Private Equity Debt Investors

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Abstract

We provide an economic rationale for the expansion of private equity (PE) groups into the business of private debt investing. We argue and show empirically that combining PE with private debt provides dual benefits for the parent entity. On the one hand, in the primary loan market, the parent uses its debt management division as a source of cheap funding for the PE funds' portfolio companies which boosts the funds' equity returns. On the other hand, there is information spillover from the PE to the debt division, enabling the debt manager to profitably trade on this information in the secondary loan market. Our results suggest that PE firms with affiliated debt management arms benefit from competitive advantages relative to their single-market peers.

Keywords: Syndicated loans, private equity, private information, information diffusion, conflicts of interest.

JEL Classification: G11, G14, G23

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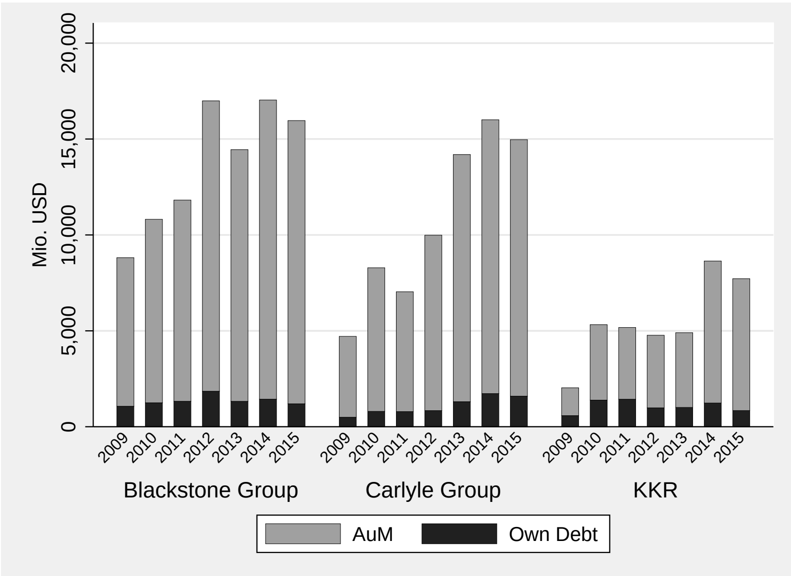
1 Introduction

The recent past has witnessed a new trend on Wall Street: the joint operation of private equity (PE) and *private debt* divisions within the same asset management group. Specifically, either through the acquisition of existing collateralized loan obligation (CLO) management firms or through the foundation of debt management divisions, a large number of some well-known PE firms are expanding into the institutional leveraged loan market. Blackstone, Carlyle or KKR, for example, now rank among the top 10 CLO managers after entering this market as their traditional LBO business waned at the start of the new decade. In our sample, the Blackstone Group nearly doubled its CLO assets under management (AuM) over the period from 2009 to 2015, reaching a record value of almost 16 billion USD at the end of 2015 (see Figure 1). Similar patterns can be found for Carlyle and KKR, and numerous other PE firms.[1]

Figure 1: This figure shows end of year CLO AuM (gray bars) for three large private equity affiliated debt managers (Blackstone, Carlyle, KKR) in our sample. The black bars indicate the portion of the portfolio that is invested in affiliated debt. Equity securities have been removed from the sample before building the chart.



This new trend has gone almost completely unnoticed by academic research and regulatory authorities, despite its potential implications for the functioning of the LBO market and the market for leveraged loans. One major concern comes from the possibility that being part of

[1] Canderle (2016) calculates the private debt (including CLO) related AuM of the seven largest *listed* alternative asset managers for the year 2015 as: Apollo (110 billion USD), Ares (75 billion USD), Blackstone (>80 billion USD), Carlyle (25 billion USD), Fortress (17.5 billion USD), KKR (20 billion USD) and Oaktree (>80 billion USD). Including non-listed managers, he estimates the AuM of traditional PE firms in private debt to significantly exceed 500 billion USD. Furthermore, PE groups grow their private debt business at an annual rate of 20% to 40% in recent years, much higher than the growth rates they experienced in their traditional LBO activity. Consequently, at Apollo, for example, debt went from 25% of total AuM in 2007 to 68% in 2014. Similarly, for Blackstone the increase is from 12% to 25%, and from 17% to 26% for KKR.

the CLO business gives PE firms the opportunity to provide (or "manage") the debt financing for their *own* LBO deals.[2] In fact, Figure 1 suggests that own debt investments by PE-affiliated CLOs might be a common phenomenon. Using again Blackstone as an example, over the period 2009–2015, CLOs affiliated with this entity hold on average about 9.9% (or 37 million USD per CLO) of their AuM in debt instruments (loans and bonds) issued by companies owned by Blackstone's PE division. The corresponding average own debt investments by Carlyle and KKR CLOs are 10.5% (42 million USD) and 17.7% (72 million USD), respectively. Against this background, we address the following two questions in this paper: *Do PE-affiliated CLO managers exhibit a preference for affiliated investments?* And if yes, *what is the mechanism that drives this preference?*

Because the observation of own debt investments is just a necessary, but not a sufficient condition for establishing own debt preferences, we start with a series of tests to check whether such preferences exist. All of our tests attempt to control for factors that might lead to a spurious finding. For example, if PE-affiliated CLO managers prefer, for some unidentified reasons, loans or borrowers with particular characteristics, and these traits happen to be more prevalent among borrowers owned (or "sponsored") by their parent's PE entity, then it will appear as if CLO managers prefer own debt investments, when in fact no such preference exists.

We begin with a standard benchmark portfolio approach commonly used in related settings (e.g., Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005). Basically, we compare the fraction of the portfolio nominal that a PE-affiliated CLO ("treatment") holds in a given quarter in debt instruments sponsored by its parent's PE firm to the average percentage that three matched control (i.e., unaffiliated) CLOs hold in the same group of borrowers. We refer to the deviation from the benchmark (the matched sample) as the *Own Debt Bias* (henceforth – ODB). If treatment and control CLOs differ only with respect to the PE-affiliation, then the ODB is an unbiased estimate of own debt preferences. For the 83 PE-affiliated CLO managers in our sample, we were able to construct 23,805 matched pairs at the CLO-quarter level. Using these matched pairs, we find that PE-affiliated managers purchase more debt from borrowers sponsored by their parent's PE division than other unaffiliated CLOs. On average, they invest an additional 1.8% of their AuM into these instruments, which amounts to roughly 7 million USD per CLO. The benchmark portfolio approach, however, underestimates own debt preferences in situations when no affiliated debt instruments are on the market (are investable). We address this limitation in two ways. First, we calculate a conditional version of the ODB by restricting the sample to matched pairs where one of the CLOs (treatment or controls) hold at least one loan or bond affiliated with the treatment manager. This way, we hope to isolate quarters during which affiliated instruments are likely part of the investable universe for the treatment

[2] A paper by Fang et al. (2013) compares LBO deals of bank-affiliated and stand-alone PE groups. The authors differentiate bank-affiliated deals into those that are partially financed by the parent bank, and those who are not. We complement this work by showing that for stand-alone PE deals "parent-financing" is also possible through affiliated CLOs.

CLO. Under this condition, the mean ODB amounts to 2.7% (11 million USD), and the median is 1.5% (5.8 million USD).

Second, we refer to a dyadic analysis based on the "potential dyad" approach (Lin and Viswanathan, 2016). Here, we match to each realized debt purchase of a CLO manager all hypothetical alternatives available to her at the time of the investment decision. We find the odds for a purchase to be 36% higher for affiliated bonds or loans relative to comparable but unaffiliated debt instruments. Furthermore, own debt preferences appear to be particular strong whenever there is no previous lending relationship between the CLO and the borrower.

Finally, we use M&A activity in the CLO market to strengthen the causal interpretation of our results. In particular, we exploit the fact that after a CLO is taken over by a(nother) PE-affiliated manager, part of the CLO's investment universe changes its affiliation status. Importantly, such movements are unlikely to be associated with changes in borrower characteristics, thereby generating exogenous variation in affiliation. Our quasi-experiment verifies the existence of significant own debt preferences. The average ODB almost triples from 1 to 3% within the twelve quarters following the takeover.

Having confirmed the existence of own debt preferences among PE-affiliated managers, we aim to identify the economic rationale underlying this phenomenon. We focus on a rational story and argue that the ODB emerges as the result of a cross-division subsidization strategy applied by the parent entity to maximize overall revenues.[3] This strategy intends to generate dual benefits for the parent. On the one hand, in the primary loan market, the parent uses its CLO management division as a source of cheap funding for the PE fund's portfolio companies. Lower cost of debt for portfolio companies, in turn, boost PE funds' equity returns, and consequently, the parent's PE AuM, fees and carried interest.[4] We call this the *funding (or price) support* channel. On the other hand, there is private information spillover from the PE to the CLO division, enabling the CLO manager to profitably trade on this information in the secondary loan market. This is the *information advantage* channel.[5]

[3]See Bhattacharya et al. (2013) and Gaspar et al. (2006) for evidence on cross-fund subsidization strategies ("favoritism") applied by mutual fund families.

[4]General partners (GPs) of PE funds benefit from higher fund returns in two ways: Directly through carried interest and indirectly through the effect of current fund performance on GPs' abilities to raise capital for future funds.

[5]Anecdotal evidence in line with the funding support channel can be found in a Creditflux article (Kadiri, 2016) covering Highland Capital Management. According to the article "*Highland's private equity arm was attempting to buy a South American manufacturer, but did not have the funds available. In order to raise cash, it is alleged that Highland founder Jim Dondero proposed that loans to portfolio companies that he owned be extended, thereby providing him with liquidity. These loans are ultimately held by Highland's CLOs, which were due to pay down. Josh Terry (a former Highland CLO portfolio manager) says that Highland has not acted in the best interest of its CLO investors by attempting to extend the deal's loans.*" Besides, anecdotal evidence also points to information spillover effects. For example, in an Wall Street Journal interview (see Tan, 2014), Brian Sheth, one of the two founders of Vista Equity Partners, was asked the question:"*You've got a debt fund, Vista Credit Opportunities. Does it invest alongside your equity fund?*" He replied: "*We've made 35 investments across 21 companies. Of those [investments], only six are not affiliated with Vista and three are Vista minority investments. We've got unique insights on how these companies are managed and how credit should be priced.*"

We start our investigation of the funding support channel by introducing a novel proxy for the total cost of borrowing (the *effective spread*) that explicitly allows for the fact that a large number of institutional leveraged loan facilities is issued at a discount to par (*original issue discount* — OID). While previous research on loan pricing relies almost exclusively on the *All-In-Spread-Drawn* (AISD), we argue and provide supporting evidence that the AISD alone is an incomplete and likely misleading measure of borrowing cost.[6] In our sample of 3,106 institutional loan facilities from DealScan, the AISD underestimates effective borrowing costs by more than 22 basis points (bp) on average, and the bias even exceeds 75 bp for 5% of the facilities.[7]

We then proceed by regressing the effective spread at issuance on the facility amount funded by affiliated CLOs and on an extensive set of control variables. The endogenous matching of borrowers and CLO lenders is addressed in two ways. First, the amount of funding provided by *unaffiliated* CLOs is included as a right-hand-side variable. This way, we control for omitted time-varying and/or facility-level factors driving both spreads and overall CLO demand. Second, we run instrumental variable (IV) regressions and instrument affiliated funding by the expected aggregate funds available for investments to all CLOs affiliated with the facility in question ("affiliated dry powder"). The regression results verify that affiliated price support is significant: a one standard deviation increase in the amount of affiliated funding is associated with 4 bp (for OLS) and 13 bp (for 2SLS) lower spreads, conditional on controls. These numbers increase to 25 bp and 47 bp, respectively, when we replace the affiliated funding amount by a dummy variable differentiating between facilities that have at least one affiliated lender, and those without. We estimate that the lower spreads and the resulting annual interest cost savings for the PE portfolio companies translate into higher equity returns for PE fund investors of up to 2.5%, an economically significant number in view of the generally low risk-adjusted performance of PE investments (at about 3% annually according to Harris et al., 2014).

Next, we turn to the information advantage channel. Our tests of informed trading by PE-affiliated CLO managers in the secondary loan market comprise two parts. We first look at round-trip trades in affiliated and unaffiliated facilities. We adjust *realized (net) price returns* of round-trips for general market conditions by subtracting the contemporaneous price return of the Leveraged Loan Index from the raw trade return. The baseline results indicate that affiliated round-trips outperform their unaffiliated peers by between 2.8–4.1% in terms of annualized excess returns, conditional on facility and trade-level controls. In addition, the average CLO manager generates an additional return of 3.3-4.2% per year from her affiliated investments relative to her unaffiliated trades. Furthermore, affiliated trades outperform unaffiliated trades

[6] The AISD is defined as the sum of the spread over LIBOR or EURIBOR plus the facility fee.

[7] Berg et al. (2016a) note that upfront fees and the OID are conceptually the same. These authors further report that upfront fee information is largely missing in DealScan and that this deficiency is likely non-ignorable. Since we do not rely on DealScan data to calculate the OID, our research is not subject to any shortcomings resulting from DealScan's limited coverage of upfront fees.

in the *same* borrower by 2.2-2.6% per year. These findings demonstrate that PE-affiliated CLO managers have substantial timing and facility selection abilities with respect to affiliated borrowers. CLO managers appear to earn excess returns in their affiliated trades as compensation for information they may acquire through a PE link. Consistent with this view, the gains from affiliated investments are larger among information-sensitive (e.g., low priced or risky) facilities for which the value of private information is highest.

In a second set of tests, we focus on buy-and-hold trades, i.e., facility purchases for which we do not observe subsequent sales. We find that affiliated purchases by the average manager outperform the same manager's unaffiliated purchases by 13–22 bp in terms of effective spreads earned per Dollar and year of investment. We also show that these higher effective spreads are unlikely to be a pure compensation for higher ex post default risk. These findings suggest that managers are better able to identify *undervalued* affiliated facilities relative to similar but unaffiliated ones. In sum, all of our results from round-trip and buy-and-hold trades imply a strong informational link between PE-affiliation and investment performance. For our sample, we estimate the total monetary benefits of informed trading by affiliated CLOs in the secondary loan market to be about 51.6 million USD a year, 46.8 million from round-trip trades and 4.8 million from buy-and-hold trades.

Our paper contributes to the growing body of literature on conflicts of interest in the financial services industry. In particular, we add to the literature on informational spillover effects between different business units within the same group. Consistent with the information advantage hypothesis, Massa and Rehman (2008) find that bank-affiliated U.S. mutual funds overweight lending clients' stock around new loan announcements and that this strategy has a *positive* effect on fund performance in the short term. Other papers reporting evidence of informational spillover and informed trading in equity markets include Bodnaruk et al. (2009), Bushman et al. (2010), Ivashina and Sun (2011b), and Massoud et al. (2011).

In contrast, Ferreira et al. (2017) and Hao and Yan (2012) document a significant *underperformance* of bank-affiliated mutual funds, and show that this underperformance is positively related to investments in client stocks. A reason might be that banks sacrifice fund performance and try to support their client stock prices for the sake of additional lending business. Further evidence in line with the funding support hypothesis comes from Golez and Marin (2015) who show that bank-affiliated funds support the prices of their parent stock and Gil-Bazo et al. (2017) who argue that bank-affiliated funds stand in for their parent bank's bond issues after the onset of the 2007–2008 global financial crisis and during the European sovereign debt crisis.

We differ from this work by not testing the funding support channel *against* the information advantage channel, but instead argue that both channels can act hand-in-hand to generate dual benefits for the parent entity. We also differ in that we focus on syndicated loan (and not equity or bond) investment decisions of business units affiliated with PE groups (not commercial banks). We therefore make important contributions in terms of the markets and data analyzed.

Specifically, while most other studies rely on publicly traded companies, we shed light on the much less covered market for non-listed firms. Moreover, to the best of our knowledge, we are the first to study how PE information translates into activities on the syndicated loan market, a market that is – compared to the equity market – much less known but more important in terms of size.

2 Data and variables

While PE firms utilize different vehicles to conduct their expansion into the field of private debt, CLOs are among the most important. Essentially, a CLO is similar to a managed[8] closed-end fund that invests primarily in the institutional segment of the leveraged loan market and to a lesser extent into high-yield bonds.[9] These investments are financed through the issuance of several debt and (one or two) equity tranches.

Our major data source covering the European and U.S. CLO markets is Creditflux's CLO-i.[10] CLO-i provides detailed information on CLO portfolio compositions and trading activity. This data is collected from monthly trustee reports that are sourced from CLO managers and investors alike. Although these parties report voluntarily to CLO-i, we believe a selection bias is unlikely to be present due to investors strong incentives to report about bad-running CLOs. In line with this argument, Liebscher and Mählmann (2017) do not find any indication for an overrepresentation (underrepresentation) of good (bad) performing CLOs in CLO-i. Importantly, once CLO-i processes a trustee report the *full* sample of trades and holdings in this month is added to their data.[11] Of course, CLO-i does not give a complete picture of the CLO market – neither in the time-series nor in the cross-section. Since CLO-i started covering the market in mid 2008 they tracked a growing number of CLOs but always relied on sources with interest in the CLO. In cases where an investor or manager missed sending out a trustee report to CLO-i the panel exhibits gaps. Moreover, there are cases where the CLO-i team uploaded a trustee report but did not copy trades and holdings into the respective data tables. To fill these gaps to the best possible extent we manually add data whenever we get hands on a trustee report that has not been processed. Figure IA.1 in the Internet Appendix provides an insight into the depth of our sample, in terms of trading activity (monthly number of trades) and CLO portfolio

[8] A smaller fraction of the CLO market is not actively managed (balance sheet CLOs). These CLOs are not part of our study.

[9] Under the Volcker Rule CLOs that do not only hold loans are regarded as "covered funds". Because banks are prohibited to invest in these kind of funds CLOs renounce from bond investments nowadays. However, our sample also covers pre-Volcker Rule CLOs whose portfolios consist of bonds to a notable extent.

[10] Several recent papers use the same database, see for example Benmelech et al. (2012), Liebscher and Mählmann (2017) and Loumioti and Vasvari (2016). Liebscher and Mählmann (2017) also detail important institutional features of CLOs and provide a discussion of coverage and selection bias issues potentially associated with CLO-i.

[11] Holdings are currently only available on their html-sites. That's why we build a little scraper to download these files (program available upon request). Trade data is downloadable as a spreadsheet-file though.

observations. As can be seen, coverage climbs strongly during the year 2008 and remains high thereafter. While we cannot benchmark the trade figures to publicly available data sources covering the overall market, we can compare the portfolio volume of U.S. CLOs in our sample to the USD-denominated outstanding CLO volume as published by the Securities Industry and Financial Markets Association (SIFMA). Using this data as a benchmark, we estimate that over the period 2009Q1 to 2015Q4 our sample has an average (median) coverage of 53% (52%).[12]

To classify CLO loan (or bond) investments as either affiliated or unaffiliated, we follow two steps. In a first step we determine whether a particular CLO management firm is affiliated with a PE firm. We use information from Fitch Ratings (2014), CLO manager websites and prospectuses downloaded from CLO-i to determine the ultimate parent of the CLO manager, and we take particular care of the dynamic nature of this relationship. Next, we have to determine whether and during which period a borrowing firm is part of a PE fund's portfolio. We term such borrowers that are owned by PE firms (financially- or PE-) *sponsored* borrowers and name the loans granted to them *sponsored* loans. To identify sponsored loans, we rely on the DealScan variable *Sponsor* that contains the name of the PE investor, if any, holding the borrower's equity at the time a loan is issued. Then, for each borrower-sponsor combination we register the start and the end date of their relationship using the issuance date of their first loan (*FacilityStartDate*) and the minimum of the latest maturity date (*FacilityEndDate*) for this borrower-sponsor combination and the earliest issuance date of a loan of the same borrower with another sponsor. Loans and bonds are then classified as affiliated if a PE firm under the same control as the CLO manager is the sponsor at the time the instrument is held (or traded). The resulting link between the sponsor and the affiliated debt manager is best illustrated using an example. In our holding data we observe the portfolio composition of Race Point VII – a CLO managed by Sankaty. Sankaty is the name of the debt management arm of Bain Capital. Consequently, all loans in the portfolio of Race Point VII that are granted to borrowers in Bain Capital's equity portfolio are tagged as affiliated. One of these borrowers is BMC Software. This business software maker was taken private by a group led by Bain Capital and Golden Gate Capital in early 2013.[13] Race Point VII held a loan of BMC Software as of January 2014. We therefore set the *Affiliation* dummy to one for this particular loan-CLO-date observation (see Figure 2).

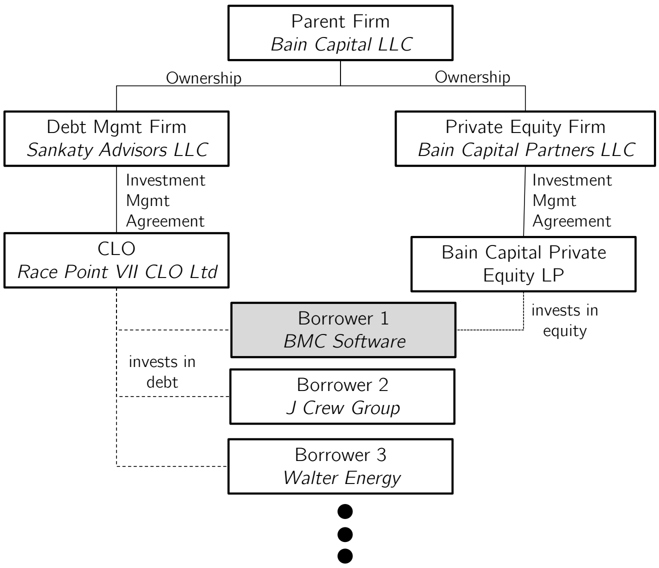
Overall, we detect 83 PE-affiliated CLO management firms which manage 742 CLOs. Of these, 480 CLOs invest in 449 affiliated borrowers. With respect to the trading data we are able to identify 6,330 affiliated trades (2,909 purchases, 3,421 sales) within a sample of 504,915 transactions (315,650 purchases, 182,935 sales).

In several of our analyses below, we rely on an extensive set of loan characteristics as con-

[12]The SIFMA data can be downloaded from http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/SF-US-ABS-SIFMA.xls?n=47606. In this data arbitrage and balance sheet CLOs are aggregated suggesting that our estimate of the sample coverage is rather conservative.

[13]http://www.reuters.com/article/us-bmcsoftware-offer-idUSBRE9450F520130506.

Figure 2: This figure illustrates the definition of *Affiliation*. A private equity sponsor (Bain Capital) of a borrower (BMC Software) is related to a debt management firm (Sankaty) that invests into debt of the borrower via its CLO.



trol variables. Since CLO-i contains only limited loan-level information, we match facilities in CLO-i to DealScan using a multi-step approach, which is detailed in the Internet Appendix. This matching procedure results in 5,113 DealScan matched *sponsored* facilities traded by (affiliated or unaffiliated) CLOs in our sample. 4,826 have non-missing spread information and of these facilities, 662 (from 297 different borrowers) are affiliated, i.e., they exhibit at least one investment by an affiliated CLO. Recall that our sample is restricted to sponsored borrowers because, for an affiliation to exist at all, a borrower has to be sponsored (owned by a PE firm). In Table 1 we present summary statistics for the 662 affiliated and 4,164 unaffiliated facilities.

Before discussing the numbers in Table 1, we want to highlight two important points that represent unique advantages of our setting compared to former studies that look at either institutional participation in the leveraged loan market or, more broadly, at loan pricing. First, we believe our CLO-i vs. DealScan match, while manually cumbersome, offers the invaluable benefit of providing a wider and cleaner look into the lending activity of CLOs than DealScan alone. Other studies that investigate the role of institutional investors like CLOs in leveraged loans (e.g., Benmelech et al., 2012; Lim et al., 2014) rely solely on the information provided by DealScan to identify lenders in the syndicate. However, the lender composition seems incomplete in DealScan and underrepresents CLOs. The main reason for this incompleteness and the likely bias in DealScan's institutional loan share information is based on the fact that for the majority of loans, DealScan collects this information from regulatory filings that normally contain only the names of the lead underwriters/arrangers of the loan package. Hence, non-lead underwriter institutional investments are systematically missing. This is important in our context since

CLOs are never lead arrangers of loan packages.[14]

Second, a voluminous literature in finance looks at loan pricing by taking the DealScan variable *All-In-Spread-Drawn* (AISD) as a proxy for total borrowing costs (see Berg et al. (2016a) and Berg et al. (2016b) for recent notable exceptions). One important underlying assumption is that loans are issued at par. However, the summary statistics shown in Table 1 indicate that the *Price at Issuance* is usually below 100. Indeed, the mean price across the whole sample of 3,106 facilities for which we observe purchase prices in the primary market is 99.1, significantly lower than 100. This implies an average price discount of 90 bp. Moreover, the median price is 99.5 and about two thirds of sample facilities are priced below 100. Price discounts can even become extreme. For example, 10% of facilities are priced at a discount of 200 bp and more! Looking only at the AISD would severely underestimate borrowing costs in these cases. Finally, the cross-sectional standard deviation in price discounts (or premiums) is large at about 82 bp. The main takeaway here is that one cannot ignore the price when studying total costs of borrowing, at least not for institutional leveraged loans. This has long-since been recognized by practitioners. They usually add the price discount (called OID – original issue discount – in market jargon) to the spread by assuming an effective maturity for the loan (usually fixed at four years). We follow their approach and define a variable *Effective Spread* exactly this way:

$$\text{Effective Spread} = \text{AISD in \%} + \underbrace{(100 - \text{price})/4}_{OID} \tag{1}$$

Hence, for the average facility yearly effective borrowing costs are 22.5 bp (over four years) higher than implied by the AISD.

Comparing the two subsamples presented in Table 1, affiliated facilities show a 41 bp lower mean AISD although having a similar default risk in terms of ratings (B2 on Moody's scale). The table already offers a couple of explanations for this. For instance, affiliated facilities are on average larger (870 vs. 448 million USD) and larger facilities typically have lower spreads (e.g., Bharath et al., 2011; Jiang et al., 2010). Also, relationship variables might play a role. In particular, prior research finds borrowers benefit from lower spreads if they have a stronger relationship with their lead arranger (Bharath et al., 2011), when the sponsoring PE firm brings more volume to the lead arranger's books (Ivashina and Kovner, 2011), or has a higher market share (Demiroglu and James, 2010). Constructing relationship variables in a similar fashion, we find that affiliated facilities are associated with stronger relationships across all three dimensions.

[14] Our finding of this institutional participation misrepresentation in DealScan is backed by the observation that according to the LSTA, roughly 60% of leveraged loan issuance is financed through CLOs but only a small fraction of sponsored loan facilities in DealScan have a lender in the syndicate classified as CDO (including CLOs), Hedge Fund or other institutional investor ($< 8\%$). Furthermore, Ivashina and Sun (2011b) report that the average loan amendment agreement shows eight more entities than the original syndicate according to DealScan, which is probably the result of an incomplete collection of lender information in DealScan.

Table 1: This table presents summary statistics for DealScan matched facilities in our CLO trading data. A facility has to be “sponsored” to be eligible for inclusion in our sample. The sample is further split into affiliated and unaffiliated facilities. The affiliated sample comprises all facilities that have at least once been purchased by a CLO affiliated with the borrowing company – either at the primary or the secondary market. All variables are measured as of the issuance of the facility. As measures of dispersion we report the standard deviation (sd) as well as the median absolute deviation (mad). We test the null hypothesis of no differences in means (medians) between the two subsamples with the corresponding p-values reported in parentheses. All variables are detailed in Appendix A.1.

	Unaffiliated			Affiliated			Difference	
	N	mean (sd)	p50 (mad)	N	mean (sd)	p50 (mad)	mean (p-val.)	p50 (p-val.)
Panel A: Facility characteristics (metric)								
AISD	4,164	396.2	375.0	662	354.9	350.0	-41.2	-25.0
		(150.5)	(100.0)		(115.3)	(75.0)	(0.000)	(0.000)
Effective Spread	2,619	439.6	425.0	487	387.0	375.0	-52.6	-50.0
		(153.8)	(100.0)		(116.3)	(62.5)	(0.000)	(0.000)
Price at Issuance	2,619	99.1	99.5	487	99.3	99.5	0.3	0.0
		(1.7)	(0.5)		(1.0)	(0.5)	(0.000)	(0.010)
Facility Amt	4,160	448.4	270.4	662	870.1	465.6	421.7	195.1
		(644.2)	(158.0)		(1,249.9)	(333.9)	(0.000)	(0.000)
Maturity	4,114	5.0	5.1	655	4.9	5.2	-0.1	0.1
		(1.6)	(1.2)		(1.7)	(1.3)	(0.237)	(0.520)
# Syndicate Members	4,164	4.8	4.0	662	6.7	5.0	1.9	1.0
		(5.5)	(2.0)		(10.4)	(2.0)	(0.000)	(0.000)
# Facilities	4,164	1.8	2.0	662	2.8	2.0	0.9	0.0
		(1.2)	(1.0)		(2.4)	(1.0)	(0.000)	(0.000)
S&P PD	2,403	6.0	5.8	475	5.7	5.8	-0.2	0.0
		(5.7)	(0.0)		(3.6)	(1.3)	(0.240)	(0.561)
Moody’s PD	2,384	7.2	7.2	473	7.1	7.2	-0.1	0.0
		(4.9)	(2.5)		(3.8)	(2.5)	(0.802)	(0.824)
Panel B: Related party characteristics								
5yr Lead-Borrower-Vol	4,164	729.3	98.5	662	1,625.5	362.9	896.2	264.4
		(1,711.3)	(98.5)		(3,389.9)	(362.9)	(0.000)	(0.000)
5yr Lead-Sponsor-Vol	4,164	6,789.9	1,825.1	662	18,736.4	15,449.5	11,946.5	13,624.3
		(11,335.6)	(1,825.1)		(16,114.4)	(11,111.5)	(0.000)	(0.000)
5yr Sponsor Market Share	4,164	1.4	0.6	662	3.4	3.4	2.0	2.8
		(1.8)	(0.5)		(2.2)	(1.7)	(0.000)	(0.000)
Panel C: Binary variables								
Institutional Facility	4,164	87.6%		662	91.4%		3.8%	
							(0.002)	
Credit Line	4,164	3.8%		662	2.0%		-1.8%	
							(0.003)	
LBO/SBO	4,164	37.3%		662	41.5%		4.2%	
							(0.041)	
Performance Pricing	4,164	9.4%		662	17.5%		8.1%	
							(0.000)	
US	4,164	51.7%		662	57.9%		6.2%	
							(0.003)	
Secured	4,164	94.3%		662	95.8%		1.5%	
							(0.080)	

Prior aggregate transaction volume between the lead arranger and the borrower respectively the PE sponsor is much larger for affiliated facilities (average difference of 0.9 and 11.9 billion USD, respectively) than for facilities of unaffiliated borrowers. In addition, PE sponsors of affiliated facilities are of higher reputation (past five-year market share among sponsored facilities is on average 2% higher). We control for these various relationship channels potentially driving down the spreads of affiliated facilities when we run our multivariate analyses. Moreover, Carey and Nini (2007) and Berg et al. (2016b) report significant cross-market (U.S. vs. Europe) differences in the pricing of term loans. This type of regional market segmentation might also be important for our sample of sponsored facilities since affiliated facilities are 6% more likely to be issued in the U.S. market.

Concerning the overall sample a few final notes are in order: CLOs do not only invest in LBO or SBO loans. Loans of this type do account for a mere 38% of the sample. This indicates that in addition to their importance for the LBO market, CLOs finance a range of other "corporate purposes". In other words, although we rely on buyout data to identify the sponsor-borrower relation we do not restrict ourselves to a pure sample of LBO loans. Furthermore, credit lines as defined in Berg et al. (2016a) are almost non-existent in our sample. The primary facilities bought by CLOs are institutional loan facilities (i.e., term loans B, C, and D). For this reason, we do not treat credit lines different in our analysis and abstain from making any assumptions about the amount drawn.

3 Do CLO managers exhibit a preference for own debt?

3.1 Benchmark portfolio approach

We now address our first research question: *Do PE-affiliated CLO managers tilt their portfolio towards loans from affiliated borrowers?* As a starting point we use a benchmark portfolio approach and measure the preference for own debt by the deviations from this portfolio. However, in contrast to mutual funds CLOs do not "trade against" a prespecified benchmark portfolio. Moreover, with the bulk of investments taking place at the issuance date of the CLO the benchmark portfolio would also have to consist of loans available at this point in time. We therefore use a non-parametric approach and match CLOs of the "treatment" group (manager is affiliated with a PE sponsor) with CLOs whose manager has no affiliation with this particular sponsor. For any treatment CLO-quarter we match three controls from the same quarter and CLO vintage year but managed by a different management company. We additionally control for portfolio size and investment style (approximated by the average portfolio default risk and the percentage of the portfolio nominal invested in USD).[15] We then calculate the fraction of

[15]This matching approach has the additional benefit that it does not require the calculation of the overall market share of loans sponsored by a given PE group. Using this overall market share of loans as a benchmark is probably misleading because it might not necessarily represent a PE firm's share of loans which are investable

the portfolio nominal that the treatment CLO invested in debt instruments sponsored by the affiliated PE firm. Finally, we compare this figure to the average percentage that matched CLOs hold in the same borrowers. We refer to the deviation from the benchmark (the matched sample) as the *Own Debt Bias* (ODB in what follows).

The matching procedure results in 23,805 matched pairs of CLO-quarters. Roughly one third of these show a zero weight on affiliated loans in both groups. Nevertheless, because the distribution of the ODB is positively skewed the mean ODB is a significant 1.8% as can be seen in Table 2, Panel A, first row.[16] In view of the evidence presented in Figure 1, readers might be concerned about the potentially impact of a handful of large managers like Blackstone, Carlyle, and KKR. To address this issue, we run robust regressions yielding a smaller ODB estimate of 0.4%. As another way to confine the impact of the positive skewness in the distribution of the ODB we estimate the median ODB (instead of the mean). Here the zero-inflation in our sample results in an ODB equal to zero.

Table 2: This table presents ODB estimates for a sample of CLOs whose management company also has a private equity arm (affiliated CLO). For each of these CLOs quarterly observations are matched to three quarters of unaffiliated CLOs that have been issued in the same year as the "treatment" CLO and are similar in terms of percentage invested in U.S. dollar securities, average default risk as measured by ratings and portfolio size. We normalize all three variables and choose the three CLO quarters for which the Euclidean distance is minimal. That is, for each affiliated CLO quarter i we search CLO quarters j that minimize $\sum_k (x_{i,k} - x_{j,k})^2 \ \forall \ i \neq j$. For each j to be matchable, we require $|x_{i,k} - x_{j,k}| < 0.2$ (caliper matching). The ODB is than computed as the difference between the percentage of the portfolio notional that the treatment CLO invests in borrowers affiliated with the CLO manager minus the average percentage that the control CLOs invest in loans and bonds of these borrowers. Standard errors are double-clustered (Cameron et al., 2011) at the quarter and affiliated manager level when using OLS and in a Huber (1967) like fashion for the quantile regressions.

Procedure	Estimate	p-value	N
Panel A: No Restriction			
OLS	1.80%	0.001	23,805
Robust Regression	0.40%	0.000	23,805
Median Regression	0.00%	1.000	23,805
Panel B: $\%CLO^{Aff} > 0$ *or* $\%CLO^{Unaff} > 0$			
OLS	2.74%	0.000	15,610
Robust Regression	1.66%	0.000	15,610
Median Regression	1.48%	0.000	15,610
Panel C: $\%CLO^{Aff} > 0$			
OLS	3.26%	0.000	14,001
Robust Regression	2.04%	0.000	14,001
Median Regression	1.82%	0.000	14,001

What if we take the 0 minus 0 differences as a sign that no affiliated loan or bond was part of the investable universe – neither for the treatment CLOs nor for the controls? To see how this would affect our estimates we rerun our analysis for the subsample of differences where one

for CLOs. Focusing only on realized benchmark portfolios (which are by definition investable) circumvents this problem.

[16]Histograms for each of the panels in Table 2 are available in the Internet Appendix.

of the CLOs (treatment or controls) hold at least one loan or bond affiliated with the treatment manager. A priori, there is no obvious direction in which the results should turn. In particular, there is no obvious reason why the ODB estimates should increase. Yet, as it turns out in Panel B of Table 2 the ODB is indeed much larger than in Panel A if we apply this restriction. Throughout, the null hypothesis of the ODB being zero is rejected at the 1% level suggesting that part of the small(er) ODB from Panel A might be explained by a lack of investable affiliated debt instruments.

In Panel C we estimate a conditional version of the ODB, namely the deviation from the benchmark weight in case the treatment CLO holds more than one loan or bond issued by any affiliated borrower. Compared to the former results we find an unsurprisingly larger ODB between 1.8% and 3.2%.[17] We interpret the results in Table 2 as support for the existence of a positive ODB for the aggregate sample. In order to identify the sources of this finding more precisely we now switch from the macro to the micro level and look at the ODB on an individual manager basis.

Table IA.3 in the Internet Appendix displays the full list of average ODBs for all 83 PE-affiliated CLO managers. Looking at this list unveils a large cross-sectional variation with the difference between the lowest (-1.9% for TCW) and the highest average ODB (11.4% for KKR) being an astonishing 13%. What are likely first-order explanations for this degree of variation? We suspect a larger PE business broadens the universe of affiliated investment opportunities, and thereby the scope for own debt preferences to materialize. This implies a positive correlation between the size of a group's PE business and the corresponding average ODB. Investigating this prediction, we find that for seven of the top 10 managers with the largest PE business, according to Private Equity International's (PEI) May 2015 ranking, the ODB is more than twice the overall mean (1.8%) and highly statistically significant (see Table 3). Moreover, the Spearman correlation between a manager's PEI rank and the average ODB is 0.58, further verifying the assumed association.[18]

[17] A context for evaluating the magnitude of own debt preferences can be found in related research. For example, Gil-Bazo et al. (2017) analyze Spanish mutual funds between 2000 and 2012. They find that bank-affiliated mutual funds invest on average *0.06%* (or 2.3 million EUR per bond issue) more of their AuM into their parent bank's bonds than other unaffiliated funds. This number increases to *1.11%* when parent debt also includes short term paper and term deposits, and the analysis is restricted to the post-crisis period 2008Q1 to 2012Q2. In addition, Ferreira et al. (2017) investigate an international sample of actively managed domestic equity mutual funds in the 2000-2010 period. They report commercial bank-affiliated funds hold on average 14.7% of their total net assets in stocks of firms for which their parent bank acted as a lead arranger in syndicated loans over the past three years. The corresponding mean "lending client bias" is *5.9%*, compared to passive funds that track the same benchmark.

[18] The correlation coefficient is computed using only the 30 managers that we are able to find in the PEI 300 report.

Table 3: This table presents the average ODB for the ten CLO managers with the largest PE business according to the May 2015 ranking of Private Equity International. Managers are ranked as per their five-year-fundraising total. The p-values are computed using the wild clustered bootstrap t procedure (Cameron et al., 2008) at the quarter level to mitigate the problem of a small number of clusters.

PEI Rank (2015)	Manager	# CLO-Quarters	ODB	p-value
1	Carlyle Group	566	6.3%	(0.000)
2	TPG	16	5.0%	(0.000)
3	KKR	138	11.4%	(0.000)
4	Blackstone (incl. GSO after 3/2008)	818	5.1%	(0.000)
5	Apollo Global Management	260	-1.6%	(0.000)
6	CVC Capital Partners	326	4.7%	(0.000)
10	Sankaty (Bain Capital)	168	4.9%	(0.000)
12	Partners Group	10	1.8%	(0.000)
17	Permira	20	5.8%	(0.000)
22	Ares	399	1.2%	(0.000)

3.2 Dyads approach

While the benchmark portfolio approach is well established in the field of financial economics, especially in research studying geographic preferences of investors (e.g., Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005), it neglects potential alternatives available to investors at the time of their investment decision. This weakness of the portfolio approach might lead to an underestimation of own debt preferences for periods when there are no affiliated facilities available on the market. To address this issue we apply an alternative *potential dyads* approach (Lin and Viswanathan, 2016) where we identify all possible pair-wise combinations between facilities and CLOs trading at a given point in time.

More specifically, we build the sample for this analysis by extracting all purchases of affiliated CLOs from our trading data. Then, for each affiliated CLO-month we add all other facilities that have been bought by other CLOs in the same month. These matched trades constitute a sample of loans the CLO could have purchased but decided to leave aside. We subsequently define a dummy variable *Realized Purchase* taking on the value one for the actual facility purchases of the affiliated CLO, and zero for the matched observations. We also construct a dummy *Affiliation*, taking on the value one for facilities that are sponsored by the affiliated PE firm of the CLO, and zero otherwise. We are particularly interested in the coefficient on this dummy. A positive coefficient would imply that the odds for making a trade are higher if an affiliation exists.

Our vector of control variables is supposed to capture characteristics which could also determine the preference for a certain facility. Overall, a CLO manager's willingness (or permission) to purchase further debt instruments obviously decreases in the distance from the issuance date of the CLO because then proceeds from the portfolio are more likely to be used to pay down the debt tranches. We aim to capture this effect with the *Age* variable. Moreover, we proxy for the economic attractiveness of the facility and add a variable for the rating-adjusted spread, for risk as measured by the rating-implied PD and for the facility's maturity relative to the mean maturity of facilities in the corresponding CLO portfolio. We also control for overall debt market conditions using the variable *HY bond spread over LIBOR* (Axelson et al., 2013), overall loan market liquidity (the variable *Market Depth*) and within-manager trades (the dummy *Affiliated Sale*) that may be motivated by an attempt to meet CLO covenants (Loumioti and Vasvari, 2016). Finally, we consider relationship effects on the purchase decision and add a indicator variable (*Relation*) for the presence of a past lending relationship between the CLO manager and the borrower.

Because of the large sample size and the resulting high statistical power the findings in Table 4 have to be discussed in light of economic rather than statistical significance. In Column (1) the coefficient on *Affiliation* suggests a strong preference for managers to choose affiliated facilities. For affiliated facilities the odds of a purchase are 36% ($\exp(0.306) - 1$) larger than for otherwise comparable facilities. Besides that, the likelihood of a realized purchase increases with the spread of the facility and its "fit" to the remaining portfolio, i.e., its similarity in terms of maturity and currency.

However, the *Affiliation* dummy becomes a less important predictor for purchases when we add the *Relation* dummy. The results in Column (2) suggest that the odds of a purchase are three times larger if a prior lending relationship between manager and borrower exists. In contrast, the coefficient on *Affiliation* is now only one fourth of its size in Column (1). This is consistent with the idea that private information through the PE channel is less valuable once the CLO becomes a member of the lender syndicate. This makes intuitively sense because being part of a lending syndicate provides financial institutions with access to material borrower-specific information, including financial statements, covenants compliance information, waiver requests, financial projections, and plans for acquisitions (e.g., Ivashina and Kovner, 2011). Thus, the incremental advantage of a PE affiliation is less pronounced in this case. Nevertheless, we note that *Affiliation* contributes positively and significantly to the likelihood of a purchase in this specification too.

In Columns (3) through (4) we add variables from DealScan measured at the facility level. This reduces the sample size by almost one half. Compared to the results in Columns (1) and (2) we find similar effects with the *Relation* dummy rendering the *Affiliation* dummy insignificant. *Affiliation* and *Relationship* often coincide: 83% of all observations with *Affiliation* equal to one also have a value of one for the *Relation* dummy. We therefore rerun the analyses in Columns (1) and (3) for the subset of observations where the *Relation* dummy is zero. The supposedly separated *Affiliation* effect reported in Column (5) and (6) is three to four times larger than in the overall sample. Conditional on not having purchased a facility from a borrower before, the purchase odds are now twice as large for affiliated facilities.

So far, we take the PE affiliation of a borrower as given and ask whether there is a spillover

Table 4: This table presents coefficient estimates for logit models using the dyads approach. For each affiliated CLO-month with trading information available we match all facilities purchased by other CLOs in the same month. We construct a dummy that is one if the purchase takes place, and zero for the matched facilities. This variable (*Realized Purchase*) is used as dependent variable in all columns. All control variables are explained in Appendix A.1. The constant is estimated but not reported. P-values are presented in parentheses.

	Dependent Variable: Realized Purchase					
	Full Sample				Relation = 0	
	(1)	(2)	(3)	(4)	(5)	(6)
Affiliation	0.306	0.075	0.212	0.045	0.886	0.787
	(0.000)	(0.001)	(0.000)	(0.133)	(0.000)	(0.000)
Log(Portfolio Size)$_{t-1}$	0.322	0.303	0.317	0.283	0.327	0.319
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.059	-0.063	-0.051	-0.058	-0.196	-0.197
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity $-$ Maturity$_{t-1}^{\text{Portfolio}}$	-0.105	-0.084	-0.113	-0.084	0.174	0.230
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rating adjusted Spread	0.018	0.069	0.067	0.113	0.060	0.177
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PD $-$ PD$_{t-1}^{\text{Portfolio}}$	-0.001	0.000	-0.004	-0.001	-0.004	-0.005
	(0.000)	(0.194)	(0.000)	(0.011)	(0.000)	(0.000)
PD	-0.009	-0.014	0.010	-0.005	-0.015	0.006
	(0.000)	(0.000)	(0.006)	(0.144)	(0.007)	(0.461)
Same Currency Dummy	4.589	4.502	4.667	4.566	4.838	4.911
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Affiliated Sale Dummy	0.688	0.363	0.560	0.259	3.201	3.059
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HY bond spread over LIBOR	-0.051	-0.041	-0.051	-0.040	-0.145	-0.157
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Depth	-0.004	-0.004	-0.004	-0.003	-0.006	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relation		1.200		1.294		
		(0.000)		(0.000)		
Log(# Syndicate Members)			0.072	0.023		0.319
			(0.000)	(0.077)		(0.000)
Log(Facility Amt)			0.118	0.008		0.196
			(0.000)	(0.271)		(0.000)
LBO/SBO			0.063	0.068		0.121
			(0.000)	(0.000)		(0.000)
Secured			0.014	0.003		0.174
			(0.737)	(0.933)		(0.078)
Performance Pricing			-0.017	-0.023		-0.053
			(0.300)	(0.174)		(0.214)
Log(1+5yr Lead-Borrower-Vol)			0.008	-0.017		-0.037
			(0.000)	(0.000)		(0.000)
5yr Sponsor Market Share			0.014	0.007		0.002
			(0.000)	(0.034)		(0.771)
Log(1+5yr Lead-Sponsor-Vol)			-0.004	-0.009		-0.026
			(0.122)	(0.001)		(0.000)
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,992,940	1,992,940	1,163,358	1,163,358	913,809	533,998
Uncond. Probability	2.5%	2.5%	2.6%	2.6%	1.1%	1.1%
Pseudo R^2	0.070	0.098	0.065	0.094	0.093	0.093

effect to the debt management division (i.e., the PE-affiliated CLO manager). In principle, it could also be the other way around. PE firms might acquire debt managers and use valuable borrower-specific information accessed through lending syndicate participations to identify potential LBO targets. This argument is consistent with studies finding that investment bank-affiliated (Bodnaruk et al., 2009) and lender-affiliated (Bushman et al., 2010; Ivashina and Sun, 2011b; Massoud et al., 2011) institutional investors trade profitably in equity markets ahead of corporate announcements. Such a behavior could also produce what we would misinterpret as own debt preferences of PE-affiliated CLOs. However, the findings in Columns (5) and (6) of Table 4 reject this alternative channel as a major driving force behind our results. Without past lending relationships to a PE-affiliated CLO, the PE sponsorship of such a borrower cannot be grounded on information obtained through lending syndicate participations. But, exactly in these cases, CLO preferences for affiliated facility purchases are highest, as indicated by the coefficients for *Affiliation*.

Overall, we interpret the results in this section as further support for the ODB. Conditional on risk and relationship characteristics, PE-affiliated managers have a preference for the debt of their affiliated borrowers.

3.3 Evidence from a quasi-natural experiment

A potential concern with the two approaches above is that there may be unobservable factors that simultaneously affect the affiliation status of a borrower and CLO investment decisions. Affiliation status is specific to borrower-CLO manager pairs, that is, at a given point in time the same borrower can be affiliated with a group of CLO managers but unaffiliated with all the others. Hence, unobservable factors causing endogeneity of the affiliation variable must vary at the borrower-CLO manager level, and not at the borrower or the CLO manager level alone. This limits the set of potential suspects and thereby ameliorates endogeneity concerns. To further address this issue, we use a quasi-experimental design. In particular, we exploit the fact that our sample period is characterized by frequent acquisitions of CLO management firms and takeovers of management mandates through PE-affiliated debt managers. Examples include the acquisition of GSO Capital Partners by Blackstone in 2008, the takeover of Mizuho's debt management platform by 3i in 2011 or the acquisition of the European manager Avoca Capital by KKR in 2014.

In our setting the investment universe of a CLO consists solely of unaffiliated borrowers prior to the event date. Once a(nother) PE-affiliated firm acquires the CLO management firm or takes over responsibilities for the CLO, some of the borrowers see a switch in their affiliation status. Since it is highly unlikely that PE firms' acquisition decisions are affected by unobservable factors at the individual borrower-CLO manager level, a manager change creates exogenous variation in the affiliation variable.[19] Hence, by utilizing M&A activities in the CLO

[19] Besides our "dual benefits" story, two additional forces likely drove the recent M&A boom in the CLO

market during our sample period, we are able to exploit variation in the affiliation status of a borrower-CLO manager pair that is arguably exogenous to unobservable factors affecting loan investment decisions. This way, we can identify the causal effect of affiliation on investments.

We proceed as follows: for all CLOs that change their affiliation during our sample period we measure the ODB for 12 quarters after the acquisition just as in Table 2.[20] For 12 quarters *before* the acquisition we compute the ODB as if the new affiliation with a PE firm already existed in the pre-event period. We are interested in how the ODB is affected by the CLO manager's change in affiliation status. This is equivalent to a difference-in-difference approach where we examine how cross-sectional differences (the ODB) are affected by a time-event (the manager affiliation change). If the affiliation with a PE firm really establishes an important channel for the formation of debt preferences, we should see a rising ODB after the event.

We present the results of this exercise in Figure 3 where we obtain our estimates by running event-quarter regressions of the ODB on a constant to obtain an estimate for the average ODB and its confidence interval. The time-series of the estimated parameters is relatively flat until the event quarter when the manager becomes affiliated to a(nother) PE firm. Within 12 quarters after the event the average ODB almost triples from 1 to 3%. Caused by the high attrition rate in our sample – the 12 quarter post-event sample is only half the size of the event-quarter sample – the confidence intervals widen rapidly. Nevertheless, with the even stronger results for the conditional sample, where either the treatment CLO or the controls hold at least one affiliated loan or bond, on the right hand side of Figure 3, we argue that it is very unlikely that affiliation is not causing a debt preference.

It is important to note that the results presented here cannot be explained away by a growing deal flow of the affiliated PE firm. Because we take differences in portfolio holdings between the affiliated CLOs and the matched control sample in both, the pre- and post-event period, we would see no change in our estimates if both CLO groups simply "buy the market". In order for the ODB to rise, the affiliated CLO must place higher weights on affiliated borrowers *relative* to the control group – and in fact, that is what Figure 3 suggests.

manager market. First, PE firms, especially those that are publicly listed, had a growing desire to smooth their volatile income stream from their PE business through expansion into the much less cyclical debt management sector. Second, major regulatory changes (the "risk retention rules") likely raised the minimum AuM hurdle required for a profitable CLO business and made it more costly for small independent managers with less capital to survive on their own. Again, even if some M&A activity is related to CLO manager characteristics, this is unlikely to invalidate our experimental setting which exploits *borrower-CLO manager level* variation.

[20] The sample includes 123 CLOs that experienced a manager change involving one of 21 PE-affiliated firms. The average number of treatment CLO quarters with matched controls over the 25 quarter event window is 98.

Figure 3: This figure shows the average ODB for CLOs that become affiliated with a(nother) private equity firm during their history. We compute the ODB for the post-event window in the same way as in Table 2. In addition, we compute a pre-event ODB as if the pre-event manager were the post-event manager. We run separate regressions on a constant for each event-quarter with the ODB as the left-hand-side variable. The sample is comprised of all matched CLO-quarters (left) or all CLO-quarters where either the control or the treatment CLOs hold at least one affiliated loan or bond (right). The solid line represents the quarterly estimates for the constants while the dashed lines show the 95% confidence interval that we obtain when using cluster bootstrapped standard errors at the manager level.

4 What is the mechanism behind own debt preferences?

4.1 The funding (or price) support channel

Once we confirmed the existence of own debt preferences among PE-affiliated managers, we turn to the second research question: *What is the mechanism that drives these preferences?* We test the funding support channel in this section, and investigate the information advantage channel in Section 4.2.

If funding support is real, instead of maximizing the returns of her own investors, the affiliated CLO manager may be asked to make debt investments that benefit the parent's PE fund investors. For example, affiliated CLO portfolios constitute a valuable source of funding for the companies owned by the parent's PE unit, and the artificially generated demand can help to decrease their funding costs.[21]

Actual loan pricing within the syndication process is determined through what is called "market-flex" in practitioners' jargon. Importantly, while loan amount and non-price terms (maturity, collateral, covenants) are fixed in advance, the spread (AISD) *and* the price (equivalently, the OID) will either be adjusted ("flexed") up or down during the syndication process depending on demand and general market conditions.[22] Previous research focused exclusively on the AISD to capture institutional demand pressure (e.g., Ivashina and Sun, 2011a; Nadauld and Weisbach, 2012). This might be misleading in view of the evidence presented in Table 1 verifying that the majority of institutional facilities is issued at a price below par. We address this shortcoming by combining the AISD and the OID into an effective spread measure (see Equation (1) above) which provides a more accurate picture of price support brought about by affiliated CLOs.

We run regressions of the *Effective Spread* (and alternatively the AISD) on the facility amount purchased by affiliated CLOs at issuance. The price support hypothesis predicts a negative coefficient on *Affiliated Funding*. There are, however, a number of alternative explanations pointing in the same direction. For example, since loan price terms are equilibrium outcomes, simultaneously determined by the interaction of the borrower's demand for funds and the institutional investors' demand for loans, lower effective spreads could reflect the lower demand of funds from borrowers which attract more CLO investors. Or, similarly, CLO investor interest is correlated with unobserved heterogeneity in borrower fundamentals. To distinguish between these explanations and to establish a causal effect of *Affiliated Funding* on borrowing costs, we

[21] Sebastien Canderle (a former PE fund manager) describes the funding support channel this way: "*The clearest conflict has already manifested itself and is of huge benefit to the PE groups that operate in-house debt funds: by using their private debt arms, buyout groups are able to exert pricing pressure on all potential lenders. Conventional loan providers, such as banks and mezzanine funds, have no choice but to align their pricing (that is the margin they apply to their loans) if they want to be competitive with credit fund managers. Financial sponsors do not even have to use their own credit facilities to reduce the cost of debt. Just the threat that they might do so is enough to compel independent lenders to offer cheaper terms.*"

[22] For more details on how syndicated loan pricing works, see Ivashina and Sun (2011a).

employ two strategies. First, we exploit the unique features of our detailed, micro-level data on CLO portfolio transactions, and add the facility amount funded by unaffiliated CLOs to the right-hand side of the regression equation.[23] In this way, we hope to control for omitted time-varying and/or facility-level factors driving both spreads and overall CLO demand. *Affiliated Funding*, then, captures the marginal price support achieved after adjusting for the general interest of CLOs in a given facility.

Second, we employ instrumental variable (IV) regressions. Specifically, we use variation in expected aggregate funds ("affiliated dry powder") available for investments into affiliated borrowers in the current month as an instrument for realized affiliated funding. We proxy for affiliated dry powder by summing the realized investments of all *affiliated* CLOs in the previous three months and use the past three-months average as an estimate for this period's hypothetical dry powder. Assuming that investment activity of CLO managers is persistent to some extent, last period's investments should be a reasonable estimate for the aggregate funds available in the current period. Since our dry powder measure is predetermined and constructed at the sponsor-level, it is arguably exogenous, effecting individual facility spreads only through the funding support channel, thereby meeting the validity condition. In addition, the expected sum of affiliated funds available for investments is likely positively associated with the realized funding support for a given affiliated facility. Hence, our instrument should also be relevant. Importantly, while valid instruments coming from the "supply side" (such as aggregate flows into CLOs as used in Ivashina and Sun, 2011a) suffer from low power because they generate no variation in the cross-section, this caveat does not apply here. Because the set of affiliated CLOs is specific to the PE sponsor of the particular facility, our instrument also exhibits cross-sectional variation, thereby mitigating weak instrument concerns. We instrument *Unaffiliated Funding* the same way, constructing "unaffiliated dry powder". In addition, we include an extensive set of controls into our regressions, motivated by previous studies relying on DealScan data (e.g., Bharath et al., 2011; Berg et al., 2016b).

Table 5 presents the results, separately for OLS and IV regressions and for *Effective Spread* and AISD as dependent variables. Several findings emerge. Importantly, consistent with a funding support story, the coefficient on *Affiliated Funding* is always negative and significant at least at the 10% level (except for Column 8). Using the specification in Column (1), a one standard deviation increase in *Affiliated Funding* is associated with a 7 bp lower effective spread. This number decreases to 4 bp (in Column 2) when we add the three relationship benefit proxies. This reduced effect is in line with previous literature indicating that strong past borrower-lead arranger relations (Bharath et al., 2011) and past lead arranger-PE sponsor relations (Ivashina and Kovner, 2011) lower spreads (AISD), and the finding in Table 1 that affiliated facilities are

[23] Previous research studying the effect of demand pressure from institutional investors (mainly CLOs) on syndicated loan spreads (e.g., Ivashina and Sun, 2011a; Nadauld and Weisbach, 2012; Shivdasani and Wang, 2011) generally lacks information on facility shares allocated to individual CLOs. This makes it impossible to directly identify the facilities intensively bought by CLOs.

associated with more frequent past interactions (and with higher PE sponsor market shares). Demand pressure from unaffiliated CLOs also seems to reduce borrowing costs, however the effect is measured more noisily and is therefore indistinguishable from zero.

Turning to the IV regressions, the price support estimates become larger. A one standard deviation increase in *Affiliated Funding* is associated with a 23 bp (without relation controls) respectively 13 bp (with relation controls) decrease in the effective spread. This finding points at a selection effect being associated with *Affiliated Funding* and working against the price support mechanism. In particular, CLOs tend to select affiliated facilities that are riskier (conditional on included facility and borrower controls) for some unidentified reasons. Hence, without the affiliated funding support, these facilities would demand an even higher spread (conditional on controls). This type of selection mechanism appears to be especially reasonable in our context since the marginal benefits to affiliated funding support are arguably highest among poor quality borrowers for which credit supply constraints are most binding. This highlights the need to control for the endogenous matching of CLO lenders and borrowers. Failing to do so in simple OLS regressions would underestimate the causal effect of *Affiliated Funding* on spreads. In sum, the IV results favor the funding support hypothesis and make the interpretation of a causal effect stronger.[24]

The last four columns in Table 5 present results from regressions using the AISD to proxy for borrowing costs. In line with our argument that the AISD is an incomplete measure of the total costs of debt, and that much of the price response to variation in investor demand likely involves the OID instead, we find that price support is indeed lower when estimated in terms of AISD. The one standard deviation effect varies between 3-6 bp (for OLS) and 8-21 bp (for 2SLS), depending on whether we include the relationship controls. The smaller effect on the AISD highlights the importance of price discounts/premiums as adjustment mechanisms for investor demand heterogeneity during syndication, and points to a likely bias introduced by an exclusive focus on the AISD.

Robustness and alternative channels. In a robustness test we replace *Affiliated Funding* by *Affiliation*, a dummy taking on the value one for facilities that have at least one affiliated CLO acting as participant in the original syndicate, and zero otherwise. Results of this exercise are reported in Table IA.1 in the Internet Appendix. The price support (i.e., the effect of the presence of at least one affiliated CLO lender on the spread) is, again, significant (at least at 10%, except for Column 8), and the magnitude is now in the 25-36 bp range (for OLS) or the 47-85 bp range (for 2SLS). Interestingly, these numbers compare well with results in a paper by Jiang et al. (2010) (henceforth "JLS"). JLS examine investment banks' simultaneous holdings

[24]The causal interpretation of the IV results depends on the validity and relevance of the instruments. The table reports the Kleibergen and Paap (2006) rank statistic for an underidentification test for the instruments in case of non-iid errors where the statistic is distributed χ^2_1 under the null of no correlation between the endogenous regressors and the instruments. The test rejects the null hypothesis at the 1% level in all cases, providing further confidence in the instruments.

Table 5: This table presents results from spread regressions. The dependent variable is the effective spread in Columns (1) through (4) or the AISD in Columns (5) to (8). We use the average monthly purchase amount of all affiliated (unaffiliated) managers in the three months prior to the issuance date as an instrument for affiliated (unaffiliated) investments in our instrumental variable regressions. The instrument and the (potentially) endogenous variables are defined on a log scale. The instrumental variable regressions are executed in Stata using the `ivreg2` routine (Baum et al., 2002). Variables are explained in A.1. The constant is not reported. Standard errors are clustered at the borrower level with the corresponding p-values reported in parentheses. The Kleibergen and Paap (2006) rk statistic is distributed χ^2_1 under the null of no correlation between the endogenous regressors and the instruments and is robust to non-iid errors.

	Effective Spread				AISD			
	OLS		2SLS		OLS		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Affiliated Funding	-13.015	-7.981	-42.326	-24.315	-10.399	-5.082	-38.135	-14.422
	(0.000)	(0.018)	(0.001)	(0.094)	(0.000)	(0.080)	(0.001)	(0.260)
Unaffiliated Funding	1.598	-2.071	-31.660	-51.779	-0.496	-3.478	-8.525	-24.972
	(0.527)	(0.407)	(0.293)	(0.101)	(0.826)	(0.123)	(0.728)	(0.329)
Log(# Syndicate Members)	-15.641	-10.147	-8.022	-0.767	-11.721	-7.000	-8.463	-2.837
	(0.000)	(0.009)	(0.212)	(0.911)	(0.001)	(0.048)	(0.111)	(0.615)
# Facilities	-5.479	-1.577	-7.571	-4.565	-6.120	-2.732	-6.547	-4.050
	(0.027)	(0.461)	(0.015)	(0.101)	(0.005)	(0.170)	(0.012)	(0.092)
Log(Facility Amt)	-21.298	-13.563	-4.670	10.076	-20.698	-13.883	-15.493	-3.596
	(0.000)	(0.000)	(0.740)	(0.507)	(0.000)	(0.000)	(0.179)	(0.772)
Log(Maturity)	0.573	-8.531	2.121	-7.902	2.019	-5.560	2.669	-5.244
	(0.871)	(0.025)	(0.564)	(0.052)	(0.535)	(0.115)	(0.416)	(0.145)
LBO/SBO	30.779	10.949	37.601	16.341	22.583	7.071	24.347	9.381
	(0.000)	(0.062)	(0.000)	(0.023)	(0.000)	(0.170)	(0.000)	(0.112)
Secured	-17.485	-7.709	-13.719	-1.633	-16.672	-8.459	-16.122	-5.946
	(0.227)	(0.597)	(0.380)	(0.920)	(0.194)	(0.513)	(0.226)	(0.663)
Performance Pricing	-35.511	-32.717	-30.816	-28.114	-31.693	-29.406	-28.963	-27.281
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US	-5.065	-4.472	-4.899	-5.020	-4.440	-3.575	-4.169	-3.845
	(0.341)	(0.380)	(0.374)	(0.353)	(0.345)	(0.432)	(0.379)	(0.402)
HY bond spread over LIBOR	33.623	32.851	33.581	33.892	21.729	20.878	21.037	21.272
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(1+5yr Lead-Borrower-Vol)		-9.120		-10.879		-7.083		-7.842
		(0.000)		(0.000)		(0.000)		(0.000)
5yr Sponsor Market Share		-0.838		1.184		-2.324		-1.286
		(0.545)		(0.526)		(0.096)		(0.446)
Log(1+5yr Lead-Sponsor-Vol)		-2.897		-3.089		-2.388		-2.471
		(0.007)		(0.008)		(0.019)		(0.020)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Letter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	3,087	3,087	3,087	3,087	3,087	3,087	3,087	3,087
Adj. R^2	0.376	0.420			0.366	0.403		
Kleibergen and Paap statistic			25.972	23.871			25.972	23.871

of equity and syndicated loan positions in the same firm, a phenomenon called "dual holding". The authors find that the presence of at least one dual holder reduces syndicated loan spreads (AISD) by 18-32 bp within OLS specifications, and by 67-87 bp when the authors control for the endogenous matching of dual holders and borrowing firms.[25]

While our results are comparable to JLS, there are important differences between both studies. JLS look at *public* borrowers and at non-commercial banks (mostly large investment banks) acting as dual holders. We, instead, focus on *private* borrowers (owned by PE funds) and on "dual holding" entities with mostly just two divisions, PE and debt management. This affects the overall structure of dual holdings. While dual holder's equity stakes in JLS are small (about 0.5-0.7%), they are very large in our case (majority ownership, up to 100%). In contrast, loan positions in JLS are large (on average about 9.4% or 123 million USD), and relatively small (on average 0.6%) for the CLO lenders in our study. Hence, the loan fractions in JLS are more in line with investment banks' role as lead arrangers, whereas CLO lenders are exclusively syndicate participants. Most importantly, while JLS interpret their finding of lower spreads associated with dual holdings as reflecting an incentive alignment between the interests of debt and equity holders, we argue in favor of an affiliated price support channel.

There exists a third channel predicting lower spreads of dual holding facilities, related to the syndicate moral hazard problem studied by Sufi (2007) and Ivashina (2009). In particular, loan ownership by the lead bank can act as an important mechanism to mitigate the effects of information asymmetry between the lead and the other syndicate members. Just like a lead arranger's share might signal monitoring incentives and credit quality, the equity stake of a PE firm may work against adverse effects of information asymmetry. At the bottom line, all three channels may reasonably contribute to reduced borrowing costs associated with affiliated investments.

Funding support and equity returns. Our findings so far indicate that affiliated demand can help to decrease funding costs for PE fund portfolio companies in the primary loan market. Now, we want to quantify the economic impact of such price support in terms of incremental equity returns (IRR) received by the PE fund's investors. In line with Ivashina and Kovner (2011), we assume that affiliated facilities are used for LBO financing, and that the typical LBO capital structure consists of 30% equity and 44% leveraged loans. We further assume that a PE firm's typical exit horizon is four years and that the LIBOR is flat at 0.5%.[26] Based on the coefficients estimated in Table 5, Column 4 (2SLS, with relationship controls), the average PE portfolio firm pays a spread that is 13 bp lower, given a one standard deviation increase in *Affiliated Funding*. This results in annual interest savings of approximately 1.1 million USD on an affiliated facility of mean size (870.1 million USD, from Table 1). The present value of these

[25] Also consistent with a dual holding benefit, Fang et al. (2013) study LBO deals sponsored by bank-affiliated PE firms and find that if the parent bank of the PE sponsor is the lead bank of the lending syndicate, spreads (AISD) are on average 34 bp lower, all else equal.

[26] Over the time period between 2009 and 2015 the three month LIBOR had a mean value of 0.37%.

interest savings, received over four years (the PE firms' exit horizon) and discounted at 4.25% (LIBOR of 0.5% + median effective spread of 375 bp for affiliated facilities in Table 1), is 4.1 million USD. This yields an incremental IRR of 69 bp, given a 30% (or 593 million USD) equity share in the LBO's initial capital structure.

The coefficients on the *Affiliation* dummy (Table IA.1 in the Internet Appendix) suggest that the incremental IRR impact is even larger when we just differentiate between facilities with at least one affiliated CLO lender and those without. Using the coefficient (−47.2) in Column (4) of Table IA.1, the incremental equity return due to favorable facility spreads amounts to 2.5%. Given that we instrument *Affiliation* these higher returns do not come at the price of higher risk for equity investors. Hence, in view of the generally low average risk-adjusted equity returns in LBOs, the affiliated funding support impact on LBO IRRs appears economically large.[27]

Two final points are noteworthy. One the one hand, we likely underestimate the economic impact of affiliated funding on borrowing conditions and LBO equity returns. While we look only at price terms (OID and AISD), affiliated funding support might also have a favorable impact on non-price terms like maturity and financial covenants. One the other hand, PE firms may share some of the funding support benefits with company sellers by paying higher transaction prices (bidding more aggressively). Evidence presented in Axelson et al. (2013) based on economy-wide credit conditions is consistent with this prediction.

How costly is funding support for investors in affiliated CLOs? Our sample in Table 5 contains 223 facilities with affiliated CLO lenders at origination. The average affiliated investment in these facilities is 8.8 million USD. Taking the funding support estimate of -47.2 bp from Column (4) in Table IA.1 (based on the *Affiliation* dummy specification), the annual loss in interest income for affiliated CLOs is 41,540 USD per facility, or 9.3 million USD in total across all facilities. These numbers appear rather low compared to the large benefits accruing to PE fund companies and investors as outlined above. This supports the rationality underlying the cross-division subsidization strategy applied by the parent entity.

4.2 The information advantage channel

The informational advantage hypothesis suggests that PE firms' superior access to information as majority owners of their portfolio companies can have positive spillover effects to affiliated CLOs. That is, without effective "Chinese walls", communication between the PE and the debt management division may confer private information from the equity to the debt management part of the business. Eventually, affiliated debt managers may exploit this information when trading at the secondary loan market. In this case, we would expect the trades in affiliated facilities to be a source of outperformance for PE-affiliated managers. However, if affiliated

[27] Harris et al. (2014), for example, report average public market equivalent (PME) returns of about 3% annually for U.S. buyout funds.

CLOs are informed traders ("insiders"), who are the "outsiders", the ones that trade at an informational disadvantage? Indeed, since trading in the secondary market for a given facility is typically organized by the facilities' lead arranger acting as dealer, informational advantages on the part of affiliated CLOs are not obvious. Moreover, it is generally believed that the number of uninformed liquidity (or "noise") traders is limited in the institutional syndicated loan market, compared to equity markets (Allen et al., 2012). Hence, consistent with the idea of secondary loan market trading being informationally efficient, Addoum and Murfin (2016) find that the public prices of traded facilities predict cross-sectional variation in future stock returns. On the other hand, however, Liebscher and Mählmann (2017) present evidence of significant performance persistence among CLO managers, a finding in line with exploitable loan market inefficiencies. At the end, it remains an empirical question whether CLOs benefit from informational advantages over their counterparty. We proceed in two steps to validate the information advantage hypothesis. In the next section we look at *realized, net* (after deduction of implicit trading costs – bid-ask spread, price impact) returns of affiliated and unaffiliated round-trip (RT) trades. In Section 4.2.2, we focus on buy-and-hold (BH) trades.

4.2.1 Round-trip trades

Because spreads (AISD) in DealScan are only measured at origination and are therefore time-invariant, we rely on pure "price returns" to capture the information acquired and "priced" by secondary market traders. We compute returns according to the FIFO principle, i.e., we assume that the first sale of a loan or bond belongs to its first purchase.[28] Importantly, all prices are *realized*, that is, actual prices paid or received by the CLO. Hence, we do not rely on quoted midpoints to construct *paper* returns. We restrict our analysis to trades in facilities from sponsored borrowers to address the concern that sponsored borrowers might be fundamentally different from non-sponsored ones (Ivashina and Kovner, 2011).

Our setting offers several important advantages compared to studies trying to determine the returns to informed trading in equity markets. For equity markets, data limitations make it generally impossible to infer true holding periods which in turn prevent researchers from computing actual returns to insider trading (Jeng et al., 2003). Instead, researchers have to rely on proxy returns. Even worse, some studies (e.g., Ivashina and Sun, 2011b) must employ SEC 13(f) institutional investor filings and deduce informed trading from quarterly holding changes. However, nothing is known about the exact trading behavior of investors within a quarter. Moreover, equity studies often utilize close-to-close (*paper*) returns computed from daily closing midpoints, not from actual prices paid or received by informed traders. Our return calculation, in contrast, is not subject to any of these limitations. Hence, we believe that our analysis of RT returns provides a valid proxy for what potential insiders (PE-affiliated

[28] The results are unchanged if we follow the LIFO approach instead.

CLOs) can earn in the secondary loan market.

Par building trades. Before we turn to our return comparison exercise, we highlight an important institutional feature that likely influences the trading behavior of CLOs. As a result of their compensation structure, CLO managers are motivated to sell appreciating facilities ("winners") early and depreciating facilities ("losers") only at times when liquidity is needed. This behavior is commonly referred to as "par building" and helps managers to fulfill CLO covenants.[29] Consequently, we would expect to see higher returns for "younger" trades and weaker results for trades with a longer time period between purchase and sale.

To investigate this issue, Table IA.4 in the Internet Appendix provides descriptive information for affiliated (in Panel A) and unaffiliated trades (in Panel B). Trades are affiliated when both, the trading CLO and the PE firm owning the borrower underlying the trade belong to the same asset management group. The table shows separate return statistics for winning and losing trades and also the corresponding holding period statistics. Looking at affiliated trades, the mean winning return is 3.6% and the mean losing trade returns -2.7% (medians are 1.5% and -0.8%, respectively). As expected, there are large differences in holding periods. Winners are on average realized after 325 calendar days whereas losers are hold for additional 184 days (or 56.6% longer). A similar picture emerges for unaffiliated trades in Panel B. Hence, the par building effect generates a negative relation between holding periods and returns. Note that the par building effect can be considered the rational twin of the likely irrational disposition effect found among individual investors in equity markets (Odean, 1998).

Univariate tests. We now look at the association between returns and affiliation. We start with univariate comparisons. To control for the par building effect, we sort all RT trades into quintiles based on the time between purchase and sale of the facility. Furthermore, to account for overall loan market conditions, we subtract the contemporaneous price return of the Leveraged Loan Index from the raw trade return.[30] We call these returns *excess* returns. Table 6 presents the results, both for simple and annualized excess returns. In line with the par building effect, price returns decrease strongly in the time between the purchase and sales date (i.e., from Q1 to Q5). This holds especially true for the larger sample of unaffiliated trades. More interestingly, looking at within-quintile differences reveals a consistent outperformance of affiliated over unaffiliated trades. Mean excess returns in the affiliated subsample are between 30 and 310 bp larger than for the group of unaffiliated trades. This translates into 40 to 330 bp on an annualized basis. While these univariate tests provide a somewhat volatile estimate of the value of private information, the overall picture strongly supports the information advantage

[29] In particular, by selling losers CLO managers likely reduce the nominal value of their portfolio. This, in turn, lowers their compensation and exposes them to the risk of violating collateral and interest rate coverage tests (Antczak et al., 2009, p. 94).

[30] We use the S&P Leveraged Loan Index for dollar trades and its European counterpart for trades in other denominations. Both indexes are designed to capture the overall price development in the respective institutional segment of the leveraged loan market. Hence, they should provide appropriate benchmarks.

hypothesis.

Table 6: This table shows two-sided t-tests for differences in excess returns – allowing for unequal variances and holding the trade duration quintile (Q1 to Q5) constant. Returns are computed according to the FIFO principle, i.e., the sale price of an instrument is matched to the price of its first purchase. All variables are winsorized at the 1% and 99% percentile. Benchmark for the excess returns is the S&P Leveraged Loan Price Index for trades in USD, respectively the S&P European Leveraged Loan Index for trades in Euro. The p-values for the two-sided t-tests are reported in parentheses and the number of observations within each group stands below each group-level mean.

	Excess Return			Annualized Excess Return		
	Unaffiliated	Affiliated	Difference	Unaffiliated	Affiliated	Difference
Q1	0.8%	1.1%	0.3%	30.3%	33.6%	3.3%
	9,190	193	(0.022)	9,190	193	(0.366)
Q2	0.3%	1.4%	1.1%	2.6%	5.0%	2.4%
	9,165	148	(0.000)	9,165	148	(0.004)
Q3	-0.3%	1.4%	1.7%	0.1%	2.4%	2.3%
	8,966	246	(0.000)	8,966	246	(0.000)
Q4	-2.5%	0.6%	3.1%	-2.3%	0.4%	2.7%
	9,103	225	(0.000)	9,103	225	(0.000)
Q5	-5.4%	-4.5%	0.8%	-2.4%	-2.0%	0.4%
	8,997	265	(0.176)	8,997	265	(0.244)

Multivariate tests. Table 7 presents results from multivariate tests, i.e., OLS regressions with the annualized excess return as the dependent variable. The positive *Affiliation* effect holds when we add further controls for the trading volume, a bond dummy, a dollar dummy as well as rating letter fixed effects (see Column 1). In this specification affiliated trades show a 2.9% higher annualized excess return. The regressions in the first three columns of Table 7 are run on the full set of RT trades in sponsored facilities from all CLO managers (PE-affiliated or not) for which we observe trading data. However, independent (non-PE-affiliated) managers might be fundamentally different from their affiliated peers, for example in terms of trading skill or style. This might bias the coefficient on *Affiliation* because all trade return observations from unaffiliated managers are assigned the value zero for *Affiliation*. To address this concern, we replicate the baseline regression from Column (1) for the subsample of trades executed by PE-affiliated managers. The results, shown in Column (4), remain unchanged.

Similarly, while our DealScan matched sample consists of 4,826 sponsored facilities with non-missing spread information, for only 662 facilities (14%) we observe at least one purchase by an affiliated CLO (see Table 1). Moreover, facilities from some borrowers are never traded by affiliated CLOs. If these "unaffiliated" borrowers differ in unobservable ways from their affiliated peers, and this heterogeneity is correlated with trade returns, the coefficient on *Affiliation* will still be biased. Accordingly, we verify our results in the last three columns of the table by restricting the sample to trades in facilities from affiliated borrowers. The coefficient for *Affiliation* in the baseline regression (Column 7) becomes highly statistically significant, and its magnitude is now even larger, implying an outperformance of 4.1% annually. Therefore, the findings are not specific to trades by the group of PE-affiliated CLO managers or to trades in

Table 7: This table presents results from OLS regressions of *Annualized Excess Returns* on the *Affiliation* dummy and controls. The dependent variable is winsorized at the 1% and 99% percentile. The constant is not reported. Columns (1) through (3) show results for a sample of PE-affiliated and unaffiliated managers where Columns (3) to (6) are only for a subsample of trades from managers with a private equity arm. In Columns (7) through (9) the sample is confined to observations from affiliated borrowers. Standard errors are double-clustered (Cameron et al., 2011) along sale date quarters and borrower names with the corresponding p-values reported in parentheses.

	Dependent variable: Annualized Excess Return in %								
	Full Sample			Only Affiliated Managers			Only Affiliated Borrowers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Affiliation	2.867	2.608	3.401	2.826	2.185	3.294	4.060	2.335	4.186
	(0.044)	(0.004)	(0.056)	(0.042)	(0.031)	(0.028)	(0.003)	(0.017)	(0.025)
Log(Trade Volume)	0.314	0.105	0.483	0.163	-0.035	0.237	0.815	0.411	0.961
	(0.166)	(0.506)	(0.064)	(0.577)	(0.884)	(0.366)	(0.023)	(0.231)	(0.008)
Log(Holding Time)	-9.682	-9.811	-9.668	-9.831	-9.842	-9.784	-8.620	-8.848	-8.642
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bond Dummy	5.268	6.977	5.189	5.785	6.837	6.079	8.770	12.730	8.957
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.010)	(0.014)
USD Dummy	1.719	-0.092	2.833	0.587	0.570	2.093	3.371	0.705	5.894
	(0.138)	(0.962)	(0.051)	(0.628)	(0.799)	(0.131)	(0.068)	(0.711)	(0.034)
Borrower FE	No	Yes	No	No	Yes	No	No	Yes	No
Manager FE	No	No	Yes	No	No	Yes	No	No	Yes
Rating Letter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,484	44,484	44,484	22,107	22,107	22,107	10,299	10,299	10,299
Adj. R^2	0.293	0.408	0.311	0.312	0.469	0.318	0.293	0.350	0.326

affiliated facilities in general, but only to trades by affiliated managers in affiliated facilities.

The outperformance of affiliated trades is consistent with the spillover of non-public information from the PE division to the debt management division within the same asset management group. However, access to private information may not be the only possible explanation for the observable outperformance. To further rule out alternative explanations of this result, we start by addressing the concern that there might be something special about the sponsored borrowers in which affiliated trades take place. If this is true, then all trades in a given borrower's facilities should perform equally well, i.e., outperformance should not be characteristic of the affiliated traders. We turn to demanding specifications and add borrower fixed effects in Columns (2), (5) and (8). Hence, the coefficient on *Affiliation* is now identified by affiliated and unaffiliated trades in facilities from the *same* borrower. The estimated coefficients are reduced but remain strong in economic terms, implying outperformance of affiliated trades by 2.2-2.6%, and always statistically significant at least at the 5% level. These findings suggest that affiliated managers beat their unaffiliated peers in terms of timing trades in affiliated borrowers.

As argued above, it could be that there is something unique about PE-affiliated CLO managers. For example, they follow superior investment styles or are simply more skilled as a result of manager self-selection when talented managers view PE-affiliated debt management companies as presenting more prestigious career paths. Taking into account this alternative we add manager fixed effects in Columns (3), (6) and (9). In this way, we compare the performance of affiliated and unaffiliated trades across the *same* manager. The intuition is that if there is something special about the manager, then there is no reason why this "special" skill should only apply to affiliated facilities. For the within-manager regressions, average outperformance of affiliated trades increases to 3.3-4.2%. This implies that private information acquired through PE-affiliations is not only valuable for market timing, but also helps to evaluate which facilities to select for trading.

Overall, the fixed effects regressions verify that outperformance is manager-specific (affiliated trades outperform unaffiliated trades within the same borrower) *and* borrower-specific (affiliated trades outperform unaffiliated trades within the same manager). Hence, outperformance is not representative of managers' or borrowers' overall characteristics.

We can use the findings in Table 7 to estimate the total benefits of informed trading for affiliated CLOs. In particular, assuming an average within-manager outperformance of affiliated trades of 4.2% (from Column 9), and setting the size of all affiliated RT trades to 1,114 million USD (grand total across years), the monetary benefit of insider trading amounts to 46.8 million USD (on an annualized basis). To better understand the economic value of this number, several points are noteworthy. One is that we look at *excess* returns, over and above what can be earned by simply investing in the market. Furthermore, the returns are *price* returns of debt instruments which do not include interest income and naturally provide only limited upside potential. And finally, while the number of affiliated trades is relatively low (annual average of

152 over the period 2009-2015), the growth rate is high, at 140% a year. Hence, this type of informed trading in the loan market might become an even bigger issue in the future.

What are the likely sources of affiliated managers' informational advantages in affiliated facilities? One obvious possibility is that affiliated managers are better able at timing rating changes due to tips received from the PE division regarding upcoming rating events. Hence, they buy before unanticipated rating upgrades and/or sell in advance of downgrades.[31] This strategy, however, is unlikely to be profitable here due to the institutional structure of loan trading. Investors trade with lead arrangers acting as dealers in the secondary market, and lead arrangers should be equally well informed about upcoming major events like rating changes. Nevertheless, to test this "rating tipping" mechanism, we control for the change in facility ratings (transformed into one-year implied probabilities of default) over the course of a trade. Results for regressions similar to the ones in Table 7 are displayed in the Internet Appendix (Table IA.2). Unsurprisingly, we find that rating upgrades are associated with higher trade returns: a one standard deviation (8.26%) decrease in the rating-implied PD over the life of a trade raises the return by 1.43%. More importantly, the coefficients for *Affiliation* are qualitatively similar to those in Table 7, inconsistent with a rating tipping story.

Cross-sectional tests. We now examine cross-sectional predictions of the information advantage hypothesis. We rely on the notion that informed investors will concentrate their trades on information-sensitive instruments, because these are the ones from which they can hope to earn informational rents. Hence, if privileged access to private information is indeed the driver behind the results in Table 7, we would expect the marginal effect of *Affiliation* to vary with a facilities' information-sensitivity and, more broadly, with the value of information. To test this hypothesis, we run regressions where we interact *Affiliation* with proxies for a facility's information sensitivity.

Our first proxy is the rating-implied one-year probability of default (*PD*). Han and Zhou (2014) provide evidence indicating that bonds become more information-sensitive when the issuer is closer to default. If a borrower's credit quality is low but the affiliated manager has private knowledge about upcoming positive fundamentals, buying facilities before the positive news become public results in excess returns. We thus expect the sign on the interaction between *Affiliation* and *PD* to be positive.

Similarly, the return on private information may be stronger for facilities that are priced at a discount. Since lead arrangers (informed relationship banks) act as dealers and post daily bid and ask quotes, secondary market prices (or midquotes) should be more timely measures of credit quality than infrequently updated ratings (Addoum and Murfin, 2016). To account for time-series variation in market liquidity and other market-wide characteristics, we define an adjusted "price discount" dummy that is one if the trade price is lower than the median

[31] Irvine et al. (2007) find evidence consistent with tipping behavior before the release of stock analysts' initial buy recommendations.

price of all traded instruments (loans and bonds) in the same quarter, and zero otherwise. We conjecture that the interaction term between this variable (*Distress*) and *Affiliation* is positive.

As our final proxy, we take the fraction of managers in our sample that hold the instrument in question in the month prior to the start of the trade. We argue that if more managers invest in a given facility, private information about the borrower is more widespread. This might be because lenders benefit from information rights through their participation as syndicate members (e.g., Ivashina and Sun, 2011a; Bushman et al., 2010). In contrast, if the number of managers holding a facility is low, the information asymmetry between the affiliated manager and the rest of the market should be high. This suggests that the value of private information is decreasing in the number of managers holding a facility, implying a negative coefficient for the interaction term between *Affiliation* and *# Managers*.

Turning to the results shown in Table 8, all the interaction terms have the predicted sign. The coefficients for the *PD* proxy in Column (1) indicate that affiliated trades do not outperform their unaffiliated peers for BB- rated facilities (one-year PD of 3.8%), but the outperformance becomes a significant 4.9% ($8.1 * 1.245 - 5.233$) a year for facilities rated one full letter below at B-, representing a one-year PD of 8.1%. Moreover, Column 2 suggests that the outperformance of affiliated trades is concentrated in *Distress* instruments (at 5% a year) and is not significant for instruments without a noticeable price discount as measured relative to other instruments of the same type (loan or bond) and quarter. Although showing the hypothesized sign, the interaction term with *# Managers* is insignificant. All the results remain qualitatively similar when we restrict the sample to trades executed by affiliated managers (Columns 4 to 6) or in affiliated borrowers (Columns 7 to 9). In sum, the cross-sectional tests strongly support the information advantage hypothesis.

4.2.2 Buy-and-hold trades

Although RT trades present a convenient way to test implications of the information advantage hypothesis, they come with an important disadvantage: CLO managers are to some extent buy-and-hold (BH) investors. While we have about 44,000 RT trades in our data, for almost 70,000 facility buys we do not see any corresponding sale. This raises the concern that private information is confined to the smaller "trade sample". To enhance our confidence in information spillover effects being indeed a real phenomenon, we would like to know whether affiliated managers also outperform with their BH trades (buys without subsequent sales). Put differently, we want to understand whether affiliated managers are better able to pick *undervalued* affiliated facilities, that is, facilities that trade at effective spreads *too* high relative to their inherent risk. Again, we rely on our effective spread measure to detect potential mispricings which has the obvious advantage that it captures current valuations through its OID component.

Results from OLS regressions with the *Effective Spread* "purchased" as dependent variable are presented in Table 9, where we restrict our analysis to purchases initiated in the secondary

Table 8: This table displays coefficient estimates from a regression of *Annualized Excess Returns* on the *Affiliation* dummy, an information sensitivity proxy and the interaction term between these two. PD is the one-year rating-implied probability of default averaged over Moody's and S&P's rating. Distress is a dummy equal to one if the price of the loan or bond is below the median for all trades in the same quarter. # Man (short for # Manager) is the number of managers that hold the loan or bond in the month before the trade. Other control variables are the same as in Table 7. The dependent variable is winsorized at the 1% and 99% percentile. Standard errors are double-clustered (Cameron et al., 2011) along sale date quarters and borrower names with the corresponding p-values reported in parentheses.

	Dependent variable: Annualized Excess Return								
	Full Sample			Only Affiliated Managers			Only Affiliated Borrowers		
	PD	Distress	# Man	PD	Distress	# Man	PD	Distress	# Man
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Affiliation	-5.233	-1.070	2.980	-3.536	-0.773	3.072	-5.846	-0.686	4.375
	(0.184)	(0.459)	(0.128)	(0.383)	(0.540)	(0.112)	(0.100)	(0.610)	(0.011)
Inf. Sens. Proxy	-0.385	1.336	-3.731	-0.149	1.052	-2.854	-0.597	0.615	-2.064
	(0.001)	(0.159)	(0.015)	(0.356)	(0.287)	(0.058)	(0.000)	(0.556)	(0.187)
Affiliation*Inf. Sens. Proxy	1.245	5.095	-1.300	0.994	4.657	-1.801	1.474	6.146	-3.229
	(0.000)	(0.011)	(0.738)	(0.000)	(0.007)	(0.658)	(0.000)	(0.006)	(0.335)
Rating Letter FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Further Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,484	44,484	44,484	22,107	22,107	22,107	10,299	10,299	10,299
Adj. R^2	0.300	0.293	0.294	0.312	0.312	0.312	0.319	0.294	0.293

market. We use the same set of borrower and facility controls as in Table 5. To account for the ordinal nature of agency ratings, we transform rating notches into implied one-year PDs and use these PDs (and their squares) to control for heterogeneity in borrower default risk. We are interested in the coefficient for *Affiliation* measuring differences in "traded" effective spreads between affiliated and unaffiliated buys, conditional on controls. Results for the baseline specification are reported in Column (1). The coefficient for *Affiliation* turns out positive and marginally significant once we control for manager fixed effects in Column (3). The estimates for the full sample imply that purchases in affiliated loans are associated with up to 13 bp higher spreads compared to purchases in unaffiliated loans. This is in line with the information advantage story, but the magnitude of the informed trading effect is much lower than the one observed for RT trades.

While the sample in Columns (1) to (3) includes all purchases, we form subsamples to take systematic differences between affiliated managers (borrowers) and unaffiliated managers (borrowers) into account. In Columns (4) to (6) we restrict the sample to buys from PE-affiliated CLO managers to address the concern that PE-affiliated and independent CLO managers differ in important ways (e.g., skill, style) that are correlated with trade performance. Compared to the results for the full sample in Column (1), the coefficients on *Affiliation* turn marginally significant in Column (4). In Columns (7) through (9), we include only facilities from borrowers for which we observe at least one affiliated trade (buy or sell) over our sample period. Restricting

Table 9: This table presents results from effective spread regressions at the trade ("buy") level. The sample is restricted to secondary market purchases of loans without a subsequent sale. All variables are detailed in Appendix A.1. Standard errors are double-clustered at the borrower and quarter level. Corresponding p-values are presented in parentheses.

	Dependent variable: Effective Spread								
	Full Sample			Only Affiliated Managers			Only Affiliated Borrowers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Affiliation	8.639	4.354	13.239	10.203	4.681	13.963	15.934	3.079	22.398
	(0.149)	(0.388)	(0.056)	(0.098)	(0.383)	(0.034)	(0.012)	(0.518)	(0.010)
Log(# Syndicate Members)	-11.637	-20.411	-11.486	-14.831	-17.896	-14.448	-11.732	-25.420	-12.619
	(0.008)	(0.003)	(0.008)	(0.002)	(0.008)	(0.002)	(0.166)	(0.010)	(0.137)
# Facilities	-9.075	-11.980	-8.920	-8.754	-12.786	-8.472	-3.341	-9.606	-2.956
	(0.004)	(0.004)	(0.007)	(0.009)	(0.002)	(0.011)	(0.363)	(0.044)	(0.422)
Log(Facility Amt)	-14.238	-7.995	-13.559	-12.520	-5.542	-12.434	-9.012	5.522	-8.173
	(0.000)	(0.077)	(0.000)	(0.000)	(0.251)	(0.000)	(0.078)	(0.290)	(0.099)
Log(Maturity)	69.237	63.803	71.391	65.853	59.472	67.811	55.772	44.341	59.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log(Trading Volume)	5.272	1.714	4.157	4.842	1.600	4.079	5.571	2.169	5.936
	(0.000)	(0.027)	(0.003)	(0.000)	(0.042)	(0.001)	(0.001)	(0.029)	(0.001)
LBO/SBO	0.994	-12.787	1.874	-4.153	-16.561	-2.766	0.604	7.128	1.853
	(0.879)	(0.184)	(0.774)	(0.521)	(0.111)	(0.665)	(0.954)	(0.603)	(0.859)
Secured	-24.030	-40.365	-22.969	-11.043	-42.105	-12.707	-26.246	11.806	-26.513
	(0.445)	(0.246)	(0.463)	(0.733)	(0.266)	(0.700)	(0.192)	(0.563)	(0.207)
Performance Pricing Dummy	-34.709	-19.465	-33.748	-36.502	-26.277	-35.950	-34.661	-28.748	-34.870
	(0.000)	(0.064)	(0.000)	(0.000)	(0.020)	(0.000)	(0.005)	(0.035)	(0.005)
US	6.272	5.789	5.295	3.630	3.673	2.092	7.078	-2.429	5.022
	(0.260)	(0.556)	(0.342)	(0.528)	(0.742)	(0.707)	(0.403)	(0.848)	(0.559)
HY bond spread over LIBOR	-0.066	-0.580	-0.163	-1.278	-1.030	-1.198	-0.294	0.029	-0.234
	(0.827)	(0.122)	(0.768)	(0.006)	(0.080)	(0.019)	(0.728)	(0.946)	(0.777)
Log(1+5yr Lead-Borrower-Vol)	-1.775	-4.781	-1.895	-2.424	-4.895	-2.488	0.683	1.119	0.523
	(0.084)	(0.004)	(0.082)	(0.020)	(0.009)	(0.018)	(0.612)	(0.598)	(0.700)
5yr Sponsor Market Share	1.992	6.299	2.035	1.565	6.217	1.568	2.275	8.402	2.197
	(0.227)	(0.113)	(0.244)	(0.338)	(0.097)	(0.332)	(0.344)	(0.091)	(0.366)
Log(1+5yr Lead-Borrower-Vol)	-3.791	-4.556	-3.624	-3.421	-2.973	-3.295	-3.040	2.762	-2.670
	(0.003)	(0.104)	(0.004)	(0.011)	(0.280)	(0.013)	(0.235)	(0.600)	(0.296)
PD	8.195	5.415	8.256	10.615	5.005	10.316	11.116	5.150	11.195
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.027)	(0.000)
PD^2	-0.128	-0.095	-0.130	-0.217	-0.098	-0.210	-0.236	-0.102	-0.235
	(0.001)	(0.000)	(0.011)	(0.000)	(0.001)	(0.000)	(0.000)	(0.025)	(0.000)
Borrower FE	No	Yes	No	No	Yes	No	No	Yes	No
Manager FE	No	No	Yes	No	No	Yes	No	No	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC Code Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	69,917	69,917	69,917	29,745	29,745	29,745	25,441	25,441	25,441
Adj. R^2	0.369	0.790	0.389	0.364	0.806	0.379	0.415	0.748	0.443

the sample in this way eliminates the effect of systematic differences between affiliated and unaffiliated borrowers on the coefficient estimates. The coefficient for *Affiliation* is now almost twice its magnitude in the full sample. With respect to the borrower fixed effects specifications in Columns (2), (5), and (8), we see little indication of an within-borrower effect. This suggests that managers do not earn significantly higher spreads by timing the market of affiliated facilities. Rather, the results in Table 9 point at cross-sectional opportunities for "informed buying".

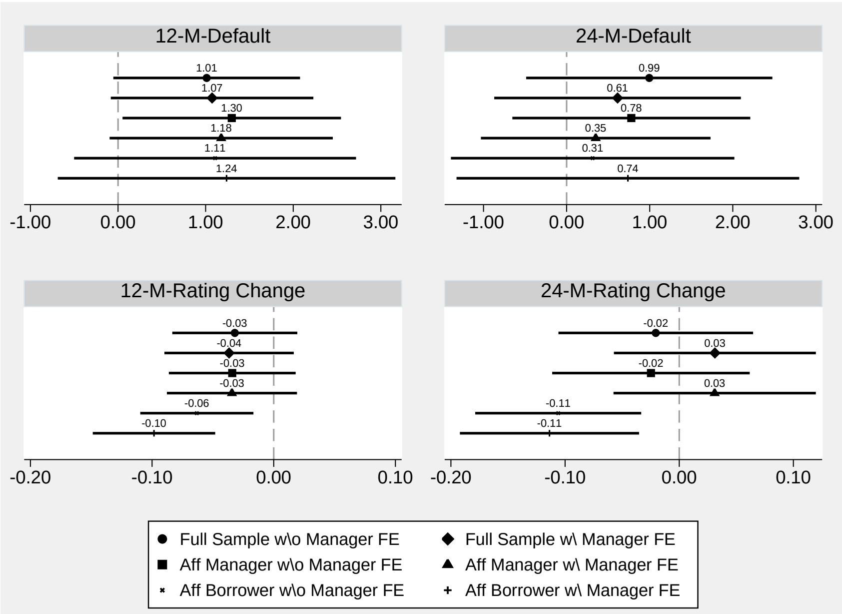
Of course, the higher spreads for affiliated purchases might represent compensation for higher default risk priced in by loan traders. While we control for the borrower's rating-implied PD at the time of purchase, this might be an imprecise and stale proxy of true default risk. To address this concern, we look at ex post (after trade) *realized* performance at 12-months or 24-months horizons. We measure ex post performance by changes in rating-implied PDs (variable ΔPD) and defaults. If affiliated buys are really more risky, conditional on controls, they should underperform ex post (i.e., exhibit rating downgrades and higher default frequencies). The results of this test are summarized in Figure 4 and leave us with an ambiguous picture. At least over the 12-month horizon affiliated purchases show a higher default risk than unaffiliated trades with the average probability of default being 1% higher. But the marginally significant effect diminishes once we increase the time-horizon over which we measure defaults. Moreover, with regards to rating changes affiliated purchases in affiliated borrowers perform significantly better. Taking into account that rating upgrades are usually correlated with price increases this may even raise the benefits from affiliated buying. All in one, the conflicting results on ex post ratings and defaults in addition to the high variability in the coefficient estimates make it hard to relate the higher spread in Table 9 to pure risk compensation.

So, what are the total economic benefits of informed buying? We use the regression results from Table 9, based on 1,153 affiliated purchases with an average volume of 1.9 million USD. The estimated within-manager outperformance is 22 bp in Column (9). This translates into an economic benefit of 4,180 USD per year for the average affiliated purchase or – for the whole sample – 4.8 million USD p.a. By putting these numbers together with the ones for RT trades from Section 4.2.1, we can come up with an overall benefit from informed trading of 51.6 million USD a year for affiliated managers, 46.8 million from round-trip trades and 4.8 million from buy-and-hold trades. This total benefit due to informed trading in the secondary market appears large compared to the small losses caused by funding support in the primary market.

5 Conclusion

After the outbreak of the financial crisis in 2007/2008 financial institutions around the world faced a host of new regulations (e.g., the Volcker Rule) at least in part designed to curb the banking system's instability by restricting commercial banks' involvement in risky activities like LBO lending. As a consequence, traditional bank lenders partially refrained from financing

Figure 4: This figure displays 95% confidence intervals for average marginal effects of *Affiliation* on four different ex post performance measures controlling for the same variables as in Table 9. 12-M-Default (24-M-Default) indicates whether the borrower defaulted within the 12 months (24 months) period after purchase. 12-M-Rating Change (24-M-Rating Change) is the change in the rating-implied PD within the 12 months (24 months) period after the purchase. The performance metric is always measured in % in each of the plots. We use the `coefplot` package by Jann (2014) to produce these plots.



LBOs, and a new type of lenders, PE-affiliated private debt managers emerged to fill the void. We rationalize the PE expansion into private debt by employing and verifying a cross-division subsidization ("dual benefits") argument. Our results demonstrate that the strategic entering of PE groups into the private lending market is not solely motived by "diversifying" their PE fee income stream, as frequently claimed by industry representatives. Furthermore, since the dual benefits argument suggests competitive advantages from combining PE with private debt, it is highly likely that additional single-market PE firms also expand their business model, and that the overall market share of PE groups in private lending continues to grow. These developments carry some important implications for financial market stability in general, and the functioning of LBO and leveraged loan markets in particular.

First, while regulators intended to limit systemic risk by making the LBO lending market less dependent on a small number of "too-big-to-fail" banks, quite the opposite might have occurred. Put differently, by squeezing conventional leveraged lenders out of LBOs, regulations do not reduce risk, but merely transfer the same risks to a different part of the market. Second, and even worse, the risk is transferred to the rather dark corner of financial markets. Compared to banks, PE and alternative asset managers in general, are almost entirely outside regulatory reach. Hence, regulation that fosters shadow lending in exchange for regulated lending is misguided. Third, the affiliated price support we document most likely entails a misallocation of resources, higher LBO valuation multiples, and a significant wealth transfer from debtholders to equity claimants, thereby jeopardizing the regular working of the LBO market. Finally, the significant loan trading excess returns that we find for affiliated managers could be viewed as a symptom of a market that is unfair to outside investors, who would apparently be trading at an informational disadvantage. If widely recognized, such a disadvantage would diminish outsiders' confidence in the secondary loan market, reduce their willingness to trade, and thereby undermines the market's overall liquidity and efficiency.

We believe that our research highlights and addresses a number of important but previously overlooked policy issues and advises government officials, legislators, and central bankers to start looking more closely into the shadow banking business established by PE groups.

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A Appendix

A.1 Variables

Table A.1: In this table the variables in use are described.

Variable	Source	Unit	Description
Panel A: Metric Facility Characteristics			
# Facilities	DealScan	count	Number of facilities in the loan package (PackageID).
# Syndicate Members	DealScan	count	Number of lenders in the syndicate according to DealScan.
# Manager	CLO-i (own computation)	count	Number of CLO managers that currently hold the facility.
5yr Lead-Borrower-Vol	DealScan	Mio. USD	For every lead arranger of the facility the sum of all inflation-adjusted facility amounts the arranger had with the same borrower in the five years prior to the issuance date is computed. The mean value across all lead arrangers is taken.
5yr Lead-Sponsor-Vol	DealScan	Mio. USD	For every lead arranger of the facility the sum of all inflation-adjusted facility amounts the arranger had with the same sponsor in the five years prior to the issuance date is computed. The mean value across all lead arrangers is taken.
5yr Sponsor Market Share	DealScan	%	The ratio of the sponsor's sum of all facility amounts in the five years prior to issuance to the total amount issued in this time.
Affiliated Funding	CLO-i (own computation)	Mio. USD	$Log(1 + \sum_i \text{Affiliated Investments}_i)$ across all affiliated CLOs i, measured at the primary market. The purchase amount of each CLO is inflation adjusted.
AISD	DealScan	basis points	All-In-Spread-Drawn, defined as the sum of the spread over LIBOR or EURIBOR plus the facility fee.
Facility Amt	DealScan, FRED	Mio. USD	Facility amount as available from DealScan adjusted to end of 2015 USD (FRED ticker CPIAUCSL).
Maturity	CLO-i, DealScan	years	Difference between variables *FacilityEndDate* and *FacilityStartDate* from DealScan divided by 365. If *FacilityEndDate* is not available in DealScan then Maturity is computed as the difference between the expiration date according to CLO-i minus *FacilityStartDate* from DealScan.

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Variable	Source	Unit	Description
Moody's PD	CLO-i, Yoshizawa (2003)	%	One year rating-implied probability of default. The measure is constructed by mapping Moody's rating into an idealized default rate using the table in Yoshizawa (2003, p. 19).
Price at Issuance	CLO-i	%	Price CLOs paid at the issuance date of a facility.
PD	CLO-i (own computation)	%	Mean of Moody's PD and S&P's PD.
Rating adjusted Spread	CLO-i (own computation)	%	Spread on facility in excess of the average spread of all facilities traded in the same month and displaying the same rating letter (averaged over Moody's and S&P).
S&P PD	CLO-i, Barnett-Hart (2009)	%	One year rating-implied probability of Default. The measure is constructed by mapping S&P's rating into an idealized default rate using the table in Barnett-Hart (2009, p. 113).
Unaffiliated Funding	CLO-i (own computation)	Mio. USD	$Log(1 + \sum_i \text{Unaffiliated Investments}_i)$ across all unaffiliated CLOs i, measured at the primary market. The purchase amount of each CLO is inflation adjusted.
Panel B: Facility Indicator Variables			
Affiliation	CLO-i, DealScan (own computation)	0/1	Indicator variable that is one if sponsor of loan or bond is affiliated with CLO manager trading (holding) the instrument. See Section 2 for details.
Credit Line	DealScan	0/1	Following Berg et al. (2016a, p. 1382) facilities of *LoanType* "Revolver/Line < 1 Yr.", "Revolver/Line ≥ 1 Yr.", "364-Day Facility", "Limited Line", or "Revolver/Term Loan".
Industry	DealScan	factor	Indicator variable for the 2-digit SIC code obtained from variable *PrimarySICCode* in DealScan.
Institutional Facility	DealScan	0/1	Dummy variable that is one if the *LoanType* of the facility contains the word "Term Loan" and is not of *LoanType* "Term Loan A" or "Revolver/Term Loan"
LBO/SBO	DealScan	0/1	Dummy that is one if *PrimaryPurpose* of loan is "LBO" or "SBO".
Performance Pricing	DealScan	0/1	Dummy that is one if facility has a performance pricing schedule.
Secured	DealScan	0/1	Dummy that is one if facility is secured.

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Variable	Source	Unit	Description
SIC Code Division	DealScan	0/1	Division belonging to the two-digit SIC Code as stated on the website of the U.S. Department of Labor.
US	DealScan	0/1	Dummy that is one if *Country* is "USA".
USD	CLO-i	0/1	Dummy that is one if facility is denominated in USD.
Panel C: Trade-Level Variables			
Affiliated Sale Dummy	CLO-i (own computation)	0/1	Dummy variable that is one if affiliated CLO sells the same loan at same date, motivated by the findings in Loumioti and Vasvari (2016).
Distress	CLO-i (own computation)	0/1	Binary indicator that is one if price of traded facility is below the median of all traded facilities in the same quarter.
Effective Spread	DealScan, CLO-i	% or basis points	Effective spread, defined as the sum of AISD and the price discount distributed over four years: Effective Spread = AISD in $\% + (100 - \text{price})/4$. In most analyses converted into bp.
Holding Time	CLO-i (own computation)	days	Difference between sale and purchase date. If more than one purchase is associated with the sale the principal weighted average of the time differences is computed.
$Maturity^{Asset} - Maturity^{Portfolio}_{t-1}$	CLO-i (own computation)	years	Absolute difference between the lagged average portfolio maturity and the maturity of the facility.
Realized Purchase	CLO-i	0/1	Dummy that is one if facility is purchased and zero otherwise.
Relation	CLO-i (own computation)	0/1	Indicator variable that is one if the CLO manager had a lending relationship with the borrower in the past and zero otherwise.
Same Currency Dummy	CLO-i (own computation)	0/1	Indicator variable that is one if facility is denominated in the same currency as the majority of the CLO's assets.
Panel D: CLO Variables			
Age	CLO-i (own computation)	years	Years since the closing date of the CLO.
Log(Portfolio Size)	CLO-i (own computation)	Mio. USD	Inflation adjusted log size of all assets held by a CLO.
Panel E: Macro Variables			
HY bond spread over LIBOR	Merril Lynch, FRED	%	U.S. High Yield Corporate Bond Index (Yield) minus 3-month-LIBOR motivated by its use as proxy for debt market conditions in Axelson et al. (2013).

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Variable	Source	Unit	Description
Market Depth	CLO-i (own computations)	count	Number of instruments that are currently traded in the European or U.S. loan market, respectively.

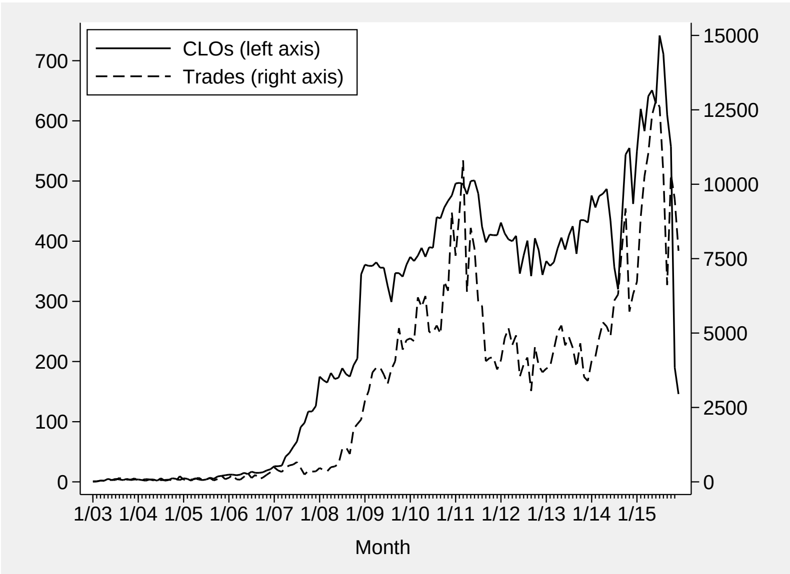
B Internet Appendix

B.1 Data coverage and preparation

B.1.1 Trading and holding data from CLO-i

We obtain data on CLO trading activity and portfolio composition from CLO-i. We drop all observations that belong to structured finance instruments or equity securities. Moreover, we delete duplicate entries and delete restructurings which we identify as purchases and sales with the same size and in the same borrower, at the same date, at the same price. The following figure shows the final number of CLOs and trades in each month of our sample period.

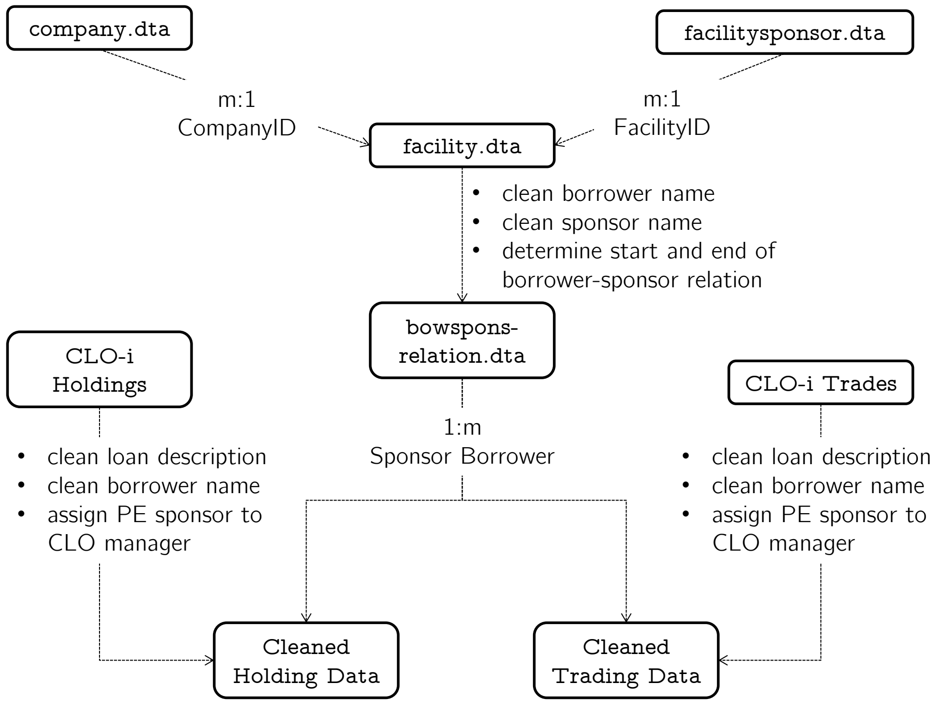
Figure IA.1: This figure shows the number of trades and portfolio observations. The trade series is based only on loans and bonds but no equities or structured finance products. For the portfolio observations we only count one observation per CLO-month.



B.1.2 Loan and borrower matching between CLO-i and DealScan

Although DealScan provides a – not always unique – identifier (LIN) CLO-i does not offer such a variable. This complicates the matching of the two databases. Therefore, we conduct a rigorous revision of the crucial string variables in DealScan and CLO-i. This involves, e.g., the loan description in CLO-i as well as the name of the borrower. The Stata files that are used for cleansing the loan description and the borrower name in CLO-i can be downloaded from one of the authors' websites. Specifically, we rename the borrower to conform with the name in DealScan. As for the DealScan data, we aggregate different borrower names in case they represent the same legal entity or are subsidiaries of one and the same parent firm. We further clean the sponsor variable in DealScan. For instance, we aggregate the sponsors named "Kravis Kohlberg Roberts", "Kohlberg Kravis Roberts & Co [KKR]", "KKR Capital Markets" etc. to one single entity labelled "KKR". This enables us to measure the relationship variables more precisely. Moreover, we use this cleaned data for the identification of the borrower-sponsor-relation (see Section 2). Figure IA.2 illustrates how we merge the cleaned datasets to finally identify *Affiliation*.

Figure IA.2: This figure illustrates the matching procedure to identify affiliated facilities.



Because the *FacilityEndDate* and *LoanType* variables in DealScan have counterparts in CLO-i we are able to match DealScan data with CLO-i on a loan-by-loan basis. To identify the appropriate loan we merge all sponsored loans of a borrower in DealScan to all observations of the same borrower in CLO-i. To nail down the "correct" match we successively delete observations based on a comparison of the variables in DealScan with those in CLO-i[32]:

1. We delete loan tranches whose issuance date (*FacilityStartDate*) comes later than the holding date (or trade date) in CLO-i.

2. We drop observations where the holding or trade date in CLO-i is later than the maturity of the loan according to DealScan (*FacilityEndDate*).

[32]Data in CLO-i has been cleaned before this procedure is applied. The clearance includes borrower names, maturities, loan descriptions and the issue variable.

3. We exclude observations where the maturity in CLO-i and the *FacilityEndDate* in DealScan differ by more than 30 days.

4. From the remaining observations we keep all cases where the *LoanType* variable from DealScan aligns with the corresponding variable in CLO-i, i.e., we match institutional loan tranches to institutional loan tranches, revolving loans to revolvers and bank loan tranches to bank loan tranches etc.

5. Based on the loan description in CLO-i we construct a *Seniority* variable like the one in DealScan and drop subordinated loans[33] that have been matched to senior loans from DealScan and vice versa.

6. We drop observations where the "coupon" in CLO-i (the yield) is *smaller* than the AISD in DealScan.

7. From the resulting matches we search for the observation[34]:

   (a) with the same Loan Identification Number (LIN)

   (b) with the same spread

   (c) with the LoanType closest to the issue in CLO-i. For example, from the two remaining matches of the LoanTypes "Term Loan" and "Term Loan B" we would take the latter if the issue according to CLO-i is "Term Loan B".

   (d) with the smallest difference between maturity according to CLO-i and *FacilityEndDate*.

B.1.3 Default data

We construct a database on defaulted borrowers using several sources. We begin with default data from CLO-i and once again apply our cleaning procedure on the loan description and subsequently the borrower name. This data also gives us information on the time of default. However, in a number of cases we had conflicting information about this date. We therefore used S&P's "Annual Global Corporate Default Study And Rating Transitions" files for the years 2008 to 2015 to correct these cases. In addition, we use these files to screen for defaults that have not been originally recorded in CLO-i. Finally, we compare our interim result with LCD and add all defaults that we find there. Because we had access to the above mentioned data only until the end of 2015, defaults in 2016 have been missing. To fill this gap, we used Thomson Reuters Leveraged Loan Monthly reports. The resulting dataset comprises 1,198 default-months of 935 borrowers.

[33] We define a loan as subordinated if the description contains one of the words "subordinated", "second lien", "third lien" or "junior".

[34] In descending order. If variables are not in both datasets, go to next step. The LIN and spread information in the CLO-i data was manually added by us in a few cases and is not available in the original data.

B.2 Robustness checks

B.2.1 Price support in the primary market: Dummy variable

Table IA.1: This table presents results from spread regressions. The dependent variable is the effective spread in Columns (1) through (4) or the AISD in Columns (5) to (8). We use the average monthly purchase amount of all affiliated (unaffiliated) CLOs in the three months prior to the issuance date as an instrument for Affiliation (Unaffiliated Funding) in our instrumental variable regressions. Affiliation is a binary indicator that is one in case an affiliated manager invested in the facility and zero otherwise. Unaffiliated Funding is the investment amount of unaffiliated investors (log of 2015 USD). The instrumental variable regressions are executed in Stata using the `ivreg2` routine (Baum et al., 2002). Variables are explained in Appendix A.1. The constant is not reported. Standard errors are clustered at the borrower level with the corresponding p-values reported in parentheses. The Kleibergen and Paap (2006) rk statistic is distributed χ_1^2 under the null of no correlation between the endogenous regressors and the instruments and is robust to non-iid errors.

	Effective Spread				AISD			
	OLS		2SLS		OLS		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Affiliation	-36.057	-25.337	-85.199	-47.194	-30.471	-19.336	-76.764	-27.992
	(0.000)	(0.001)	(0.001)	(0.101)	(0.000)	(0.003)	(0.000)	(0.258)
Unaffiliated Funding	1.717	-1.885	-31.090	-51.695	-0.348	-3.255	-8.011	-24.921
	(0.496)	(0.449)	(0.300)	(0.101)	(0.877)	(0.148)	(0.743)	(0.329)
Log(# Syndicate Members)	-15.429	-10.034	-8.364	-0.956	-11.508	-6.880	-8.771	-2.949
	(0.000)	(0.009)	(0.190)	(0.889)	(0.002)	(0.052)	(0.096)	(0.600)
# Facilities	-5.376	-1.549	-7.352	-4.418	-6.027	-2.718	-6.350	-3.963
	(0.029)	(0.467)	(0.017)	(0.110)	(0.005)	(0.172)	(0.014)	(0.099)
Log(Facility Amt)	-21.434	-13.760	-5.788	9.557	-20.800	-14.042	-16.500	-3.903
	(0.000)	(0.000)	(0.679)	(0.528)	(0.000)	(0.000)	(0.151)	(0.752)
Log(Maturity)	0.538	-8.494	1.872	-8.018	1.995	-5.514	2.445	-5.313
	(0.879)	(0.025)	(0.608)	(0.048)	(0.539)	(0.117)	(0.454)	(0.138)
LBO/SBO	30.792	10.984	37.508	16.524	22.587	7.079	24.263	9.490
	(0.000)	(0.060)	(0.000)	(0.021)	(0.000)	(0.168)	(0.000)	(0.108)
Secured	-17.930	-8.211	-14.606	-2.058	-17.064	-8.903	-16.921	-6.198
	(0.216)	(0.574)	(0.350)	(0.899)	(0.184)	(0.492)	(0.204)	(0.649)
Performance Pricing	-34.886	-32.270	-30.257	-27.818	-31.123	-29.010	-28.459	-27.105
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US	-4.844	-4.385	-4.503	-4.728	-4.246	-3.523	-3.812	-3.671
	(0.362)	(0.388)	(0.412)	(0.382)	(0.366)	(0.438)	(0.420)	(0.424)
HY bond spread over LIBOR	33.598	32.816	33.894	34.063	21.686	20.824	21.319	21.374
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(1+5yr Lead-Borrower-Vol)		-9.086		-10.828		-7.054		-7.812
		(0.000)		(0.000)		(0.000)		(0.000)
5yr Sponsor Market Share		-0.594		0.963		-2.066		-1.417
		(0.668)		(0.589)		(0.139)		(0.382)
Log(1+5yr Lead-Sponsor-Vol)		-2.880		-3.059		-2.375		-2.453
		(0.007)		(0.008)		(0.020)		(0.021)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Letter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	3087	3087	3087	3087	3087	3087	3087	3087
Adj. R^2	0.378	0.421	0.320	0.310	0.367	0.404	0.355	0.376
Kleibergen and Paap statistic			25.966	23.887			25.966	23.887

B.2.2 Trade returns controlling for change in PDs

Table IA.2: This table presents results from OLS regressions of *Annualized Excess Returns* on the *Affiliated* dummy and controls. Specifically and contrary to Table 7, we add a variable that captures the change in the rating-implied one-year PD between purchase and sale date (ΔPD). The dependent variable is winsorized at the 1% and 99% percentile. The constant is not reported. Columns (1) through (3) show results for a sample of private equity affiliated and unaffiliated managers, whereas Columns (3) to (6) are only for a subsample of trades from managers with private equity arms. In Columns (7) through (9) the sample is confined to observations from affiliated borrowers. Standard errors are double-clustered (Cameron et al., 2011) along sale date quarters and borrower names with the corresponding p-values reported in parentheses.

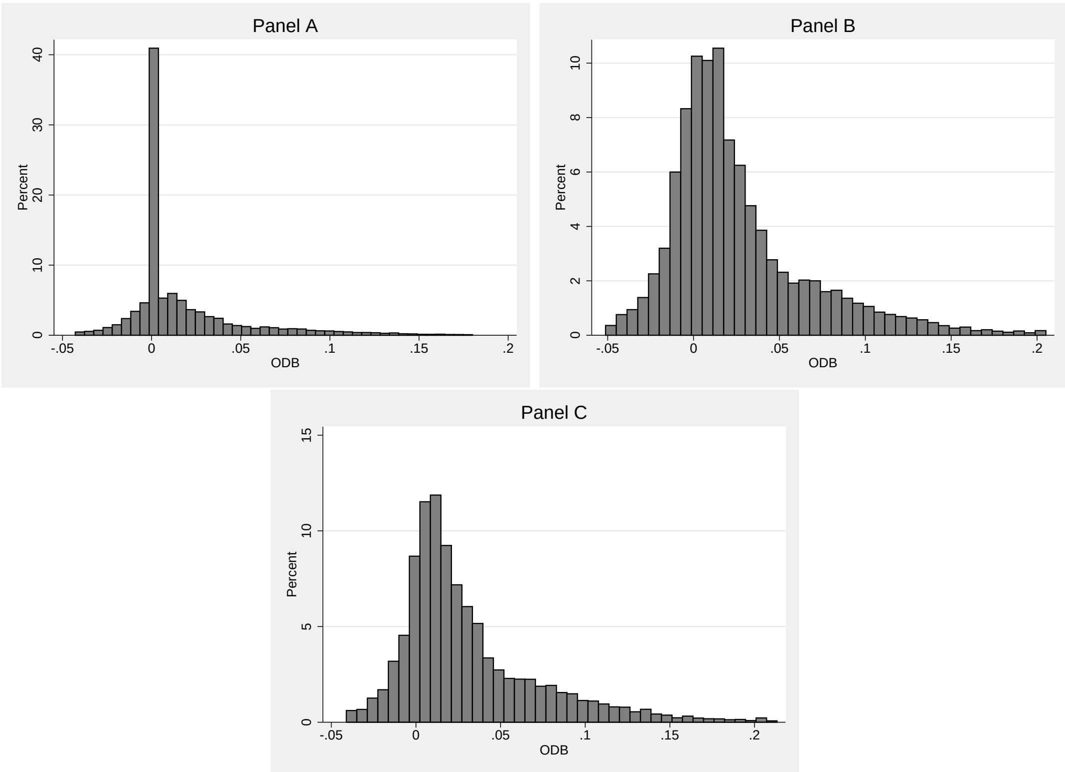
	Dependent variable: Annualized Excess Return in %								
	Full Sample			Only Affiliated Managers			Only Affiliated Borrowers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Affiliation	2.605	2.573	3.115	2.637	2.165	3.087	3.604	2.239	3.884
	(0.065)	(0.005)	(0.077)	(0.056)	(0.034)	(0.036)	(0.007)	(0.025)	(0.037)
Log(Trade Volume)	0.270	0.091	0.446	0.132	-0.034	0.226	0.689	0.358	0.853
	(0.225)	(0.558)	(0.087)	(0.644)	(0.884)	(0.384)	(0.019)	(0.260)	(0.007)
Log(Holding Time)	-9.534	-9.759	-9.522	-9.713	-9.806	-9.671	-8.403	-8.701	-8.494
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bond Dummy	5.189	6.899	5.149	5.755	6.838	6.099	8.579	12.015	8.846
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.006)	(0.008)
USD Dummy	1.648	-0.096	2.809	0.593	0.488	2.104	2.931	0.447	5.336
	(0.151)	(0.960)	(0.050)	(0.625)	(0.827)	(0.133)	(0.078)	(0.823)	(0.047)
Δ PD	-0.173	-0.094	-0.180	-0.128	-0.083	-0.129	-0.403	-0.304	-0.358
	(0.003)	(0.103)	(0.015)	(0.035)	(0.078)	(0.029)	(0.004)	(0.167)	(0.006)
Borrower FE	No	Yes	No	No	Yes	No	No	Yes	No
Manager FE	No	No	Yes	No	No	Yes	No	No	Yes
Rating Letter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,484	44,484	44,484	22,107	22,107	22,107	10,299	10,299	10,299
Adj. R^2	0.295	0.409	0.314	0.313	0.469	0.320	0.308	0.356	0.336

B.3 Additional information

B.3.1 Empirical distribution of the ODB

For each of the three panels in Table 2 we show histograms to equip the reader with a detailed understanding of how the ODB is distributed across our sample.

Figure IA.3: This figure shows histograms for the three panels in Table 2. Panel A shows the unrestricted version of the ODB. In Panel B only observations are included where either the treatment or the control CLOs have more than 0% invested into debt of borrowers affiliated with the treatment CLO. Panel C conditions on the percentage in the treatment CLO being greater than 0%.



B.3.2 Manager-level ODB

Table IA.3: This table presents the average ODB and the average percentage of the portfolio par amount invested in loans or bonds of affiliated borrowers on an invididual management company level. P-values are clustered at the quarter level and wild cluster t bootstrapped at the quarter-level (Cameron et al., 2008) in Columns (6) and (11) to mitigate problems caused by the small number of clusters.

	No Condition					if Own Debt > 0				
Manager	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Boot-strap)	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Boot-strap)
3i	258	1.59%	0.71%	(0.000)	(0.000)	135	3.06%	1.89%	(0.000)	(0.000)
Alcentra Group	583	0.53%	0.50%	(0.000)	(0.000)	188	1.66%	1.57%	(0.000)	(0.000)
Allianz Capital Partners	63	0.00%	0.00%			0				
Allied Capital	33	0.81%	0.71%	(0.000)	(0.000)	31	0.86%	0.76%	(0.000)	(0.000)
Allstate Investments	4	0.00%	0.00%			0				
American Capital	53	1.56%	1.41%	(0.000)	(0.000)	25	3.31%	3.24%	(0.000)	(0.000)
Anchorage Capital Group	4	2.46%	2.38%	(0.046)	(0.000)	3	3.28%	3.17%		
Angelo, Gordon & Co	119	0.25%	0.10%	(0.031)	(0.034)	48	0.62%	0.38%	(0.000)	(0.000)
Apollo Global Management	260	1.58%	-1.63%	(0.000)	(0.000)	215	1.91%	-1.42%	(0.000)	(0.000)
Ares Management	399	1.67%	1.19%	(0.000)	(0.000)	265	2.51%	1.88%	(0.000)	(0.000)
Avenue Capital Group	59	0.00%	0.00%	(0.078)	(0.088)	0				
AXA Investment Managers	130	0.84%	-1.28%	(0.000)	(0.000)	55	2.00%	-0.83%	(0.000)	(0.000)
Babson Capital Management	242	0.37%	0.36%	(0.000)	(0.000)	62	1.41%	1.41%	(0.000)	(0.000)
Bear Stearns	3	0.00%	0.00%			0				
Benefit Street Partners	22	3.99%	1.72%	(0.000)	(0.000)	22	3.99%	1.72%	(0.000)	(0.000)
Black Diamond Capital Management	136	2.01%	2.01%	(0.000)	(0.000)	70	3.86%	3.85%	(0.000)	(0.000)
BlackRock	44	0.02%	0.00%	(0.831)	(0.881)	2	0.44%	0.35%	(0.000)	(0.513)
Blackstone (incl. GSO after 3/2008)	818	10.04%	5.11%	(0.000)	(0.000)	793	10.36%	5.34%	(0.000)	(0.000)
Callidus	53	0.74%	0.75%	(0.000)	(0.000)	18	2.29%	2.24%	(0.000)	(0.000)
Carlyle Group	566	10.55%	6.34%	(0.000)	(0.000)	553	10.81%	6.51%	(0.000)	(0.000)
Cerberus Capital Management	8	0.00%	-0.88%	(0.000)	(0.000)	0				
Churchill Financial	2	1.58%	1.58%	(0.000)	(0.000)	2	1.58%	1.58%	(0.000)	(0.000)

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	No Condition					if Own Debt > 0				
Manager	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)
CIFC	46	0.55%	0.49%	(0.000)	(0.000)	20	1.27%	1.23%	(0.000)	(0.000)
Citigroup	40	2.69%	0.42%	(0.040)	(0.096)	40	2.69%	0.42%	(0.040)	(0.106)
Credit Suisse Asset Management	335	0.81%	-0.12%	(0.180)	(0.220)	201	1.35%	0.30%	(0.003)	(0.010)
CVC Capital Partners	326	7.29%	4.68%	(0.000)	(0.000)	296	8.03%	5.16%	(0.000)	(0.000)
Deerfield Capital Management	6	0.00%	-0.05%	(0.086)	(0.168)	0				
Deutsche Asset & Wealth Management	113	0.41%	-0.01%	(0.870)	(0.839)	48	0.98%	0.32%	(0.000)	(0.000)
Fidelity Investments	60	0.20%	0.03%	(0.402)	(0.464)	42	0.28%	0.05%	(0.246)	(0.246)
Fortress Investment Group	63	0.41%	-0.09%	(0.496)	(0.549)	14	1.84%	1.00%	(0.000)	(0.000)
Four Corners Capital Management	75	0.00%	-0.33%	(0.000)	(0.000)	0				
GE Asset Management	55	0.00%	-0.08%	(0.000)	(0.004)	0				
GoldenTree Asset Management	185	1.16%	1.10%	(0.000)	(0.000)	64	3.34%	3.23%	(0.000)	(0.000)
GSC Group	118	0.00%	-0.51%	(0.000)	(0.000)	0				
GSO	10	0.44%	0.32%	(0.004)	(0.254)	3	1.47%	1.30%	(0.000)	(0.000)
Guggenheim Partners Investment Management	25	0.66%	0.66%	(0.000)	(0.016)	20	0.83%	0.83%	(0.000)	(0.000)
Halcyon Asset Management	69	0.49%	0.43%	(0.000)	(0.000)	8	4.19%	4.05%	(0.000)	(0.000)
HarbourView Asset Management	14	0.00%	0.00%			0				
HIG WhiteHorse	45	0.58%	0.51%	(0.000)	(0.008)	26	1.00%	0.87%	(0.000)	(0.002)
Highland Capital Management	193	0.76%	0.74%	(0.000)	(0.000)	112	1.30%	1.26%	(0.000)	(0.000)
ING Group	50	0.00%	0.00%	(0.101)	(0.186)	0				
Intermediate Capital Group	198	1.16%	0.91%	(0.000)	(0.000)	91	2.53%	2.30%	(0.000)	(0.000)
Invesco Private Capital	70	0.06%	0.04%	(0.073)	(0.152)	16	0.27%	0.21%	(0.000)	(0.000)
Jefferies Finance	27	0.22%	0.14%	(0.189)	(0.190)	6	0.99%	0.96%	(0.000)	(0.000)
Katonah Capital	21	0.00%	-0.17%	(0.000)	(0.002)	0				
KCAP Financial	17	1.11%	0.97%	(0.013)	(0.020)	6	3.13%	2.83%	(0.000)	(0.000)
KKR	138	18.07%	11.42%	(0.000)	(0.000)	127	18.99%	12.57%	(0.000)	(0.000)
Lehman Brothers	10	0.88%	0.34%	(0.000)	(0.000)	6	1.85%	0.45%	(0.001)	(0.000)

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	No Condition					if Own Debt > 0				
Manager	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)
Littlejohn & Co.	1	1.72%	1.38%			1	1.72%	1.38%		
Loomis, Sayles & Co	15	0.00%	0.00%			0				
Lyxor	3	0.00%	0.00%			0				
M&G Investments	100	3.13%	3.03%	(0.001)	(0.006)	92	3.31%	3.29%	(0.001)	(0.000)
Madison Capital Partners	13	0.00%	-0.19%	(0.003)	(0.000)	0				
MatlinPatterson Global Advisers	40	1.11%	0.24%	(0.066)	(0.058)	33	1.35%	0.54%	(0.000)	(0.000)
MidOcean Partners	9	0.00%	-0.06%	(0.013)	(0.000)	0				
Morgan Stanley Group	33	0.91%	-0.14%	(0.508)	(0.501)	32	0.94%	-0.14%	(0.507)	(0.501)
N M Rothschild & Sons	68	0.00%	0.00%			0				
Neuberger Berman	4	0.34%	0.34%	(0.000)	(0.000)	4	0.34%	0.34%	(0.000)	(0.000)
New York Life Investment Management	103	0.07%	-0.02%	(0.504)	(0.527)	21	0.34%	0.21%	(0.000)	(0.000)
NIBC Bank	87	0.00%	-0.16%	(0.000)	(0.000)	0				
Oak Hill Capital Partners	203	1.11%	0.76%	(0.000)	(0.000)	135	1.67%	1.20%	(0.000)	(0.000)
Oaktree Capital Management	28	2.12%	1.20%	(0.000)	(0.000)	21	2.83%	1.74%	(0.000)	(0.000)
Octagon Credit Investors	212	2.18%	0.64%	(0.000)	(0.000)	207	2.22%	0.74%	(0.000)	(0.000)
Onex	8	0.49%	-0.83%	(0.000)	(0.000)	6	0.65%	-0.59%	(0.007)	(0.000)
Partners Group	10	1.92%	1.77%	(0.000)	(0.000)	10	1.92%	1.77%	(0.000)	(0.000)
Permira	20	11.82%	5.75%	(0.000)	(0.000)	20	11.82%	5.75%	(0.000)	(0.000)
PIMCO	129	0.00%	-0.05%	(0.000)	(0.000)	0				
PineBridge	52	0.02%	-0.02%	(0.001)	(0.002)	6	0.15%	0.03%	(0.555)	(0.547)
RBS Asset Management	9	0.00%	-0.39%	(0.002)	(0.018)	0				
Sankaty	168	10.07%	4.93%	(0.000)	(0.000)	165	10.29%	5.06%	(0.000)	(0.000)
Seix Advisors	29	0.00%	-0.01%	(0.022)	(0.110)	0				
SilverPoint Capital	25	1.98%	1.65%	(0.001)	(0.012)	14	2.98%	2.84%	(0.000)	(0.002)
Sound Point Capital	22	0.90%	0.29%	(0.000)	(0.000)	19	1.04%	0.41%	(0.000)	(0.000)
Stein, Roe & Farnham	3	0.00%	0.00%			0				
Stone Tower Capital	102	0.00%	-0.03%	(0.002)	(0.010)	0				

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	No Condition					if Own Debt > 0				
Manager	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)	# CLO-Quarters	Own Debt	ODB	p-value (Cluster)	p-value (Bootstrap)
Structured Asset Investors	4	0.00%	-0.03%	(0.021)	(0.000)	0				
Symphony Asset Management	168	4.54%	2.26%	(0.000)	(0.000)	166	4.60%	2.31%	(0.000)	(0.000)
TCW Group	17	2.19%	-1.91%	(0.000)	(0.002)	11	3.38%	-1.05%	(0.006)	(0.020)
Tennenbaum Capital Partners	14	1.17%	1.21%	(0.011)	(0.034)	10	1.95%	1.93%	(0.001)	(0.048)
THL Credit	52	3.28%	0.31%	(0.415)	(0.408)	49	3.48%	0.53%	(0.114)	(0.130)
TPG	16	8.65%	5.02%	(0.000)	(0.000)	16	8.65%	5.02%	(0.000)	(0.000)
Trimaran Capital Partners	62	0.00%	-0.02%	(0.003)	(0.004)	0				
WCAS Fraser Sullivan	31	4.52%	3.37%	(0.000)	(0.000)	31	4.51%	3.37%	(0.000)	(0.000)

B.3.3 Conditional trade return distributions

Table IA.4: This table shows summary statistics for affiliated (Panel A) and unaffiliated trades (Panel B). The returns are computed according to the FIFO principle, i.e., first sale of a loan is assumed to belong to the first purchase of this loan. Holding Time measures the difference in calendar days between the purchase and the sale date.

	N	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A: Affiliated Trades										
– **Winners**										
Returns	554	3.6%	4.9%	0.3%	0.3%	0.6%	1.5%	4.1%	12.0%	15.6%
Holding Time	554	325	353	3	13	48	241	455	818	1,025
– **Losers**										
Returns	472	-2.7%	6.4%	-8.6%	-5.7%	-2.3%	-0.8%	-0.6%	-0.3%	-0.1%
Holding Time	472	509	432	69	136	174	344	867	1,209	1,221
Panel B: Unaffiliated Trades										
– **Winners**										
Returns	28,560	4.3%	12.6%	0.2%	0.3%	0.6%	1.4%	4.1%	10.2%	16.2%
Holding Time	28,560	292	325	5	12	53	177	412	749	991
– **Losers**										
Returns	14,942	-6.5%	11.6%	-29.6%	-19.3%	-6.4%	-2.0%	-0.6%	-0.3%	-0.1%
Holding Time	14,942	411	372	35	64	143	293	553	951	1,245