Biased Beliefs and Institutional Overcrowding

Francesco Nicolai
BI Norwegian Business School

Simona Risteska
Warwick Business School

March 2025 – Latest Version
June 2024 – First Version
(Most recent version available here)

Abstract

Understanding the determinants of overcrowding behaviour is challenging due to the difficulty in measuring investor beliefs and preferences. This paper addresses this challenge by exploring the dynamics of investor behaviour within the leveraged loan market. Our major findings reveal that overcrowding among institutional investors in this market is driven by incorrect beliefs about their peers' actions rather than unobservable asset characteristics or positive spillovers across investors. Using a structural model of entry, along with exclusion restrictions and instrumental variables, we assess the accuracy of investor beliefs regarding their peers' investment decisions. Our findings refute the hypothesis of unbiased beliefs, indicating that overcrowding is driven by investors' incorrect assumptions about peer behaviour. Additionally, we recover the out-of-equilibrium beliefs of investors, providing insights into the determinants of their investment choices. These insights have significant implications for understanding market dynamics and quantifying the effect of overcrowding on asset prices.

Keywords: Investor Behaviour, Biased Beliefs, Financial Intermediation, Portfolio Choice, Institutional Overcrowding, Leveraged Loans, CLOs, Market Dynamics.

JEL Classification: G11, G12, G14, G23, C58, D84.

1 Introduction

In his Presidential Address to the American Finance Association, Stein (2009) warned that the rising role of institutional investors undermines market efficiency in two fundamental ways: by fostering excessive leverage and by triggering systemic overcrowding. Although the risks of leverage have been widely examined, the drivers behind overcrowding remain obscure. Why do institutional investors converge on the same trades? Is this behavior a rational response to shared fundamentals, or does it reflect deeper, systematic biases? Answering these questions is critical, as overcrowding not only distorts asset prices but also magnifies systemic risks—especially in opaque markets.

To shed light on these questions, we examine a market uniquely suited to analyzing institutional investor behavior: the leveraged loan market. Dominated by Collateralized Loan Obligation (CLOs)[1], this market provides an ideal environment to explore whether institutional overcrowding results from rational responses to market fundamentals or systematic biases in investors' beliefs. CLO managers play a pivotal role in shaping market outcomes through their strategic choices, making this setting particularly revealing for understanding the roots of overcrowding.

This paper makes four key contributions. First, we demonstrate that the largest institutional investors in the leveraged loan market—namely, CLOs—tend to crowd into the same primary market issuances, thereby affecting the loan spreads that firms face when raising capital. Second, drawing on the insights of Aguirregabiria and Magesan (2020), we develop a novel test to assess whether CLOs' beliefs about the likelihood of other investors participating in a given loan issuance are systematically biased. Third, our empirical evidence decisively rejects the hypothesis of unbiased beliefs, confirming Stein (2009)'s warning that institutional investors consistently fail to anticipate their peers' actions, which exacerbates trade overcrowding. Fourth, we advance the literature by moving beyond the equilibrium assumption of fully unbiased beliefs and estimate investors' utilities without imposing this constraint. Collectively, these contributions offer a framework for understanding how biased beliefs among sophisticated investors drive overcrowding, with implications for asset pricing and market stability.

Investigating overcrowding behaviour presents several econometric and theoretical challenges. The first major difficulty arises from the potential presence of unobservable factors—for example, shared private information unavailable to the econometrician—that may lead investors to rationally align their investment decisions. An additional challenge lies in the existence of positive externalities or spillovers among investors—for instance, increased monitoring by a larger group of investors may reduce the probability of default. Such factors further complicate the analysis, as they can naturally promote the desire to coordinate in investment decisions. As a result, observing correlated portfolios alone is insufficient to conclusively attribute the phenomenon to overcrowding driven by biased beliefs.

We address these challenges by showing that, within the framework of an optimal portfolio choice

[1] Collateralized Loan Obligations (CLOs) are structured finance vehicles that invest primarily in leveraged loans, which are debt instruments issued to companies with below investment-grade credit ratings. CLOs raise capital by issuing tranches of securities with varying risk profiles to investors, using the proceeds to purchase a diversified portfolio of leveraged loans. These vehicles are actively managed by specialized asset managers who make strategic decisions about loan selection, portfolio composition, and risk management, aiming to generate returns for investors across different tranches while navigating credit risks and market conditions in the leveraged loan market.

problem, it is possible to employ reasonable exclusion restrictions to empirically disentangle beliefs from preferences. Our approach draws on the literature on estimating out-of-equilibrium beliefs in static and dynamic games of entry (Aguirregabiria and Magesan, 2020; Aguirregabiria, 2021). We leverage insights and methodological approaches from the literature on oligopolistic competition. Traditional rational equilibrium models of competition rest on two fundamental assumptions. First, firms form beliefs about uncertain elements—such as competitors' actions—and maximize expected profits conditional on these beliefs. Second, these beliefs accurately reflect the true underlying probability distributions of uncertainties, a condition we refer to as rational equilibrium beliefs.[2] In practice, however, firms typically face significant uncertainty about competitors' strategies and vary considerably in their capacity to acquire and interpret information. These differences generate heterogeneity in firms' uncertainty levels and learning rates, undermining the standard assumption of homogeneous rational expectations. Consequently, behavioural models—which explicitly allow for bounded rationality and adaptive expectations rather than perfectly rational or static beliefs—have emerged as compelling alternatives. Yet, a critical methodological challenge remains: simultaneously identifying firms' subjective beliefs and the structural parameters of their payoff functions without relying on the restrictive assumption of rational expectations. Recent advancements have successfully tackled this problem by modeling firms' out-of-equilibrium beliefs—that is, explicitly permitting deviations from rational expectations. Our paper makes use of these econometric innovations to rigorously identify both institutional investors' beliefs and payoffs, shedding new light on their decision-making processes beyond the rational equilibrium framework.

We model the portfolio allocation decisions of institutional investors in the primary market for newly issued loans. Since higher investor demand typically lowers loan spreads and thus reduces expected returns,[3] managers must form expectations about the probability that other investors will participate in the same loan issuance. In Section 4, we confirm a strong negative (positive) relationship between CLO demand and loan spreads (prices): a 1% increase in CLO demand, instrumented by incumbency status, results in a reduction of all-in-drawn spreads by approximately 55 to 99 basis points. Additionally, we confirm that CLO managers systematically crowd into the same loans. Following the approach of Lakonishok et al. (1992), we compare actual CLO investment behavior with a simulated scenario where investment choices are randomly allocated. We find clear evidence that CLOs are significantly more likely to participate in loans already targeted by a larger number of their peers than would occur by random chance alone. However, as emphasized by Manski (1993), this correlation alone does not reveal the underlying reason for the observed clustering: unobserved (by the econometrician) confounding variables could simultaneously influence multiple investors' choices, driving them to concentrate investments in specific loans.

To explicitly address this identification challenge, we adopt an instrumental variable approach designed to clearly disentangle investors' beliefs from their underlying preferences. Specifically, this method requires instrumental variables that influence an investor's beliefs about a competitor's ac-

[2]In our investment context, the price (or equivalently, the rate of return) of an asset depends positively (negatively) on investor demand. Consequently, investors must forecast the residual demand they expect to face. Investors' beliefs are unbiased when their expectations about competitors' actions exactly match the probabilistic distribution of actual investment behaviors.

[3]See, for example, Kundu (2023), Nicolai (2020), and Fleckenstein et al. (2020), which document how exogenous shocks to CLO demand directly affect primary market loan spreads.

tions—after conditioning on the competitor's actual decision to invest or not—without directly affecting the investor's own utility. These instruments allow us to distinguish whether investors' beliefs about their competitors' behavior align with equilibrium—that is, whether their expectations match the actual probability distribution of realized competitor actions. In our setting, two suitable instrumental variables satisfying this exclusion criterion are the incumbency status and CLO lifecycle stage. Prior research shows that incumbency—previous investment in a given firm—significantly increases the likelihood that a CLO manager will participate in future loan issuances by that same firm (Nicolai, 2020; Hinzen, 2023; Bhardwaj et al., 2024). Similarly, CLO lifecycle stage—such as being newly issued or far from the end of the reinvestment period—is also associated with a higher probability of participating in new loan issuances (Fleckenstein, 2022). Crucially, conditional on the actual decision of a competitor (to invest or not), these characteristics (incumbency and lifecycle stage) do not directly influence an investor's payoff. For instance, investors may correctly anticipate that loans with many incumbents will attract higher overall demand. However, conditional on facing a given level of residual demand, an investor's payoff (and thus utility) is unaffected by whether competitors are incumbents or not. Likewise, conditional on a competitor's participation choice, the specific lifecycle stage of that competitor should have no direct bearing on the investor's utility.[4] This insight, first proposed by Aguirregabiria and Magesan (2020), enables us to rigorously test whether CLO managers hold equilibrium beliefs. The intuition behind this test is as follows: since our instrumental variables (competitors' incumbency status and CLO lifecycle stage) do not directly affect investor utility, we can construct a test statistic linking an investor's observed investment choices solely to their beliefs about competitors' actions. Specifically, we estimate two models: one that imposes equilibrium belief restrictions on utility parameters, and another that leaves these parameters unconstrained. Comparing the log-likelihoods of these two models provides a formal test of whether observed investment decisions are consistent with equilibrium beliefs. In Section 3.2, we strongly reject the equilibrium hypothesis. Our results clearly demonstrate that CLO managers systematically misjudge the likelihood that other investors will choose similar investments, highlighting biased beliefs as a key determinant of overcrowding. These findings confirm Stein (2009)'s concern that markets dominated by institutional investors are susceptible to overcrowding precisely because investors fail to accurately anticipate the actions of their peers. To the best of our knowledge, our study is the first to provide formal empirical evidence of this phenomenon.

Since we provide clear evidence that managers' beliefs about competitors' actions are biased, estimating portfolio choice models under the assumption that expectations align with competitors' realized actions will inevitably yield biased parameter estimates. Consequently, observed correlations in CLOs' investment decisions need not imply the presence of positive externalities or other strategic spillovers among investors. In Section 5.2, we relax the strict equilibrium beliefs assumption, allowing beliefs to be unbiased only within a specific subset of market states. Compared to the restrictive equilibrium assumption applied universally, this weaker condition significantly reduces the potential for biased estimates in our portfolio choice model. Under these less restrictive assumptions, our estimation reveals a key insight: CLO managers exhibit a clear preference for investments

[4] It is important to clarify that while competitors' incumbency status and lifecycle stage must satisfy this exclusion condition (i.e., not directly affect an investor's utility), an investor's own incumbency status and lifecycle stage clearly do influence their own payoff and thus their utility.

with lower participation by their peers. This aligns intuitively with the notion that lower residual demand translates into higher loan spreads and expected returns. Importantly, this result underscores that overcrowding is primarily driven by systematic errors in managers' expectations about competitors' actions, rather than by strategic complementarities or the sharing of fundamental information. Moreover, our analysis reveals that investors exhibit a strong preference for loans from firms in which they have previously invested, indicating the presence of substantial entry costs. Additionally, investors favor loans with shorter maturities and better credit ratings, as well as loans with higher idiosyncratic volatility and lower systematic volatility. This preference aligns with CLO managers effectively holding a call option-like position on their assets.[5] Consequently, CLO managers prefer investments with low asset correlation, as higher tranches are primarily at risk only when idiosyncratic defaults become widespread.

The findings of this study have broad implications. As Stein (2009) emphasized, the inability to accurately anticipate the investment decisions of other market participants represents a significant threat to market efficiency, contributing to non-fundamental volatility. Observing overcrowding behavior in a market dominated by sophisticated investors—who possess specialized knowledge, employ advanced strategies, and utilize rigorous risk assessment techniques (Fabozzi et al., 2020), as seen in the CLO market—suggests that similar, and potentially more severe, effects may arise in less specialized markets, particularly those dominated by retail investors or less sophisticated institutional investors. Moreover, our focus on leveraged loans, the primary assets of CLOs, is particularly relevant given the distinct characteristics of this market. Leveraged loans exhibit relatively inelastic residual demand, meaning that shifts in investor interest can lead to significant price swings that take time to stabilize. Additionally, the leveraged loan market is characterized by a smaller and more concentrated investor base compared to many other financial markets: in 2022, CLOs purchased 69% of all newly issued leveraged loans and owned 70% of the total supply (Guggenheim Investments, 2023). The market is further concentrated at the manager level, with approximately 150 CLO managers active in the U.S., and the top 30 managers collectively holding more than 55% of total CLO assets (CLO Research Group, 2023). This high degree of concentration underscores the importance of strategic, informed decision-making—sharply contrasting with markets that feature broader and more dispersed investor participation. The structure of the leveraged loan market provides an ideal setting for studying overcrowding behavior. The limited number of active participants magnifies the impact of individual investment decisions, while frequent transactions among a relatively stable set of players increase the scope for strategic behavior. Furthermore, information asymmetry—where access to specialized knowledge plays a pivotal role—adds an additional layer of complexity to investor interactions. These market conditions create an environment in which strategic motives are central, offering a unique opportunity to study the dynamics of overcrowding among sophisticated

[5] CLO managers typically earn management fees consisting of both senior and subordinated components, totaling approximately 40–50 basis points annually on the par value of the underlying loan portfolio. They also receive incentive fees contingent on the equity tranche surpassing a specified hurdle rate, usually set between 10% and 12%. Both subordinated management fees and incentive fees closely align managers' interests with equity tranche performance. Furthermore, under the Dodd-Frank Act's risk retention rules (effective until February 2018), CLO managers were required to retain at least 5% of the credit risk of the assets they securitized, typically by holding equity tranches of their own CLOs. Although these rules were invalidated by the U.S. Court of Appeals in February 2018, market constraints—particularly the limited availability of investors for equity tranches—continue to strongly incentivize CLO managers to prioritize equity tranche performance (Thiele, 2024).

investors. Yet, the insights derived from this analysis extend beyond the leveraged loan market, providing a broader perspective on the drivers of coordinated investment behavior in financial markets more generally. Our findings have direct relevance for discussions on market efficiency, the risks associated with concentrated positions, and potential regulatory interventions aimed at mitigating the adverse effects of investor misperceptions.

Related literature: This paper connects to four main strands of literature. First, we contribute to research on institutional investor coordination and herding behavior. Early empirical work documented and measured institutional herding (Lakonishok et al., 1992; Sias, 2004; Wermers, 1999), while theoretical studies explained how both rational and irrational herding can emerge (Bikhchandani et al., 1992; Banerjee, 1992; Scharfstein and Stein, 1990). More recent work has examined additional mechanisms driving institutional correlation: Anton and Polk (2014) document how portfolio similarities affect asset prices and create fragility, Lou (2012) shows how institutional trading flows lead to coordinated price pressure, and Falato et al. (2021) demonstrate how fire-sales by mutual funds create significant spillover effects in debt markets. Jiang and Verardo (2018) find that herding behavior often signals poor investment skill, aligning with our result that overcrowding stems more from biased beliefs than rational motives. On the other hand, herding is not inherently irrational, particularly when relative performance is a key driver of investor payoffs (Scharfstein and Stein, 1990)[6]. Our work advances this literature by distinguishing overcrowding from both rational and irrational herding, showing that correlated investment decisions can arise from errors in perceiving others' actions, even absent information cascades or strategic complementarities.

Second, we contribute to the growing literature on belief formation in financial markets. Greenwood and Shleifer (2014) document systematic biases in return expectations, while Koijen et al. (2024) show how heterogeneous beliefs drive demand for financial assets. We add to this literature by explicitly modeling and testing belief formation about other investors' actions, rather than just market outcomes or fundamentals, identifying a new channel through which biased beliefs impact market efficiency.

Third, we add to our understanding of CLO markets and leveraged loan trading. Fabozzi et al. (2020) analyze CLO managers' investment strategies, while Fleckenstein (2022) examines how CLO constraints affect credit cycles. Elkamhi and Nozawa (2020), Kundu (2023) and Nicolai (2020) study the impact of nonfundamental trading by CLOs on leveraged loan prices in the primary and secondary markets. Hinzen (2023) and Bhardwaj et al. (2024) study the persistence of CLO investment decisions and how they affect the cost of capital for firms. Compared to this literature, our study is the first to examine the strategic interactions between CLO managers, uncovering biased beliefs about competitor actions as a key driver of their behavior and consequent market impact. This suggests overcrowding reflects managers' misperceptions more than the collective wisdom of sophisticated investors.

Finally, we make a methodological contribution by introducing techniques from industrial organization to finance. While IO methods have been previously applied to financial markets (e.g., Koijen and Yogo (2019)), to the best of our knowledge we are the first to adapt frameworks for testing and estimating games with potentially biased beliefs (Aguirregabiria and Magesan, 2020; Aguirregabiria,

[6]See Chevalier and Ellison (1999), Dasgupta and Prat (2008) and Chen and Pennacchi (2009), among others.

2021) to an institutional investment setting. While these methods were originally developed to study firm competition in industrial organization, our application demonstrates their utility in understanding strategic behavior in financial markets, allowing researchers to disentangle preferences from beliefs and test whether market participants correctly anticipate others' actions. This methodological innovation provides new tools for disentangling preferences from beliefs, opening new avenues for research on strategic interactions in asset markets.

The structure of the paper is as follows: Section 2 provides a detailed description of the data used. In Section 3, we develop a model of portfolio choice, wherein CLO managers decide whether to invest in newly issued loans in the primary market. This decision involves balancing expected returns against risk while forming expectations about the investment behaviour of other managers. Section 3.2 analyzes the strategic environment and demonstrates that it is feasible to test the hypothesis of equilibrium beliefs among investors. In Section 4, we present reduced-form evidence indicating that CLOs' investment decisions are often correlated. We also establish the relevance of our instrumental variables—specifically, the incumbency status and the timing within the CLO lifecycle, as measured by the distance to the end of the reinvestment period—for investment decisions. Additionally, we show that CLO demand significantly influences pricing in the leveraged loan market. In Section 5, we conduct our proposed test and find strong evidence against the hypothesis of equilibrium beliefs. We then estimate investors' preferences without assuming equilibrium beliefs in Section 5.2. Finally, Section 6 concludes the paper.

2 Data

The dataset for this study is derived from two key sources: Crediflux CLO-i and DealScan, covering the timeframe from 2010 to 2019. The Crediflux CLO-i dataset provides comprehensive details on CLO holdings, transactions, tranches. CLOs are required to submit quarterly payment and monthly trustee reports to their investors, which CreditFlux has been compiling since 2009. The study concentrates on US-based CLOs for the period from January 2010 to December 2019. On the other hand, syndicated loan information is obtained from the facility and pricing datasets from DealScan. To integrate data from Crediflux CLO-i and DealScan, we have implemented a matching procedure the relies on Cohen et al. (2018). In particular, it is not trivial to reconcile the information contained in both datasets, since there is no common identifier across the two. We proceed as follows. From Crediflux we keep only USD-denominated loans issued by US-based companies. We exclude companies that are classified to be in the banking, insurance and financial industries, as well as, loans issued by sovereign and supranational entities. We then keep only term loans issued between January 2010 and December 2019. We try to construct a matching set from Dealscan, by including USD-facilities syndicated within the US, concentrating on syndicated loans with an All-In-Drawn spread exceeding 225 basis points. We also focus on loans issued between January 2010 and December 2019.

As pointed out by Cohen et al. (2018), there is no standardization across datasets covering the syndicated loan market. We therefore need to proceed by relying on the names of the companies as reported in the two datasets. For this purpose, all names have been converted to lowercase, punctuation has been removed, and common corporate terms have been eliminated. This standardization process ensures uniformity in issuer and security names from both Crediflux and DealScan, thereby reducing discrepancies arising from naming variations. Following this, we have applied a fuzzy matching techniques[7] to identify potential correspondences between the datasets. We have subsequently filtered the fuzzy matching results to retain those with significant overlap in names and loan characteristics. Overall, we have been able to match 6,669 facilities from 5,253 packages issued by 2,812 companies. The upper panel of Table 1 reports summary statistics for this sample. The average

Table 1 Summary Statistics

Panel A: Loans						
	Nr.Obs	Min	Max	Median	Mean	Std.Dev
Facility Amount ($M)	6669	1	15401.88	280	483.14	639.87
Maturity (Months)	6669	4	120.00	72	70.71	14.86
Secured	6669	0	1.00	1	0.90	0.30
AIDS (bps)	6669	225	1400.00	425	460.98	167.18
Panel B: CLOs						
Variable	Nr.Obs	Min	Max	Median	Mean	St Dev
Avg. Holding Amount ($M)	60277	0	27.30	1.50	1.72	1.24
Nr. Distinct Holdings	60277	1	458.00	119.00	118.80	66.76
Total Holdings Amount ($M)	60277	0	12558.74	457.96	467.24	262.67
Outside Holdings Amount ($M)	60277	0	8413.03	202.75	222.15	162.82
Age (Months)	60277	-4	215.00	41.00	46.42	32.13
Dist. Reinv. End (Months)	60277	-123	126.00	25.00	23.23	32.14

facility amount is $483.14 million, with a standard deviation of $639.87 million, indicating significant heterogeneity in loan sizes. Loan maturities range from 4 to 120 months, with the median loan with a maturity of 6 years (72 months). The greatest majority (90%) of loans are secured. If we look at the pricing of loans, the average all-in drawn spread (AIDS) is 460.98 basis points, with a median of 425 basis points. The wide range in both facility amounts and spreads highlights the diversity in the loan structures within the dataset.

We then proceed to describe the 1,929 CLOs in our sample managed by 170 unique managers. Panel B in Table 1 reports the descriptive statistics for this sample. We analyze data from 60,227 unique reports. On average, each CLO in our sample has $467.24 million in assets, with a median value of $457.96 million. These assets are spread across approximately 120 distinct loans (an average of 118.8 and a median of 119). For the loans we can track from their issuance on DealScan, the average amount is $1.72 million, while the median amount is $1.50 million. Loans that are not tracked through DealScan are classified as Outside Holdings. These Outside Holdings average $222.15 million per CLO report, with a median value of $202.75 million.

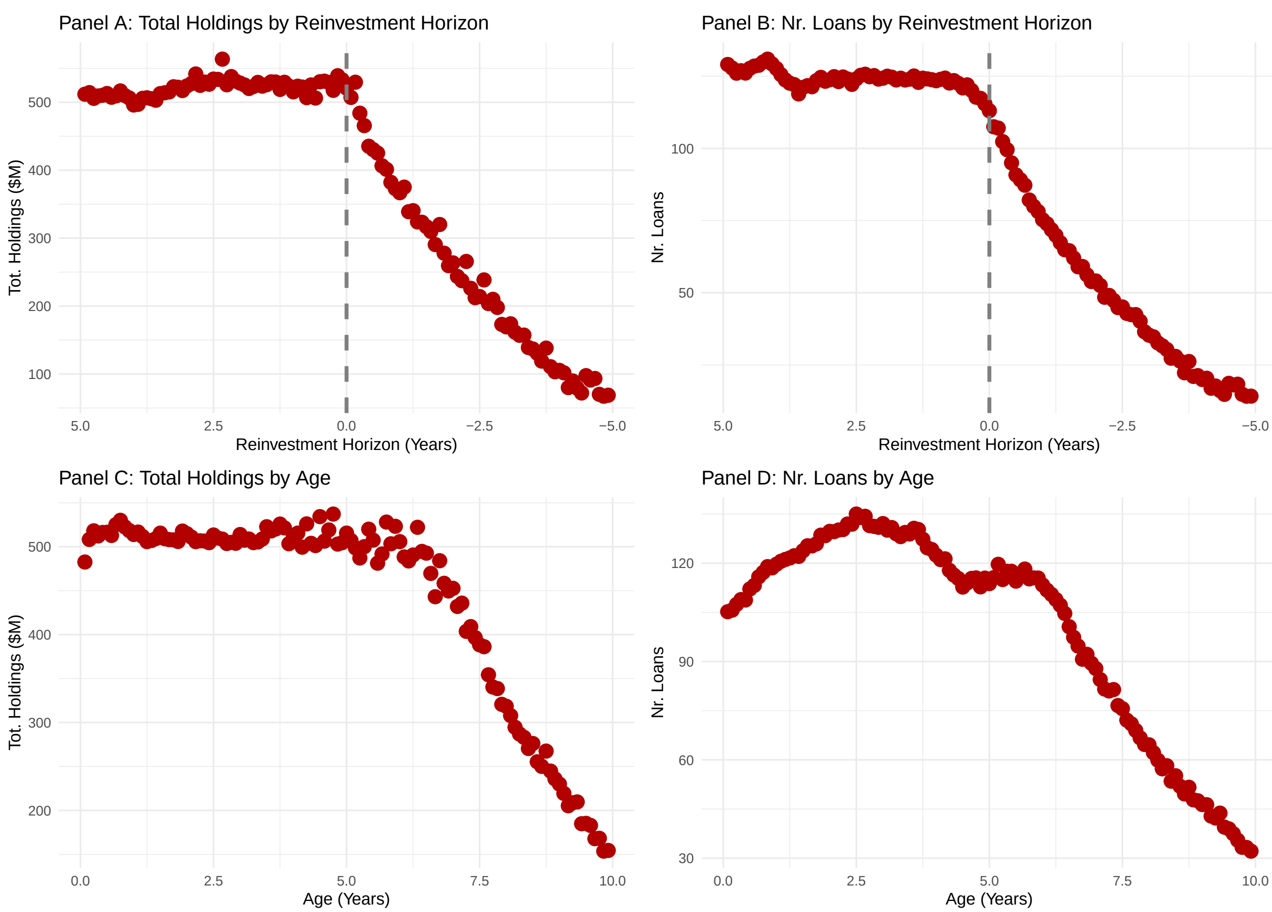
The last rows of Panel B in Table 1 detail variables related to the lifecycle of a CLO. The lifecycle begins with the CLO's formation, where a special purpose vehicle (SPV) pools a diverse portfolio of leveraged loans from various borrowers. Next, the CLO issues multiple tranches of debt and equity securities to investors, each with different risk and return profiles. A CLO manager then actively

[7]The matching process utilized the fedmatch package in R as described by Cohen et al. (2018).

oversees the portfolio, making decisions about buying, selling, and reinvesting loans to maximize returns while ensuring compliance with investment criteria. Cash flows from the underlying loans are distributed to investors according to the seniority of their tranches, with senior tranches receiving payments before junior ones. As the CLO approaches the end of its reinvestment period, it enters an amortization phase focused on repaying debt. Finally, at the end of its term, any remaining assets are liquidated and distributed to investors. As shown in the table, the median CLO is approximately 3.86 years old (or 46.42 months), with a median age of 3.42 years (or 41 months). On average, the remaining time until the end of the reinvestment period is about 1.94 years (or 23.23 months), with a median of 2.08 years (or 25 months).

Figure 1 : CLO Holdings and Loan Count by Reinvestment Horizon and Age

The figure illustrates the distribution of total holdings and the number of loans based on a CLO's proximity to the end of its reinvestment period and its age. Data are binned by month. Panel A depicts total holdings (in million USD) relative to the time remaining until the reinvestment period ends, measured as the difference between the reinvestment end date—when CLOs can no longer reinvest principal—and the current date. Panel B shows the number of loans held by CLOs as a function of the reinvestment horizon. In both Panels A and B, the x-axes are reversed to reflect the chronological order of events. The vertical dashed lines indicate the transition from the reinvestment to the non-reinvestment period. Panel C presents total holdings by CLO age, defined as the difference between the CLO's closing date and the current date. Panel D displays the number of loans held by CLOs across different ages.



The age and the distance to the end of the reinvestment period also have an influence on the portfolios of CLOs. Figure 1 displays the evolutions of CLO holdings as a function of age and distance to the end of the reinvestmention period. The top panels show the relationship between total holdings (Panel A) and number of holdings (Panel B) as a function of age: it is clear that CLOs have a period in which they tend to increase the size of their holdings, especially in terms of number of loans held. They achieve this goal by purchasing loans in the primary and secondary markets. CLOs are usually allowed to buy loans until the end of their reinvestment period, which is set by contract in the CLO indenture. The bottom panels of Figure 1 show that after the end of the reinvestment period, CLOs reduce the size of their balance sheet. This is generally achieved by repaying the CLOs tranches in order of decreasing seniority with the proceeds of the loans that have reached maturity. We will provide evidence in Section 4 that the likelihood that a CLO participates in the issuance of a new loan can be strongly predicted using its age and the distance to the end of the reinvestment period.

3 A Stylised Model

3.1 Investor Preferences

In this section, we introduce a stylized one-period investment model in which a CLO manager i decides whether to invest in a newly issued loan extended to firm j at time t. The utility that manager i derives from the investment is given by:

$$U_{i,t}(\mathbf{x}) = \underbrace{u_{i,t}(\mathbf{x})}_{\text{Mean–Variance Preferences}} + \underbrace{\varepsilon_{i,t}}_{\text{Private Information}}, \tag{1}$$

where:

- $u_{i,t}(\mathbf{x})$ is the baseline utility. For simplicity, we assume that managers have mean–variance preferences.
- $\varepsilon_{i,t}$ captures idiosyncratic private information affecting the investment decision and enters additively. This shock is unobservable to both the econometrician and other investors, so all market participants must form their expectations based on its known distribution. Under standard assumptions on the distribution of $\varepsilon_{i,t}$, the model yields an equilibrium characterized by threshold strategies, where each manager's decision depends on whether their private signal exceeds a certain cutoff.[8]
- $\mathbf{x}$ is the realization of the random vector $\mathbf{X}$ which collects the state variables that influence the manager's utility. In our empirical analysis, these include market characteristics (e.g., the number of incumbent CLOs and new entrants), investor attributes (e.g., age, incumbency), and loan features (e.g., time to maturity, credit rating, industry).

In what follows we present the main results of the model; the full derivations and additional details are provided in Appendix D. We consider a CLO with existing assets $A_{i,t}$, AAA–rated liabil-

[8] Similar approaches are common in the global games literature, where private information leads to unique equilibrium threshold strategies (e.g., Carlsson and Van Damme (1993)), or in oligopoly entry models (e.g., Doraszelski and Satterthwaite (2010)).

ities $L_{i,t}$, and a cash position $C_{i,t}$ at time t. At time t, firm j issues a loan with return $r_{j,t+1}$. The CLO manager may invest an amount $I_{i,j,t}$ in this loan (with $I_{i,j,t} \ll C_{i,t}$ so that the CLO remains cash–sufficient). When the CLO invests, it incurs an entry cost κ if it has not previously lent to firm j. The terminal equity at time $t+1$ is given by:

$$E_{i,t+1} = A_{i,t}(1 + r_{A_i,t+1}) - (L_{i,t} - C_{i,t})(1 + r_f) + I_{i,j,t}(r_{j,t+1} - r_f) - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t},$$

where $\mathbb{1}(\text{first time})_{i,j,t}$ is an indicator for the entry cost, incurred only when the CLO manager invests in a loan from firm j for the first time—i.e., when no prior loans from firm j have been held by any CLO within the same managerial family. In that case, the manager incurs a fixed cost κ. Empirical evidence suggests that the relationship between CLOs and borrowing firms is highly persistent (Nicolai, 2020; Hinzen, 2023; Bhardwaj et al., 2024). In our framework, the entry cost serves as a reduced-form mechanism to capture such stickiness. Several factors can explain a sticky lender–borrower relationship. For instance, creditors that build long-term relationships with fewer firms—through repeated lending—can reduce screening and monitoring costs (Sufi, 2007), achieve higher recovery rates in default, and gain bargaining power during restructuring (Acharya et al., 2006). Additionally, there may be learning costs associated with dealing with new firms, such that economies of scale arise when CLOs hold multiple loans from the same borrower[9]. Behavioural factors might also be at play, suggesting that the entry cost reflects a preference for investing in familiar assets (Huberman, 2001).

With mean–variance preferences and a risk–aversion parameter $\gamma > 0$, the manager's utility is:

$$U_{i,t} = \mathbb{E}[E_{i,t+1}] - \frac{\gamma}{2}\,\mathrm{Var}(E_{i,t+1}) + \varepsilon_{i,t}(I_{i,j,t}),$$

where $\varepsilon_{i,t}(I_{i,j,t})$ is an additive private information shock that is unobservable to others. Optimizing with respect to $I_{i,j,t}$ leads to the optimal investment:

$$I^*_{i,j,t} = \frac{\mu_j - r_f}{\gamma\,\sigma_j^2} - A_{i,t}\,\beta_{Aj}, \quad \text{with } \beta_{Aj} = \frac{\sigma_{Aj}}{\sigma_j^2}.$$

Substituting $I^*_{i,j,t}$ back into the utility function, the net gain from investing is:

$$\Delta U = \frac{1}{\sigma_j^2}\left[\frac{(\mu_j - r_f)^2}{2\gamma} - A_{i,t}\,\sigma_{Aj}\,(\mu_j - r_f) + \frac{\gamma}{2}(A_{i,t}\,\sigma_{Aj})^2\right].$$

A CLO invests (i.e., $I^*_{i,j,t} > 0$) if and only if $\Delta U - \kappa\,\mathbb{1}(\text{first-time})_{i,j,t}$ exceeds the difference in private shocks. Under standard assumptions (with the private shock difference following an extreme value type I distribution), this yields the logit choice probability:

$$\Pr\{I^\star_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\} = \frac{\exp\bigl(\Delta U - \kappa\,\mathbb{1}(\text{first-time})_{i,j,t}\bigr)}{1 + \exp\bigl(\Delta U - \kappa\,\mathbb{1}(\text{first-time})_{i,j,t}\bigr)}. \tag{2}$$

It is generally possible to invert equation (2) to express the utility difference as a function of the

[9]The optimality of concentrated portfolios under costly information acquisition has been theoretically examined by Van Nieuwerburgh and Veldkamp (2010) and empirically validated by Kacperczyk et al. (2005) and Anton et al. (2021), among others.

conditional choice probabilities[10]. More precisely, there exists a function $q\Big(\Pr\{I^{\star}_{i,j,t} \mid \mathbf{X} = \mathbf{x}\}\Big) \equiv q\Big(\Pr\{I^{\star}_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}, \Pr\{I^{\star}_{i,j,t} = 0 \mid \mathbf{X} = \mathbf{x}\}\Big)$ that returns the difference in observable utilities, after having integrated out the private information, $\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}$. In the case of Extreme Type I (Gumbel) errors, one can show that $q(x_1, x_2) = \log(x_1) - \log(x_2)$, which implies that:

$$\Delta U(\mathbf{X} = \mathbf{x}) - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}(\mathbf{X} = \mathbf{x}) = \log\left(\frac{\Pr\{I^{\star}_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}}{\Pr\{I^{\star}_{i,j,t} = 0 \mid \mathbf{X} = \mathbf{x}\}}\right). \tag{3}$$

This relationship aligns with the concept of revealed preferences: if an agent frequently chooses a positive investment given a particular configuration of state variables, then the utility from investing must exceed that of not investing. As long as we have reliable estimators for the conditional choice probabilities $P(I^{\star}_{i,j,t} \mid \mathbf{X} = \mathbf{x})$, we can use them to infer the corresponding utility differences. Since these probabilities can be readily estimated from observed investment decisions (conditional on the state variables $\mathbf{X}$), the transformation in Equation (3) allows us to recover an estimate of investors' preferences as a function of the state variables. This, in turn, enables us to identify which state variables significantly influence the investors' decision-making.

3.2 Strategic Environment and Testing for Biased Beliefs

In this section, we describe the strategic environment faced by investors. The actions of other market participants significantly affect key payoff determinants. For example, assuming no recovery in default, the expected payoff can be written as the product of the probability that the firm avoids default and the promised interest rate $\mu_{i,j,t} = \big(1 - P(\text{default})_{j,t}\big) \times r_{j,t}$. If promised interest rates are affected by demand for loans, making inferences about competitors' actions is crucial for the determination of expected returns. Empirical evidence indicates that the leveraged loan market is highly sensitive to capital supply. For instance, Nicolai (2020) and Kundu (2023) exploit exogenous shocks to CLO constraints to measure their impacts on both primary and secondary markets. Specifically, Nicolai (2020) finds a differential impact of up to 55 basis points between loans typically acquired by constrained CLOs and those purchased by unconstrained ones. Moreover, Fleckenstein et al. (2020) demonstrates that the cyclicality in syndicated loan issuance is largely driven by fluctuations in CLO demand. Consequently, CLO managers must anticipate the actions of other market participants. In Section 4, we provide evidence that since residual demand is not infinitely elastic, loans with higher CLO demand are associated with lower all-in drawn spreads. This implies that investors should forecast the prospective popularity of a loan issuance, as the expected return is inversely related to the number of participating CLOs, all else equal.

To capture the strategic environment, we assume that once the observable state $\mathbf{X} = \mathbf{x}$ is realized, each investor i forms beliefs $\mathbf{B}_i(\mathbf{x})$ regarding the actions of all other investors. Consequently, the expected observable payoff from choosing action a_i can be written as:

$$q(a_i \mid \mathbf{X} = \mathbf{x}) = \mathbf{B}_i(a_{-i} \mid \mathbf{X} = \mathbf{x})'\, \mathbf{u}(a_i, a_{-i} \mid \mathbf{X} = \mathbf{x}).$$

[10] See, for instance, Hotz and Miller (1993) and Berry (1994); even when the distribution of private information is unknown, one can nonparametrically invert conditional choice probabilities to infer utility differences (Matzkin, 1992).

For simplicity, we assume that the identity of the investing CLOs is irrelevant and that only the total number of investors, denoted by N_{INV}, affects expected returns. In a game with N players, each choosing from the binary action space $a_{i,j,t} \in \{I^{\star}_{i,j,t} > 0, I^{\star}_{i,j,t} = 0\} = \{1, 0\}$, define $N_{INV_{j,t}} = \sum_{k \neq i} a_{k,j,t}$. The expected payoff can be expressed as:

$$\begin{aligned} q(a_i \mid \mathbf{X} = \mathbf{x}) = & B_i(N_{INV_{j,t}} = 0 \mid \mathbf{X} = \mathbf{x})\, u(a_i, N_{INV_{j,t}} = 0 \mid \mathbf{X} = \mathbf{x}) \\ & + B_i(N_{INV_{j,t}} = 1 \mid \mathbf{X} = \mathbf{x})\, u(a_i, N_{INV_{j,t}} = 1 \mid \mathbf{X} = \mathbf{x}) \\ & + \cdots \\ & + B_i(N_{INV_{j,t}} = N-1 \mid \mathbf{X} = \mathbf{x})\, u(a_i, N_{INV_{j,t}} = N-1 \mid \mathbf{X} = \mathbf{x}). \end{aligned}$$

Because the model is typically underidentified, we impose additional structure to disentangle investors' beliefs from their utilities. We assume that the state variables can be partitioned as $\mathbf{X} = (\mathbf{S}_i, \mathbf{S}_{-i}, \mathbf{W})$, where $\mathbf{S}_i$ contains the state variables that affect only player i's utility, $\mathbf{S}_{-i}$ comprises the state variables that influence the utilities of all other players but not player i's utility, and $\mathbf{W}$ includes the state variables that affect the utilities of all players. Under this partition, the following exclusion restriction holds:

$$u(a_i, \mathbf{a}_{-i} \mid \mathbf{S}_i = \mathbf{s}_i, \mathbf{S}_{-i} = \mathbf{s}_{-i}, \mathbf{W} = \mathbf{w}) = u(a_i, \mathbf{a}_{-i} \mid \mathbf{S}_i = \mathbf{s}_i, \mathbf{S}_{-i} = \mathbf{s}'_{-i}, \mathbf{W} = \mathbf{w}) \quad \forall\, \mathbf{s}_{-i} \neq \mathbf{s}'_{-i}. \tag{4}$$

Here, the index $-i$ denotes the actions $\mathbf{a}_{-i}$ and state variables $\mathbf{S}_{-i}$ corresponding to all players other than i. In our setting, a natural candidate for a variable that satisfies the exclusion restriction in Equation (4) is the incumbency status of the player. For example, consider a simple case with two players (i.e., $i = 1$ and $-i = 2$). Conditional on player 2's decision to invest in a loan of firm j, player 2's incumbency status does not directly affect player 1's payoff. However, it indirectly influences player 1's expected utility by altering the probability that player 2 will invest. In other words, the conditional likelihood of participation as a function of the competitors' incumbency status provides information that helps infer the beliefs about the likelihood of competitors' entry. Variables related to the lifecycle of a CLO can also serve as identifying instruments, as they influence a CLO's propensity to invest without directly affecting the payoffs of its competitors. In Section D.1 of the Appendix, following Aguirregabiria and Magesan (2020) and Aguirregabiria (2021), we derive two main results. First, we obtain a test for equilibrium beliefs. In equilibrium, investors' beliefs about competitors' actions must equal the observed conditional probabilities, that is:

$$\mathbf{B}_{i,t}(\mathbf{a}_{-i} \mid \mathbf{x}) = \mathbf{P}_{-i,t}(\mathbf{a}_{-i} \mid \mathbf{x}).$$

This equilibrium condition implies the following restriction:

$$\frac{q_{i,t}(a_i, \mathbf{s}_i, \mathbf{s}^{(a)}_{-i}, \mathbf{w}) - q_{i,t}(a_i, \mathbf{s}_i, \mathbf{s}^{(c)}_{-i}, \mathbf{w})}{q_{i,t}(a_i, \mathbf{s}_i, \mathbf{s}^{(b)}_{-i}, \mathbf{w}) - q_{i,t}(a_i, \mathbf{s}_i, \mathbf{s}^{(c)}_{-i}, \mathbf{w})} = \frac{P_{-i,t}(a_{-i}, \mathbf{s}_i, \mathbf{s}^{(a)}_{-i}, \mathbf{w}) - P_{-i,t}(a_{-i}, \mathbf{s}_i, \mathbf{s}^{(c)}_{-i}, \mathbf{w})}{P_{-i,t}(a_{-i}, \mathbf{s}_i, \mathbf{s}^{(b)}_{-i}, \mathbf{w}) - P_{-i,t}(a_{-i}, \mathbf{s}_i, \mathbf{s}^{(c)}_{-i}, \mathbf{w})}. \tag{5}$$

In Equation (5), the vectors $\mathbf{s}^{(a)}_{-i}$, $\mathbf{s}^{(b)}_{-i}$, and $\mathbf{s}^{(c)}_{-i}$ represent different realizations of the competitors' state variables, $\mathbf{S}_{-i}$. Here, $\mathbf{s}^{(c)}_{-i}$ serves as the baseline or reference state for the competitors, while $\mathbf{s}^{(a)}_{-i}$ and

$\mathbf{s}_{-i}^{(b)}$ are alternative states that differ both from $\mathbf{s}_{-i}^{(c)}$ and from each other. A sketch of a proof is provided in Section D.1 in the Appendix. The intuition behind the condition in Equation (5) is as follows: since the utility of player i is assumed to be unaffected by the specific realization of the competitors' states (i.e., by $\mathbf{s}_{-i}^{(a)}$, $\mathbf{s}_{-i}^{(b)}$, or $\mathbf{s}_{-i}^{(c)}$), the differences in the expected utility function $q_{i,t}(a_i, \mathbf{s}_i, \cdot, \mathbf{w})$ across these realizations depend solely on the conditional choice probabilities of the other players and a common utility difference that can be factored out. The same logic applies to both the numerator and the denominator in Equation (5). Consequently, all terms involving the utilities cancel out, leaving an expression that depends only on the observed conditional choice probabilities, as shown on the right-hand side of the equation. The terms on the left-hand side of Equation (5) are recovered from the expected utility differences of player i as inferred from her actions, while the terms on the right-hand side are directly observed from the conditional choice probabilities of the other players. Therefore, by comparing these two expressions, we can empirically test whether the beliefs held by the investors are consistent with the actual actions of their competitors. Intuitively, if the normalized differences in the expected utilities $q_{i,t}(\cdot)$ align with the corresponding differences in observed choice probabilities, then beliefs are unbiased.

Second, if we can identify a subset of states, denoted by $\mathbf{s}_{-i}^{*}$, where beliefs are known to be unbiased (i.e., where $\mathbf{B}_{i,t}(\mathbf{a_{-i}}, \mathbf{s}_{-i}^{*}) = \mathbf{P}_{-i,t}(\mathbf{a_{-i}}, \mathbf{s}_{-i}^{*})$), these states serve as crucial "anchor points" for recovering the underlying utility differences. This step is essential because, in most empirical studies, researchers are forced to assume that beliefs are in equilibrium (i.e., unbiased) everywhere when estimating the parameters of investors' utility functions. Such an all-encompassing assumption may lead to biased estimates if, in reality, beliefs deviate from equilibrium in some states. By contrast, we relax this strong assumption and only require that beliefs are unbiased at a subset of states $\mathbf{s}_{-i}^{*}$. We then use data from these unbiased states to estimate the utility parameters accurately. Once these utility parameters have been identified, they can be employed to recover the full, non-parametric structure of beliefs even in states where beliefs may be biased. For a more detailed derivation and further discussion—including our specific choices for reducing the state-space in our estimation—please refer to Section D.1 in the Appendix.

4 Reduced Form Results

We begin by presenting reduced-form evidence of the following three facts. First, CLOs are more likely to purchase *popular* loans—that is, loans acquired by other CLOs relative to a counterfactual model in which trades occur randomly. Second, CLO investment decisions are highly predictable, as they are more inclined to purchase loans from firms in which they have previously invested and tend to invest when further from the end of their reinvestment period. Third, loan spreads are negatively affected by CLO demand.

4.1 Evidence of Overcrowding

Our aim is to demonstrate that CLO investment decisions are correlated, with managers tending to crowd into the same loans. Specifically, we investigate whether the likelihood that a manager buys a loan is influenced by the decisions of other managers. It is important to note that, at this stage, we document only correlations in investment choices without establishing causation. In the spirit of Lakonishok et al. (1992), we compare the actual investment behavior with a counterfactual scenario in which CLOs invest randomly. For each investor–loan pair, we create a random binary variable, where the probability of investment is equal to the unconditional probability observed in our sample. For each loan, we then compute the total number of investors in the real data and in the fictitious, randomly generated data. Finally, for each CLO manager, we estimate the following regression:

$$\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \beta_i \left(\sum_{k \neq i} \mathbb{1}(\text{buy})_{k,j,t} \right) + \epsilon_{i,j,t}, \tag{6}$$

where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one if investor i buys the loan of firm j issued at time t, and $\sum_{k \neq i} \mathbb{1}(\text{buy})_{k,j,t}$ denotes the number of investors, other than i, who also invest in that loan.

Figure 2 : Evidence of Overcrowding

The figure plots the regression coefficients β_i, obtained from the following regression: $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \beta_i \left(\sum_{k \neq i} \mathbb{1}(\text{buy})_{k,j,t} \right) + \epsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ denotes a binary investment decision for manager i on loan j at time t, and the regressor represents the number of other participants in the same loan at time t. The regressions are estimated for each manager across all loans using a leave-one-out approach. The blue line corresponds to a sample of randomly generated trading decisions, whereas the red line reflects the coefficients estimated using the actual data. The coefficients are ordered by size.

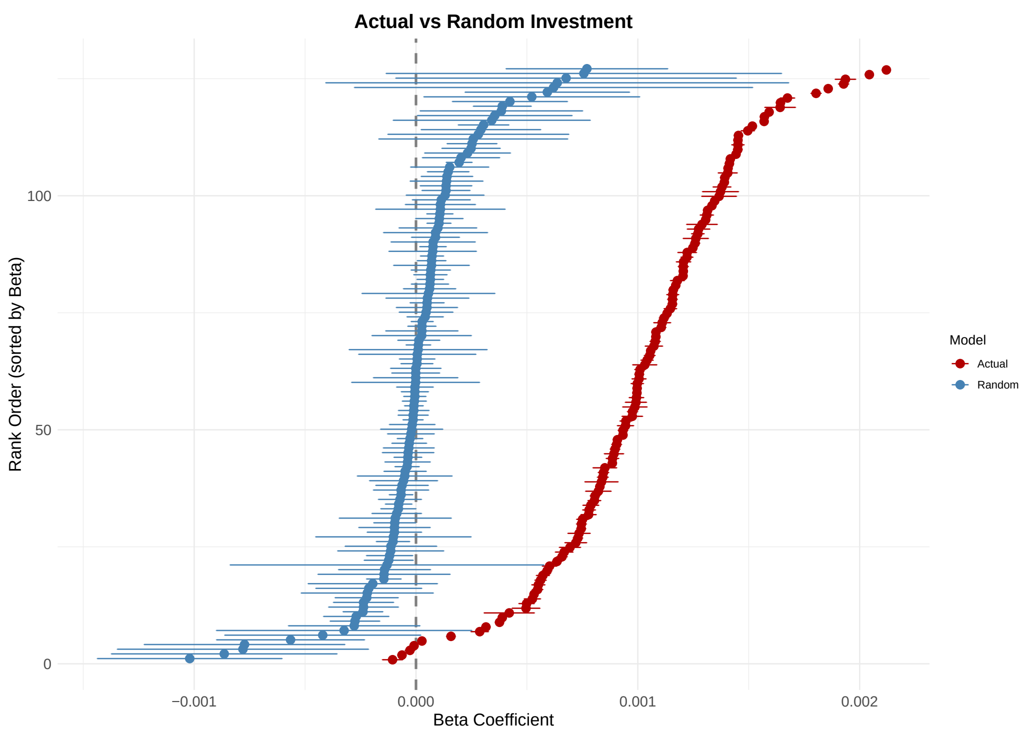


Figure 2 displays the β_i coefficients from equation (6), estimated by running a separate regression for each manager over the cross-section of loans issued while the manager had at least one outstanding CLO. The blue dots represent the coefficient estimates based on randomly generated investment decisions, while the red dots correspond to estimates from the actual data. The coefficients should be interpreted as follows: a value of 0.001 indicates that manager i is 0.1 percent more likely to purchase a given loan for each additional manager investing in the same loan. The data clearly show that actual investment decisions are more correlated with those of other investors than would be expected under random investment. As anticipated, the average effect of other investors is zero in the randomly generated data, whereas it is positive in the actual data. Figure C4 in the Appendix further illustrates the distribution of β_i, which is shifted to the right relative to zero in the real data.

The results presented so far provide convincing evidence that CLOs exhibit correlated investment behavior. However, these findings must be interpreted with caution, as they may be driven by unobserved factors that render some loans inherently more attractive to investors. This situation represents an instance of the Manski (1993) *reflection problem*, which complicates the inference of peer effects. In the remainder of the paper, we aim to disentangle whether the observed correlations stem from unobserved loan characteristics, positive externalities across investors, or judgment errors by CLO managers.

4.2 Evidence of CLO Investment Predictability

In this section, we document that CLO investment decisions are highly predictable. In particular, we show that incumbency status—having previously invested in a firm's loans—and the distance to the end of the reinvestment period are significant predictors of investment decisions. This step is crucial for the subsequent analysis, as it provides variables that allow investors to forecast competitors' behavior while not directly affecting the attractiveness of the loan once competitors' investment decisions are taken into account. The remainder of this section presents results indicating that these two variables have predictive power both at the individual investor level and at the aggregate level. Specifically, we find that the probability of investing in a given loan increases when the CLO is an incumbent and is farther from the end of the reinvestment period. We also show that loans issued by firms with many incumbents or younger investors tend to experience greater demand.

We begin by examining incumbency. It is well known (Nicolai, 2020; Hinzen, 2023; Bhardwaj et al., 2024) that CLO investment decisions exhibit persistence. To confirm this, we estimate linear probability models in which the likelihood of investing in any given loan is a function of the manager's incumbency status. Specifically, we estimate the following regression:

$$\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \mathbb{1}(\text{Incumbent})_{i,j,t} + \mathbf{x}^\top \delta + \varepsilon_{i,j,t}, \tag{7}$$

where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one when investor i purchases a loan of firm j issued at time t, and $\mathbb{1}(\text{Incumbent})_{i,j,t}$ is a dummy variable equal to one if investor i has previously invested in firm j's loans prior to time t. The terms α_i and α_t represent manager and year fixed effects, respectively, while $\mathbf{x}$ is a vector of control variables that includes rating fixed effects, industry fixed effects based on SIC codes, the natural logarithm of the loan size, and the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Column (1) in Table 2 shows that the likelihood of a CLO purchasing any given loan increases by almost 12% when the manager has previously invested in that firm's loans. This magnitude is hardly affected when we include year, rating, and industry fixed effects (column (2)), control for the size and maturity of

Table 2 : Incumbency and the Likelihood of Purchasing a Loan

The table shows the results of the following regression: $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \mathbb{1}(\text{Incumbent})_{i,j,t} + \mathbf{x}^\top \delta + \varepsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one when investor i purchases a loan of firm j issued at time t, and $\mathbb{1}(\text{Incumbent})_{i,j,t}$ is a dummy variable equal to one if investor i has previously invested in firm j's loans prior to time t. α_i and α_t represent manager and year fixed effects, respectively, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

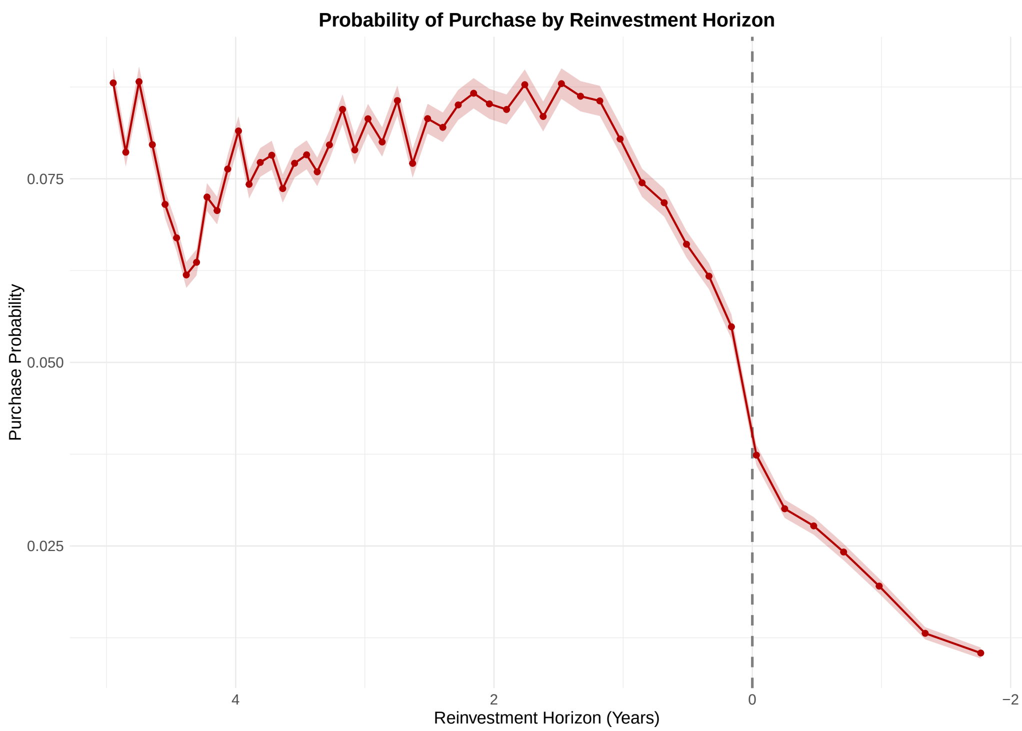
	(1)	(2)	(3)	(4)
Constant	0.0312***			
	(0.0001)			
$\mathbb{1}(\text{Incumbent})_{i,j,t}$	0.1177***	0.1129***	0.1100***	0.1060***
	(0.0002)	(0.0104)	(0.0103)	(0.0051)
Size			0.0138***	0.0141***
			(0.0017)	(0.0008)
Maturity			0.0189***	0.0185***
			(0.0029)	(0.0015)
Fixed-effects				
Year	No	Yes	Yes	Yes
Rating	No	Yes	Yes	Yes
Industry	No	Yes	Yes	Yes
Manager	No	No	No	Yes
Fit statistics				
Observations	4,977,940	4,895,583	4,861,703	4,861,703
R^2	0.04674	0.05883	0.06203	0.06841
Within R^2		0.03877	0.04209	0.03719

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

the loan (column (3)), and add manager fixed effects (column (4)). The full specification in column (4) indicates that a manager is 10.6% more likely to purchase the loan of a firm in which she has previously invested, compared to an equivalent firm in terms of rating and industry issuing a loan in the same year, even after accounting for the average propensity of the manager to purchase loans. While some managers (e.g., those with greater assets under management) might be unconditionally more inclined to purchase loans, we show that this has virtually no effect on the increase in the likelihood of purchasing new loans driven by incumbency status.

Figure 3 : Reinvestment Horizon and Probability of Purchase

The figure plots the probability of purchasing a loan in the primary market by CLOs as a function of the time remaining until the end of the reinvestment period. The data are divided into 50 bins, each containing an equal number of observations, with each point representing the average probability estimate within a bin. The shaded red area depicts the 95% confidence intervals. The x-axis is reversed to reflect the chronological order of events, and the vertical dashed lines indicate the transition from the reinvestment to the non-reinvestment period.



Next, we study the effect of the reinvestment horizon on CLO investment decisions. Fleckenstein (2022) shows that CLOs are less likely to purchase loans as they approach the end of their reinvestment period. Figure 3 confirms these findings by plotting the probability that CLOs purchase a loan in the primary market as a function of the time remaining until the end of the reinvestment period. As illustrated in the figure, this probability remains roughly constant throughout the life of the CLO, but begins to decline approximately one year before the reinvestment horizon ends. Exploiting this observation, we construct a dummy variable, $\mathbb{1}(\text{Far from End})_{i,t}$, which equals one when CLO i is more than one year away from the end of its reinvestment period at time t. The results of the follow-

Table 3 : Reinvestment Horizon and the Likelihood of Purchasing a Loan

The table shows the results of the following regression: $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \mathbb{1}(\text{Far from End})_{i,t} + \mathbf{x}^\top \delta + \varepsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one when investor i purchases a loan of firm j issued at time t, and $\mathbb{1}(\text{Far from End})_{i,t}$ is a dummy variable equal to one if investor i is more than one year away from the end of her reinvestment period at time t. α_i and α_t represent manager and year fixed effects, respectively, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)	(4)
Constant	0.0345***			
	(0.0002)			
$\mathbb{1}(\text{Far from End})_{i,t}$	0.0406***	0.0435***	0.0437***	0.0415***
	(0.0003)	(0.0106)	(0.0106)	(0.0026)
Size			0.0239***	0.0238***
			(0.0022)	(0.0010)
Maturity			0.0082**	0.0082***
			(0.0032)	(0.0013)
Fixed-effects				
Year	No	Yes	Yes	Yes
Rating	No	Yes	Yes	Yes
Industry	No	Yes	Yes	Yes
Manager	No	No	No	Yes
Fit statistics				
Observations	4,900,839	4,819,258	4,786,360	4,786,360
R^2	0.00464	0.02597	0.03253	0.04320
Within R^2		0.00512	0.01185	0.01103

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

Table 4 : Aggregate Impact of Incumbency on Loan Issuance Participation

The table shows the results of the following regression: $\log(\text{Nr. Investors})_{j,t} = \alpha_t + \beta \cdot \log(\text{Nr. Incumbents})_{j,t} + \mathbf{x}^\top\delta + \varepsilon_{j,t}$, where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLOs that participate in a given loan issuance by firm j at time t, and $\log(\text{Nr. Incumbents})_{j,t}$ is the natural logarithm of the number of incumbents, i.e., managers that have previously invested in loans of firm j prior to time t. α_t represent year fixed effects, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	1.730***		
	(0.0438)		
log(Nr. Incumbents)	0.5006***	0.3394***	0.2696***
	(0.0140)	(0.0341)	(0.0316)
Size			0.2526***
			(0.0243)
Maturity			0.2989***
			(0.0450)
Fixed-effects			
Year	No	Yes	Yes
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	5,455	5,389	5,343
R^2	0.18950	0.34767	0.37772
Within R^2		0.06655	0.11204

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

ing regression are reported in Table 3:

$$\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \mathbb{1}(\text{Far from End})_{i,t} + \mathbf{x}^\top\delta + \varepsilon_{i,j,t} \tag{8}$$

where all variables are defined as in previous specifications. Being far from the end of the reinvestment period increases the likelihood of purchasing any given loan by approximately 4%. This effect is robust to the inclusion of controls for general macroeconomic conditions (year fixed effects), loan riskiness (rating fixed effects), industry effects, loan size and maturity, as well as time-invariant manager characteristics. These findings are robust to alternative specifications. Figure C5 in the Appendix illustrates that the probability of purchasing a loan begins to decline four years after the CLO's closing date. Table B2 demonstrates that young CLOs—defined as those with less than four years since their closing date—are more likely to participate in a loan issuance. Finally, Table B3 confirms that these results hold under alternative measures of reinvestment horizon and age.

We now proceed to show that incumbency status not only predicts whether a given CLO will purchase a loan, but also that the total number of incumbents prior to a new loan issuance predicts the total number of participants in the loan. To examine this relationship, we estimate the following regression:

$$\log(\text{Nr. Investors})_{j,t} = \alpha_t + \beta \cdot \log(\text{Nr. Incumbents})_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}, \tag{9}$$

where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLOs participating in a loan issuance by firm j at time t, and $\log(\text{Nr. Incumbents})_{j,t}$ is the natural logarithm of the number of incumbents—that is, managers who have previously invested in firm j's loans prior to time t. Column (1) shows that, without controls, a 1% increase in the number of incumbents raises the total number of participants by 0.5%. This effect is robust to the inclusion of year, rating, and industry fixed effects (yielding an effect of 0.34%) and to additional controls for the size and maturity of the loan (yielding an effect of 0.27%). We show in the Appendix that the results are robust to using the logarithm of the number of CLO managers participating in a loan issuance as the dependent variable (Table B4). The findings also remain consistent when we estimate a regression analogous to equation (9) in levels (Table B5), as well as when we use the number of managers in levels as the dependent variable (Table B6). Figure C6 in the Appendix visually depicts this relationship.

Finally, we show that the reinvestment horizon has predictive power also when we aggregate at the loan level. In particular, we show that the number of CLOs with more than one year to the end of the reinvestment horizon predicts the number of investors that participate in a given loan. Table 5 presents the results of the following regression:

$$\log(\text{Nr. Investors})_{j,t} = \alpha + \beta \cdot \log(\text{Nr. Far from End})_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}, \tag{10}$$

where all variables are defined as above, and $\log(\text{Nr. Far from End})_{j,t}$ is the natural logarithm of the number of CLOs that are more than one year away from the end of their reinvestment period. For instance, focusing on column (3), we find that a 1% increase in the number of CLOs more than one year away from the end of their reinvestment period is associated with a 0.80% increase in the number of investors participating in a loan issuance, controlling for the size, maturity of the loan, and the rating and industry of the issuing firm[11]. Table B7 in the Appendix shows similar results when we use the number of young CLOs as the dependent variable instead of the number of CLOs far from the end of their reinvestment period. Figures C7 and C8 in the Appendix visually depict the relationship between the number of CLOs far from the end of their reinvestment period, as well as young CLOs, and the total number of investors participating in a loan issuance.

4.3 Evidence of Pricing Effects

In this section, we document that the pricing of leveraged loans is affected by total CLO demand. We begin with suggestive evidence presented in Figures 4 and 5. For each loan, we collect the all-in-drawn spread of its Term Loan B tranche as well as the other tranches. CLOs and other institutional investors tend to invest in Term Loans—particularly in Term Loan Bs—because they typically feature minimal or no amortization, thereby reducing reinvestment risk. We regress the all-in-drawn spread on the loan size, maturity, and include industry, time, and rating fixed effects. We then collect the residuals to capture the portion of spreads not explained by observable characteristics and plot these

[11] Time fixed effects are not included because they would be collinear with the dependent variable.

Table 5 : Aggregate Impact of Reinvestment Horizon on Loan Issuance Participation

The table shows the results of the following regression: $\log(\text{Nr. Investors})_{j,t} = \alpha + \beta \cdot \log(\text{Nr. Far from End})_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}$, where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLOs that participate in a given loan issuance by firm j at time t, and $\log(\text{Nr. Far from End})_{j,t}$ is the natural logarithm of the number of CLOs that are more than one year away from the end of their reinvestment period at time t. $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	-2.636***		
	(0.2240)		
$\log(\text{Nr. Far from End})_{j,t}$	0.9294***	0.9991***	0.7996***
	(0.0363)	(0.0413)	(0.0342)
Size			0.4349***
			(0.0352)
Maturity			0.1691***
			(0.0474)
Fixed-effects			
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	7,137	7,033	5,672
R^2	0.08426	0.21577	0.28591
Within R^2		0.09512	0.16204

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

residualized spreads against the number of CLOs or CLO managers participating in the loan. Figure 4 shows an almost linear and negative relationship between the residualized spreads and the natural logarithm of the number of CLOs and CLO managers purchasing the loan, as presented in Panels A and B, respectively. In contrast, Figure 5 indicates that no such relationship exists when focusing on the residualized spreads of non-institutional tranches.

Figure 4 : Residualized Spreads - Term Loan B

The figure displays the residualized all-in drawn spread on Term Loan B facilities as a function of the number of CLO investors (in logs) participating in the loan issuance. Panel A measures demand using the number of distinct CLOs involved in the issuance, while Panel B uses the number of distinct CLO managers. A manager may oversee multiple CLOs at any given time. The residualized spreads are obtained from a regression of all-in drawn spreads on the natural logarithm of the loan size, the natural logarithm of the loan maturity, industry, time, and rating fixed effects. The data are grouped into 10 equal-sized buckets, with each plot showing the average residualized spread within each bucket. The shaded red areas represent 95% confidence intervals.

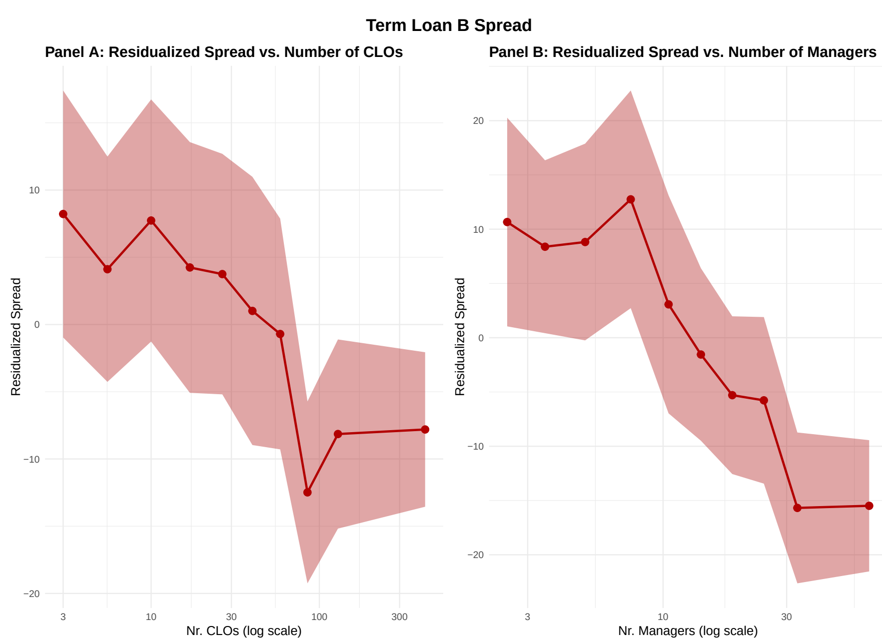
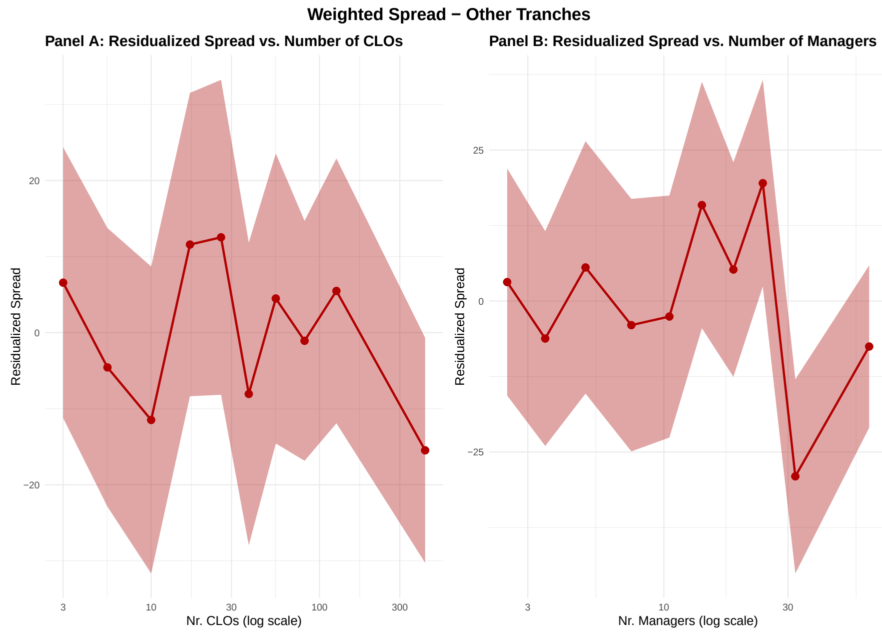


Figure 5 : Residualized Spreads - Other Loans

The figure displays the residualized all-in drawn spread on loans other than Term Loan B as a function of the number of CLO investors (in logs) participating in the loan issuance. Panel A measures demand using the number of distinct CLOs involved in the issuance, while Panel B uses the number of distinct CLO managers. A manager may oversee multiple CLOs at any given time. The residualized spreads are obtained from a regression of all-in drawn spreads on the natural logarithm of the loan size, the natural logarithm of the loan maturity, industry, time, and rating fixed effects. The data are grouped into 10 equal-sized buckets, with each plot showing the average residualized spread within each bucket. The shaded red areas represent 95% confidence intervals.



While suggestive, the downward-sloping relationship between spreads and the number of investors should be interpreted with caution, as it may be subject to endogeneity if loans that are more attractive for unobservable reasons also exhibit lower spreads. To address this concern and establish that the relationship is driven by increasing demand from CLOs, we estimate the following two-stage least squares specification:

$$\text{First Stage:} \quad \log(\text{Nr. Investors})_{j,t} = \alpha_t + \delta_1 \log(\text{Nr. Incumbents})_{j,t} + \mathbf{x}^\top \delta_2 + u_{j,t},$$

$$\text{Second Stage:} \quad AIDS_{j,t} = \alpha_t + \beta_1 \widehat{\log(\text{Nr. Investors})}_{j,t} + \widehat{\mathbf{x}}^\top \beta_2 + \varepsilon_{j,t},$$

where we instrument the number of investors participating in a loan issuance with the number of CLOs whose managers have previously invested in the firm. As demonstrated in the previous section, the instrument is relevant. The exclusion restriction requires that the number of incumbents affects the spread of a loan solely through its impact on the number of potential buyers, and not via any other channel.

Table 6 reports the results of this analysis. The first three columns present the first-stage estimates, which essentially replicate the results from the previous section, restricted to the sample of loans for which we have Term Loan B spread data. The coefficients in the first stage are nearly identical to those in Table 4: a 1% increase in the number of incumbents increases participation by between 0.26% and 0.51%. We then turn to the second-stage results, where we regress the all-in-drawn spread on the predicted number of participants from the first stage. The findings indicate that a 1% increase in instrumented demand leads to a decrease of between 55 and 99 basis points in the all-in-drawn spread.[12]

Table 6 : Pricing Impact of CLO Demand

The table shows the estimates of the following TSLS regression. The first stage is: $\log(\text{Nr. Investors})_{j,t} = \alpha_t + \delta_1 \log(\text{Nr. Incumbents})_{j,t} + \mathbf{x}^\top \delta_2 + u_{j,t}$, and the second stage is: $AIDS_{j,t} = \alpha_t + \beta_1 \log(\widehat{\text{Nr. Investors}})_{j,t} + \widehat{\mathbf{x}}^\top \beta_2 + \varepsilon_{j,t}$ where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLOs that participate in a given loan issuance by firm j at time t, $\log(\text{Nr. Incumbents})_{j,t}$ is the natural logarithm of the number of incuments, i.e., managers who have previously invested in loans of firm j prior to time t, $\log(\widehat{\text{Nr. Investors}})_{j,t}$ is the predicted number of CLO partipicants from the first stage, and $AIDS_{j,t}$ is the all-in-drawn spread on Term Loan B tranches. α_t represent year fixed effects, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	First Stage			Second Stage		
Variable	(1)	(2)	(3)	(1)	(2)	(3)
Constant	1.807***			551.6***		
	(0.0501)			(11.68)		
$\log(\text{Nr. Incumbents})_{j,t}$	0.5134***	0.3388***	0.2621***			
	(0.0159)	(0.0346)	(0.0315)			
Size			0.2977***			12.57**
			(0.0222)			(5.714)
Maturity			0.4418***			61.18***
			(0.0564)			(20.11)
$\log(\widehat{\text{Nr. Investors}})_{j,t}$				-55.24***	-94.51***	-98.79***
				(3.468)	(11.86)	(14.06)
Fixed Effects:						
Year	No	Yes	Yes	No	Yes	Yes
Rating	No	Yes	Yes	No	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes
Observations	4,338	4,298	4,246	4,338	4,298	4,246

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

Armed with reduced-form evidence that CLOs tend to crowd into the same loans, that their investment decisions are predictable, and that such behavior influences loan pricing, we now turn to

[12]In untabulated results, we obtain similar findings for TSLS regressions using the number of managers investing in any given loan as the dependent variable, for regressions in which the instrument is the number of CLOs far from the end of their reinvestment period, and for specifications using the number of young CLOs as an instrument.

the next section to investigate the underlying drivers of these dynamics.

5 Biased Beliefs

We now proceed to test whether CLO managers' beliefs are biased. Recall from Section 3 that we can assess whether managers' beliefs about the actions of others are consistent with their own investment decisions, as illustrated in equation (5). We assume that the expected observable utility of a manager is given by:

$$\begin{aligned} q_{i,t}(a_{i,t} = 1 \mid \mathbf{x}) = & \left[1 - B_{i,t}(D_{j,t} = H \mid \mathbf{x})\right] U_{i,t}(1, D_{j,t} = L \mid \mathbf{s}_{i,t}, \mathbf{w}) \\ & + B_{i,t}(D_{j,t} = H \mid \mathbf{x})\, U_{i,t}(1, D_{j,t} = H \mid \mathbf{s}_{i,t}, \mathbf{w}), \end{aligned} \tag{11}$$

where we partition competitors' demand for a loan into two buckets: high (H) and low (L). Each manager, given her current state $\mathbf{s}_{i,t}$ and a set of loan characteristics $\mathbf{w}$, forms beliefs about whether the demand will be high or low. The beliefs $B_{i,t}(D_{j,t} = H \mid \mathbf{x})$ are manager-specific (indexed by i, t) and may depend on the full set of state variables $\mathbf{x}$, including incumbency status and the life-cycle stage of other competitors.

Next, we parameterize the utility function of each investor as:

$$U_{i,t}(.) = b_0 + b_1\, \text{ExpDemand}_{i,j,t} + b_2\, \text{Incumbent}_{i,j,t} + b_3\, \text{TTR}_{i,t} + b_4\, \text{Rating}_{j,t} + b_5\, \text{TTM}_{j,t} + b_6\, \sigma_j + b_7\, \beta_j,$$

where $\text{ExpDemand}_{i,j,t}$ denotes the number of CLOs that the manager expects to participate in the loan issued by firm j at time t; $\text{Incumbent}_{i,j,t}$ is a dummy variable equal to one if the manager has previously invested in any other loan issued by the firm; $\text{TTR}_{i,t}$ represents the time remaining until the end of the reinvestment period for CLO i at time t; $\text{Rating}_{j,t}$ is the credit rating of firm j at time t; $\text{TTM}_{j,t}$ is the time to maturity of the loan issued by firm j at time t; σ_j denotes the firm's volatility; and β_j is the market beta of the firm.

The effects of several variables on investor utility are intuitive. Being an incumbent, for example, reduces information and entry costs, thereby enhancing utility. In addition, Section 4 demonstrates that a longer time until the end of the reinvestment period strongly predicts investment decisions. It is plausible to expect that better ratings and shorter maturities are desirable. However, the effect of risk is less straightforward. On one hand, CLO managers effectively hold a call option on the CLO's assets, suggesting that greater volatility could increase the value of their claim. On the other hand, because a CLO's value is strongly negatively related to the correlation among its assets, it is optimal for a manager to minimize exposure to systematic risk. Consequently, we expect managers to derive lower utility from loans issued by higher-beta firms, while they may prefer loans with higher idiosyncratic volatility.

Finally, one might anticipate a negative coefficient b_1 on expected demand: all else equal, loans expected to be more popular should be less attractive, given that Section 4 shows higher popularity is associated with lower spreads. Nonetheless, empirical evidence suggests that some managers tend to cluster around specific loans. We therefore aim to test whether this clustering results from unobserved loan characteristics that affect investment preferences or from a failure to accurately predict the actions of others when deciding whether to invest in a new loan.

As detailed in Section 3.2, equilibrium beliefs impose a series of constraints as shown in equation (5). To test whether these constraints are consistent with investors' actions, we estimate an unconstrained investment model and compare its log-likelihood to that of a model in which we impose the equilibrium constraints, using a likelihood ratio test.

Specifically, we jointly estimate by maximum likelihood the conditional choice probabilities that CLO i will invest in a given loan, $P_i(a_{i,j,t} = 1 \mid \mathbf{x})$, and the conditional probability that the demand from other investors is high, $\tilde{P}_t(D_{j,t} = H \mid \mathbf{x})$. The unconstrained log-likelihood is given by:

$$
\begin{aligned}
\mathcal{L}(P_i, \tilde{P}) = & \sum \mathbb{1}\{a_{i,t} = 1\} \log P_i(a_{i,t} = 1 \mid \mathbf{x}) + (1 - \mathbb{1}\{a_{i,t} = 1\}) \log (1 - P_i(a_{i,t} = 1 \mid \mathbf{x})) \\
& + \sum \mathbb{1}\{D_{j,t} = H\} \log \tilde{P}(D_{j,t} = H \mid \mathbf{x}) + (1 - \mathbb{1}\{D_{j,t} = H\}) \log \Big(1 - \tilde{P}(D_{j,t} = H \mid \mathbf{x})\Big) .
\end{aligned} \tag{12}
$$

We denote the maximum of this unconstrained log-likelihood by $\mathcal{L}^{UNC}(\hat{P}_i, \hat{\tilde{P}})$. Next, we re-estimate the same conditional probabilities subject to the following constraints:

$$
\frac{q(1 \mid s_i, \tilde{s} = a, w) - q(1 \mid s_i, \tilde{s} = c, w)}{q(1 \mid s_i, \tilde{s} = b, w) - q(1 \mid s_i, \tilde{s} = c, w)} = \frac{\tilde{P}(D_{j,t} = H \mid s_i, \tilde{s} = a, w) - \tilde{P}(D_{j,t} = H \mid s_i, \tilde{s} = c, w)}{\tilde{P}(D_{j,t} = H \mid s_i, \tilde{s} = b, w) - \tilde{P}(D_{j,t} = H \mid s_i, \tilde{s} = c, w)}, \tag{13}
$$

where a, b, and c represent different configurations of the special state variables—namely, the number of incumbents and the number of CLOs that are at least one year away from the end of their reinvestment period.[13] We denote the maximum of the constrained log-likelihood by $\mathcal{L}^{CON}(\hat{P}_i, \hat{\tilde{P}})$. The log-likelihood ratio is then computed as

$$
\lambda_{LR} = 2\Big[\mathcal{L}^{UNC}(\hat{P}_i, \hat{\tilde{P}}) - \mathcal{L}^{CON}(\hat{P}_i, \hat{\tilde{P}})\Big],
$$

which, under the null hypothesis that the equilibrium constraints hold, is asymptotically χ^2 distributed with degrees of freedom equal to the number of constraints (NC).

Table 7 reports the results of this analysis. The first three columns present the unconstrained log-likelihood, while the fourth column reports the constrained log-likelihood. The estimated λ_{LR} is much larger than the critical value of the χ^2 distribution with NC degrees of freedom, leading us to strongly reject the hypothesis of unbiased beliefs.

These findings imply that the constraints in equation (13)—which should be satisfied if managers' beliefs about the actions of others are consistent with their actual ex-post investment behavior—do not hold in the data. In other words, the constrained likelihood is substantially lower than the unconstrained likelihood, suggesting that it is extremely unlikely that investors are able to accurately predict the investment choices of their competitors. We thus conclude that CLO managers' beliefs are not in equilibrium.

[13] For computational reasons, we partition the state variables into three buckets.

Table 7 : Likelihood Ratio Test

	$\mathcal{L}^{UNC}(\hat{P}_i, \hat{P}_j)$	$\mathcal{L}^{CON}(\hat{P}_i, \hat{P}_j)$	NC	λ_{LR}	χ^2 Test (99%)	P Value
Value	-1,536,576	-15,437,528	37,314	27,801,904	37,952.45	0.00

5.1 Preference Estimation

The previous section demonstrated that the hypothesis of equilibrium beliefs can be strongly rejected. This finding suggests that we cannot rely on the assumption of equilibrium beliefs when estimating investors' preferences. However, the available data does not provide sufficient restrictions to separately estimate preferences and beliefs based solely on investment choices. To overcome this challenge, we assume the existence of a subset of the state space where beliefs are unbiased, allowing us to estimate utilities. The key question is how to identify the regions of the state space where beliefs are most likely to be unbiased.

Following Aguirregabiria and Magesan (2020), we adopt a conservative approach by minimizing the total deviation of unrestricted beliefs from realized probabilities. This method involves assuming that beliefs are unbiased in certain parts of the state space, and we select these regions to minimize bias.

Table 8 : Beliefs Deviations

	MAD	MSD
High	0.1964	0.2419
Medium	0.1554	0.1771
Low	0.2846	0.3003

Table 8 presents the deviations from realized probabilities under different assumptions about the state $\tilde{s}$, which in this case refers to the number of CLOs that are more than one year away from the end of their reinvestment period. In each row, we assume that beliefs are unbiased for a given level of $\tilde{s}$. For example, in the first row, we assume that beliefs align with observed probabilities when $\tilde{s}$ is High, i.e., $B_{i,t}(D_{j,t} \mid s_i, s_j = \text{High}, w) = \tilde{P}(s_i, s_j = \text{High}, w)$, while allowing beliefs to vary freely for $s_j =$ Medium and Low number of CLOs far from the end of the reinvestment horizon.

We calculate the mean absolute deviation (MAD) and the mean squared deviation (MSD) as follows:

$$\text{MAD} = E\left[\left|\tilde{P}(\mathbf{x}) - B_{i,t}(D_{j,t} \mid \mathbf{x})\right|\right], \quad \text{MSD} = E\left[\left(\tilde{P}(\mathbf{x}) - B_{i,t}(D_{j,t} \mid \mathbf{x})\right)^2\right]$$

The results show that assuming unbiased beliefs for the Medium category yields the lowest deviations (MAD of 0.155 and MSD of 0.177), compared to the High (MAD of 0.196 and MSD of 0.242) and Low categories (MAD of 0.285 and MSD of 0.300). We will therefore proceed with the estimation of utility parameters assuming beliefs are indeed ubiased for $\tilde{s} = \text{Medium}$.

5.2 Utility Estimation

In this section we proceed with the estimation of utility parameters. Recall that we parametrized the investor's utility as:

$$U_{i,t}(.) = b_0 + b_1 \,\text{ExpDemand}_{i,j,t} + b_2 \,\text{Incumbent}_{i,j,t} + b_3 \,\text{TTR}_{i,t} + b_4 \,\text{Rating}_{j,t} + b_5 \,\text{TTM}_{j,t} + b_6 \,\sigma_j + b_7 \,\beta_j \tag{14}$$

Recall also that, if we fix beliefs to be unbiased for $\tilde{s} = M$, we can recover utilities as:

$$U_{i,t}(a_{i,t}, s_{i,t}, w) = \left[\tilde{\mathbf{P}}(\tilde{s} = M, s_i, w)^\top \tilde{\mathbf{P}}(\tilde{s} = M, s_i, w)\right]^{-1} \tilde{\mathbf{P}}(\tilde{s} = M, s_i, w)' \mathbf{q}(a_{i,t}, s_{i,t}, w) \tag{15}$$

The utilities we recover can then be regressed on the variables in (14) to obtain estimates of the parameters of interest.

The results of the utility estimation are presented in Table 9. Most of the coefficients in the table make economic sense. The results indicate that CLOs exhibit a strong preference for loans where they have incumbent status across all specifications, as shown by the positive and highly significant coefficients on the Incumbent variable. This finding is consistent with the hypothesis that large entry costs and economies of scale play a significant role in CLOs' investment decisions. As expected, CLOs do prefer to invest in a loan when the time to the end of their reinvestment period is long (baseline effect), compared to when its medium (TTR_M), or short (TTR_S). This is consistent with the structural constraints managers face regarding their investments. Interestingly, and consistent with their incentives, CLOs have a preference for loans from firms with high (σ_H) and, especially, medium (σ_M) volatility, compared to firms with low volatility, which represents the baseline effect; however they do prefer loans with lower systematic risk, compared to ones with medium (β_M) and higher (β_H) such risk. Finally, and most notably, investors exhibit a strong preference for loans for which they expect lower demand. Although this finding is intuitive—since lower demand typically leads to higher spreads—it appears to contradict the reduced-form evidence presented in Section 4. How can these seemingly contradictory results be reconciled? Recall that the estimates in Table 9 do not impose the restriction that beliefs about others' actions are in equilibrium, a constraint that is implicitly enforced in the reduced-form analysis. This discrepancy underscores the paper's main result: the overcrowding observed on certain loans is not merely a consequence of unobservable loan characteristics, but rather stems from a systematic failure of some investors to accurately anticipate the actions of their competitors when deciding whether to participate in a loan issuance.

6 Conclusions

This paper investigates the influence of biased beliefs on overcrowding behaviour among institutional investors, with a specific focus on the leveraged loan market and the investment decisions of CLO managers. Our findings challenge the hypothesis that institutional overcrowding primarily stems from rational responses to market conditions or positive spillovers among investors. Instead, we provide evidence that a significant portion of overcrowding behaviour is driven by incorrect beliefs about the actions of peers. These misguided perceptions lead to correlated investment decisions that contribute to market inefficiencies. Our analysis highlights that overcrowding is more a consequence of systematic errors in judgment than of strategic complementarities, emphasizing the need to understand how institutional investors form and act upon their expectations regarding the behaviour of competitors.

Through a structural model and empirical analysis, we demonstrate that the correlation observed in CLOs' investment choices is not merely a result of common information or externalities but is largely due to inaccuracies in managers' beliefs about their competitors' actions. This insight has profound implications for market dynamics, suggesting that biased beliefs among even the most sophisticated investors can lead to overcrowding in specific asset classes, thereby distorting asset prices and potentially increasing market volatility.

Given the significant role that biased beliefs play in shaping the investment behaviour of institutional investors, future research should extend the analysis to other asset classes and markets, especially those dominated by retail investors or less sophisticated institutional participants. Such studies would help assess the broader applicability of our findings. Additionally, exploring the potential for regulatory interventions to mitigate the adverse effects of biased beliefs on market efficiency presents another fruitful area for investigation. By pursuing these avenues, future research can deepen our understanding of the underlying dynamics of overcrowding behaviour and its broader implications for financial markets, ultimately contributing to more effective policy measures and market stability.

Table 9 : Utility Estimation Results

Dependent Variable:		U_i	
Model:	(1)	(2)	(3)
(Intercept)	-2.380***	-2.703***	-2.505***
	(0.0158)	(0.0175)	(0.0191)
Incumbent	0.8736***	0.9257***	0.9382***
	(0.0142)	(0.0142)	(0.0142)
ExpDemand	-0.4663***	-0.6333***	-0.5981***
	(0.0185)	(0.0188)	(0.0189)
TTR_S	-0.3521***	-0.3869***	-0.3873***
	(0.0134)	(0.0134)	(0.0134)
TTR_M	-0.0651***	-0.0711***	-0.0733***
	(0.0134)	(0.0134)	(0.0134)
Rating_L	0.9498***	1.044***	1.096***
	(0.0163)	(0.0165)	(0.0166)
Rating_M	0.3858***	0.3447***	0.3724***
	(0.0140)	(0.0140)	(0.0140)
Maturity_L	-1.152***	-0.9980***	-0.8670***
	(0.1533)	(0.1532)	(0.1534)
Maturity_M	-1.033***	-1.150***	-1.118***
	(0.0182)	(0.0183)	(0.0185)
σ_M		0.9112***	0.8899***
		(0.0136)	(0.0137)
σ_H		0.1941***	0.1048***
		(0.0143)	(0.0149)
β_M			-0.3729***
			(0.0141)
β_H			-0.2414***
			(0.0139)
Observations	1,311,619	1,311,619	1,311,619
R^2	0.00877	0.01272	0.01326
Adjusted R^2	0.00876	0.01271	0.01325

References

Acharya, Viral V, Iftekhar Hasan, and Anthony Saunders, "Should banks be diversified? Evidence from individual bank loan portfolios," *The Journal of Business*, 2006, *79* (3), 1355–1412.

Aguirregabiria, Victor, "Identification of firms' beliefs in structural models of market competition," *Canadian Journal of Economics/Revue canadienne d'économique*, 2021, *54* (1), 5–33.

— and Arvind Magesan, "Identification and estimation of dynamic games when players' beliefs are not in equilibrium," *The Review of Economic Studies*, 2020, *87* (2), 582–625.

Anton, Miguel and Christopher Polk, "Connected stocks," *The Journal of Finance*, 2014, *69* (3), 1099–1127.

— , Randolph B Cohen, and Christopher Polk, "Best ideas," *Available at SSRN 1364827*, 2021.

Banerjee, Abhijit V, "A simple model of herd behavior," *The Quarterly Journal of Economics*, 1992, *107* (3), 797–817.

Berry, Steven T, "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics*, 1994, pp. 242–262.

Bhardwaj, Abhishek, Shan Ge, and Saptarshi Mukherjee, "Does Loan Securitization Expose Borrowers to Non-Bank Investor Shocks?," 2024.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, "A theory of fads, fashion, custom, and cultural change as informational cascades," *Journal of Political Economy*, 1992, *100* (5), 992–1026.

Carlsson, Hans and Eric Van Damme, "Global games and equilibrium selection," *Econometrica: Journal of the Econometric Society*, 1993, pp. 989–1018.

Chevalier, Judith and Glenn Ellison, "Career concerns of mutual fund managers," *The Quarterly Journal of Economics*, 1999, *114* (2), 389–432.

CLO Research Group, "League Table: US CLO Manager AUM (as of 30 Dec 2022)," January 2 2023. Accessed: 2025-03-17.

Cohen, Gregory, Melanie Friedrichs, Kamran Gupta, William Hayes, Seung Jung Lee, W Blake Marsh, Nathan Mislang, Maya Shaton, and Martin Sicilian, "The US Syndicated Loan Market: Matching Data," *Federal Reserve Bank of Kansas City Working Paper*, 2018, (18-09).

Dasgupta, Amil and Andrea Prat, "Information aggregation in financial markets with career concerns," *Journal of Economic Theory*, 2008, *143* (1), 83–113.

Doraszelski, Ulrich and Mark Satterthwaite, "Computable Markov-perfect industry dynamics," *The RAND Journal of Economics*, 2010, *41* (2), 215–243.

Elkamhi, Redouane and Yoshio Nozawa, "Too Big to Diversify: A Stress Test on Collateralized Loan Obligations," *Available at SSRN 3635086*, 2020.

Fabozzi, Frank, Sven Klingler, Pia Mølgaard, and Mads Stenbo Nielsen, "Active Loan Trading," *Journal of Financial Intermediation*, 2020, p. 100868.

Falato, Antonio, Ali Hortacsu, Dan Li, and Chaehee Shin, "Fire-sale spillovers in debt markets," *The Journal of Finance*, 2021, *76* (6), 3055–3102.

Fleckenstein, Quirin, "Intermediary frictions and the corporate credit cycle: Evidence from CLOs," *Available at SSRN 4278636*, 2022.

_ , Manasa Gopal, German Gutierrez Gallardo, and Sebastian Hillenbrand, "Nonbank Lending and Credit Cyclicality," *Available at SSRN 3629232*, 2020.

Greenwood, Robin and Andrei Shleifer, "Expectations of returns and expected returns," *The Review of Financial Studies*, 2014, *27* (3), 714–746.

Guggenheim Investments, "Understanding Collateralized Loan Obligations (CLOs)," December 7 2023. Accessed: 2025-03-17.

Hinzen, Franz J, "Nonbank market power in leveraged lending," Technical Report, NYU Working Paper 2023.

Hotz, V Joseph and Robert A Miller, "Conditional choice probabilities and the estimation of dynamic models," *The Review of Economic Studies*, 1993, *60* (3), 497–529.

Huberman, Gur, "Familiarity breeds investment," *The Review of Financial Studies*, 2001, *14* (3), 659–680.

Ivashina, Victoria and Zheng Sun, "Institutional Demand Pressure and the Cost of Corporate Loans," *Journal of Financial Economics*, 2011, *99* (3), 500–522.

Jiang, Hao and Michela Verardo, "Does herding behavior reveal skill? An analysis of mutual fund performance," *The Journal of Finance*, 2018, *73* (5), 2229–2269.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, "On the industry concentration of actively managed equity mutual funds," *The Journal of finance*, 2005, *60* (4), 1983–2011.

Koijen, Ralph SJ and Motohiro Yogo, "A demand system approach to asset pricing," *Journal of Political Economy*, 2019, *127* (4), 1475–1515.

_ , Robert J Richmond, and Motohiro Yogo, "Which investors matter for equity valuations and expected returns?," *Review of Economic Studies*, 2024, *91* (4), 2387–2424.

Kundu, Shohini, "The externalities of fire sales: Evidence from collateralized loan obligations," 2023.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, "The impact of institutional trading on stock prices," *Journal of Financial Economics*, 1992, *32* (1), 23–43.

lang Chen, Hsiu and George G Pennacchi, "Does prior performance affect a mutual fund's choice of risk? Theory and further empirical evidence," *Journal of Financial and Quantitative Analysis*, 2009, *44* (4), 745–775.

Lou, Dong, "A flow-based explanation for return predictability," *The Review of Financial Studies*, 2012, *25* (12), 3457–3489.

Manski, Charles F, "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 1993, *60* (3), 531–542.

Matzkin, Rosa L, "Nonparametric and distribution-free estimation of the binary threshold crossing and the binary choice models," *Econometrica: Journal of the Econometric Society*, 1992, pp. 239–270.

Nicolai, Francesco, "Contagion in the market for leveraged loans," Technical Report, Working Paper 2020.

Nieuwerburgh, Stijn Van and Laura Veldkamp, "Information acquisition and under-diversification," *The Review of Economic Studies*, 2010, *77* (2), 779–805.

Scharfstein, David S and Jeremy C Stein, "Herd behavior and investment," *The American economic review*, 1990, pp. 465–479.

Sias, Richard W, "Institutional herding," *The Review of Financial Studies*, 2004, *17* (1), 165–206.

Stein, Jeremy C, "Presidential address: Sophisticated investors and market efficiency," *The Journal of Finance*, 2009, *64* (4), 1517–1548.

Sufi, Amir, "Information asymmetry and financing arrangements: Evidence from syndicated loans," *The Journal of Finance*, 2007, *62* (2), 629–668.

Thiele, Victoria, "CLO equity finally back in fashion as bankers foresee rapid start to 2025," *Global Capital*, December, 12 2024.

Weintraub, Gabriel Y, C Lanier Benkard, and Benjamin Van Roy, "Markov perfect industry dynamics with many firms," *Econometrica*, 2008, *76* (6), 1375–1411.

Wermers, Russ, "Mutual Fund Herding and the Impact on Stock Prices," *The Journal of Finance*, 1999, *54* (2), 581–622.

Appendix for "Biased Beliefs and Institutional Overcrowding"

A Data Matching

This section describes the process of matching loans from the CreditFlux CLO-i dataset with those in LPC Dealscan (LoanConnector). There is no universally accepted procedure for linking these datasets (Cohen et al., 2018). Many scholars (Nicolai, 2020; Kundu, 2023; Bhardwaj et al., 2024) employ fuzzy matching algorithms similar to the approach described by (Cohen et al., 2018). Below, we outline the steps of our matching procedure.

We begin by selecting loans in the CLO-i dataset that are denominated in U.S. dollars and syndicated in the United States. Additionally, we exclude loans from the following industries: Banking, Insurance, Finance, Sovereign and Supranational. In the CLO-i dataset, we define a loan facility as a unique combination of issuer, security name, issue type, and maturity date. Due to inconsistencies across CLO reports, the same loan may appear under different names in reports from different managers. The data on loan characteristics is obtained from WRDS-Refinitiv LoanConnector DealScan. From this dataset, we select all unique tranches of deals syndicated in the United States.

The first step of the matching procedure involves a fuzzy matching process based on company and security names in both datasets.[14] We standardize borrower and parent names in DealScan, as well as issuer and security names in CLO-i. This process involves removing commonly used business terms (e.g., Inc., Corp.), eliminating punctuation, and removing duplicate words. Securities matched using this procedure are set aside.

Next, we proceed with matching securities that could not be linked through fuzzy matching on company names. We begin by matching securities across the datasets based on their maturity dates. Matches are excluded if the security first appears in CLO-i before appearing in DealScan or more than 180 days after syndication. Finally, we retain only loan instances where at least two words are shared between borrower and parent company names in DealScan and issuer and security names in CLO-i. Among these, we retain only those that agree on loan type across both datasets and set this group aside[15]. If we are unable to distinguish between two tranches of the same deal, we match the security in CLO-i to the overall deal without specifying the exact loan tranche.

Table B1 presents balance tests comparing matched and unmatched observations across different datasets. The balance is noticeably weaker in the full sample of all loans, where matched and unmatched observations differ significantly in terms of Deal Amount, Tranche Amount, Tenor Maturity, and All-In Spread Drawn. These differences are statistically significant, with t-tests indicating p-values below 0.01 in most cases. However, the balance improves considerably when restricting the analysis to Term Loan B, which is particularly relevant for this study as it represents the primary loan type securitized in CLOs. While differences in means remain statistically significant, their economic magnitudes are relatively small, suggesting that the matched and unmatched Term Loan B samples are more comparable in terms of key loan characteristics.

[14]For this step, we use the `fedmatch` R package, as described in Cohen et al. (2018).

[15]If multiple securities are matched (e.g., a loan appears as *Term Loan* in one dataset and as *Term Loan B*, *Term Loan C*, etc., in another), we select the one with the syndication date closest to the first appearance of the security in the CLO-i dataset.

B Additional Tables

Table B1 : Balance Matched and Unmatched Loans

This table presents balance tests comparing matched and unmatched observations across different datasets. The observations in Dealscan are at the loan tranche level, while those in CreditFlux are at the CLO report x loan holding level. The samples include all loans and Term Loan B, with separate panels for each classification. The analysis is restricted to loans issued on or after January 1, 2010, in Dealscan and loans that appear in CLO reports on or after January 1, 2010, in CreditFlux. The variables include Deal Amount (total loan facility in million USD), Tranche Amount (amount allocated to a specific tranche), Tenor Maturity (loan maturity in months), and All-In Spread Drawn (bps) (total cost of borrowing, including interest and fees). Dummy variables indicate whether a loan is a Term Loan, a Term Loan B, Senior debt, or Secured by collateral. For CreditFlux securities, we include Current Balance (outstanding security balance in million USD), Maturity Months, Interest Rate, Credit Rating (where lower values indicate higher credit quality), and a Default Dummy (1 if the security has defaulted, 0 otherwise). For each variable, we report the number of matched and unmatched observations, their mean values, and the results of a t-test for differences in means.

Sample	Nr. Matched	Nr. Unmatched	Matched Mean	Unmatched Mean	t-statistic	p-value
Dealscan: All Loans						
Deal Amount	28,219	72,768	1,175.05	729.61	29.25	0.000***
Tranche Amount	28,221	72,777	374.02	354.37	3.57	0.000***
Tenor Maturity	27,656	70,426	57.21	49.98	51.46	0.000***
All In Spread Drawn (bps)	25,956	55,697	415.63	293.77	90.97	0.000***
Term Loan Dummy	28,222	72,846	0.63	0.43	55.95	0.000***
Term Loan B Dummy	28,222	72,846	0.38	0.08	97.80	0.000***
Senior Dummy	28,222	72,846	1.00	1.00	-4.96	0.000***
Secured Dummy	28,222	72,846	0.83	0.32	181.92	0.000***
Dealscan: Term Loan B						
Deal Amount	10,640	5,714	1,219.12	1,068.43	6.27	0.000***
Tranche Amount	10,641	5,715	528.51	524.40	0.36	0.72
Tenor Maturity	10,552	5,575	62.87	65.97	-10.64	0.000***
All In Spread Drawn (bps)	10,387	5,200	409.43	448.14	-16.37	0.000***
Senior Dummy	10,641	5,721	1.00	1.00	-1.00	0.32
Secured Dummy	10,641	5,721	0.99	0.96	12.15	0.000***
CreditFlux: All Securities						
Current Balance	10,603,609	6,897,001	1,368,410.22	1,362,002.98	6.83	0.000***
Maturity Months	10,597,718	6,823,014	55.30	56.77	-62.52	0.000***
Interest Rate	10,567,873	6,842,016	4.94	5.40	-460.17	0.000***
Term Loan Dummy	10,604,464	6,898,168	0.96	0.89	548.28	0.000***
Term Loan B Dummy	10,604,464	6,898,168	0.45	0.35	400.24	0.000***
Rating	10,252,578	6,509,975	14.68	14.98	-347.27	0.000***
Default Dummy	10,604,464	6,898,168	0.01	0.02	-170.55	0.000***
CreditFlux: Term Loan B						
Current Balance	4,745,281	2,431,144	1,366,523.38	1,413,453.08	-38.17	0.000***
Maturity Months	4,743,219	2,429,969	56.36	58.44	-131.35	0.000***
Interest Rate	4,729,234	2,424,655	4.74	4.99	-202.86	0.000***
Rating	4,662,541	2,368,409	14.34	14.48	-105.88	0.000***
Default Dummy	4,745,591	2,431,299	0.01	0.01	-81.36	0.000***

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

Table B2 : Age and the Likelihood of Purchasing a Loan

The table shows the results of the following regression: $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \mathbb{1}(\text{Young})_{i,t} + \mathbf{x}^\top \delta + \varepsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one when investor i purchases a loan of firm j issued at time t, and $\mathbb{1}(\text{Young})_{i,t}$ is a dummy variable equal to one if CLO i is less than four years old at time t. α_i and α_t represent manager and year fixed effects, respectively, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)	(4)
Constant	0.0440***			
	(0.0003)			
$\mathbb{1}(\text{Young})_{i,t}$	0.0260***	0.0258*	0.0261**	0.0289***
	(0.0003)	(0.0123)	(0.0123)	(0.0030)
Size			0.0236***	0.0236***
			(0.0022)	(0.0010)
Maturity			0.0080**	0.0080***
			(0.0031)	(0.0013)
Fixed-effects				
Year	No	Yes	Yes	Yes
Rating	No	Yes	Yes	Yes
Industry	No	Yes	Yes	Yes
Manager	No	No	No	Yes
Fit statistics				
Observations	4,977,940	4,895,583	4,861,703	4,861,703
R^2	0.00160	0.02217	0.02863	0.04045
Within R^2		0.00134	0.00797	0.00829

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

Table B3 : Alternative Measures of Reinvestment Horizon and Age Effects on the Likelihood of Loan Purchase

The table shows the results of the following regression: $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot Z_{i,t} + \mathbf{x}^\top \delta + \varepsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ is a dummy variable equal to one when investor i purchases a loan of firm j issued at time t. α_i and α_t represent manager and year fixed effects, respectively, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P. $Z_{i,t}$ is equal to $\mathbb{1}(\text{Far from End})_{i,t}$, i.e., a dummy variable equal to one if CLO i is before the end of the reinvestment period in columns (1) and (2), and equal to $\mathbb{1}(\text{Young})_{i,t}$, i.e., a dummy variable equal to one if the CLO is less than five years old at time t in columns (3) and (4).

	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Far from End})_{i,t}$	0.0615***	0.0602***		
	(0.0092)	(0.0032)		
Size	0.0238***	0.0238***	0.0236***	0.0236***
	(0.0022)	(0.0010)	(0.0022)	(0.0010)
Maturity	0.0082**	0.0082***	0.0080**	0.0080***
	(0.0032)	(0.0013)	(0.0031)	(0.0013)
$\mathbb{1}(\text{Young})_{i,t}$			0.0213*	0.0233***
			(0.0107)	(0.0027)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Manager	No	Yes	No	Yes
Fit statistics				
Observations	4,786,360	4,786,360	4,861,703	4,861,703
R^2	0.03465	0.04537	0.02851	0.04026
Within R^2	0.01402	0.01327	0.00785	0.00809

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

Table B4 : Aggregate Impact of Incumbency on Loan Issuance Participation - Managers

The table shows the results of the following regression: $\log(\text{Nr. Investors})_{j,t} = \alpha_t + \beta \cdot \log(\text{Nr. Incumbents})_{j,t} + \mathbf{x}^\top\delta + \varepsilon_{j,t}$, where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLO Managers that participate in a given loan issuance by firm j at time t, and $\log(\text{Nr. Incumbents})_{j,t}$ is the natural logarithm of the number of incumbents, i.e., managers that have previously invested in loans of firm j prior to time t. α_t represent year fixed effects, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	1.137***		
	(0.0306)		
log(Nr. Incumbents)	0.4029***	0.3223***	0.2607***
	(0.0098)	(0.0242)	(0.0223)
Size			0.2159***
			(0.0191)
Maturity			0.1912***
			(0.0330)
Fixed-effects			
Year	No	Yes	Yes
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	5,455	5,389	5,343
R^2	0.23784	0.35238	0.39060
Within R^2		0.11200	0.16617

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

Table B5 : Aggregate Impact of Incumbency on Loan Issuance Participation - Levels

The table shows the results of the following regression: Nr. $\text{Investors}_{j,t} = \alpha_t + \beta \cdot \text{Nr. Incumbents}_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}$, where Nr. $\text{Investors}_{j,t}$ is the number of CLOs that participate in a given loan issuance by firm j at time t, and Nr. $\text{Incumbents}_{j,t}$ is the number of incumbents, i.e., managers that have previously invested in loans of firm j prior to time t. α_t represent year fixed effects, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	15.09***		
	(1.379)		
Nr.Incumbents	1.332***	1.085***	0.9315***
	(0.0348)	(0.1268)	(0.1173)
Size			10.66***
			(1.677)
Maturity			7.921***
			(1.890)
			(0.0330)
Fixed-effects			
Year	No	Yes	Yes
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	5,455	5,389	5,343
R^2	0.21200	0.34862	0.36318
Within R^2		0.10318	0.12443

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

Table B6 : Aggregate Impact of Incumbency on Loan Issuance Participation - Managers & Levels

The table shows the results of the following regression: Nr. Investors$_{j,t} = \alpha_t + \beta \cdot$ Nr. Incumbents$_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}$, where Nr. Investors$_{j,t}$ is the number of CLO Managers that participate in a given loan issuance by firm j at time t, and Nr. Incumbents$_{j,t}$ is the number of incumbents, i.e., managers that have previously invested in loans of firm j prior to time t. α_t represent year fixed effects, while $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	6.683***		
	(0.2644)		
Nr.Incumbents	0.2995***	0.2679***	0.2264***
	(0.0067)	(0.0205)	(0.0181)
Size			2.810***
			(0.2865)
Maturity			1.914***
			(0.4159)
Fixed-effects			
Year	No	Yes	Yes
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	5,455	5,389	5,343
R^2	0.26989	0.37063	0.39629
Within R^2		0.15506	0.19068

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

Table B7 : Aggregate Impact of CLO Age on Loan Issuance Participation

The table shows the results of the following regression: $\log(\text{Nr. Investors})_{j,t} = \alpha + \beta \cdot \log(\text{Nr. Young})_{j,t} + \mathbf{x}^\top \delta + \varepsilon_{j,t}$, where $\log(\text{Nr. Investors})_{j,t}$ is the natural logarithm of the number of CLOs that participate in a given loan issuance by firm j at time t, and $\log(\text{Nr. Young})_{j,t}$ is the natural logarithm of the number of CLOs that are less than four years away from their closing date at time t. $\mathbf{x}$ is a vector of control variables. Size is the natural logarithm of the deal size; maturity is the natural logarithm of the weighted maturity of all tranches in the package issued by firm j at time t. Industry fixed effects are based on SIC codes. Rating fixed effects are based on the worst credit rating between Moody's and S&P.

	(1)	(2)	(3)
Constant	-1.436***		
	(0.1876)		
$\log(\text{Nr. Young})_{j,t}$	0.7297***	0.7753***	0.6272***
	(0.0301)	(0.0224)	(0.0321)
Size			0.4437***
			(0.0359)
Maturity			0.1736***
			(0.0470)
Fixed-effects			
Rating	No	Yes	Yes
Industry	No	Yes	Yes
Fit statistics			
Observations	7,137	7,033	5,672
R^2	0.07588	0.20726	0.28193
Within R^2		0.08530	0.15737

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

C Additional Figures

Figure C1 : Percentage Holdings by Issue Type on CreditFlux

Percentage holdings by issue type. The percentages represent the fraction of total holdings in CreditFlux allocated to each loan type. The top five categories are shown separately, while all other types are grouped under Other. Term Loan (Other) is a residual category that includes term loans that CreditFlux cannot specifically classify as Term Loan B, Term Loan C, Term Loan D, or other defined subcategories. The sample is restricted to USD-denominated loans issued in the United States, excluding loans from the banking, insurance, finance, and sovereign or supranational sectors.

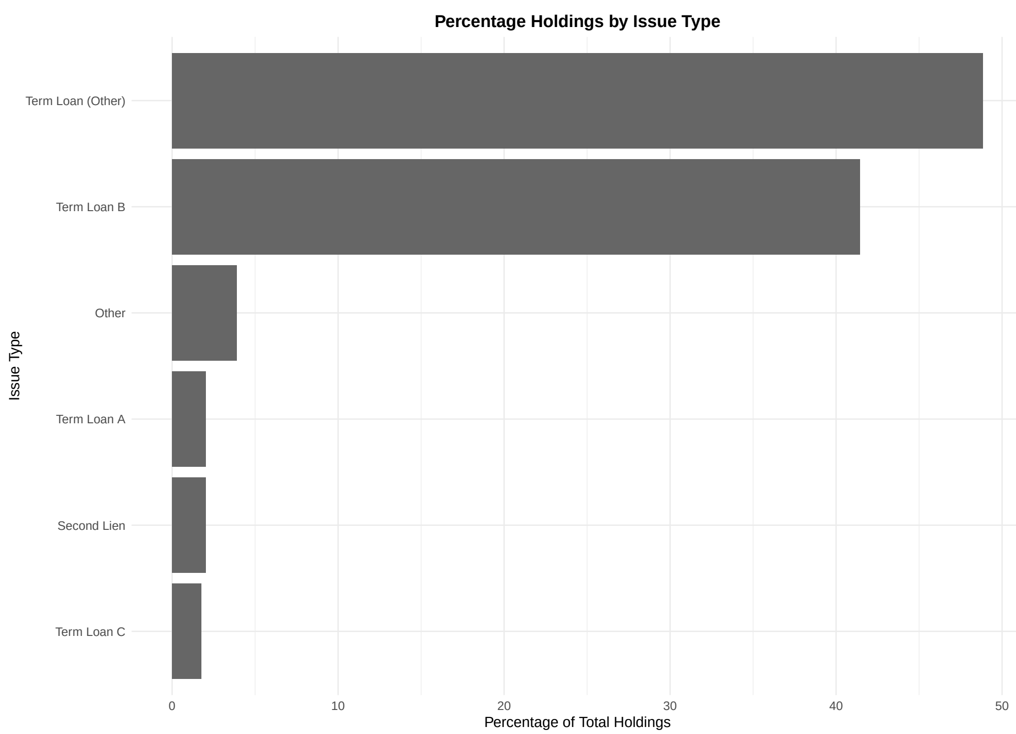


Figure C2 : Syndicated Deal Amount by Tranche Type

Percentage deal amount by tranche type. The percentages represent the fraction of the total deal amount in DealScan allocated to each tranche category. The top five tranche types are displayed separately, while all other types are grouped under "Other." The sample is restricted to USD-denominated deals syndicated in the United States, excluding deals associated with banks, non-bank financial institutions, and government entities.

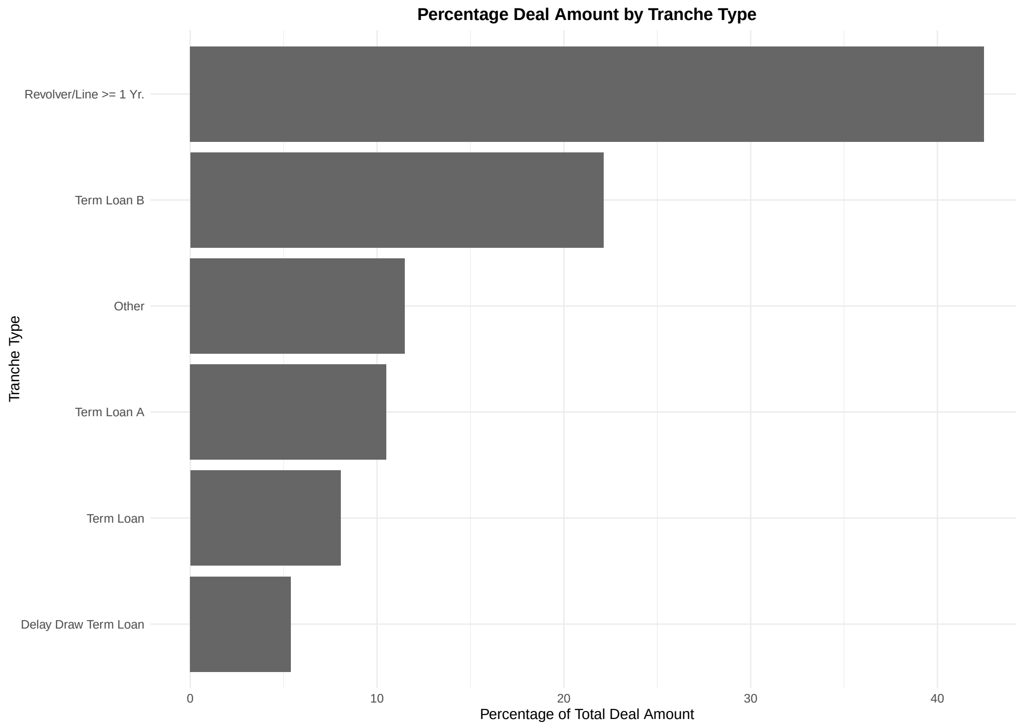


Figure C3 : Fraction of Variation Explained by Buckets

This figure presents the fraction of variation, measured by R^2, explained by different bucket specifications. Panel A regresses the actual number of CLOs participating in a loan issuance on 2, 3, 5, 10, and 20 equal-sized buckets formed from the same variable. Panel B regresses the actual number of Incumbent CLOs in a loan issuance on 2, 3, 5, 10, and 20 equal-sized buckets formed from the same variable. Panel C regresses the actual number of CLOs participating in a loan issuance on 2, 3, 5, 10, and 20 equal-sized buckets formed from the number of incumbents in a loan; the blue bar indicates the R^2 of a regression of the number of participating CLOs on the logarithm of the number of incumbents. Panel D regresses the All-In-Drawn Spread of a loan issuance on 2, 3, 5, 10, and 20 equal-sized buckets formed from the number of CLOs participating in the loan; the blue bar shows the R^2 of a regression of the All-In-Drawn Spread on the logarithm of the number of participating CLOs.

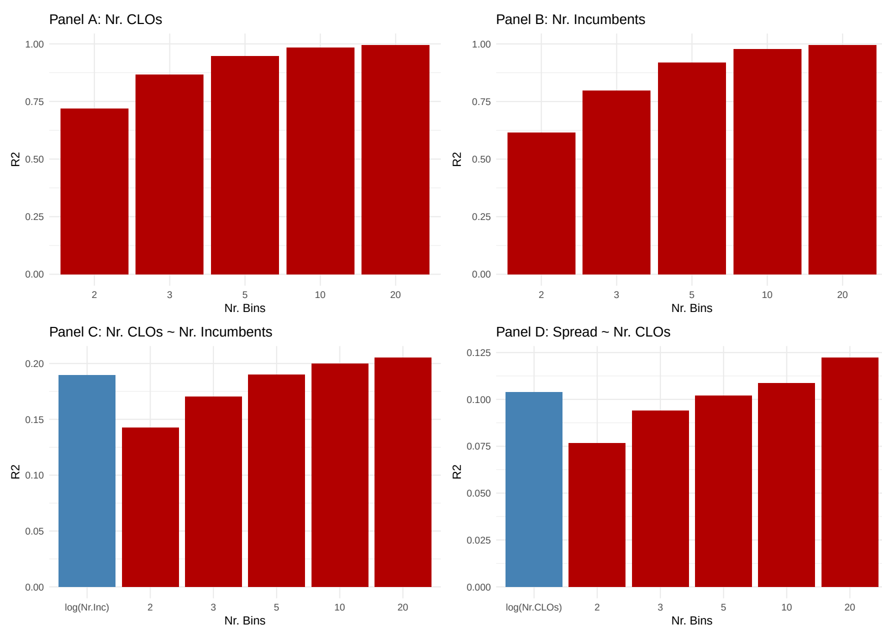


Figure C4 : Distribution of Estimated Regression Coefficients for Crowding Behavior

This figure compares the distributions of estimated regression coefficients, β_i, obtained from the regression $\mathbb{1}(\text{buy})_{i,j,t} = \alpha_i + \beta_i \left(\sum_{k \neq i} \mathbb{1}(\text{buy})_{k,j,t}\right) + \epsilon_{i,j,t}$, where $\mathbb{1}(\text{buy})_{i,j,t}$ denotes a binary investment decision for manager i on loan j at time t, and the regressor represents the number of other participants in the same loan at time t. The regressions are estimated for each manager across all loans using a leave-one-out approach. The blue density corresponds to a sample of randomly generated trading decisions, whereas the red density reflects the actual data.

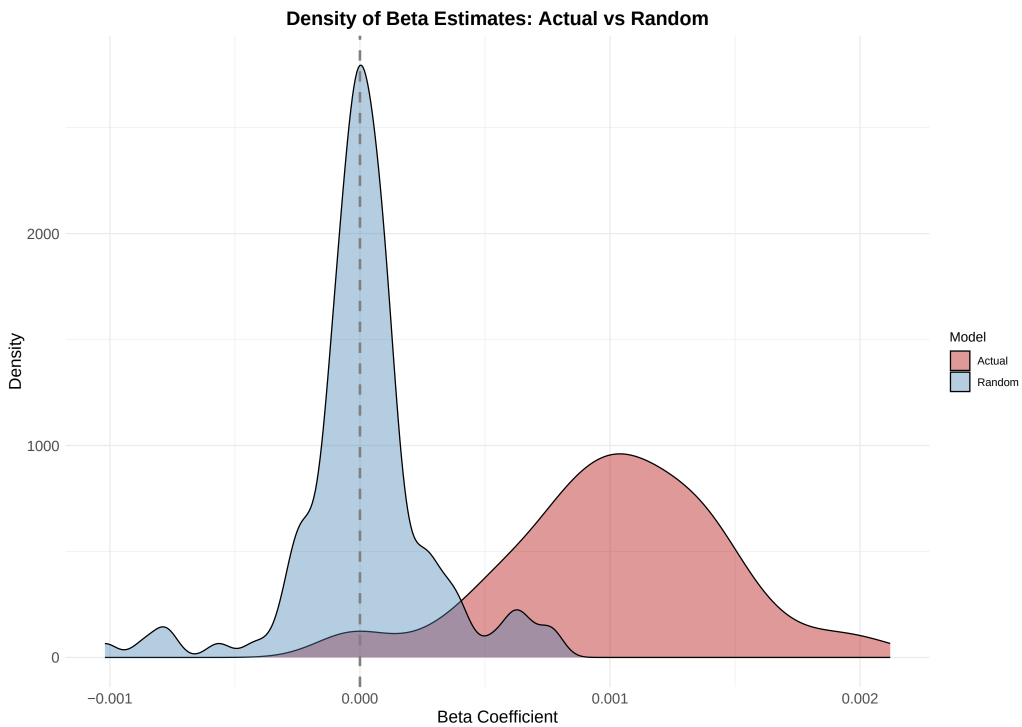


Figure C5 : Age and Probability of Purchase

The figure plots the probability of purchasing a loan in the primary market by CLOs as a function of its age. The data are divided into 50 bins, each containing an equal number of observations, with each point representing the average probability estimate within a bin. The shaded red area depicts the 95% confidence intervals.

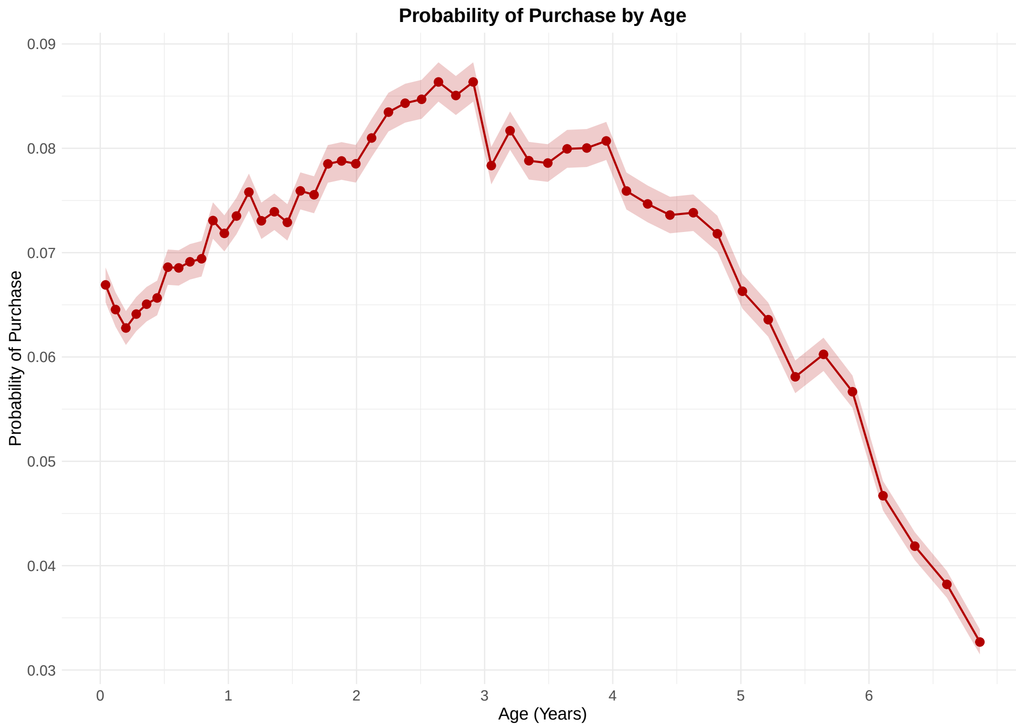


Figure C6 : Number of Investors and Number of Incumbents

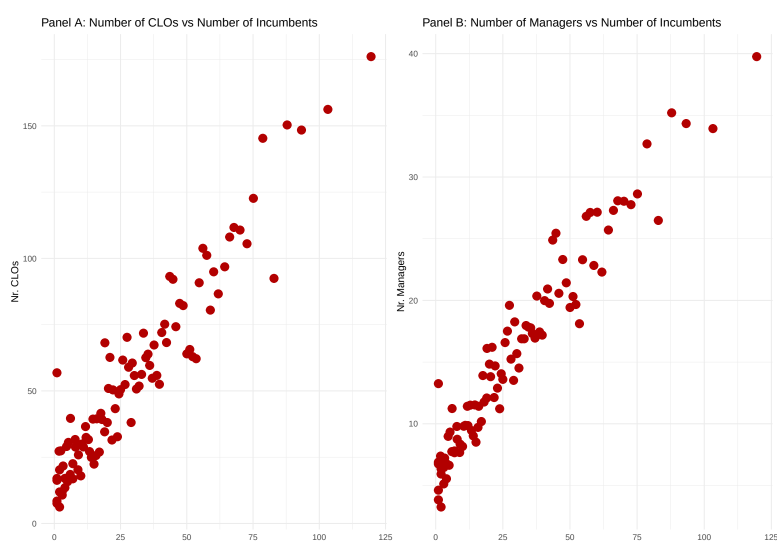


Figure C7 : Number of Investors and Number of CLOs far from End of Reinvestment Period

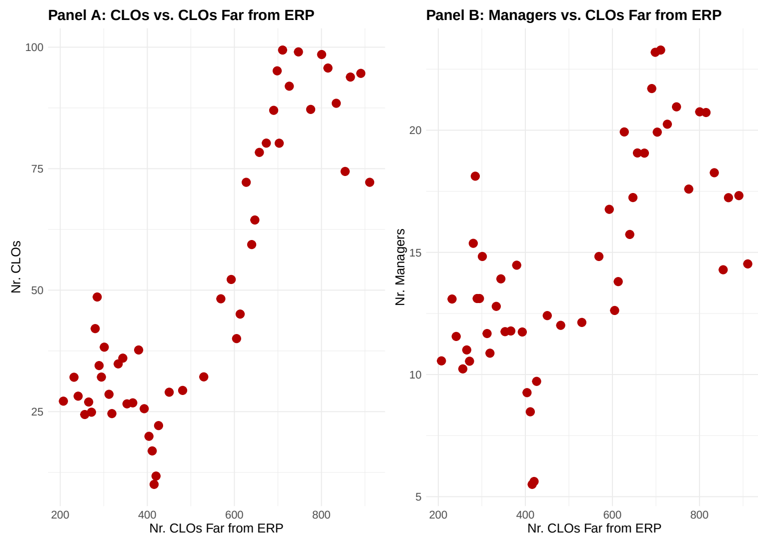
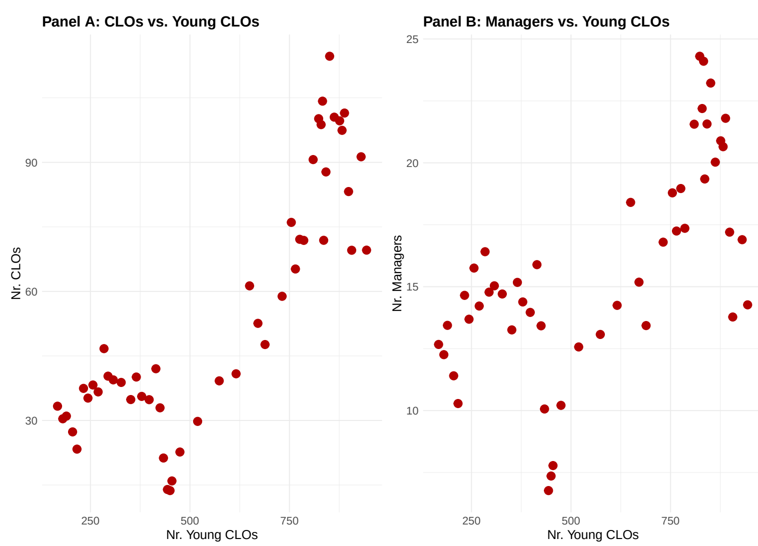


Figure C8 : Number of Investors and Number of Young CLOs



D Model

We consider a CLO with assets in place at time t given by $A_{i,t}$. These assets earn a stochastic net return $r_{A_i,t+1}$. The CLO has AAA–rated liabilities $L_{i,t}$, which earn the risk–free rate r_f, and a cash position $C_{i,t}$, also earning r_f. Thus, the net liabilities are defined as $NL_{i,t} = L_{i,t} - C_{i,t}$. At time t, firm j issues a loan that earns a return $r_{j,t+1}$. The CLO has the opportunity to invest an amount $I_{i,j,t}$ in this new loan (with $I_{i,j,t} \ll C_{i,t}$ so that the CLO is not cash–constrained). If no additional investment is made, the CLO's terminal equity at $t+1$ is given by:

$$E_{i,t+1} = A_{i,t}(1 + r_{A_i,t+1}) - (L_{i,t} - C_{i,t})(1 + r_f). \tag{16}$$

If an amount $I_{i,j,t} \geq 0$ is invested in asset j, then cash is reduced by $I_{i,j,t}$, and the new asset yields $I_{i,j,t}(1 + r_{j,t+1})$ at $t+1$. We also assume that investors incur a fixed cost κ when investing in a new company's loan for the first time. This fixed cost, which captures any learning, cognitive, or administrative expenses, is independent of the amount invested and is paid only if $I_{i,j,t} > 0$ and $\mathbb{1}(\text{Incumbent})_{i,j,t} = 0$. Here, $\mathbb{1}(\text{Incumbent})_{i,j,t}$ is a dummy variable that equals 1 if the CLO manager has previously invested in any of the loans issued by firm j, and 0 otherwise. Define the indicator $\mathbb{1}(\text{first-time})_{i,j,t} = \mathbb{1}(I_{i,j,t} > 0)\left[1 - \mathbb{1}(\text{Incumbent})_{i,j,t}\right]$, which is 1 if and only if the CLO invests in firm j's loans for the first time. Then, the terminal equity becomes:

$$\begin{aligned}
E_{i,t+1} &= \underbrace{A_{i,t}(1 + r_{A_i,t+1}) + I_{i,j,t}(1 + r_{j,t+1})}_{A_{i,t+1}} + \underbrace{\big(C_{i,t} - I_{i,j,t}\big)(1 + r_f)}_{C_{i,t+1}} - \underbrace{L_{i,t}(1 + r_f)}_{L_{i,t+1}} - \underbrace{\kappa\, \mathbb{1}(\text{first-time})_{i,j,t}}_{\text{Entry Cost}} \\
&= A_{i,t}(1 + r_{A_i,t+1}) - \big(L_{i,t} - C_{i,t}\big)(1 + r_f) + I_{i,j,t}(r_{j,t+1} - r_f) - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}.
\end{aligned} \tag{17}$$

Define $\mu_A = \mathbb{E}_t[r_{A_i,t+1}]$, $\mu_j = \mathbb{E}_t[r_{j,t+1}]$ and denote the excess return on asset j over the risk–free rate as $\mu_j - r_f$. Taking expectations, we have:

$$\mathbb{E}_t[E_{i,t+1}] = A_{i,t}(1 + \mu_A) - (L_{i,t} - C_{i,t})(1 + r_f) + I_{i,j,t}\,(\mu_j - r_f) - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}.$$

Define $\sigma_A^2 = \mathrm{Var}_t(r_{A_i,t+1})$, $\sigma_j^2 = \mathrm{Var}_t(r_{j,t+1})$, $\sigma_{Aj} = \mathrm{Cov}_t(r_{A_i,t+1}, r_{j,t+1})$. Since the liabilities and cash are assumed to be risk-free, then:

$$\mathrm{Var}_t(E_{i,t+1}) = A_{i,t}^2\,\sigma_A^2 + I_{i,j,t}^2\,\sigma_j^2 + 2A_{i,t}I_{i,j,t}\,\sigma_{Aj}.$$

The CLO manager is assumed to have mean–variance preferences over terminal equity, characterized by a risk–aversion parameter $\gamma > 0$. Moreover, we assume that the investor's utility is linearly affected by an unobservable shock ε, which is identically and independently distributed across investors. This shock represents private information that neither the econometrician nor other investors can observe, yet it influences the investment decisions of CLO i. The utility function is given by:

$$U_{i,t} = \mathbb{E}_t[E_{i,t+1}] - \frac{\gamma}{2}\,\mathrm{Var}_t(E_{i,t+1}) + \varepsilon_{i,t}\big(I_{i,j,t}\big),$$

where the term $\varepsilon_{i,t}\big(I_{i,j,t}\big)$ allows the private information to depend on the chosen investment level $I_{i,j,t}$. Substituting the expressions derived above, we obtain:

$$\begin{aligned} U_{i,t} = &\Big\{A_{i,t}(1+\mu_A) - (L_{i,t}-C_{i,t})(1+r_f) + I_{i,j,t}\,(\mu_j - r_f)\Big\} \\ &- \frac{\gamma}{2}\Big\{A_{i,t}^2\,\sigma_A^2 + I_{i,j,t}^2\,\sigma_j^2 + 2A_{i,t}I_{i,j,t}\,\sigma_{Aj}\Big\} \\ &- \kappa\,\mathbb{1}(\text{first-time})_{i,j,t} + \varepsilon_{i,t}\big(I_{i,j,t}\big). \end{aligned} \tag{18}$$

Taking the derivative of $U_{i,t}$ with respect to $I_{i,j,t}$ and setting it equal to zero, we have:

$$\frac{\partial U_{i,t}}{\partial I_{i,j,t}} = (\mu_j - r_f) - \gamma\left(I_{i,j,t}\,\sigma_j^2 + A_{i,t}\,\sigma_{Aj}\right) = 0.$$

Solving for $I^*_{i,j,t}$ yields:

$$I^*_{i,j,t} = \frac{1}{\sigma_j^2}\left(\frac{\mu_j - r_f}{\gamma} - A_{i,t}\,\sigma_{Aj}\right) = \frac{\mu_j - r_f}{\gamma\,\sigma_j^2} - A_{i,t}\,\beta_{Aj}\,,$$

where we define $\beta_{Aj} = \frac{\sigma_{Aj}}{\sigma_j^2}$, which represents the scaled covariance between the existing assets and the new loan. In this expression, the term $\frac{\mu_j - r_f}{\gamma\,\sigma_j^2}$ is the standard mean–variance optimal allocation to asset j, while the adjustment term $A_{i,t}\,\beta_{Aj}$ accounts for the covariance with the current asset portfolio. If we further assume that all returns are driven by exposure to a well-diversified market portfolio M, and that the returns on the CLO's assets closely track this index, then we can approximate $\beta_{Aj} \approx \beta_j\,\frac{\sigma_M^2}{\sigma_j^2}$, where β_j is the standard CAPM beta of asset j with respect to the market portfolio and σ_M^2 is the variance of the market portfolio. We can substitute the optimal $I^*_{i,j,t}$ into the utility function to get:

$$\begin{aligned} U_{i,t}(I^*_{i,j,t} > 0) = &\underbrace{A_{i,t}(1+\mu_A) - \big(L_{i,t} - C_{i,t}\big)(1+r_f) - \frac{\gamma}{2}\,A_{i,t}^2\,\sigma_A^2}_{\text{Baseline utility (no investment)}} \\ &+ \underbrace{\frac{1}{\sigma_j^2}\left[\frac{(\mu_j - r_f)^2}{2\gamma} - A_{i,t}\,\sigma_{Aj}\,(\mu_j - r_f) + \frac{\gamma}{2}\,(A_{i,t}\,\sigma_{Aj})^2\right]}_{\Delta U = \text{Incremental utility from investing}} \\ &- \underbrace{\kappa\,\mathbb{1}(\text{first-time})_{i,j,t}}_{\text{Entry Cost}} + \underbrace{\varepsilon_{i,t}\big(I^*_{i,j,t} > 0\big)}_{\text{Private Information}}\,. \end{aligned}$$

We assume that the optimal investment strategy depends only on a vector of state variables $\mathbf{X}$ and the private information ε. In particular, the decision to invest (i.e. $I^*_{i,j,t} > 0$) is determined by the inequality $U_{i,t}(I^*_{i,j,t} > 0) \geq U_{i,t}(I^*_{i,j,t} = 0)$, which implies:

$$\Delta U - \kappa\,\mathbb{1}(\text{first-time})_{i,j,t} \geq \varepsilon_{i,t}\big(I^*_{i,j,t} = 0\big) - \varepsilon_{i,t}\big(I^*_{i,j,t} > 0\big).$$

Defining a decision rule function $s(\mathbf{x}, \varepsilon)$ that maps the state $\mathbf{x}$ and the private shock ε into an optimal investment level, we introduce the indicator function $\mathbb{1}\{s(\mathbf{x}, \varepsilon) = I,\ I > 0\}$, which equals 1 if and only if the optimal decision is to invest (i.e. $I^*_{i,j,t} > 0$) and 0 otherwise. Then, by integrating this indicator function over the distribution of the difference in private information, denoted by $F(\Delta\varepsilon)$ (where $\Delta\varepsilon \equiv \varepsilon_{i,t}\big(I^*_{i,j,t} = 0\big) - \varepsilon_{i,t}\big(I^*_{i,j,t} > 0\big)$), we obtain the probability that the CLO invests given $\mathbf{X} = \mathbf{x}$:

$$\Pr\Big(I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\Big) \;=\; \int \mathbb{1}\{s(\mathbf{x}, \varepsilon) = I,\ I > 0\}\, dF(\Delta\varepsilon).$$

Equivalently, we can express this probability as:

$$\Pr\Big(I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\Big) \;=\; \Pr\Big\{\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t} \geq \Delta\varepsilon\Big\}.$$

Assume that the difference in the private information shocks $\Delta\varepsilon$ follows an extreme value type I distribution with cumulative distribution function $F(\Delta\varepsilon) = \exp\Big\{-\exp\big(-\Delta\varepsilon\big)\Big\}$. Standard calculations show that:

$$\Pr\Big\{I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\Big\} = \frac{\exp\Big(\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}\Big)}{1 + \exp\Big(\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}\Big)}.$$

This is the familiar logit expression, which shows that the probability of a positive investment decision is a logistic function of the net utility benefit ΔU (adjusted for the fixed entry cost κ in first-time investments). Given the conditional choice probability (CCP) $\Pr\{I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}$, the probability of not investing is $\Pr\{I^*_{i,j,t} = 0 \mid \mathbf{X} = \mathbf{x}\} = 1 - \Pr\{I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}$. Thus, the odds ratio is:

$$\frac{\Pr\{I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}}{\Pr\{I^*_{i,j,t} = 0 \mid \mathbf{X} = \mathbf{x}\}} = \exp\Big(\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t}\Big).$$

Taking logarithms, we obtain the logit (or log-odds) form:

$$\Delta U - \kappa\, \mathbb{1}(\text{first-time})_{i,j,t} = \log\left(\frac{\Pr\{I^*_{i,j,t} > 0 \mid \mathbf{X} = \mathbf{x}\}}{\Pr\{I^*_{i,j,t} = 0 \mid \mathbf{X} = \mathbf{x}\}}\right). \tag{19}$$

This linear relationship in ΔU and the entry cost κ can be used for estimation[16].

Table B8 CLO Balance Sheet at Time t

Assets	
Operating Assets	$A_{i,t}$
Cash Position	$C_{i,t}$
Total Assets	$A_{i,t} + C_{i,t}$
Liabilities & Equity	
AAA Tranches	$L_{i,t}$
Equity	$A_{i,t} + C_{i,t} - L_{i,t}$
Total Liabilities + Equity	$A_{i,t} + C_{i,t}$

[16]See, for instance, Hotz and Miller (1993) and Berry (1994), among others.

Table B9 : CLO Balance Sheet at Time $t+1$

Assets	
Old Operating Assets	$A_{i,t}(1+r_{A_i,t+1})$
New Loan Investment	$I_{i,j,t}(1+r_{j,t+1})$
Cash Position	$(C_{i,t}-I_{i,j,t})(1+r_f)-\kappa\,\mathbb{1}(\text{first-time})_{i,j,t}$
Total Assets	$A_{i,t}(1+r_{A_i,t+1})+I_{i,j,t}(1+r_{j,t+1})+(C_{i,t}-I_{i,j,t})(1+r_f)-\kappa\,\mathbb{1}(\text{first-time})_{i,j,t}$
Liabilities & Equity	
AAA Tranches	$L_{i,t}(1+r_f)$
Equity	$A_{i,t}(1+r_{A_i,t+1})+I_{i,j,t}(1+r_{j,t+1})+(C_{i,t}-I_{i,j,t})(1+r_f)-L_{i,t}(1+r_f)-\kappa\,\mathbb{1}(\text{first-time})_{i,j,t}$
Total Liabilities + Equity	$A_{i,t}(1+r_{A_i,t+1})+I_{i,j,t}(1+r_{j,t+1})+(C_{i,t}-I_{i,j,t})(1+r_f)-\kappa\,\mathbb{1}(\text{first-time})_{i,j,t}$

D.1 Tests of Unbiased Beliefs

To facilitate the identification of beliefs, we adopt the approach developed in Aguirregabiria and Magesan (2020) and Aguirregabiria (2021). As outlined in the main text, we partition the state vector as follows:

$$\mathbf{X}=(\mathbf{S}_i,\,\mathbf{S}_{-i},\,\mathbf{W}),$$

where $\mathbf{S}_i$ represents the set of state variables that influence only the utility of player i, $\mathbf{S}_{-i}$ contains those variables that affect the utilities of all other players (but not player i's utility), and $\mathbf{W}$ comprises the state variables that impact the utilities of all players. Under this partition, we impose the following exclusion restriction:

$$u(a_i,\mathbf{a}_{-i}\mid \mathbf{S}_i=\mathbf{s}_i,\,\mathbf{S}_{-i}=\mathbf{s}_{-i},\,\mathbf{W}=\mathbf{w})=u(a_i,\mathbf{a}_{-i}\mid \mathbf{S}_i=\mathbf{s}_i,\,\mathbf{S}_{-i}=\mathbf{s}'_{-i},\,\mathbf{W}=\mathbf{w})\quad \forall\,\mathbf{s}_{-i}\neq\mathbf{s}'_{-i}. \tag{20}$$

Here, the subscript $-i$ denotes the actions $\mathbf{a}_{-i}$ and the state variables $\mathbf{S}_{-i}$ corresponding to all players other than i. As demonstrated in Aguirregabiria and Magesan (2020), we can test whether players' beliefs are in equilibrium. In an entry game, equilibrium beliefs imply that each player's beliefs about the actions of the others match the observed conditional choice probabilities, i.e.,

$$\mathbf{B}_{it}(\mathbf{a}_{-i}\mid\mathbf{X}=\mathbf{x})=P_{-i}(\mathbf{a}_{-i}\mid\mathbf{X}=\mathbf{x}).$$

For illustration, consider a game with two players ($i=1,2$) and two possible actions ($a_i\in\{I>0,\,I=0\}=\{1,0\}$). Following Aguirregabiria and Magesan (2020), equilibrium beliefs imply the following restrictions linking the actions of player 1 and player 2:
For player 1:

$$\frac{q_{1,t}(1,\mathbf{s}_1,\mathbf{s}_2^{(a)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{s}_2^{(c)},\mathbf{w})}{q_{1,t}(1,\mathbf{s}_1,\mathbf{s}_2^{(b)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{s}_2^{(c)},\mathbf{w})}=\frac{P_{2,t}(1\mid\mathbf{s}_1,\mathbf{s}_2^{(a)},\mathbf{w})-P_{2,t}(1\mid\mathbf{s}_1,\mathbf{s}_2^{(c)},\mathbf{w})}{P_{2,t}(1\mid\mathbf{s}_1,\mathbf{s}_2^{(b)},\mathbf{w})-P_{2,t}(1\mid\mathbf{s}_1,\mathbf{s}_2^{(c)},\mathbf{w})}. \tag{21}$$

For player 2:

$$\frac{q_{2,t}(1,\mathbf{s}_2,\mathbf{s}_1^{(a)},\mathbf{w})-q_{2,t}(1,\mathbf{s}_2,\mathbf{s}_1^{(c)},\mathbf{w})}{q_{2,t}(1,\mathbf{s}_2,\mathbf{s}_1^{(b)},\mathbf{w})-q_{2,t}(1,\mathbf{s}_2,\mathbf{s}_1^{(c)},\mathbf{w})} = \frac{P_{1,t}(1\mid \mathbf{s}_2,\mathbf{s}_1^{(a)},\mathbf{w})-P_{1,t}(1\mid \mathbf{s}_2,\mathbf{s}_1^{(c)},\mathbf{w})}{P_{1,t}(1\mid \mathbf{s}_2,\mathbf{s}_1^{(b)},\mathbf{w})-P_{1,t}(1\mid \mathbf{s}_2,\mathbf{s}_1^{(c)},\mathbf{w})}. \tag{22}$$

In these equations, $\mathbf{s}_{-i}^{(a)}$, $\mathbf{s}_{-i}^{(b)}$, and $\mathbf{s}_{-i}^{(c)}$ denote three distinct realizations of the competitor's state vector $\mathbf{S}_{-i}$, with $\mathbf{s}_{-i}^{(c)}$ serving as the baseline state. The function $q_{i,t}$ represents the expected utility of player i when choosing action 1, and $P_{-i,t}$ denotes the conditional probability for player $-i$ (the competitor). To sketch a proof for player 1, note that by definition the utility of player 1 does not change with different realizations of player 2's state, that is:

$$u_1(a_1,a_2,\mathbf{s}_1,S_2=\mathbf{s}_2^{(a)},\mathbf{w}) = u_1(a_1,a_2,\mathbf{s}_1,S_2=\mathbf{s}_2^{(b)},\mathbf{w}) = u_1(a_1,a_2,\mathbf{s}_1,S_2=\mathbf{s}_2^{(c)},\mathbf{w}).$$

This implies that differences in the expected utility $q_{1,t}$ across the states $\mathbf{s}_2^{(a)}$, $\mathbf{s}_2^{(b)}$, and $\mathbf{s}_2^{(c)}$ arise solely from differences in beliefs. Consequently, the ratio of these differences, as given in Equation (21), isolates differences in beliefs, and similarly for player 2 in Equation (22). These restrictions provide a testable implication: if the normalized differences in the expected utilities match those in the observed conditional probabilities, then the investors' beliefs are in equilibrium. To prove this, notice that the difference in expected utilities for player 1 when $\mathbf{S}_2=\mathbf{s}_2^{(a)}$ versus $\mathbf{S}_2=\mathbf{s}_2^{(c)}$ is given by:

$$\begin{aligned} q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(a)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w}) = &\Big(B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(a)},\mathbf{w}) \\ &-\ B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})\Big) \\ &\times\Big(u_1(a_1,a_2=1,\mathbf{s}_1,\mathbf{w})-u_1(a_1,a_2=0,\mathbf{s}_1,\mathbf{w})\Big). \end{aligned} \tag{23}$$

(Note that we have omitted the dependence on $\mathbf{S}_2$ in the utility function u_1 since player 1's payoff is not directly affected by it.) Similarly, for states $\mathbf{S}_2=\mathbf{s}_2^{(b)}$ and $\mathbf{S}_2=\mathbf{s}_2^{(c)}$, we obtain:

$$\begin{aligned} q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(b)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w}) = &\Big(B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(b)},\mathbf{w}) \\ &-\ B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})\Big) \\ &\times\Big(u_1(a_1,a_2=1,\mathbf{s}_1,\mathbf{w})-u_1(a_1,a_2=0,\mathbf{s}_1,\mathbf{w})\Big). \end{aligned} \tag{24}$$

Taking the ratio of these differences yields:

$$\begin{aligned} &\frac{q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(a)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})}{q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(b)},\mathbf{w})-q_{1,t}(1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})} = \\ &\frac{B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(a)},\mathbf{w})-B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})}{B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(b)},\mathbf{w})-B_{1,t}(a_2=1,\mathbf{s}_1,\mathbf{S}_2=\mathbf{s}_2^{(c)},\mathbf{w})}. \end{aligned} \tag{25}$$

That is, the measurable ratio on the left of the equal sign depends solely on the ratio of beliefs about player 2's action. Under the assumption of equilibrium beliefs, we have:

$$P_{2,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2, \mathbf{w}) = B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2, \mathbf{w}),$$

which leads to the following testable restriction:

$$\frac{q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(a)}, \mathbf{w}) - q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w})}{q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(b)}, \mathbf{w}) - q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w})} = \frac{P_{2,t}(1 \mid \mathbf{s}_1, \mathbf{s}_2^{(a)}, \mathbf{w}) - P_{2,t}(1 \mid \mathbf{s}_1, \mathbf{s}_2^{(c)}, \mathbf{w})}{P_{2,t}(1 \mid \mathbf{s}_1, \mathbf{s}_2^{(b)}, \mathbf{w}) - P_{2,t}(1 \mid \mathbf{s}_1, \mathbf{s}_2^{(c)}, \mathbf{w})}. \tag{26}$$

In other words, under equilibrium beliefs, the normalized differences in expected utilities for player 1 correspond exactly to the normalized differences in the observed conditional probabilities of player 2. Notice that Equation (26) provides a test for the unbiasedness of beliefs, but does not allow us to determine beliefs in any specific state. To achieve that, we must assume that beliefs are unbiased for some subset of states $\mathbf{S_2} = \mathbf{s_2}$; then, using those as anchors, we can recover the full set of beliefs and the corresponding utilities for player 1. A sketch of the argument is as follows[17]: Assume that beliefs are unbiased at $\mathbf{S}_2 = \mathbf{s}_2^{(b)}$ and $\mathbf{S}_2 = \mathbf{s}_2^{(c)}$, so that:

$$P_{2,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 \in \{\mathbf{s}_2^{(b)}, \mathbf{s}_2^{(c)}\}, \mathbf{w}) = B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 \in \{\mathbf{s}_2^{(b)}, \mathbf{s}_2^{(c)}\}, \mathbf{w}).$$

The utility difference for player 1 can be recovered from Equation (24) as:

$$u_1(a_1, a_2 = 1, \mathbf{s}_1, \mathbf{w}) - u_1(a_1, a_2 = 0, \mathbf{s}_1, \mathbf{w}) = \frac{q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(b)}, \mathbf{w}) - q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w})}{B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(b)}, \mathbf{w}) - B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w})}. \tag{27}$$

Substituting this expression into Equation (23), we obtain the beliefs at state $\mathbf{S}_2 = \mathbf{s}_2^{(a)}$ as:

$$\begin{aligned} B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(a)}, \mathbf{w}) &= B_{1,t}(a_2 = 1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w}) \\ &\quad + \frac{q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(a)}, \mathbf{w}) - q_{1,t}(1, \mathbf{s}_1, \mathbf{S}_2 = \mathbf{s}_2^{(c)}, \mathbf{w})}{u_1(a_1, a_2 = 1, \mathbf{s}_1, \mathbf{w}) - u_1(a_1, a_2 = 0, \mathbf{s}_1, \mathbf{w})}. \end{aligned} \tag{28}$$

This derivation shows that by anchoring on states where beliefs are known to be unbiased—namely, $\mathbf{s}_2^{(b)}$ and $\mathbf{s}_2^{(c)}$—we can infer the entire beliefs structure. In particular, observable choices and the recovered utility differences allow us to determine the beliefs at state $\mathbf{s}_2^{(a)}$ without having to assume that beliefs are unbiased in every state.

In our setting, the state space is too large to estimate directly. Therefore, as described in Section 5, we test whether CLO beliefs are in equilibrium under some simplifying assumptions. First, we assume that each manager's action space is binary, that is:

$$\{I^{\star}_{i,j,t} > 0,\ I^{\star}_{i,j,t} = 0\} = \{1, 0\}.$$

Although one could, in principle, use the continuous optimal investment $I^{\star}_{i,j,t}$ to estimate parameters,

[17] We again leave the formal proof to Aguirregabiria and Magesan (2020).

oversubscription and subsequent rationing mean that the observed investment level often deviates from $I^{\star}_{i,j,t}$ in the market for leveraged loans (Ivashina and Sun, 2011).

We then assume that investors face a downward-sloping relationship between spreads and number of investors of the form:

$$r_{j,t} = a - b\log(N_{j,t}),$$

where $N_{j,t}$ is the total number of CLOs that decide to participate in the loan issuance. Under this specification, each CLO manager is effectively playing a game against the *market*, forming beliefs about the aggregate number of participating CLOs. This approach is similar to the notion of an *oblivious equilibrium* as defined by Weintraub et al. (2008), where managers form expectations regarding market aggregates rather than tracking individual competitors' actions. Furthermore, we partition the market's action space into two buckets—high and low demand. As Figure C3 demonstrates, using two buckets (i.e., a binary classification) in place of the full $\log(N_{j,t})$ leads to only a minimal loss of information. Consequently, all the derivations above can be equivalently interpreted with player 1 representing an individual investor and player 2 representing the market as a whole.