

Relationship Nonbankers

Abstract. Failure to successfully syndicate a leveraged loan can impose substantial costs on the underwriter's capital. We show that banks' personal relationships with investors play an important role in mitigating this underwriting risk. Using novel data on the credit committees of the largest leveraged loan investors, collateralized loan obligations, we document that nearly three-quarters of committee members previously worked at investment banks. A committee member's prior bank affiliation increases loan purchases from that bank. We find that banks disproportionately rely on relationship-driven demand for loans that pose significant underwriting risk, but not for loans with higher default risk. Our results highlight the importance of relationships between financial institutions for loan origination.

Keywords: Banks, Loan Underwriting, Personal Relationships, Leveraged Loans, CLO Managers

JEL Classification: G14, G21, G23

1 Introduction

For non-investment grade borrowers in the US, the leveraged loan market is the primary source of credit. In 2024, 82% or 595 USD billion of debt financing to non-investment grade borrowers has been provided as loans. [Hinzen \(2023\)](#) reports that 63% of this market is funded by CLOs – a class of nonbank investor with actively managed fund structure.

CLOs’ investment decisions, i.e., the choice of loans to invest in, are made by their credit committee. The credit committee of the median CLO manager consists of 5 very senior financial professionals. We hand-collect information on the composition of the credit committees of virtually all CLO managers active in the US. By hand-matching those individuals to their LinkedIn employment history, we can link credit committee members to selling banks through previous employment relationships. Utilizing this novel detailed data we analyze the value of relationships on the leveraged loan market between nonbank investors, the buy-side, and banks, the sell-side. We find that a bank is, on average, allocating a higher loan volume to a CLO manager – both at the intensive and extensive margin – if the bank has a personal relationship to the manager’s credit committee. This effect is stronger if the credit committee member through which the relationship exists, is more senior. Moreover, the relationship value is particularly important for large loans which – keeping borrower characteristics fixed – are harder to generate sufficient demand for among investors. As a compensation for relationship demand, banks provide higher issuing discounts and spreads (reminiscent of [Benveniste and Spindt \(1989\)](#)). Thus, in this paper, we provide evidence that personal relationships help banks to alleviate pipeline risk in loan syndication (cf. [Bruche, Malherbe, and Meisenzahl \(2020\)](#), [Sina, Billio, Dufour, Rocciolo, and Varotto \(2025\)](#)).

Through the creation of our novel data set of individuals working at credit committees, we can provide the first systematic overview of the characteristics of those high-level professionals. To that end, we first hand-collect all names of credit committee members from the 2014 to 2024 vintages of the so-called Fitch Assets Manager Handbooks. We then hand-match these individuals to their LinkedIn profiles and extract both their professional and educational history. We find that the average person on a credit committee has 10 years of work experience at the CLO manager, 22 years of work experience in the credit industry as a whole, and attained a title of Managing Director or partner. From these statistics it is easy to see that credit committee members are senior financial experts. Importantly, 72% of the individuals in our sample have worked at a bank before, meaning they transitioned from the sell-side to the buy-side of the market. These career moves create personal relationships between banks and CLO managers. The average CLO manager has such personal relationships to 3.6 different banks, on average.

In a descriptive exercise, we find that even though the leveraged loan market, together with the CLO market, underwent strong growth dynamics over the last decade, the number of individuals that make up a credit committee barely increased. This implies that an individual credit committee member is responsible, on average, for managing USD 700 million in recent years – a number that was less than half at the beginning of our sample. Thus, shifts in the preferences or the information set of credit committee members through personal relationships to banks can affect large volumes of loan purchases and can prove crucial both for selling banks, but also issuing non-financial companies. Moreover, we document a strong positive correlation in the raw data for banks between their underwriting market share and the number of individuals to which they have a personal relationship through a previous employment history.

Personal relationships can alleviate informational frictions ([Petersen and Rajan \(1994\)](#), [Engelberg, Gao, and Parsons \(2012\)](#), [Herpfer \(2021\)](#)), change preferences of individuals ([Gurun, Stoffman, and Yonker \(2021\)](#)), or lead to cronyism ([Kramarz and Thesmar \(2013\)](#), [Haselmann, Schoenherr, and Vig \(2018\)](#)). To analyze more systematically how personal relationships between banks and non-banks affect loan allocation decisions, we first estimate regressions at the bank-CLO manager level. For this purpose, we aggregate all loan purchases between a bank and a CLO manager in a given quarter. We then specify regressions of the loan purchase volume on a relationship dummy that takes the value of 1 whenever an individual at the CLO manager’s credit committee has worked at the given bank before, and 0 otherwise. In our preferred specification, we control for bank-quarter fixed effects as well as CLO manager-quarter fixed effects to control for all observable and unobservable factors that could confound the effect of relationships. For example, without the inclusion of this extensive fixed effects structure one might be concerned that larger banks have more relationships as they train more employees or that larger CLO managers purchase bigger loans. We find strong evidence that banks allocate higher loan volumes to relationship managers, with the point estimate being highly statistically significant at USD 4.6 million. That is, per quarter, a bank allocates USD 4.6 million more to a CLO manager with a personal relationship compared to a CLO manager without a personal relationship. When zooming into the intensive margin, this effect grows to USD 5.3 million, while at the extensive margin, the likelihood of participation in a loan rises by 1.1 percentage point through personal relationships. By a back-of-the-envelope exercise, we can then quantify the value of all relationships that banks have to roughly USD 200 million per year of additional underwriting capacity. On top of the fact that this finding is consistent across purchase margins, we document that our results are robust to changing the FE structure or changing the relationship variable from a dummy to a more continuous version.

If personal relationships change the allocation of loans from banks to CLO managers, is this related to active decisions being made by credit committee members? We investigate this question by interacting the relationship dummy variable with characteristics of the linked individuals. First, we find no differential effect of relationships between credit committee members that spent more or less time at the connected bank before moving to the CLO manager. Second, we find a very strong positive effect of the time the credit committee member has already spent working at the CLO manager. Third, a weaker but still positive effect can be found for credit committee members that have the role of portfolio managers. These results together seem to suggest that credit committee members need to reach a certain level of seniority for their relationship-based preferences or information to affect the loan purchase decisions. Once they do, however, the duration of the previous employment spell of the bank does not affect the intensity to which loan purchases are being increased.

To further strengthen the identification of relationship effects, we estimate regressions at the loan-CLO manager level. This level of analysis allows us to include loan fixed effects, which rule out the possibility that differences in borrower characteristics (e.g., risk) or contract characteristics (e.g., maturity) drive our results. In the specification most comparable to our baseline bank-CLO manager regressions, we find that, on average, banks allocate USD 0.12 million per loan more to relationship managers than to non-relationship managers. Given that banks underwrite roughly 43 loans per quarter, this amounts to an additional USD 5.2 million allocated to CLO managers with a personal relationship. This estimate closely matches our point estimate from the bank-CLO manager regressions, indicating that borrower characteristics, on average, exert little influence on allocation decisions.

Consequently, we ask whether connected CLO managers purchase more loans overall or disproportionately invest in specific deals. If banks exploit these relationships to place underperforming loans with connected CLO managers, we should observe a higher share of relationship-driven purchases for loans that perform worse ex-post, for example as proxied by secondary-market prices or default rates. If, instead, banks use these relationships to mitigate pipeline risk, we should find a higher share of relationship-driven purchases for loans with greater pipeline risk. Pipeline risk can arise from two sources: a large underwriting commitment by the lead arranger in the event of insufficient investor demand (the quantity channel), or a sudden deterioration in borrower credit quality during syndication that is not fully reflected in the spread (the price channel). We conduct an analysis in the spirit of [Meisenzahl, Niepmann, and Schmidt-Eisenlohr \(2025\)](#), showing that banks pass on most changes in risk conditions through spread adjustments during the syndication phase. Thus, the price channel poses minimal risk to banks, as investors typically agree to adjust

the spread commensurate with the new risk level. The quantity channel, however, is highly relevant, as loan volumes are rarely adjusted ex-post, forcing banks to commit more of their own capital than anticipated. In both cases, we expect CLO managers to be compensated for their risk-mitigation services through higher issuance discounts or spreads.

We test these hypotheses by estimating regressions at the loan level. Our key explanatory variable captures the share of each loan purchased by relationship CLO managers (*relationship reliance*), which raises an identification concern. For example, if a loan is particularly attractive and all investors increase their allocations, relationship CLO managers will also purchase more by construction. To account for overall investor demand, we control for the fraction of the total loan volume sold to all investors. Our results show that loans with higher relationship reliance are identical in long-term performance but are larger in size and offer higher issuance discounts and spreads. This finding indicates that CLO managers do not preferentially purchase deals of higher or lower credit quality but instead acquire loans with greater pipeline risk. As compensation, banks adjust pricing terms to make these deals more attractive to investors.

Literature. There is an active literature analyzing the impact of personal relationships between banks and firms on lending outcomes: [Engelberg et al. \(2012\)](#) document that if the leadership of banks and firms have linkages through the same alma mater or previous employers, firms obtain favorable credit terms. Similarly, [Fisman, Paravisini, and Vig \(2017\)](#) report that loan officers are more likely to provide credit to a firm if there is cultural proximity to firm management. Both papers report improved loan performance suggesting relationships are effective in reducing asymmetric information or instilling discipline – a finding echoed in [Herpfer \(2021\)](#). [Karolyi \(2018\)](#) shows positive externalities for the (financial) resilience of firms who benefit from credit that is based on personal relationships. [Haselmann et al. \(2018\)](#), conversely, find evidence for cronyism in bank lending decision built on personal relationships. In our paper, we shift the focus away from the bank-borrower relationship to the nonbank-bank dimension.¹ The value of relationships to nonbank investors is a topic that deserves attention as nonbanks are less regulated (i.e., individuals have more leeway in their decisions), usually have a far fewer employees than banks (i.e., the decision of a single person has higher impact) and nonbank investing has grown tremendously over the recent years and

¹There is a large literature on relationship lending which analyzes the value of a entity-level relationship between lenders and borrowers. Seminal papers include [Petersen and Rajan \(1994\)](#), [La Porta, Lopez-de Silanes, and Zamarripa \(2003\)](#), and [Bharath, Dahiya, Saunders, and Srinivasan \(2011\)](#). While our paper speaks to this strand of the literature, too, we think the link to the literature discussing personal-level relationships between lenders and borrowers is tighter.

is now, in some market segments, the primary source of credit for firms (i.e., understanding the modern credit market requires understanding nonbanks’ decision making).

A similar strand of literature analyzes the characteristics of individual bankers or borrower executives and their effect on lending outcomes. [Bushman, Gao, Martin, and Pacelli \(2021\)](#), similar to [Herpfer \(2021\)](#), document that bankers have preferences regarding loan contract design. [Carvalho, Gao, and Ma \(2023\)](#) and [Dagostino, Gao, and Ma \(2023\)](#) show how optimism originating from personal experience, respectively, partisanship can affect loan officers’ decision making. [Gao, Kleiner, and Pacelli \(2020\)](#) report that bankers’ careers suffer from issuing underperforming loans. [Fogel, Jandik, and McCumber \(2018\)](#) and [Liu, Xu, Yang, and Zhang \(2023\)](#) identify a positive impact of firm executives’ social capital on loan pricing. To the best of our knowledge, we are the first paper to provide a systematic overview of individual characteristics of the decision makers of a class of non-bank investors and the influence of these characteristics on investment outcomes.

Roadmap. The remainder of the paper is structured as follows: [Section 2](#) describes the data and discusses relevant institutional details. [Section 3](#) establishes the prevalence of prior employment at sell-side banks of CLO manager committee members. [Section 4](#) shows that resulting underwriter networks to nonbanks are important to create loan demand. [Section 5](#) concludes.

2 Data and Institutional Background

2.1 Data Sources

Our analysis combines data from four sources: CLO portfolio holdings data at the security-level from LSEG LPC Collateral, loan origination data from LSEG Loan Connector, CLO manager credit committee information from Fitch Rating’s CLO Asset Manager Handbooks, and hand-collected biographical information. We reference data from other sources in the analysis.

First, LPC Collateral contains CLO portfolio holdings information. LSEG gathers this information from CLO trustee reports. For quarters in which a CLO has multiple reports available, we keep only the latest report. Since LPC Collateral assigns a CLO to its current manager as of the date of data retrieval, we use data from [Hinzen \(2023\)](#) to account for CLO management changes.

Second, we obtain loan characteristics as of loan origination from LSEG Loan Connector, formerly Refinitiv DealScan. To link loan-level origination information to CLO holdings,

we employ a loan’s Loan Identification Number (LIN) as common identifier between the origination data and CLO holdings data. We fill in loan characteristics that are missing in Loan Connector with information from LPC Collateral when available.

Third, central to our analysis, we utilize novel data on CLO managers’ credit committees from Fitch Ratings CLO Asset Manager Handbooks. These annual industry publications contain detailed individual-level committee information on the committee member identities, their titles, their roles, as well as each member’s firm and industry tenure. We manually match CLO managers in our credit committee sample to portfolio holdings in LPC Collateral. Five CLO managers, which account for 2.8% of CLO manager-quarters, maintain separate committees for their broadly syndicated and their middle market loan investments during some period in our sample. We match these committees to the manager’s broadly syndicated loan and middle market CLOs, respectively.

Some individuals have roles with rotating credit committee memberships, for example, as “rotating senior analyst.” In rare instances, rotating members lack identifying information. We remove less than 1% of our sample that corresponds to unidentified individual and individuals who appear exclusively in a rotating capacity. The final sample includes 1,141 unique individuals.

Fourth, we use identity and CLO manager employer information to manually match individuals in our credit committee sample to their respective online professional profiles. We find profiles for 1,009 individuals. For these individuals, we hand-collect resume information on their employment and education histories. In 125 cases, professional profiles contain no employment history other than the current employer.

2.2 Institutional Setting

The syndicated loan market plays a central role in financing leveraged firms, providing large-scale credit that is arranged by a group of lenders rather than a single institution. In a typical syndication, a lead arranger (usually a bank) originates the loan and structures the financing. The process generally unfolds in several stages. First, the arranger secures the mandate from the borrowing firm. As there is competition for the mandates, banks have incentives to offer and arrange fair deals for their borrowers. Second, the loan is marketed to potential investors during the syndication phase. These investors can both be other banks or nonbank financial intermediaries. Third, loan terms may be adjusted during the “flex and allocation” stage in response to investor demand. For example, the loan could have been marketed with a spread that during the 10 to 14 days of syndication proves to be too

low because there is insufficient demand and/or the riskiness of the borrower has increased due to unanticipated macroeconomic events. Finally, the loan closes with final allocations to participating lenders.

A significant share of demand in this market comes from collateralized loan obligations (CLOs). CLOs are structured credit vehicles that invest primarily in portfolios of leveraged loans. Each CLO is managed by an asset management firm – the CLO manager – that is responsible for selecting and monitoring the underlying loans. Investment decisions are typically made by a credit committee within the CLO management firm, which evaluates opportunities in both the primary syndication market and the secondary loan market. CLO managers thus play a key role in providing liquidity and pricing discipline in the leveraged loan market.

3 Underwriter Networks

3.1 Descriptive statistics

To give an overview of our dataset, we provide summary statistics in [Table 1](#). In Panel A, we describe variables at the credit committee-quarter level. The average committee size, measured as the number of members, is 5.66 with the median being 5. Of these 5 people, on average 3.71 or, at the median, 3 have the role of portfolio manager. The average credit committee member works at the CLO manager for 11 years and has 24 years of industry experience. This clearly shows that credit committee members are seasoned experts in credit markets and the position in the committee represents a highly competitive top-level job profile. A further indication for this is that per year only 0.15 (0.12) individuals enter (exit) the average committee. Thus, committee compositions are very stable. Most important for our analysis, the table reports that 93% of all credit committees have a relationship with a bank through a credit committee member that previously worked at a bank. Moreover, the average credit committee has relationships to 3.6 banks either through one person having worked at several banks or through several people with different previous bank employers. There is some concentration among those relationships. The relationship intensity variable that measures how many credit committee members have a relationship to the same bank, scaled by the total number of committee members, is 37%, on average. That is, for a credit committee of 5 people, on average, 2 people have worked at the same bank.

In Panel B of the same table, we report individual level statistics. The average individual is in our sample for 17 quarters and works for one credit committee. There is a female

share of the employees that we observe of 11%. While 48% of the credit committee members with matched LinkedIn profiles have an MBA, 72% have previously worked at a bank. Not reported in this table, 147 individuals previously worked for JP Morgan (or one of the banks that merged into JPM at some point, such as Chase Bank), 121 individuals previously worked at Merrill Lynch and 79 individuals previously worked at Citi, making these the top three US banks in this respect. In total, we find relationships to 56 different banks. Looking into the highest attained title for credit committee members further corroborates the point that these are senior experts with 22% being C-level or founders and 57% being Managing Directors or partners. These patterns are described in more detail in [Figure 1](#).

3.2 Institutional patterns

In [Figure 2](#) we display the average assets under management per credit committee member in USD million from 2014 to 2024. In line with the general growth trend in the industry described above, this ratio is monotonically increasing from 2014 to 2022 with the values more than doubling from slightly below USD 300 million assets under management to above USD 700 million assets under management per committee member. That is, the expansion of the leveraged loan market and the CLO industry was not paired with a comparable growth in the size of credit committees. An individual credit committee member, while always having been responsible for a large volume of loan purchases, has seen a stark increase in his/her responsibility over the last decade. Thus, the findings in our paper regarding the value of relationships between credit committee members and banks, to the extent they are estimated as averages over the whole sample period, are likely an underestimation of the relevance of those relationships in the current market environment.

In [Figure 3](#) we plot the number of connected credit committee members at the bank level against the underwriting share of the same bank in the leveraged loan market. The data exhibits a clear upward trend such that banks with more connections also have a higher market share. At the descriptive level, this data can be interpreted in various ways. One valid interpretation is that larger banks usually have a larger market share but also, on average, train more employees who might later work for CLO managers. Thus, the number of relationships and the market share are spuriously correlated through the size of the bank. In our regression analyses in the following sections, we will, however, uncover a different interpretation to complement the size-based explanation. Banks that have more personal relationships to CLO managers see a relief in their pipeline risk that enables them to underwrite more and, in particular, larger deals and grow their market share. Thus, even for banks of equal size, building more connections leads to more underwriting. The following

sections carefully develop this argument empirically.

4 Nonbank Relationships and Loan Underwriting

We established in Section 3.1 that a vast majority of credit committee members have previously worked at banks. Given the prevalence of such career paths, we want to understand whether the move from the sell-side of the market to the buy-side of the market has structural implications for the leveraged loan market. The literature on credit market relationships proposes that relationships might help reducing informational asymmetries (Petersen and Rajan (1994), Bharath et al. (2011)). At the same time, previous personal relationships might affect preferences (Gurun et al. (2021)) or simply result in cronyism (Kramarz and Thesmar (2013)). Thus, it is an empirical question how relationships between non-banks and banks affect loan allocation.

4.1 Bank-CLO manager Level Analysis

4.1.1 Baseline

As a first step, we investigate if previous bank employment relationships of credit committee members affect their loan purchase decisions.

To take this question to the data, we estimate regressions with the following setup:

$$PA_{b,m,t} = Relationship_{b,m,t} + \mu_{b,t} + \mu_{m,t} + \epsilon_{b,m,t}, \quad (1)$$

where $PA_{b,m,t}$ is the primary allocation of all loans issued by bank b at quarter t to CLOs managed by manager m . That is, all loan purchases for a given CLO manager-bank pair are added up for each quarter. $Relationship_{b,m,t}$ is a dummy variable that takes the value 1 if any member of the acting credit committee of manager m at quarter t had previously worked at bank b , and 0 otherwise. $\mu_{b,t}$ are bank-time fixed effects capturing heterogeneity between bank such as differential credit supply or general involvement with the CLO market. $\mu_{m,t}$ are manager-time fixed effects capturing heterogeneity between managers such as differences in size, available funding or industry specialization.

The results of estimating several small variations of the setup described above are summarized in Table 2. In the first three columns, we alternate the fixed effects structure with Column (1) using bank-time FE only, Column (2) using manager-time FE only, and Column

(3) representing specification 1 which employs both types of FE simultaneously. In Columns (4) to (6) we repeat the same sequence of fixed effects but focus on the intensive margin of loan purchases by restricting the sample to those CLO manager-bank-quarter triplets where we observe a nonzero purchase amount. Lastly, Columns (7) to (9) while again keeping the sequence of fixed effects analyze the extensive margin by replacing the purchase amount ($PA_{b,m,t}$) by a purchase dummy that takes the value of 1 if $PA_{b,m,t} > 0$, and 0 otherwise.

Columns (1) to (3) consistently show an economically and statistically significant positive coefficient. In our preferred specification in Column (3) we find that, on average, a CLO manager purchases USD 4.6 million more from banks where there is a personal relationship than from banks where there is none. This effect is five times as large in Column (2) and almost twice as large in Column (1) highlighting that there are important (unobserved) bank-specific and manager-specific characteristics that affect this link meaningfully. Thus, controlling for both dimensions of heterogeneity with fixed effects is crucial. In the respective specification for the intensive margin in Column (6), we find the point estimate to increase to USD 5.3 million. That is, conditional on allocating anything to certain CLO manager, banks are able to allocate USD 5.3 million more to a CLO manager with an existing personal relationship than to CLO managers without such a relationship. As a back-of-the-envelope calculation, we can multiply this coefficient (5.3) with the standard deviation of the number of relationship CLOs (9), to measure the value of a typical increase of relationships for banks' underwriting capacity. This results in USD 50 million per quarter, or USD 200 million a year – a sizeable number. Finally, in our preferred specification for the extensive margin in Column (9), we report an increase in the likelihood of allocating any loan to a CLO manager of 1.1 percentage points if there is a personal relationship between the bank and the CLO manager.

One might be concerned that the way we measure the existence of relationships is skewed towards larger CLO managers. If a CLO manager has 10 credit committee members, the probability that at least one of them worked at one of the larger banks is higher than if the CLO manager has only 5 committee members. At the same time, if a CLO manager has 10 credit committee members, it is probably a larger CLO manager and purchases more than the smaller competitors. Thus, there could be a spurious correlation between the existence of a relationship and the amount purchased. To avoid this concern, we estimate an alternative specification to Equation 1 where we exchange the relationship dummy by a relationship intensity variable. This variable captures, for every CLO manager-bank pair, the share of committee members with previous work experience at the given bank out of all committee members employed by the given CLO manager. This way, for the CLO manager with 10

committee members to have the same relationship intensity to a given bank as the CLO manager with 5 committee members, the larger CLO manager needs to have twice as many employees that worked at the given bank before.

The results from replacing the relationship dummy by the relationship intensity variable are displayed in [Table 3](#). The structure of the Table is identical to [Table 2](#). Columns (1) to (3) alternative the FE structure for total purchases, while Columns (4)/(7) to (6)/(9) analogously show the results for the intensive/extensive margin. In line with the results in [Table 2](#), we document that the relationship intensity is an economically and statistically significant positive factor in explaining primary allocation outcomes on the leveraged loan market. Our preferred specification in Column (3) indicates that an increase of the relationship intensity from 0 to 0.2 (e.g., 1 out of 5 credit committee members worked at the given bank before) increases the allocated amount by USD 1.5 million, a value that rises to USD 2 million in Column (6) when zooming in on the intensive margin. A similar change in the relationship intensity increases the likelihood of allocating any loan to the CLO manager by 1.25 percentage points.

Put together, these baseline tables establish strong evidence that personal relationships matter for the allocation of loans from banks to CLO managers both at the intensive and extensive margin. Thus, in the following analyses we will, for the sake of brevity, not further distinguish between external and intensive margin results. Moreover, from comparing [Table 2](#) and [Table 3](#) we conclude that using the relationship dummy appears robust to other specifications of the relationship variable. In the following analyses, we therefore prefer to use the relationship dummy for ease of interpretation.

4.1.2 Heterogeneity

We show that the previous employment history of credit committee members affects their loan purchase decision at their current employer. However, it is natural to assume that the extent to which different relationships are relevant for today’s decisions and the extent to which credit committee members can act on their relationship-based preferences vary. In this section, we are going to analyze the heterogeneity of the previously documented effect of relationships along dimensions of the individuals who possess the relationship. For this purpose we estimate the following regression framework:

$$PA_{b,m,t} = Relationship_{b,m,t} + Relationship_{b,m,t} \times Characteristics_{b,m,t} + \mu_{b,t} + \mu_{m,t} + \epsilon_{b,m,t}, \quad (2)$$

where *Characteristics* is either of the following three variables: i) *Bank Tenure* $_{b,m,t} = \frac{1}{N_{b,m,t}} \sum Bank\ Tenure_{b,m,i,t}$ where $N_{b,m,t}$ is the number of individuals that are in the credit committee of CLO manager m at quarter t and previously worked at bank b . *BankTenure* $_{b,m,i,t}$ is the number of years an individual i has been employed at bank b , for each individual i that is in the credit committee of CLO manager m at quarter t and previously worked at bank b ; ii) *Firm Tenure* $_{b,m,t} = \frac{1}{N_{b,m,t}} \sum Firm\ Tenure_{b,m,i,t}$ which is defined analogously to i) using the number of years an individual has already spent at the CLO manager (*Firm Tenure* $_{b,m,i,t}$) as the relevant characteristic; iii) *Portf. Manager* $_{b,m,t}$ which is a dummy variable that takes the value 1 if any individual that is in the credit committee of CLO manager m at quarter t and previously worked at bank b is a portfolio manager.

The results of these estimations are summarized in [Table 4](#). For the ease of interpretation, *Bank Tenure* $_{b,m,t}$ and *Firm Tenure* $_{b,m,t}$ have been demeaned such that the standalone coefficient of the relationship dummy can be interpreted as the effect at the mean rather than the effect for credit committee members that have zero years of tenure which do not exist. We again alternate the FE structure with Columns (3), (6), and (9) being the tightest and preferred specifications. In Columns (1) to (3) we find no indication of a heterogeneity of the relationship effect along the number of years spent at the previously employing bank. That is, relationships between CLO managers and banks are an extensive margin concept more than an intensive margin concept. As long as any previous work experience exists, the increased allocation effects can be documented. In Columns (4) to (6) we document strong heterogeneity with respect to the length of the work experience of the relationship individuals at their CLO manager. Our preferred specification in Column (6) indicates that only after an employee has spent five years at the CLO manager, the relationship s/he has built to a bank affects the purchases of the CLO manager positively. This seems to suggest that there is heterogeneity in the final decision power between credit committee members with senior members carrying a higher weight. In line with this hypothesis, Columns (7) to (9) show that if at least one of the relationship individuals is a portfolio manager this further boosts the amount allocated to the CLO manager, albeit this coefficient is outside of the margin of statistical significance in our preferred specification in Column (9).

In summary, we document that the strength of the relationship between CLO managers and

banks is unaffected by the length of the employment spell at the bank. The extent to which an individual can affect the purchase decisions at the CLO manager, however, is linked to the seniority of the individual as measured by firm tenure or portfolio manager status. To provide further evidence for this claim, [Table A2](#) displays the results for further individual characteristics. The first three columns summarize the estimations where the interaction term is a dummy which takes the value 1 if at least one of the connected committee member is a C-level employee at the CLO manager. The results are similar to the portfolio manager dummy in that there is a consistently positive effect across all columns that is just slightly outside the statistically significant region in our preferred specification in Column (3). In Columns (4) to (6) we analyze whether having obtained an MBA – again measured as a dummy variable that takes the value 1 if at least one connected committee member obtained an MBA – changes how much a personal relationship matters for loan purchases. The coefficient for the interaction term is economically large and statistically significant. In our preferred specification in Column (6), the additional amount purchased by relationship managers almost doubles if the relationship is linked to a person which obtained an MBA. Lastly, in columns (7) to (9), we interact the relationship dummy variable with a dummy that takes the value 1 if the at least one of the connected individuals is female. The results are striking. The purchase volume from credit committees that have connected females is five times as large as the one for credit committees with only connected males. While these results could suffer from small sample bias, as we only observe an 11% female share among our individuals, it is still a noteworthy result that could suggest that women, if they manage to attain such a high-level position against all the career obstacles they face, have a much higher influence than a comparable man (positive selection).

4.2 Loan-manager Level Analysis

So far we have aggregated the allocations of loans to the CLO manager-bank level. This allowed us to measure the importance of personal relationships for banks and their presence in the leveraged loan market as a whole. In this section we will instead analyze the importance of relationships between CLO managers and banks at the loan level enabling us to control for characteristics of the borrowers or the loan contracts that might affect the allocation decision.

To update our baseline finding to the CLO manager-loan level, we estimate the following regression framework:

$$PA_{l,m} = Relationship_{b,m,t} + \mu_l + \mu_{m,t} + \epsilon_{b,m,t}, \quad (3)$$

where $PA_{l,m}$ is the primary allocation of the loan l to CLOs managed by manager m . Note that both the issuing quarter and the issuing bank (the lead arranger) are subsumed by the l subscript as every loan gets uniquely issued at one date by one bank. $Relationship_{b,m,t}$ is a dummy variable that takes the value 1 if any member of the acting credit committee of manager m at quarter t had previously worked at bank b , and 0 otherwise, identical to the analysis at the CLO manager-bank level analysis. μ_l are loan fixed effects that capture, on the one hand, bank and time characteristics as explained above, and, on the other hand, heterogeneity between borrowers (e.g., the default risk) and loan contract design (e.g., the maturity). $\mu_{m,t}$ are manager-time fixed effects, identical to the analysis at the CLO manager-bank level analysis.

The results of estimating several small variations of the setup described above are summarized in [Table 5](#). In the first two columns, we alternate the fixed effects structure with Column (1) using loan FE only and Column (2) representing specification [3](#) which employs both types of FE simultaneously. In Columns (3) to (4) we repeat the same sequence of fixed effects but measure the allocation of loans not in USD million but instead in shares of the total loan volume. That is, for each CLO manager-loan pair, the variable *Purchase Share(Loan)* measures the share of the loan that was allocated to the CLO manager. Columns (5) to (6) while again keeping the sequence of fixed effects analyze another relative allocation variable, *Purchase Share(Manager)*. This variable measures, out of the total loan purchases that a CLO manager has conducted, what is the share that went to a specific loan. First, these relative measures allows us to investigate the importance of relationships without worrying about effects of scale (as $PA_{l,t}$ is measured in levels). Second, with the relative measures we more tightly identify the relationship effect as they directly compare the commitment CLO managers make to relationship banks vs non-relationship banks.

Our preferred specification for the absolute amounts in Column (2) indicate that, for every loan, on average, a relationship CLO manager gets a USD 0.12 million higher primary allocation – an effect that is highly statistically significant. Given the average involvement in 43 loans this translates into USD 5.2 million dollars in total, comparable to the estimate from [Table 5](#). Column (4) as our preferred specification for the variable *Purchase Share(Loan)* reports a statistically significant increase of 0.059. That is, in loans that are issued by relationship banks, CLO managers purchase a 6 percentage point larger stake, on average,

compared to loans that are issued by non-relationship banks. This is an economically sizeable amount. Lastly, Column (6) documents that for *Purchase Share(Manager)*, the point estimate is 0.026 meaning that a CLO manager invests 2.6 percentage points more of its total funds in relationship loans vs. non-relationship loans.

The above results highlight that the value of personal relationships for allocation decision between banks and CLO managers exists even if we control for characteristics of individual loans such as risk, borrower industry or maturity.

4.3 Loan-Level analysis

To understand, the economic nature of CLO manager’s increased relationship demand, we ask, are increased purchases evenly distributed across all loans syndicated by relationship banks, or does this demand vary with loan characteristics?

4.3.1 Pipeline risk – quantity and price channel

One potentially important characteristic could be a loan’s pipeline risk, i.e., the risk faced by the lead arranger in underwriting a deal (Bruche et al., 2020). In Section 2.2, we briefly described the syndication process. A crucial aspect is that when a bank wins the mandate, it commits to providing the borrower with a loan of a given size and within a specified range of spreads. During the subsequent syndication phase, typically lasting 10 to 14 days, the bank must generate sufficient investor demand at the targeted spread. The lead arranger therefore faces two types of risk. First, demand from other investors may be insufficient, forcing the bank to retain a larger share of the loan than planned (quantity channel). Second, a deterioration in economic conditions may render the initial spread too low. In such cases, the bank may be left with a so-called “hung deal” (Ivashina and Scharfstein (2010)). This outcome can be avoided if the spread is “flexed” – i.e., adjusted upward – sufficiently to reflect the new risk (price channel). If relationship CLO managers help banks mitigate pipeline risk, banks should compensate them for this service by adjusting pricing terms – analogous to the IPO mechanism described in Benveniste and Spindt (1989).

While loan volumes are essentially never flexed and the quantity channel is ubiquitous, the existence of a price channel remains an empirical question. To investigate this question, we estimate the following regression, in the spirit of Meisenzahl et al. (2025), at the loan level:

$$Flex_l = \beta \Delta LSTA Index_{m,t,t+4} + X_l + \Delta X_{t,t+4} + \mu_{r,q} + \epsilon_l, \quad (4)$$

where $Flex_l$ denotes the change (“flex”) in the interest rate for loan l , measured in basis

points, $LSTA\ Index_{t,t+4}$ is the change in the secondary loan market index over the first four days of the syndication, also in basis points, X_l is a set of loan controls, $\Delta X_{t,t+4}$ represents changes in macro controls over the same four days, and $\mu_{r,q}$ are rating-notch quarter fixed effects.

The estimate of β captures the extent to which deteriorations in secondary-market prices for leveraged loans pass through to the flex of a given loan during its syndication stage. The idea is that if an adverse shock occurs in the first four days of syndication, investors will expect the spread on the current deal to adjust accordingly. Two scenarios can arise. First, if the flex does not adjust, banks must sell an overpriced deal that generates insufficient demand, resulting in a “hung deal”. Second, if the flex adjusts appropriately, the market is sufficiently flexible to accommodate short-term changes in risk conditions, such that little or no pipeline risk materializes through the pricing channel.

We report the results in Table 6. Between Columns (1) and (4), we add additional macro controls to our main variable of interest, the secondary loan market yield. Column (1) estimates the coefficient on its own, Column (2) adds stock market proxies, Column (3) adds fixed-income rate proxies, and Column (4) adds the Euro-Dollar exchange rate as in Meisenzahl et al. (2025). While changes to the VIX and the Euro-Dollar exchange rate are statistically significant predictors of flex, changes to the S&P 500, the federal funds rate or the 3-month treasury yield are not. Regardless of the setup, changes to the secondary loan market index remain a robust predictor that is highly statistically significant and economically meaningful. For each basis point that loan market conditions deteriorate, the loan is flexed by almost 0.7 basis points. That is, there is a pass through of risk of 70%. Thus, “hung deals” in which the flex does inadequately adjust for risk changes because investors are not willing to participate – the pricing channel – seem not to be a major determinant of pipeline risk.

4.3.2 The nature of relationship demand

Given the analysis above, we are left with the hypothesis that relationship demand alleviates pipeline risk that operates through the quantity channel. This hypothesis can be tested by examining whether larger loans have a greater share of purchases by relationship managers. If relationship managers indeed provide this service, they should be compensated through more attractive pricing terms – a further testable implication. However, an alternative hypothesis for relationship demand is a cronyism. Banks might exploit their relationships with credit committee members to generate sufficient demand for unattractive deals. Alternatively, banks might actively invite relationship CLO managers more aggressively to

participate in attractive deals (favorism), or, due to the shared employment histories, are able to communicate the deal’s attractiveness more efficiently. The latter two hypotheses can be tested by analyzing the subsequent performance of loans purchased disproportionately by relationship CLO managers.

Therefore, we now turn to the following regression setup:

$$Y_l = \beta \textit{Relationship Reliance}_l + \gamma \textit{Share Sold}_l + X_l + \mu_{r,s,t} + \epsilon_l, \quad (5)$$

where Y_l is an outcome variable at the loan level, *Relationship Reliance* is the share of the total loan volume purchased by relationship CLO managers, *Share Sold* is the share of the total loan volume purchased by any investor, X_l are loan controls such as indicators for whether the deal is Cov-lite, sponsored, middle market or first lien, and $\mu_{r,s,t}$ are rating-notch $\times$ industry $\times$ quarter fixed effects.

As left-hand-side variables, we first use price-return measures based on secondary-market loan prices relative to either the issuance price or the first-day trading price, capturing changes in market perceptions of the borrower’s credit quality. A positive (negative) price return indicates an improvement (deterioration) in borrower quality relative to the time of underwriting, i.e., better (worse) performance. We measure these returns over the first year following issuance.² To capture the quantity channel of underwriting risk, we use the logarithm of the loan volume as a left-hand side variable. If relationship CLO managers alleviate pipeline risk, they will, all else equal, purchase larger shares in bigger loans. Lastly, to measure compensation in pricing terms, we use the original issue discount (OID) and the loan’s spread, both of which, when higher, effectively make the loan cheaper for the CLO manager.

Controlling for *Share Sold* is crucial in this setting because estimating Specification 5 with *Relationship Reliance* only, comes with an identification, respectively measurement, concern. First, loans that are more attractive for investors, in general, and have higher investor participation will mechanically also have a higher share of relationship purchases. If all investors buy a (larger) stake, so do relationship CLO managers. Second, *Relationship Reliance* gets scaled by total loan volume. That is, larger loans might artificially see lower reliance on relationships just because the raw size of the loan makes it difficult for many investors – with and without relationships – to participate. Both problems are controlled for by adding

²Changing the time window over which we measure performance does not qualitatively affect the results.

Share Sold. In this specification, β measures how much the left hand-side variable changes if, for the same overall demand, and, for the same scale of purchases to total loan size, one additional percentage point of the purchases was provided by relationship CLO managers instead of any other investor.

We display the results of estimating Specification 5 in Table 7. In the first two columns, we relate relationship demand to return measures based on secondary market prices. We do not detect statistically significant differences between the returns, and thus the performance, of loans depending on relationship demand. Therefore, cronyism, favoritism, or more efficient information flow between banks and relationship managers seem not to be the underlying economic driver of relationship demand. In those cases we would have expected a worse or better performance, respectively. In Column (3), we investigate the quantity channel of pipeline risk. Indeed, we find statistically significant and economically meaningful differences. Overall, there is a negative relation between loan volume and the share of the loan sold to investors, largely mechanically. However, the more of the demand is coming from relationship CLO managers, the larger the loans get. One percentage point of additional relationship demand increases loan size by 0.9%. This provides evidence that relationship CLO managers alleviate pipeline risk for lead arrangers. In Columns (4) and (5) we then investigate whether CLO managers get compensated for this service with better pricing terms. Indeed, we find that both original issuing discount and spread are statistically significantly higher the more relationship demand there is for the loan. Thus, investors get compensated in the spirit of Benveniste and Spindt (1989) for filling the book of underwriters.

5 Conclusion

In this paper, we analyze the importance of personal relationships between banks and non-banks for the leveraged loan market. We create a novel data set by matching hand-collected information on the composition of CLO managers credit committees – their main decision-taking body – with employment histories from LinkedIn. Utilizing this data, we can identify relationships between the buy-side and the sell-side of the leveraged loan market by linking credit committee members and their former bank employers. Following a long literature on the value of relationships in financial markets, we then analyze the impact of such personal employment-based relationships for the allocation of loans from underwriting banks to investing CLO managers.

We find that banks allocate a higher loan volume – both at the intensive and extensive margin – to relationship CLO managers than non-relationship CLO managers. This finding holds

across a multitude of specifications varying the fixed effects structure, variable definitions or the level of analysis. We also document that relationships are particularly important for senior credit committee members who have longer tenure at the CLO manager and/or occupy a leading role such as portfolio manager. Moreover, we show that this relationship demand is concentrated in the largest deals – the ones for which it is hardest to create sufficient demand among investors. This shows that relationship CLO managers alleviate pipeline risk of lead arranger banks. In turn, banks compensate CLO managers with higher issuing discounts and spreads on the loans they disproportionately invest in. In a back-of-the-envelope calculation we quantify the importance of personal CLO manager relationships to banks as USD 200 million per year. These findings provide important insights into the factors which affect nonbank investors' decisions, an area that is understudied due to a lack of data, but is rapidly gaining in importance because of the enormous growth of the nonbank sector.

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6 Figures

Figure 1: Seniority in CLO Manager Credit Committees.

This figure shows the distribution of seniority of U.S. CLO manager credit committee members. We measure committee members' seniority by their title. For each title, the displayed figures present average relative frequencies at the committee-quarter level.

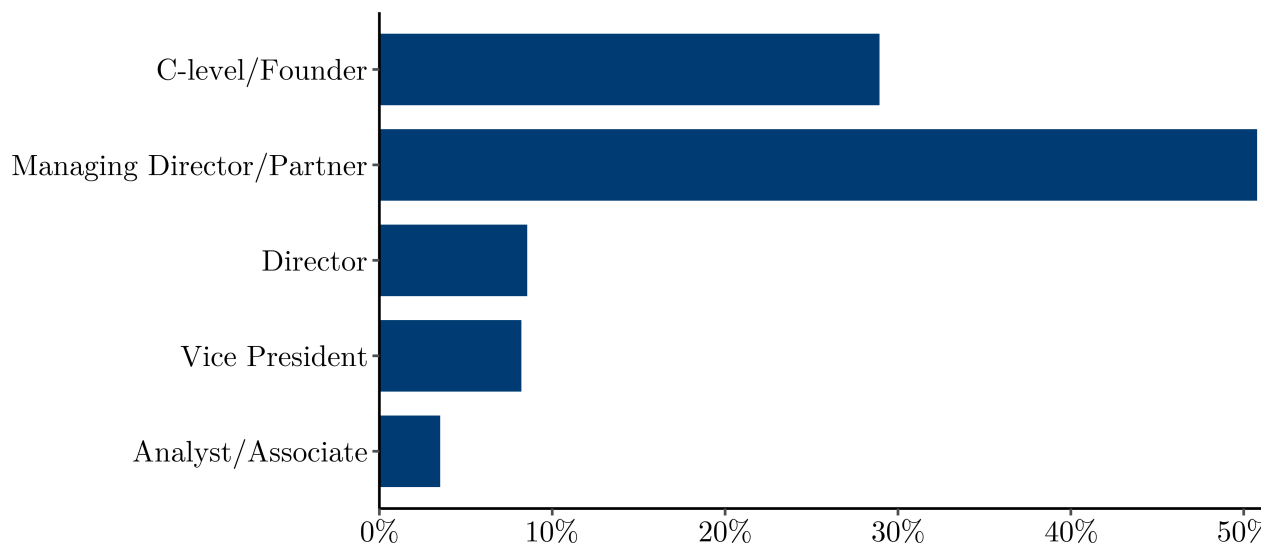


Figure 2: CLO Assets under Management per Committee Member.

This figure shows the aggregate CLO assets under management per committee member in our sample. In each quarter, we display the total size, measured in million U.S. dollars, of all active U.S. CLOs managed by CLO managers with credit committee information relative to the total number of unique individuals on their credit committees. CLO size information stems from PitchBook | LCD.

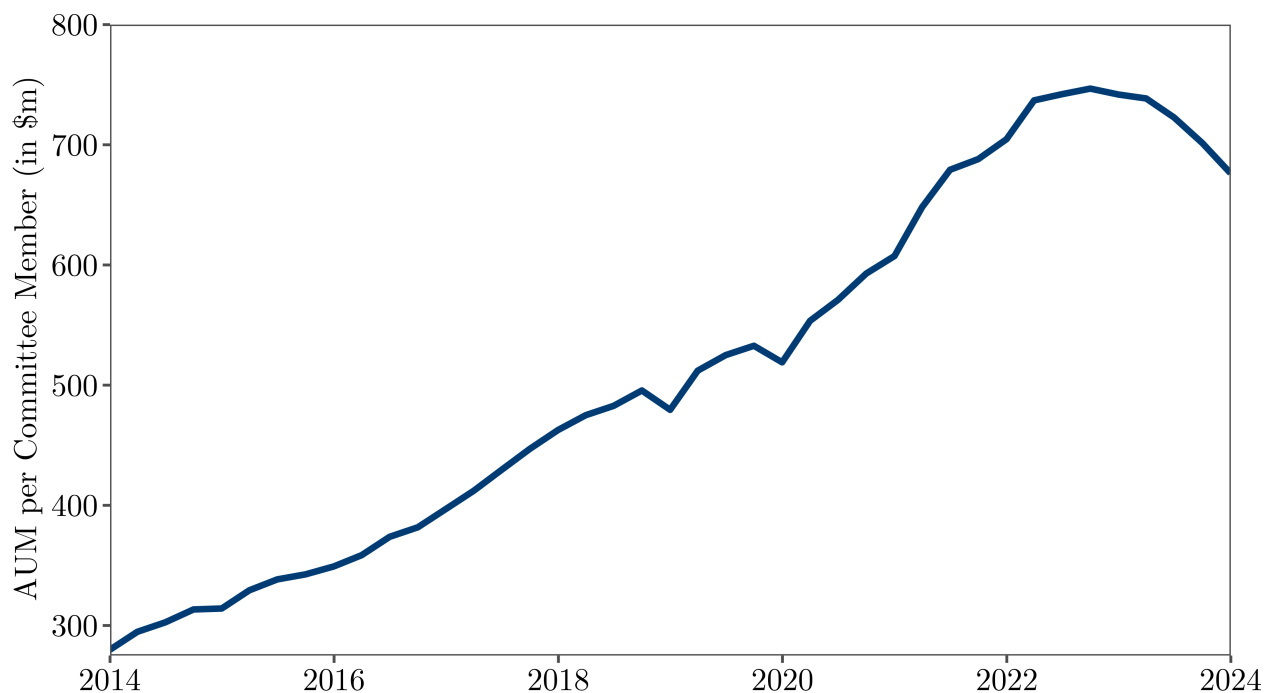
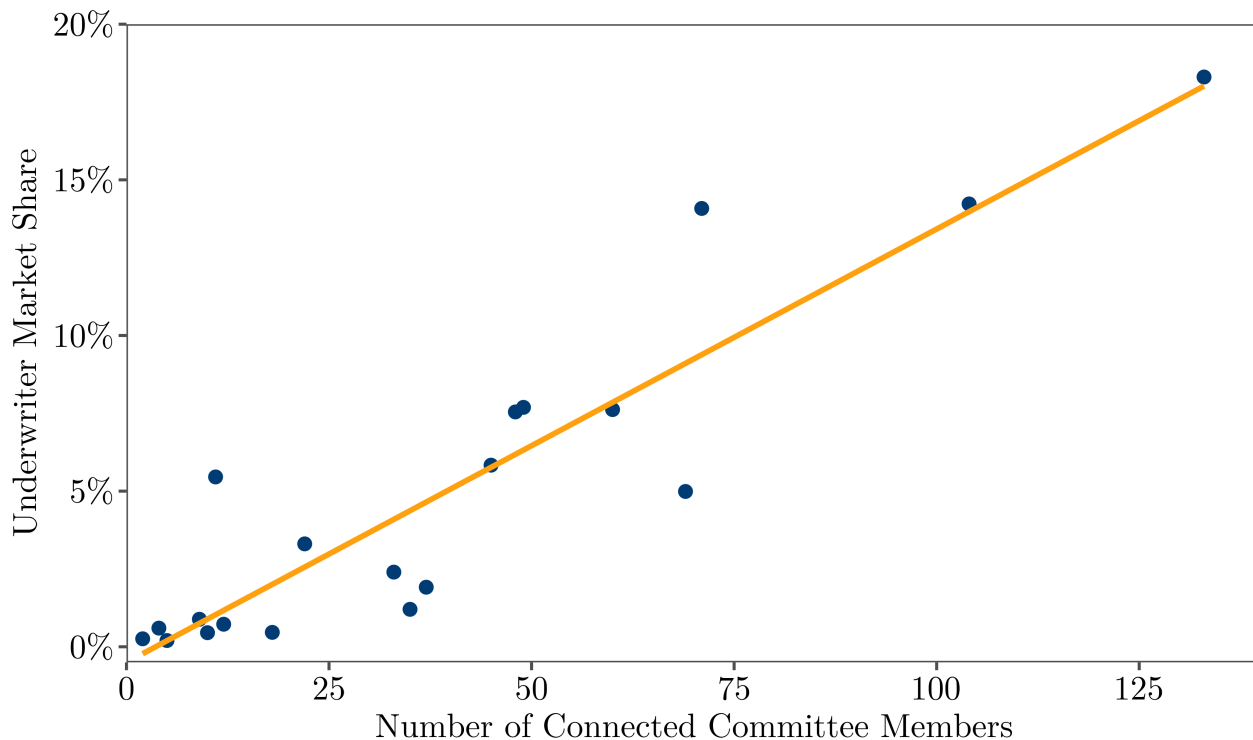


Figure 3: Underwriter Market Share and Nonbanker Networks.

This figure shows a bank's total number of relationship CLO credit committee members against its institutional loan underwriter market share. Each blue dot represents a bank. For each bank, the number of connected committee members measures the total number of unique individuals who appear in our U.S. CLO manager credit committee sample and previously worked at that bank. A bank's underwriter market share measures the volume of U.S. dollar-denominated institutional loans by U.S. borrowers arranged by the bank from 2014 through 2023 relative to the total volume arranged by all banks. Loan volume data come from PitchBook | LCD.



7 Tables

Table 1: Summary Statistics.

This table provides descriptive statistics for variables used in the main analysis. The sample includes credit committees of U.S. CLO managers between December 2013 through December 2023. Panel A contains committee-quarter-level variables and Panel B contains individual-level variables.

Variable	Unit	Mean	Std. Dev.	p25	p50	p75	Obs.
Panel A. Credit Committee-Quarter Level							
Parallel Committee		0.06	0.23	0.00	0.00	0.00	3,341
Middle Market Only		0.07	0.25	0.00	0.00	0.00	3,341
No. Members		5.66	3.15	4.00	5.00	7.00	3,341
No. Portfolio Manager		3.71	3.06	1.00	3.00	5.00	3,341
Avg. Firm Tenure	yrs	11.29	5.03	7.69	11.33	14.74	3,336
Avg. Industry Tenure	yrs	24.03	4.77	20.94	24.00	27.32	3,340
No. New Members		0.15	0.56	0.00	0.00	0.00	3,341
Share New Members	%	2.11	7.51	0.00	0.00	0.00	3,341
No. Departures		0.12	0.48	0.00	0.00	0.00	3,341
Share Departures	%	1.79	6.61	0.00	0.00	0.00	3,341
Share Members w/ Empl. History	%	75.39	23.00	60.00	75.00	100.00	3,341
Has Bank Relationship	0/1	0.93	0.26	1.00	1.00	1.00	3,341
Number of Related Banks		3.60	2.66	2.00	3.00	5.00	3,341
Avg. Relationship Intensity	%	31.84	21.80	20.00	25.00	33.33	3,101
Panel B. Individual Level							
No. Quarters		17.26	12.18	7.00	15.00	25.00	1,141
No. CLO Managers		1.06	0.24	1.00	1.00	1.00	1,141
No. Credit Committees		1.07	0.26	1.00	1.00	1.00	1,141
Average Firm Tenure	yrs	10.15	6.34	5.00	9.18	14.62	1,141
Average Industry Tenure	yrs	22.37	8.21	16.88	22.00	27.82	1,141
Female	0/1	0.11	0.31	0.00	0.00	0.00	1,141
Employment History	0/1	0.77	0.42	1.00	1.00	1.00	1,141
Prior Bank Experience	0/1	0.72	0.45	0.00	1.00	1.00	884
MBA	0/1	0.48	0.50	0.00	0.00	1.00	855
Highest Attained Title							
C-level/Founder	0/1	0.22	0.41	0.00	0.00	0.00	894
Managing Director/Partner	0/1	0.57	0.50	0.00	1.00	1.00	894
Director	0/1	0.09	0.29	0.00	0.00	0.00	894
Vice President	0/1	0.09	0.29	0.00	0.00	0.00	894
Analyst/Associate	0/1	0.03	0.17	0.00	0.00	0.00	894

Table 2: Committee Relationships and Bank-level Loan Purchases.

This table examines the role of bank-CLO manager relationships on primary market loan purchases and displays results from the estimation of

$$Loan\ Purchases_{bmt} = \beta Relationship_{bmt} + v_{bt} + \mu_{mt} + \varepsilon_{bmt}.$$

The unit of observation is at the bank-CLO manager credit committee-quarter (bm) level. In any quarter, the sample is the Cartesian product of all banks and CLO manager credit committees included in that quarter. A bank is included if it arranged at least one institutional loan purchased by CLOs in that quarter. A credit committee is included if any primary market loan purchases by that committee are observed in that quarter. The samples in columns four through six include only observations with positive *Loan Purchases*. *Relationship* is an indicator that equals one if any member of the CLO manager credit committee previously worked at the bank. The outcome variable measures primary market *Loan Purchases* in million U.S. dollars by the credit committee of loans arranged by the bank in columns one through six, and an indicator if that variable is positive in columns seven through nine. Controls include bank-quarter, v , and credit committee-quarter, μ , fixed effects (FE). All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Loan Purchases						$\mathbb{1}\{\text{Loan Purchases} > 0\}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship	7.964*** (0.963)	25.481*** (1.093)	4.639*** (0.701)	10.126*** (1.246)	24.900*** (1.315)	5.324*** (0.878)	0.027*** (0.005)	0.224*** (0.005)	0.011** (0.005)
Bank-Quarter FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Credit Committee-Quarter FE	–	Yes	Yes	–	Yes	Yes	–	Yes	Yes
Observations	48,171	48,171	48,171	29,023	28,988	28,982	48,171	48,171	48,171
R ²	0.362	0.281	0.570	0.313	0.354	0.618	0.418	0.147	0.516
<i>Sample Restrictions</i>									
Loan Purchases > 0				Yes	Yes	Yes			

Table 3: Committee Relationship Intensity and Bank-level Loan Purchases.

This table examines the role of bank-CLO manager relationship intensity on primary market loan purchases and displays results from the estimation of

$$Loan\ Purchases_{bmt} = \beta Relationship_{bmt} + v_{bt} + \mu_{mt} + \varepsilon_{bmt}.$$

The unit of observation is at the bank-CLO manager credit committee-quarter (bm) level. Sample construction, dependent variables, and fixed effects (FE) are described in [Table 2](#). *Relationship Intensity* measures the share of credit committee members who previously worked at the bank. All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Loan Purchases						$\mathbb{1}\{\text{Loan Purchases} > 0\}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship Intensity	8.416*** (2.685)	62.130*** (3.566)	7.640*** (2.324)	9.051** (3.519)	58.786*** (4.124)	9.850*** (2.865)	0.073*** (0.014)	0.596*** (0.021)	0.063*** (0.014)
Bank-Quarter FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Credit Committee-Quarter FE	–	Yes	Yes	–	Yes	Yes	–	Yes	Yes
Observations	48,171	48,171	48,171	29,023	28,988	28,982	48,171	48,171	48,171
R ²	0.359	0.271	0.570	0.310	0.346	0.617	0.418	0.139	0.517

Table 4: Committee Relationship Heterogeneity and Bank-level Loan Purchases.

This table examines the role of bank-CLO manager relationship heterogeneity on primary market loan purchases and displays results from the estimation of

$$\text{Loan Purchases}_{bmt} = \beta \text{Relationship}_{bmt} + v_{bt} + \mu_{mt} + \varepsilon_{bmt}.$$

The unit of observation is at the bank-CLO manager credit committee-quarter (*bm*) level. Sample construction, dependent variables, and fixed effects (FE) are described in Table 2. *Relationship* is an indicator that equals one if any member of the CLO manager credit committee previously worked at the bank. *Relationship (Bank Tenure)* measures the average tenure at the bank of relationship committee members. *Relationship (Firm Tenure)* measures the average tenure at the CLO manager of relationship committee members. *Relationship (Portfolio Manager)* is an indicator that equals one if any portfolio manager of the CLO manager credit committee previously worked at the bank. All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Loan Purchases								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship	7.898*** (0.939)	25.436*** (1.107)	4.608*** (0.716)	-11.004*** (1.875)	15.775*** (1.606)	-5.744*** (1.361)	6.769*** (1.832)	25.107*** (1.736)	3.678*** (1.256)
Relationship (Bank Tenure)	0.141 (0.380)	0.103 (0.387)	0.069 (0.288)						
Relationship (Firm Tenure)				2.002*** (0.190)	1.009*** (0.174)	1.082*** (0.143)			
Relationship (Portfolio Manager)							2.481 (2.305)	3.662* (2.109)	1.559 (1.727)
Bank-Quarter FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Credit Committee-Quarter FE	–	Yes	Yes	–	Yes	Yes	–	Yes	Yes
Observations	48,171	48,171	48,171	48,171	48,171	48,171	41,655	41,655	41,655
R ²	0.362	0.281	0.570	0.368	0.283	0.572	0.368	0.284	0.575

Table 5: Committee Relationships and Loan Purchases.

This table examines the role of bank-CLO manager relationships on primary market loan purchases at the loan-level and displays results from the estimation of

$$Loan\ Purchases_{lm} = \beta Relationship_{b(l)mt} + \lambda_l + \mu_{mt} + \varepsilon_{lm}.$$

The unit of observation is at the loan-CLO manager credit committee (lm) level. In any quarter, the sample is the Cartesian product of all loans and CLO manager credit committees included in that quarter. A loan is included if it is an institutional loan with CLO primary market purchases. A credit committee is included if any primary market loan purchases by that committee are observed in that quarter. *Relationship* is an indicator that equals one if any member of the CLO manager credit committee previously worked at the arranger bank. The outcome variable *Loan Purchases* measures primary market purchases in million U.S. dollars by the credit committee of that loan. *Purchase Share (Loan)* measures *Loan Purchases* relative to the total *Loan Purchases* of that loan by all CLO managers. *Loan Purchases* relative to the total *Loan Purchases* by that CLO manager in that quarter. Controls include loan, λ , and credit committee-quarter, μ , fixed effects (FE). All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Loan Purchases		Purchase Share (Loan)		Purchase Share (Manager)	
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	0.626*** (0.075)	0.120*** (0.035)	0.321*** (0.039)	0.059** (0.024)	0.022*** (0.008)	0.026*** (0.009)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Committee-Quarter FE	—	Yes	—	Yes	—	Yes
Observations	446,083	446,083	446,083	446,083	446,083	446,083
R ²	0.126	0.233	0.003	0.072	0.191	0.191

Table 6: Flex and the pricing channel of pipeline risk.

This table examines the flex during a syndication phase in relationship to deteriorating economic conditions measured as changes in the secondary market index as well as other standard macro variables:

$$Flex_l = \beta \Delta LSTA Index_{m,t,t+4} + X_l + \Delta X_{t,t+4} + \mu_{r,q} + \epsilon_l.$$

The unit of observation is at the loan(l) level. $\Delta LSTA Index_{m,t,t+4}$ is the return of the secondary loan market index for leveraged loans over the first four days of the syndication period. The vector X_l contains loan controls such as the logarithm of size and the talk spread. $\Delta X_{t,t+4}$ contains returns of macroeconomic variables such as the S&P 500 or the Feds Fund rate, also measured over the same four day horizon. All estimates are ordinary least squares estimates. Standard errors are clustered at the quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Flex			
	(1)	(2)	(3)	(4)
$\Delta LSTA$ Index Yield (in bps)	0.655*** (0.078)	0.683*** (0.084)	0.674*** (0.082)	0.673*** (0.083)
S&P 500 Index Return (in %)		-25.542 (40.247)	-19.432 (41.362)	-5.396 (41.756)
ΔVIX		-0.506** (0.197)	-0.457** (0.198)	-0.402** (0.199)
Δ Eff. Fed. Funds Rate (in bps)			0.084 (0.076)	0.077 (0.076)
Δ 3-month Treasury Yield (in bps)			-0.111 (0.108)	-0.137 (0.108)
Δ U.S. Dollar-Euro FX Rate				-94.200** (41.609)
Rating-Quarter FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Observations	9,693	9,693	9,641	9,641
R^2	0.114	0.115	0.148	0.148

Table 7: Nature of relationship demand.

This table examines the role of loan characand displays results from the estimation of

$$Y_l = \beta \textit{Relationship Reliance}_l + \gamma \textit{Share Sold}_l + X_l + \mu_{r,s,t} + \epsilon_l.$$

The unit of observation is at the loan(l) level. *Relationship Reliance* is the share of the total loan volume purchased by relationship CLO managers. *Share Sold* is the share of the total loan volume purchased by any investor. Controls include indicators for whether the deal is Cov-lite, sponsored, middle market or first lien, the spread flex, and – if the same variable is not on the left-hand side – the log of the loan volume and the spread. Left-hand side variables are the return of the secondary market price over one year vis-a-vis the primary price in Column (1), the return of the secondary market price over one year vis-a-vis the break price in Column (2), the logarithm of total loan volume in Column (3), the original issuing discount in Column (4) and the spread of the loan over the reference rate in Column (5). All estimates are ordinary least squares estimates. Standard errors are clustered at the rating $\times$ quarter level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Return Primary (1)	Return Break (2)	Loan Volume (3)	OID (4)	Spread (5)
Relationship Reliance	0.022 (0.684)	0.102 (0.649)	0.872** (0.367)	74.103** (24.142)	102.648** (36.616)
Share Sold	0.280 (0.517)	0.108 (0.494)	−1.274*** (0.268)	−72.255*** (19.595)	−18.260 (24.576)
Rating-Industry-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,800	1,800	1,800	1,800	1,800
R ²	0.658	0.660	0.604	0.551	0.892

Appendices

Appendix A Tables

Table A1: Committee Relationship and Loan Purchases – Robustness.

This table examines the role of bank-CLO manager relationships on primary market loan purchases and displays results from the estimation of

$$\ln(1 + \text{Loan Purchases}_{bmt}) = \beta \text{Relationship}_{bmt} + v_{bt} + \mu_{mt} + \varepsilon_{bmt}.$$

The unit of observation is at the bank-CLO manager credit committee-quarter (bm) level. Sample construction, independent variable, and fixed effects (FE) are described in [Table 2](#). The samples in columns four through six include only observations with positive *Loan Purchases*. The outcome variable measures the log of one plus *Loan Purchases* in million U.S. dollars by the credit committee of loans arranged by the bank in columns one through six, and an indicator if that variable is positive in columns seven through nine. All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter-level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	$\ln(1 + \text{Loan Purchases})$						$\mathbb{1}\{\text{Loan Purchases} > 0\}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship	0.165*** (0.021)	0.956*** (0.020)	0.057*** (0.014)	0.140*** (0.020)	0.473*** (0.016)	0.024** (0.011)	0.027*** (0.005)	0.224*** (0.005)	0.011** (0.005)
Bank-Quarter FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Credit Committee-Quarter FE	–	Yes	Yes	–	Yes	Yes	–	Yes	Yes
Observations	48,171	48,171	48,171	29,023	28,988	28,982	48,171	48,171	48,171
R ²	0.533	0.263	0.703	0.385	0.445	0.763	0.418	0.147	0.516
<i>Sample Restrictions</i>									
Loan Purchases > 0				Yes	Yes	Yes			

Table A2: Committee Relationship Heterogeneity and Loan Purchases.

This table examines the role of bank-CLO manager relationship heterogeneity on primary market loan purchases and displays results from the estimation of

$$\text{Loan Purchases}_{bmt} = \beta \text{Relationship}_{bmt} + v_{bt} + \mu_{mt} + \varepsilon_{bmt}.$$

The unit of observation is at the bank-CLO manager credit committee-quarter (bm) level. Sample construction, dependent variables, and fixed effects (FE) are described in Table 2. *Relationship* is an indicator that equals one if any member of the CLO manager credit committee previously worked at the bank. *Relationship (C-level)* is an indicator that equals one if any C-level member of the CLO manager credit committee previously worked at the bank. *Relationship (MBA)* is an indicator that equals one if any member with an MBA of the CLO manager credit committee previously worked at the bank. *Relationship (Female)* is an indicator that equals one if any female member of the CLO manager credit committee previously worked at the bank. All estimates are ordinary least squares estimates. Standard errors are clustered at the CLO manager-quarter-level, and reported in parenthesis below their corresponding point estimates. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

	Loan Purchases								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship	8.249*** (1.170)	27.186*** (1.361)	5.676*** (0.889)	6.087*** (1.368)	24.505*** (1.550)	3.594*** (1.130)	4.907*** (0.867)	22.974*** (1.066)	2.710*** (0.733)
Relationship (C-level)	10.349*** (2.579)	6.577** (2.637)	2.652 (2.071)						
Relationship (MBA)				6.395*** (1.733)	3.828** (1.834)	3.276** (1.457)			
Relationship (Female)							21.113*** (3.696)	18.029*** (3.588)	13.986*** (2.891)
Bank-Quarter FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Credit Committee-Quarter FE	–	Yes	Yes	–	Yes	Yes	–	Yes	Yes
Observations	39,358	39,358	39,358	42,049	42,049	42,049	48,171	48,171	48,171
R ²	0.366	0.284	0.574	0.352	0.286	0.564	0.364	0.283	0.571