dummy}_{i,t}$		0.903**		0.968***
		(0.998)		(0.375)
Senior cushion $(\%)_{i,t}$		2.909***		−0.123
		(1.040)		(0.393)
$\log(\text{Size})_{i,t}$		0.018		−0.381***
		(0.386)		(0.088)
Family $\text{size}_{i,t}$		−0.374		1.560***
		(0.836)		(0.312)
Equity $\text{share}_{i,t}$		0.070***		−0.008**
		(0.021)		(0.010)
Bankaffil. dummy_i		0.108		−0.462***
		(0.270)		(0.103)
Average portfolio $\text{TTM}_{i,t}$		0.472***		−0.081***
		(0.224)		(0.062)
Portfolio $\text{diversification}_{i,t}$		−0.109		−0.009
		(0.572)		(0.101)
Year-month FE	√	√	√	√
Loan-type FE	√	√	√	√
Num. obs.	134,272	122,100	194,796	172,944
Adjusted R^2	0.441	0.444	0.417	0.413

Table 8: **Active sales predict rating downgrades.** This table shows the results of a logit model predicting the probability of rating downgrade for loan k in quarter t. The dependent variable equals one if the loan rating drops from quarter $t-1$ (when we observe a sale) to quarter t and zero otherwise. $\text{Active}^{Frac}_{k,t-1}$ is the fraction of the loan sale notional that was actively sold (i.e. the portion that can be matched to a purchase within three days). Sale $\text{volume}_{k,t-1}$ is the total dollar notional sold in quarter $t-1$ (in million USD), $\text{Rating}_{k,t-1}$ is the credit rating of loan k in quarter $t-1$, and $\text{Downgrade}_{k,t-1}$ is a dummy variable that equals one if loan k was downgraded between quarter $t-2$ and quarter $t-1$. Heteroskedasticity-robust standard errors, clustered on the loan level are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016, including all sales from our filtered sample.

	(1)	(2)	(3)	(4)
$Active^{Frac}_{k,t-1}$	0.066***	0.080***		
	(0.025)	(0.030)		
Sale $\text{volume}_{k,t-1}$			−0.000	0.000
			(0.001)	(0.001)
$Active^{Frac}_{k,t-1}\times$ Sale $\text{volume}_{k,t-1}$			0.014***	0.010***
			(0.003)	(0.003)
$\text{Rating}_{k,t-1}$		0.068***		0.068***
		(0.006)		(0.006)
$\text{Downgrade}_{k,t-1}$		−0.021		−0.026
		(0.023)		(0.023)
Year-quarter FE	–	√	–	√
Num. obs.	43,794	34,317	43,794	34,317

A Additional Results and Robustness Tests

This appendix contains a variety of additional results and robustness tests that were omitted in the paper.

A.1 Additional Descriptive Statistics

In this section, we discuss the impact of the four filters on the median CLO characteristics and the amount of CLOs in our sample. After applying Filter 1, which is necessary to obtain the most basic information about the CLO, the sample comprises a total of 1.007 different deals. As shown in Table A.1, we observe the active turnover measure and the collateral default rate for 960 and 965 deals, respectively. Applying the second filter further reduces the sample size to 929 CLOs and we observe active turnover and collateral default rates for 882 and 887 deals, respectively. As we can see from the table, applying the second filter lowers the median active turnover by 0.11% and and increases the median default rate by 0.05%. Applying the third filter leaves the number of observations and the median active turnover/collateral default rate virtually unchanged.

[Table A.1 about here]

Finally, applying the fourth filter (in particular excluding year-quarters in which a CLO has repaid more than 50% of its tranche balance) increases the active turnover measure by 0.16%, lowers the collateral default rate by 0.05%, and leaves the median equity payment virtually unchanged.

A.2 Link between Equity Payments and the IRR

The equity payments in our analysis are the annualized payments to equity tranche investors, as a percentage of the equity tranche, within a quarter. These payments contain both returns on investments and principal repayments and therefore positive equity payments do not necessarily imply that investors make a profit on their investment. For closed CLOs, that is, CLOs that have repaid all their debt, we observe all cash flows to equity investors, which enables us to compute the internal rate of return (IRR). However, because our sample comprises only 225 closed deals we estimate the expected value of the remaining cashflows for non-closed CLOs. We follow Chernenko (2017) and estimate a market value of the CLOs' equity tranches at the last available period, time T. For that we use the junior OC test (defined in Equation (1)) and estimate the value of the equity tranche as

$$Equity\ Tranche_T = (OC_T^{Junior} - 1) \times TranchePar_T, \tag{8}$$

where OC^{Junior} is the result of the most junior over-collateralization test and $TranchePar$ is the par value of all debt tranches outstanding. Hence, our estimated $Equity\ Tranche_T$ captures the par value of the CLO's loan portfolio after we subtract legal claims of the debt investors.

Figure A.1, shows a scatter plot of IRR and the average equity payments of the CLOs. We see that there is a strong positive link between the two performance measures, ensuring that equity payments are a good proxy for return to equity investors.

[Figure A.1 about here]

A.3 Additional Regression Results

In this section, we first repeat our analysis from Section 4 (Table 3), replacing the equity return with the collateral default rate. Afterwards, we perform a battery of robustness checks that confirm the link between equity payments and active turnover, established in Table 3.

A.3.1 Collateral Default Rates and Active Turnover

In this section we repeat the regerssion analysis from Section 4.2, replacing the equity payments with collateral default rates. As we can see from Table A.2, the impact of lagged active turnover on collateral default rates is qualitatively similar as for equity payments as higher active turnover predicts lower collateral default rates, thereby improving the performance of the CLO. However, there are two differences worth highlighting. First, while the link between lagged active turnover and CLO equity payments was statistically significant at a 1% level in specifications (1)–(4), the link between lagged active turnover and CLO collateral default rates is less less significant. Second, controlling for manager-fixed effects does not diminish the significance of lagged active turnover for collateral default rates, suggesting that the link between the two variables is mainly driven by the time series variation.

[Table A.2 about here]

A.3.2 Equity Payments and Active Turnover – Robustness Tests

We next perform two additional robustness tests that confirm the association between lagged active turnover and CLO equity payments. First, in Table A.3, we add two more lags of the CLO equity return as control variables. In addition, we add a junior test breach dummy to our regression analysis. The dummy variable equals one if there is a test breach in the junior

OC test and zero otherwise. Adding these additional controls lowers the amount of available observations by approximately 20% but leaves the statistical and economic significance of our results intact. If anything, there is a small increase in the lagged active turnover coefficient.

[**Table A.3 about here**]

Second, to rule out that our results are driven by bank-affiliated CLO managers or by the CLO lifecycle, we examine the impact of lagged active turnover on equity payments for different subsamples of the CLO database. In column (1) of Table A.4, we drop CLOs that are affiliated with banks, which leads us to exclude approximately 28% of the observations. To avoid effects from the CLO ramp-up period, we exclude observations during the first year after the closing date in column (2). In column (3) and (4) we examine the subsample of observations during the CLOs' reinvestment period or after the CLOs' reinvestment period. The link between lagged active turnover and CLO equity return remains significant in all subsamples.

[**Table A.4 about here**]

Table A.1: **Summary statistics for filtered and unfiltered sample.** This table provides an overview how median CLO characteristics change after applying our four filters to the database. As in Table 1, we first compute CLO lifetime averages of all variables and then use these averages to compute the median. Filter 1 requires that we have the tranche information and equity payments of the CLO. Filter 2 requires that we are able to determine the original size of the CLO. Filter 3 requires that we are able to determine an equity tranche. Filter 4 only use data of CLOs when they have repaid less then 50% of the original balance.

	Filter 1		Filter 2		Filter 3		Filter 4	
	Median	N	Median	N	Median	N	Median	N
Turnover^{Active} (%)	1.68	960	1.57	882	1.60	871	1.76	848
Equity return (%)	–	–	–	–	19.69	875	19.67	845
Default rate (%)	0.67	965	0.72	887	0.71	875	0.65	854
Original size (mill USD)	–	–	485.65	929	491.38	910	499.45	892
Equity share (%)	–	–	–	–	0.10	910	0.09	892
Age (months)	33.54	1007	34.53	929	33.27	910	32.05	892
CCC bucket (%)	5.33	966	5.33	888	5.33	876	5.40	855
Family size	10.45	1007	10.29	929	10.28	910	10.19	892
# Loans	291.67	965	289.65	887	291.87	874	318.93	854

Figure A.1: **Comparison between IRR and average equity payments.** This figure illustrates the link between the IRR and the average equity return during the CLO reinvestment period. For CLOs that are not closed yet, we estimate the value of the last available observation of the junior OC test.

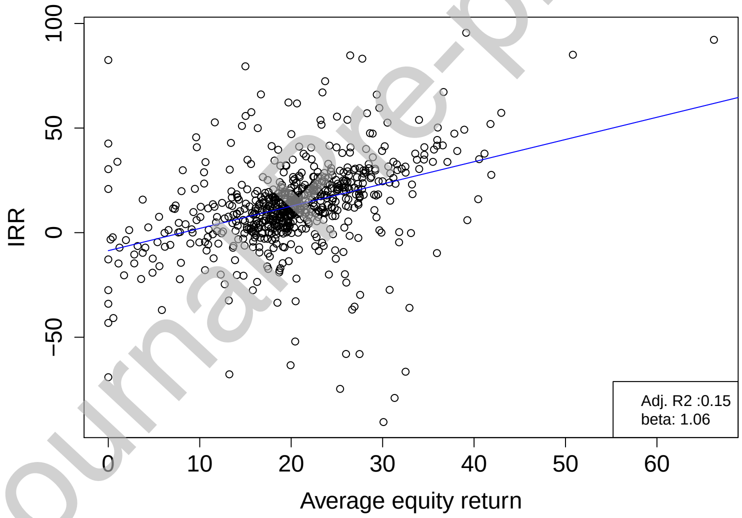


Table A.2: **Higher active turnover predicts lower CLO collateral default rates.** This table shows regressions of collateral default rates on the lagged active turnover measure constructed in Section 3.3 and controlling for the CLO and CLO collateral controls specified in the caption of Table 3. Newey-West standard errors, clustered at the CLO level are reported in parentheses. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016, including all CLOs from our filtered sample.

	(1)	(2)	(3)	(4)	(5)
$\text{Turnover}^{Active}_{i,t-1}$	-1.84^{**}	-1.42^{*}	-2.07^{**}	-1.98^{*}	-2.04^{**}
	(0.86)	(0.84)	(1.03)	(1.17)	(0.94)
Reinvest $\text{dummy}_{i,t}$		0.18	0.19	0.23	0.24
		(0.18)	(0.18)	(0.18)	(0.18)
$\text{Age}_{i,t}$		0.37^{**}	0.37^{**}	0.40^{**}	0.39^{**}
		(0.18)	(0.18)	(0.18)	(0.18)
$\text{Age}_{i,t}$ × Reinvest $\text{dummy}_{i,t}$		-0.37^{**}	-0.38^{**}	-0.41^{**}	-0.38^{**}
		(0.18)	(0.18)	(0.19)	(0.19)
Senior test breach $\text{dummy}_{i,t}$		2.44^{***}	2.36^{***}	2.43^{***}	1.97^{***}
		(0.86)	(0.82)	(0.78)	(0.51)
Senior $\text{cushion}_{i,t}$		0.44	-0.16	-0.14	-0.06
		(0.53)	(0.51)	(0.53)	(0.70)
$\log(\text{Size})_{i,t}$			0.41^{**}	0.42^{**}	0.09
			(0.18)	(0.17)	(0.12)
Family $\text{size}_{i,t}$			-0.69^{*}	-0.69^{*}	-2.10^{***}
			(0.40)	(0.40)	(0.75)
Equity share_{i}			0.06^{***}	0.06^{***}	0.04^{***}
			(0.02)	(0.02)	(0.01)
Bankaffil. dummy_{i}			0.02	0.02	
			(0.06)	(0.06)	
Average portfolio $\text{TTM}_{i,t}$				-0.03	-0.13^{***}
				(0.06)	(0.05)
Portfolio $\text{diversification}_{i,t}$				-0.06	-0.02
				(0.12)	(0.15)
Default $\text{rate}_{i,t-1}$	0.71^{***}	0.71^{***}	0.68^{***}	0.68^{***}	0.53^{***}
	(0.14)	(0.16)	(0.16)	(0.16)	(0.18)
Year-quarter FE	√	√	√	√	√
Closing year FE	√	√	√	√	√
Manager FE	–	–	–	–	√
Adj. R^2	0.54	0.59	0.60	0.60	0.62
Num. obs.	8,478	7,916	7,916	7,849	7,849

Table A.3: **Higher active turnover predicts higher CLO equity returns.** For a detailed description of the variables see the caption of Table 3. In addition to the control variables from Table 3, this regression specification also includes two additional lags of past performance and a junior test breach dummy. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016.

	(1)	(2)	(3)	(4)	(5)
$\text{Turnover}^{Active}_{i,t-1}$	17.91***	15.98***	15.63***	14.26***	9.72*
	(3.22)	(2.98)	(3.16)	(3.12)	(5.50)
Reinvest $\text{dummy}_{i,t}$		3.37***	3.11***	2.25**	2.41***
		(0.95)	(0.95)	(0.90)	(0.90)
$\text{Age}_{i,t}$		1.33	1.51	0.73	0.96
		(1.12)	(1.12)	(0.93)	(1.06)
$\text{Age}_{i,t}$ × Reinvest $\text{dummy}_{i,t}$		−1.50	−1.69	−0.90	−1.02
		(1.22)	(1.22)	(1.04)	(1.07)
Senior test breach $\text{dummy}_{i,t}$		−0.12	−0.34	−1.26	0.17
		(0.78)	(0.84)	(1.27)	(0.80)
Senior $\text{cushion}_{i,t}$		−0.09	0.06	0.07	0.12
		(0.07)	(0.08)	(0.09)	(0.09)
Junior test breach $\text{dummy}_{i,t}$		−6.44***	−6.26***	−6.46***	−6.01***
		(0.69)	(0.67)	(0.68)	(0.71)
$\log(\text{Size})_{i,t}$			0.89***	0.77**	−0.16
			(0.29)	(0.33)	(0.52)
Family $\text{size}_{i,t}$			−0.88	−1.37	4.63
			(1.08)	(1.08)	(6.13)
Equity share_i			−0.13***	−0.13***	−0.20***
			(0.03)	(0.04)	(0.05)
Bankaffil. dummy_i			−0.04	0.04	
			(0.30)	(0.30)	
Average portfolio $\text{TTM}_{i,t}$				0.54	1.50
				(0.43)	(1.03)
Portfolio $\text{diversification}_{i,t}$				−2.96*	−3.44**
				(1.60)	(1.57)
Equity $\text{return}_{i,t-1}$	0.55***	0.51***	0.50***	0.49***	0.45***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Equity $\text{return}_{i,t-2}$	0.19**	0.18**	0.18**	0.18**	0.16*
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Equity $\text{return}_{i,t-3}$	0.06	0.08	0.07	0.06	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Year-quarter FE	√	√	√	√	√
Closing year FE	√	√	√	√	√
Manager FE	–	–	–	–	√
Adj. R^2	0.46	0.48	0.48	0.50	0.51
Num. obs.	6,445	5,862	5,862	5,808	5,808

Table A.4: **Higher active turnover predicts higher CLO equity returns.** For a detailed description of the variables see the caption of Table 3. This table shows the results for different subsamples of the filtered CLO sample. Panel (1) shows the results without bank-affiliated CLO managers. Panel (2) shows the results excluding observations within the first year after the closing date. Panel (3) shows the results exluding all observations after the reinvestment date. Panel (4) shows the results excluding all observations before the reinvestment date. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2009 to December 2016.

	(1)	(2)	(3)	(4)
$\text{Turnover}^{Active}_{i,t-1}$	12.80**	13.18***	8.06**	33.78***
	(5.14)	(3.64)	(3.87)	(10.39)
Reinvest $\text{dummy}_{i,t}$	0.84	1.23		
	(1.12)	(0.86)		
$\text{Age}_{i,t}$	0.45	0.08	−0.11	−0.99
	(1.06)	(0.86)	(0.10)	(0.91)
$\text{Age}_{i,t}$ × Reinvest $\text{dummy}_{i,t}$	−0.41	−0.16		
	(1.18)	(0.97)		
Senior test breach $\text{dummy}_{i,t}$	−4.83***	−4.99***	−3.83***	−6.58
	(1.26)	(1.32)	(1.17)	(5.25)
Senior $\text{cushion}_{i,t}$	0.10	0.11	6.69**	0.03
	(0.10)	(0.09)	(3.34)	(0.13)
$\log(\text{Size})_{i,t}$	0.23	0.71**	0.79**	0.85
	(0.50)	(0.35)	(0.35)	(0.66)
Family $\text{size}_{i,t}$	−1.52	−2.22**	−2.51***	−1.71
	(1.46)	(1.01)	(0.82)	(2.91)
Equity share_i	−0.16***	−0.17***	−0.24***	−0.19**
	(0.05)	(0.04)	(0.03)	(0.09)
Bankaffil. dummy_i		0.17	0.49***	−0.79
		(0.28)	(0.17)	(0.95)
Average portfolio $\text{TTM}_{i,t}$	1.67	0.43	1.05***	0.31
	(1.04)	(0.34)	(0.25)	(0.62)
Portfolio $\text{diversification}_{i,t}$	−4.40*	−3.13*	−1.99**	−5.76
	(2.30)	(1.61)	(0.93)	(4.09)
Equity $\text{return}_{i,t-1}$	0.60***	0.66***	0.69***	0.49***
	(0.10)	(0.08)	(0.04)	(0.17)
Year-quarter FE	√	√	√	√
Closing year FE	√	√	√	√
Exclude	Bank affil.	First year	After reinvest	Before reinvest
Adj. R^2	0.39	0.46	0.75	0.14
Num. obs.	5,292	7,204	5,466	1,946

Author Contribution Section

All authors contributed equally to the completion of this paper.

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