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Abhishek Bhardwaj
Shan Ge
Saptarshi Mukherjee

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ABSTRACT

CLOs fund 65% of syndicated loans, theoretically insulating borrowers from bank and idiosyncratic investor shocks. However, concentrated capital and sticky relationships expose firms to idiosyncratic shocks to insurers, the largest CLO investors. We find that: 1) insurers experiencing favorable cash flows invest more in CLOs, especially with familiar managers; 2) CLO managers exposed to these cash flows launch more deals; 3) using an instrumental–variable approach, affected firms take out more loans at lower spreads, increase employment, and expand operations; 4) effects are stronger for private than public firms. These findings reveal significant frictions in the loan securitization market.

Abhishek Bhardwaj
A. B. Freeman School of Business
Tulane University
7 McAlister Dr
New Orleans, LA 70118
United States
abhardwaj@tulane.edu

Saptarshi Mukherjee
Northeastern University
409C Hayden Hall
360 Huntington Avenue
Boston, MA 02115
sa.mukherjee@northeastern.edu

Shan Ge
New York University
44 West 4th Street, 9-81
New York, NY 10012
sge@stern.nyu.edu

1 Introduction

Collateralized Loan Obligations (CLOs) are structured financial products that pool together loans from multiple borrowing firms and repackage them into securities with different risk levels (tranches) that are sold to investors. The CLO market has grown dramatically. Its value rose from $100 billion in 2005 to $650 billion in 2020. By 2022, CLOs purchased 65% of syndicated term loans.[1] This shift away from traditional bank balance sheet lending can fundamentally change the transmission of monetary and financial regulatory policies. Studying the CLO market is therefore critical for understanding modern credit markets, where non-bank investors play an increasingly important role.

Various institutions invest in CLOs, including insurance companies, pension funds, hedge funds, and private debt funds. In traditional banking, borrowing firms are vulnerable to idiosyncratic shocks of their relationship banks' capital supply. One might hypothesize that the CLO market reduces such vulnerability: since each securitized loan is purchased by several CLOs, and each CLO is funded by many investors, securitization could achieve diversification across investors and shield firms from not only banks', but also CLO investors' idiosyncratic shocks. Given the size of the CLO market, it is crucial to understand the effects of credit supply shocks in this market, which have important implications for financial stability.

We study the effect of idiosyncratic shocks to investors' capital supply on CLO formation, as well as the financing and real outcomes of borrowing firms. One major challenge is limited investor data. To address this challenge, we use tranche-level holding and transaction data from Life and Property & Casualty insurance companies, which are the largest investor class for US-based CLOs (DeMarco et al. 2020). Our data show that in 2020, insurers purchased 35% of all tranches and 47% of mezzanine tranches issued by CLO managers they had previously invested with (relationship managers). Insurers' capital supply is often viewed as crucial for the market.[2] Our 2002–2020 sample combines

[1] See https://www.lsta.org/news-resources/another-looming-threat-to-clos-rule-15c2-11/.

[2] "Insurer interest in the highest-rated portions of CLOs may help spark a revival in the securities after sales tumbled 98.7 percent during the seizure in credit markets between 2007 and 2009. That bodes well

insurers' data with Creditflux CLO-i for CLO and loan information, DealScan for loan terms, and Dun & Bradstreet for employment and establishment data of borrowing firms (63% private). The final dataset includes 913 CLO–investing insurers, 2,098 CLO deals, 221 CLO managers, and 9,480 borrowing firms.

The second challenge is identification—specifically, finding exogenous variation in investors' capital supply to the CLO market. We address this using insurers' cash flows as shocks to their capital supply. We find that higher cash flows lead insurers to increase their CLO investments, particularly in deals by their relationship managers. These shocks affect CLO managers differently based on their past relationships with insurers. These shocks are idiosyncratic rather than market-wide, since we control for average capital supply using time, state–by–time, or industry–by–time fixed effects. We also account for time-invariant manager and firm characteristics using manager and firm fixed effects. We argue that insurers' operating cash flows—which depend on insurance-specific factors like product demand, pricing, and mortality losses—should affect outcomes only through capital supply to the CLO market.

Our results suggest that when insurers experience positive cash flow shocks, their relationship CLO managers launch more new deals. Borrowing firms whose previous loans were purchased by these CLO managers experience lower loan spreads and take out more new loans. These firms also increase their employment and the number of establishments. These results suggest that as the securitization market continues to expand, the risks firms face through their relationship lenders have not been fully eliminated but have instead shifted from banks to non-bank investors.

Our analysis proceeds in five steps, beginning with insurers' investment behavior. We find that when insurers have favorable cash flows, they increase investments not only in CLOs but also in other assets like corporate and government bonds, suggesting general portfolio expansion.

for borrowers, who need to address the $325 billion of loans coming due in the next four years." Kristen Haunss, "CLOs Attract MetLife, Babson Seeking Wide AAA Yield Spreads," Bloomberg, September 30, 2010.

Second, we document relationship stickiness between insurers and CLO managers: if an insurer invested in a manager's deals in the past, the insurer is more likely to invest in the manager's new deals. These relationships are stickier when CLO managers are smaller or less experienced—situations where relationships should matter more due to greater information asymmetry and CLO managers' more limited marketing reach. When insurers have more cash flows, they show an even stronger preference for relationship CLO managers.

Third, we find that CLO managers with more exposure to insurers' favorable cash flows launch more deals. We measure this exposure as a weighted average of insurers' cash flows, where the weights reflect insurer–CLO manager relationships and are measured as the share of a manager's CLO liabilities held by each insurer prior to the cash flows.

Fourth, we document another sticky relationship, the one between CLO managers and borrowing firms. When launching new CLO deals, managers tend to purchase loans from firms whose loans they had previously purchased. This result can be explained by CLO managers' information advantage regarding these borrowing firms.

Finally, we examine how non-bank investors' idiosyncratic capital supply shocks affect firms' financing and real outcomes. To overcome the endogeneity challenge, we use an instrumental variable approach. The endogenous variable is the weighted average number of new CLOs launched by each firm's relationship managers. The weight reflects firm–CLO manager relationship and is the lagged share of the firm's loans held by each CLO manager. Building on our findings summarized above, we construct an instrument for this endogenous variable.

Specifically, the instrument is each firm's weighted average of its relationship CLO managers' exposure to insurers' cash flows. CLO managers' exposure is as described in the third step above. The weight is again the lagged share of the firm's loans held by each CLO manager, as in the endogenous variable construction. The instrument is constructed using the firm–CLO manager and CLO manager–insurer relationships, both observed in the quarter prior to insurers' cash flow measures. To alleviate concerns about endogenous matching between firms, CLO managers, and insurers, we use both relationships from five quarters prior to insurer cash flows in robustness tests. Our results remain similar. The first-stage result suggests that firms with greater exposure to insurers' cash flows see their relationship managers launch more CLOs.

The second-stage result suggests that when relationship managers launch new CLOs due to increased investor capital supply, borrowers see the spreads on new loans decline. In addition, firms, especially private ones that are presumably more financially constrained, are more likely to take out new loans. Importantly, we do not see an increase in revolving credit lines, which CLOs generally do not purchase. This serves as a falsification test, suggesting that our results are unlikely driven by firms' demand for credit.

Furthermore, using the same instrumental variable approach, we find that firms increase their number of employees and establishments in response to insurers' capital supply increases. Private firms exhibit strong effects, while public firms show minimal impact. This contrast is consistent with the idea that private firms have more ex-ante unmet financing needs. These results suggest that not just firms' financing is affected. In fact, firms' real outcomes are also exposed to non-bank investors' capital supply shocks through the CLO market. This result rejects the notion that banks may insulate borrowers by expanding or contracting their balance–sheet lending in response to CLO investors' shocks.

Against the backdrop of the drastic decline in bank balance sheet lending (Buchak et al., 2024b), our findings offer important insights about banks distributing loans to non-bank investors. First, by having their loans securitized and distributed to a wide set of investors, borrowers can become more insulated from shocks to banks, as Loutskina and Strahan (2009) find in the case of mortgage securitization. However, firms can become susceptible to idiosyncratic shocks to non-bank investors in the CLO market due to concentrated capital and sticky relationships. Second, increased investor capital supply to the CLO market actually affects firms' real outcomes rather than merely allowing banks to offload more loans or firms to substitute away from other forms of financing. Third, academics and industry participants attribute the growth of the market to tighter bank regulations (Acharya et al. 2013, Neuhann and Saidi 2016, Kim et al. 2018, and Irani et al. 2021), as well as borrower demand for securitizable loans due to their covenant-light nature (Prilmeier and Stulz 2020).[3] Our results suggest that investors' capital supply does not simply cater to the demand of banks and borrowing firms, but is likely an important driving force behind the growth of the CLO market.

Our study is particularly related to two papers. Ivashina and Sun (2011) find that when loans sell faster, they have lower spreads. They also instrument the speed at which loans are sold with aggregate fund flows into collateralized debt obligations (CDOs). Fleckenstein et al. (2024) find that non-bank loans, often bought by CLOs, are more cyclical than bank loans.

We make three distinct contributions beyond these two papers. First, by collecting borrowing firms' employment and establishment data, we show that non-bank investors' capital supply affects firms' real activities, not just financing. Second, both of these papers focus on *aggregate* funding shocks. Instead, we highlight that even funding shocks that are *idiosyncratic* to a group of investors matter through sticky relationships and concentrated capital. This result reveals significant frictions in this market and has important implications for financial stability. Third, our unique setting and data allow us to improve the identification of the *causal* effect of non-bank investors' funding on borrowers. Specifically, we use microdata on the largest group of investors to directly identify shocks to investors' capital supply and study the effect on borrowing firms through two layers of sticky relationships.

Our paper is also related to Merrill et al. (2019) and a concurrent paper by Fringuellotti and Santos (2023). Both papers focus on why insurers purchase non-agency Asset-Backed Securities and CLOs. They argue that insurers do so in search of high yields. We focus on the effect of insurers' capital supply on borrowing firms' financing and real outcomes, using insurers' operating performance to construct an instrument for causal

[3] Also see, https://www.ft.com/content/7a9cc064-9ab4-11e1-94d7-00144feabdc0 and https://www.forbes.com/sites/realspin/2014/09/26/leveraged-loans-should-be-lauded-not-maligned/?sh=3f8d471f1ed1.

identification. (Interested readers can see Fringuellotti and Santos (2023) for details on the regulatory aspects of insurers' holding CLOs, which should not affect the interpretation of our results.)[4]

We also contribute to the broader literature on securitization that mostly focuses on mortgages. In particular, Merrill et al. (2014) find that insurers' demand for residential mortgage-backed securities can change the price of these securities. Nadauld and Sherlund (2013) argue that mortgage securitization driven by investment banks led to the expansion of subprime credit. Chakraborty et al. (2020) document that the Federal Reserve's purchase of mortgage-backed securities increased banks' mortgage lending. Buchak et al. (2024a) build and estimate a model that indicates that secondary market disruptions have significant impacts on banks' mortgage lending. These results mirror ours, while we use granular investor data to trace the causal effect of their capital supply on borrowing firms through CLOs.[5]

Our paper also contributes to the literature on how banks' credit supply affects firm outcomes, including Khwaja and Mian (2008), Duchin et al. (2010), Ivashina and Scharfstein (2010), Cornett et al. (2011), Schnabl (2012), Almeida et al. (2012), Becker and Ivashina (2014), Chodorow-Reich (2014), Acharya and Mora (2015) and others.[6] Most of these papers study syndicated loans from DealScan, 65% of which are now being securitized. Specifically, we show that when banks distribute loans to CLO markets,

[4]Other papers in the CLO literature include the following. Nadauld and Weisbach (2012) argue that securitization reduces loan spreads. Benmelech et al. (2012), Wang and Xia (2014), and Bord and Santos (2015) study the effect of securitization on the credit quality of corporate loans. Shivdasani and Wang (2011) argue that growth in Collateralized Debt Obligations (CDOs) fueled the LBO boom of 2004 to 2007 by focusing on the role played by banks' active structured credit underwriting. Loumioti and Vasvari (2019a) and Loumioti and Vasvari (2019b) study the impact of balance sheet constraints imposed on the funds on their portfolio choice and portfolio rebalancing. Cordell et al. (2021) study the performance of CLOs. Griffin and Nickerson (2023) examine the ratings of CLO securities. Kundu (2021) and Bhardwaj et al. (2021), and Bhardwaj and Mukherjee (2022) examine how shocks to CLOs' asset side (loan holdings) affect borrowing firms. Hinzen (2023) discusses the role of market power in non-bank lending. Becker and Ivashina (2016) find that CLOs are associated with loans that have light covenants. Elkamhi and Nozawa (2022) document CLOs' fire sale of loans.

[5]Downing et al. (2009), He et al. (2012), Piskorski et al. (2015), He et al. (2016), and Griffin and Maturana (2016) study quality misrepresentation and rating inflation in mortgage-backed securities. Baghai and Becker (2020) argue that a rating agency can benefit from issuing optimistic ratings about mortgage-backed securities. Piskorski et al. (2010) and Agarwal et al. (2011) study the effect of securitization on foreclosure and renegotiation.

[6]Other papers include Leary and Roberts (2005), Peek and Rosengren (2000), Paravisini et al. (2015), Acharya et al. (2019), Acharya et al. (2018), Leary (2009), and so on.

idiosyncratic shocks to large non-bank investors can impact borrowing firms. Thus, for many firms, the risks in credit supply have shifted from banks to non-bank investors in the CLO market.

Our research contributes to the growing literature on non-bank investors in private debt markets. Prior studies have examined various non-bank lenders, including finance companies (Gopal and Schnabl, 2020), FinTech platforms (Erel and Liebersohn, 2022; Howell et al., 2021), and business development companies (Davydiuk et al., 2024, 2020).[7] Our work extends this literature by shedding light on important frictions in the CLO market, which has experienced rapid growth and substantial scale. Notably, we leverage detailed investor-level data that includes rare insights into their financial conditions, allowing us to offer novel perspectives on this important market segment.

Moreover, this paper enhances our understanding of insurers' investment behavior and their impact on financial markets and firms. Insurers are an important group of institutional investors, with $12.8 trillion in assets in 2024 Q1 (Fed Z1). It is important to understand their investment behavior and how they affect the rest of the economy. While existing research primarily examines insurers' investment in public corporate bonds, we focus on their significant role in the CLO market. The capital they supply to the CLO market, which depends on their operating performance, can affect new CLO creation, as well as borrowing firms' financing and real activities. This expands upon the popular view of insurers as "asset insulators" presented by Chodorow-Reich et al. (2021) and Coppola (2021). They argue that insurers shield the corporate bonds they *hold* and these bonds' issuers from market downturns. In contrast, we find that insurers' capital supply through their *purchase* is vulnerable to their idiosyncratic shocks. Despite insurers' infrequent sale of financial assets, such shocks can ripple through the broader economy.[8]

Our paper complements Kubitza (2024), who documents that insurers' demand in-

[7] Other papers on non-bank corporate lending include Chernenko et al. (2022) and Lim et al. (2014). Buchak et al. (2018b), Buchak et al. (2018a), and Jiang et al. (2020) study the role of non-banks on mortgages.

[8] Other studies examining insurers' investment include Ellul et al. (2011), Becker and Ivashina (2015), Ellul et al. (2015), Greenwood and Vissing-Jorgensen (2018), Ozdagli and Wang (2019), Sen and Sharma (2020), Becker et al. (2022), Ellul et al. (2022), Koijen and Yogo (2023), Ozdagli and Wang (2019) and so on.

creases corporate bond issuance and corporate investment, and Zhu (2021), who demonstrates similar effects from mutual funds' demand shocks. While these papers focus on direct transmission through bond markets, we document a novel channel: insurers' shocks are transmitted to loan-issuing firms through the CLO market. Our finding challenges two null hypotheses: (1) the CLO market's diverse investor base might shield borrowers from such shocks; (2) banks may insulate borrowers by expanding or contracting their balance–sheet lending in response to insurers' shocks. By rejecting both of these null hypotheses, we advance the understanding of the large and growing CLO market.

2 Data

2.1 CLO Deals and Managers

Detailed data on CLOs come from Creditflux CLO-i, a leading information aggregator that maintains a comprehensive database of CDOs, CLOs, and credit hedge funds. The data, sourced directly from over 45,000 trustee reports and CLO prospectuses, provide detailed information on around 3,153 CLO deals managed by 226 fund managers over the sample period of 2002 through 2020. The Creditflux CLO-i database has been widely used in the literature,[9] and provides comprehensive coverage of CLO holdings and transactions of corporate leveraged loans in the secondary market, especially after 2009 when it is nearly complete. Creditflux CLO-i data provides detailed information on the investments of CLO funds in more than 14,000 firms belonging to 35 broad Moody's industries at a monthly frequency.

Table 1 provides a summary description of the CLO balance sheet at the fund's inception. A typical CLO in our sample has total assets under management (AUM) of \$507 million. 63% of CLO liabilities are classified as senior tranches (defined as AAA-rated at inception) and 25% are classified as mezzanine tranches (defined as those rated between AA and B). The weighted average coupon rate (expressed as spreads over Libor)

[9] See Ivashina and Sun (2011), Benmelech et al. (2012), Loumioti and Vasvari (2019a), Loumioti and Vasvari (2019b), among others.

on CLO tranches is 1.73 percentage points (pp). On the asset side, a typical CLO holds loans of approximately 193 firms and the loans have an average spread of 3.85 pp over Libor. The equity holders of the CLO earn the difference between spreads received from portfolio loans and those paid to the debt investors.[10] Our sample includes 226 fund managers. As shown in Table 1, over the sample period considered in this paper, the average manager has an asset under management (AUM) of $2.31 billion and has been in the CLO business for about eight years.

2.2 Loan Syndication Data

We compile a sample of leveraged loans for 2002–2020 using the Refinitive LPC DealScan database (DealScan). Our sample comprises a subset of such syndicated loans. We include term loans with an all-in-drawn spread of more than 125 basis points. This restriction criterion leads to a total sample of 82,499 leveraged loans originated by 21,702 unique firms in the sample.

Next, we match the firms in the DealScan sample with those held by the CLO funds using fuzzy matching on names, yielding a matched sample of 9,480 unique borrowers. In terms of volume, these matched borrowers account for 90% of the CLO holdings in the sample. They have a 3.5% probability of obtaining a new leveraged loan facility in any given quarter. The average loan spread is 381 bps.

2.3 Insurance Company Data

We obtain data on insurers' financials and investments based on statutory filings through S&P Global. All US-domiciled operating insurance companies need to report these filings. Insurers' financial variables are available from 1996. We obtain data on their investment from 2002 to 2020.[11]

[10] The largest fraction of loans held in the CLO portfolio are rated BB/B, and earn a spread of about 4-5 pp, while the largest debt tranche of a CLO is rated AAA, and the fund pays a spread of about 0.75 - 1 pp over Libor.

[11] We limit our sample to these years because our Creditflux CLO-i data extends till 2020.

Insurers report detailed investment holding and transaction data at the CUSIP level in Schedule D of their statutory filings. To map insurers' investments to the CLO data, we proceed in two steps. First, we filter all CUSIPs in insurer data whose description includes the string "CLO", "CDO", "collateralized loan obligations", or "collateralized debt obligations". Then, we use the Creditflux CLO-i data to create a list of CLO tranche securities (with information on deal name, manager name, and tranche name). We hand–match each of them to CUSIPs using the information on issuers' names and issues' description in the insurer data. Insurers' holdings comprise 7,154 CLO tranches of 1,851 CLOs launched by 188 managers and amounted to $84 billion in 2020.

2.4 Firm Outcome Data

Employment- and establishment-level data for our study come from the Global Linkage file in the Dun & Bradstreet (D&B) Historical Global Archive database. D&B collects data from various sources, including state secretaries, Yellow Pages, court documents, and credit inquiries, in addition to direct telephone outreach to businesses. It distributes the data for purposes such as marketing and credit scoring.[12] These files contain detailed information on number of employees and location of establishments. They also consist of international business records that contain ownership relationships that link them in a family tree structure. The database contains a *global–ultimate–DUNS–number* for every establishment, which we use as the firm identifier. We match the D&B data with the DealScan data using firm names, locations, and industry identifiers. Table 1 presents the summary statistics of the key variables used in our analysis. The median firm in our matched sample employs 377 employees and has 6 establishments.

[12] While businesses are not legally required to contribute or provide accurate information, D&B is driven by profitability motives to ensure data accuracy. In addition, the credibility of individual businesses in terms of credit and other partnerships might hinge on the precision of the data they submit. Numerous recent studies have used D&B database and its derivative National Establishment Time Series (NETS) to study employment outcomes in the United States (Denes et al., 2020; Farre-Mensa et al., 2020; Borisov et al., 2021; Acharya et al., 2023).

3 Insurers' Cash Flows

Insurers' operating cash flows, based on statutory filings, are the sum of premiums, net investment income, and miscellaneous income, minus benefits and losses, transfers to separate accounts, commissions, dividends to policyholders, and taxes. We add back dividends to policyholders as this is an endogenous decision. We also subtract investment income related to insurers' investments in CLOs, although CLOs accounted for only 2.6% (in 2020) of insurers' cash and invested assets. This addresses the concern that insurers' past high cash flows can be correlated with the favorable performance of their relationship CLO managers, which may drive our results. We then scale this cash flow measure by insurers' lagged assets and use it to construct our instrument to analyze the effects on borrowing firms.

One may still be concerned that insurers' non-CLO investment income can be endogenously related to the outcomes we study. Specifically, insurers may tilt their portfolios toward certain industries or states in both their CLO and non-CLO investments. When firms in these industries or locations perform strongly, they generate higher lagged investment returns for insurers. Such firms may also seek increased CLO financing, creating an endogenous relationship between insurer cash flows and firm outcomes.

We address this concern in two ways. Throughout our firm-level analyses, we control for state–by–time and industry–by–time fixed effects to remove the effect of state and industry trends. In addition, we also present robustness tests in which we exclude all of insurers' net investment income. All of our main results hold at the insurer, CLO manager, and firm levels.

4 Effect of Insurers' Cash Flows on Their CLO Investments

We hypothesize that insurers increase their CLO investments when experiencing high operating cash flows. This relationship likely stems from regulatory constraints on shareholder payouts (Ge 2022), which leaves insurers with more available capital to invest in financial assets when cash flows are high.[13] In this section, we first examine whether insurers increase their CLO investments when experiencing high operating cash flows.

In Table 2, we estimate the following specification:

$$\text{Insurer CLO Investment}_{i,t} = \beta \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

$\textit{Insurer CLO Investment}_{i,t}$ denotes insurer i's investment in CLO in year–quarter t. We employ three measures of CLO investment at the insurer–year–quarter level: (1) $1(\textit{CLO Purchase})_{i,t}$ indicates whether insurer i purchased CLO securities in quarter t, (2) $\#\ \textit{CLO Purchase}_{i,t}$ represents the total number of CLO tranches acquired, and (3) $\textit{Log}(1{+}\textit{CLO Purchase})_{i,t}$ is the dollar value of CLO purchases in natural logarithm form. Our key independent variable, $\textit{Insurer Operating CF}_{i,t-4 \text{ to } t-1}$, is insurer i's operating cash flows from year–quarter $t-4$ to $t-1$ scaled by assets at $t-5$. This four-quarter measurement window serves two purposes. It smooths out the seasonality and volatility in insurers' quarterly cash flows. It also to some extent accounts for the natural lag between insurers' cash flow availability and their subsequent CLO investments. Our specification includes both insurer and year–quarter fixed effects.

The estimated coefficients on *Insurer Operating CF* are positive and statistically significant in all three columns, indicating that insurers increase their CLO investment fol-

[13] Another potential reason is related to Ge and Weisbach (2021), who document that property and casualty insurers with favorable operating performance tend to shift toward riskier bonds, reflecting an increased appetite to reach for yield. Similarly, Becker and Ivashina (2015) find that insurers' propensity to reach for yield declined during the Great Financial Crisis when their financial conditions deteriorated. These findings are particularly relevant for CLO investments, as Cordell et al. (2021) and Fringuellotti and Santos (2023) argue that CLOs specifically cater to investors seeking higher yields compared to similarly rated corporate bonds.

lowing favorable operating cash flows. The economic magnitude is substantial: according to Column (3), a one-standard-deviation increase in insurers' cash flows is associated with an 8.72% (0.08×1.09) increase in insurers' CLO purchases. When an insurer's cash flows increase by two standard deviations, their CLO purchase amount increases by \$34M (2×0.08×1.09×the average total investment, \$186M). Each insurer invests in 1.7 managers on average in a given quarter. Thus, each manager obtains on average \$20M ($\frac{\$34M}{1.7}$) extra capital supply. Here we restrict to insurers with existing CLO holdings as of year–quarter $t-5$, as they form the basis for our subsequent analyses. For robustness, we extend this analysis to the full universe of US insurers in Table A1. The results remain consistent.

In Table A2, we replace the outcome variable with insurers' quarterly purchases of industrial bonds (excluding CLOs) in Column (1) and US government bonds in (2), both expressed in natural logarithms. The estimated coefficients on insurers' cash flows are positive and statistically significant, indicating that higher cash flows lead insurers to increase their investments across asset classes. This broad investment response strengthens our identification assumption: since insurers also increase their government bond purchases following favorable cash flows, it is unlikely that omitted variables are simultaneously driving insurer cash flows and our subsequent findings regarding CLO manager and firm behavior.

5 Sticky Relationships Between Insurers and CLO Managers

We hypothesize that insurers have sticky relationships with CLO managers: they disproportionately invest in deals launched by managers with whom they have existing relationships. This behavior likely stems from two mechanisms. First, CLO managers naturally spend their marketing efforts on their existing investor base, leveraging established connections. Second, information asymmetry in the CLO market makes prior relationships particularly valuable. This mirrors findings by Barbosa and Ozdagli (2021), Coppola (2021), and Kubitza (2024) that insurers disproportionally purchase corporate bonds from familiar issuers. Given that the CLO market is characterized by greater opacity than the corporate bond market, insurers' familiarity with specific managers becomes even more crucial, as insurers may produce private information about the managers. In this section, we examine whether insurers maintain sticky relationships with CLO managers.

We present our analysis using the following model:

$$\begin{aligned}1(\text{Insurer–CLO Pair Investment})_{i,c(m,t)} = \beta \times \text{CLO Manager–Insurer Relation}_{i,m,t-5} \\ + \alpha_i + \alpha_c + \alpha_t + \varepsilon_{i,c(m,t)}.\end{aligned}$$

Each observation is an insurer–CLO deal pair, for which we match each CLO deal with potential investors (insurers who held CLOs in the previous year). The dependent variable is an indicator of whether insurer i invested in CLO c launched by manager m in year–quarter t (multiplied by 100). We only consider investments within one year of each CLO's formation.[14] Our key independent variable measures prior relationships between insurers and CLO managers, defined as an indicator of whether insurer i holds a CLO by manager m in year–quarter $t - 5$.

We use year–quarter fixed effects (α_t) to absorb aggregate trends. We include CLO fixed effects (α_c) to address the possibility that some CLOs attract more insurance companies and their managers have extensive past relationships with many insurers. We also control for insurer fixed effects (α_i), because insurer-specific factors such as the scale and breadth of their CLO investments could be related to both past relationships and new investment decisions.

Column (1) of Table 3 shows the result. The estimated coefficient on *CLO Manager–*

[14] We consider initial investments because insurers make most of their investments during this period and rarely trade CLO tranches in the illiquid secondary market (Hendershott et al. 2020). Additionally, CLO managers' decision to launch new deals, which we study later, would be most likely driven by their ability to sell the newly issued tranches.

Insurer Relation is positive and statistically significant. The economic magnitude is substantial: insurers are 1.3 times ($\frac{1.59}{1.21}$) more likely to invest in new CLOs from managers they previously financed compared to the unconditional average. This evidence suggests sticky relationships between insurers and CLO managers, similar to the literature on traditional bank lending relationships (Bharath et al. 2011).

Our subsequent analyses use insurers' cash flows as capital supply shocks to CLO managers, leveraging their sticky relationships to create variation in managers' exposure to these shocks. A necessary condition is that, when insurers experience higher cash flows, they do not break away from their sticky relationship with CLO managers. We test this condition by estimating the following model:

$$
\begin{aligned}
&1(\text{Insurer–CLO Pair Investment})_{i,c(m,t)} = \beta \times \text{CLO Manager–Insurer Relation}_{i,m,t-5} \\
&+ \gamma \times \text{CLO Manager–Insurer Relation}_{i,m,t-5} \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} \\
&+ \lambda \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_c + \alpha_t + \varepsilon_{i,c(m,t)}.
\end{aligned}
$$

Column (2) of Table 3 presents the result. The estimated coefficient on the interaction term is positive and statistically significant, suggesting that after insurers experience higher cash flows, they increase the tilt in their CLO investment toward deals by their relationship managers. The estimate suggests that a one-standard-deviation increase in an insurer's cash-flow-to-assets ratio (0.08) further increases its probability of investing in a relationship CLO by 0.44 (5.53×0.08) percentage points. This effect is economically significant, representing 36% of the average investment probability of 1.21%.[15]

As we hypothesize earlier in this subsection, the stickiness in the insurer–CLO manager relationship can stem from CLO managers' limited marketing reach or insurers producing information about managers. Building on this hypothesis, we predict that relationships will matter less for CLO managers with larger deals in the past or a longer track record, since these managers likely have a broader marketing reach and their man-

[15] As a robustness measure, we use an alternative definition of relationship based on average insurer share over the past five years. We get similar results with the baseline and the alternative measures.

agement strategies or skills are less opaque. To test this, Column (3) extends our analysis by interacting $CLO\ Manager\text{–}Insurer\ Relation_{i,m,t-1}$ with two manager characteristics: $Large\ Manager_{m,t-1}$ and $Old\ Manager_{m,t-1}$. These indicators identify managers whose CLO assets and operational history, respectively, exceed the sample median in year–quarter $t-1$.

In Column (3), the estimated coefficients on the interaction terms between *CLO Manager–Insurer Relation* with *Large Manager* and *Old Manager* are both negative and statistically significant. These results suggest that pre-existing relationships are less important for older and larger managers. While small and new managers are 3.3 ($\frac{4.00}{1.21}$) times as likely to receive funding from a relationship insurer, this advantage diminishes to 1.1 ($\frac{4.00-2.62}{1.21}$) times for large managers and 2.3 ($\frac{4.00-1.24}{1.21}$) times for old managers. These findings align with our hypothesis that as managers expand their operations and build longer track records, they develop a broader marketing reach and resolve uncertainty about their skills, reducing their dependence on existing investors. These findings are also consistent with the explanation that managers who achieve scale and longevity may be of higher quality, reducing the value of private information that relationship investors possess.

Sticky relationships between insurers and CLO managers could arise if certain insurers are dominant in some time periods or specific CLO market segments, causing CLO managers to repeatedly interact with the same insurers. In Column (4), we control for this by including additional fixed effects. We include insurer–by–year–quarter, insurer–by–CLO size quartile, and insurer–by–CLO weighted average coupon quartile fixed effects. This specification controls for each insurer's average investment probability within each quarter and market segment. The estimated coefficient on $CLO\ Manager\text{–}Insurer\ Relation$ remains similar to Column (3), indicating that sticky relationships are unlikely to result from insurer specialization.

Foley-Fisher et al. (2023) laboriously identify affiliations between certain insurers and CLO managers, which could potentially explain the relationship stickiness we observe. If insurers endogenously increase their cash flows to meet their affiliated CLO managers' capital needs, then insurers' cash flows can no longer be deemed as shocks to capital supply. However, we consider this scenario unlikely for two reasons. First, while insurers are significant CLO investors, CLOs represent only 2% of their asset portfolios on average. Given this modest allocation, the average insurer is unlikely to alter their operations to accommodate affiliated CLO managers' capital demands. Second, as described earlier, we find that when insurers' cash flows increase, they also increase their investment in publicly traded corporate bonds and treasury securities. This suggests that the variation in insurer cash flows is unlikely to be driven by affiliated CLO managers' specific capital needs.

Our subsequent identification strategy builds on the key findings of this section: insurers maintain persistent relationships with CLO managers; they do not break away from their familiar CLO managers when experiencing higher cash flows.

6 Relationship CLO Managers Respond to Insurers' Capital Supply by Launching New CLOs

In this section, we examine the effect of idiosyncratic insurer capital supply shocks on CLO managers. Specifically, we analyze whether managers with strong insurer relationships launch more CLO deals when their relationship insurers experience favorable cash flows. We use manager–insurer relationships to calculate each manager's exposure to insurers' cash flows. Since each manager is related to a different set of insurers, we can exploit the variation in managers' exposure.

We formally measure the exposure of manager m to insurer performance in quarter $t-1$ by calculating a weighted average of insurers' operating cash flows, where the weights reflect the strength of each manager–insurer relationship.

$$\text{CLO Manager Exposure}_{m,t-1} = \sum_i \left(\frac{\text{Insurer's CLO Holding}_{i,m,t-5}}{\text{Outstanding CLO Liabilities}_{m,t-5}} \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} \right).$$

$\frac{\text{Insurer's CLO Holding}_{i,m,t-5}}{\text{Outstanding CLO Liabilities}_{m,t-5}}$ represents each insurer i's share of manager m's outstanding liabilities measured in quarter $t-5$. *Insurer Operating* $CF_{i,t-4 \text{ to } t-1}$ represents insurer i's cash flows measured over quarters $t-4$ through $t-1$, normalized by the assets in quarter $t-5$.

We analyze how insurer cash flows influence CLO issuance. In Table 4, we estimate the following specification:

$$\text{CLO Issuance}_{m,t} = \beta \times \text{CLO Manager Exposure to Insurer CF}_{m,t-1} + \alpha_m + \alpha_t + \varepsilon_{m,t}.$$

The outcome variable captures manager m's CLO activity in quarter t through three measures: a binary indicator for any CLO issuance in Column (1), the number of CLOs launched in Column (2), and the natural log of CLO issuance volume plus one in Column (3). We employ manager fixed effects (α_m) and year–quarter fixed effects (α_t) to control for time-invariant manager characteristics and aggregate economic trends.

The estimated coefficients on *CLO Manager Exposure to Insurer CF* are positive and statistically significant in all columns, suggesting that greater exposure to insurer cash flows is positively correlated with increased CLO issuance activity. Column (1) indicates that a one-standard-deviation increase in the exposure to insurers' cash flows increases the probability of CLO issuance in a quarter by 2.02 percentage points (3.81×0.53), which is 13% of the unconditional probability of CLO issuance in a given quarter (15.1%). Columns (2) and (3) suggest that greater exposure of managers is also associated with a higher number and dollar volume of new CLOs. These results demonstrate that insurers' capital supply, driven by their operating performance, significantly impacts relationship managers' CLO launch decisions.

Our interpretation of the results in Table 4 relies on the idea that insurers are significant investors in CLO deals. In our data, insurers invest in 51% of CLOs. Figure A1 plots the distribution of the percentage of CLO liabilities purchased by insurers, both at the CLO deal and manager levels, for those with positive insurer investment. On average, an insurer purchases approximately 14% of newly issued liabilities in a CLO deal and 16% of all liabilities issued by a CLO manager. In 26% of the CLO deals, one insurer purchases more than 20% of all liabilities. These substantial ownership stakes suggest that insurers can significantly influence CLO managers' decisions.

7 Sticky Relationships Between CLO Managers and Borrowing Firms

Our empirical analysis thus far has revealed two findings that underpin our identification strategy. First, insurers with higher cash flows tend to increase their investments in familiar CLO managers. Second, CLO managers who are more exposed to insurer cash flows through past relationships launch more new deals. Ultimately, we are interested in the effect of increased insurer capital supply to CLOs on borrowing firms. In this section, we identify which firms are more likely to be affected by increased insurer capital supply to CLOs by analyzing the relationship stickiness between CLO managers and borrowing firms.

When launching a new CLO, managers on average acquire loans totaling more than $500 million during a one-year period (six-month warehousing followed by a six-month ramp-up). Their loan purchases likely increase capital supply to firms in the leveraged loan market. Which firms benefit from the capital flows depends on how managers select portfolio firms. We hypothesize that managers exhibit persistence in their portfolio selection: they tend to select firms whose loans they have previously purchased. Consequently, firms with existing relationships with a CLO manager may benefit disproportionately when that manager launches new deals in response to increased capital availability.

Two arguments predict that CLO managers may tend to invest in past portfolio firms. First, acquiring and producing information on borrower quality may be costly. Once a manager has already assessed a firm, the cost of repeat investments is lower (Williamson, 1987). This information advantage should matter more for opaque firms. Second, a CLO manager often consults with her underwriter bank on her loan selections (Benmelech et al. 2012). The underwriter bank may steer her toward the bank's relationship borrowers (e.g., by transferring soft information). The bank may benefit as the borrowers take out new loans to meet the increased demand and thus generate higher loan underwriting fees for the bank. This is consistent with Bhardwaj and Mukherjee (2022) who argue that banks help their relationship borrowers obtain CLO financing. These information-based and bank-driven channels can operate simultaneously to create persistent lending relationships.

We test whether a CLO manager is more likely to choose loans of their relationship borrowers, by estimating the following specification:

$$1(\text{Loan Included in CLO})_{f,c(m,t)} = \beta \times \text{Firm–CLO Manager Relation}_{f,m,t-1} + \alpha_c + \alpha_{f,t} + \varepsilon_{f,c(m,t)}.$$

The unit of observation is a CLO–firm pair, where each CLO c is matched to each firm in its consideration set. We define the consideration set for CLOs launched in year–quarter t as all firms with leveraged loans outstanding at t.[16] The dependent variable, $1(\textit{Loan Included in CLO})_{f,c(m,t)}$, equals one if firm f's loans are included in a new CLO c launched by the manager m in quarter t, and zero otherwise. The key independent variable, $\textit{Firm–CLO Manager Relation}_{f,m,t-1}$, equals one if loans from firm f were also held by manager m's existing CLOs during $t-1$, and zero otherwise. We examine loan selections during the warehousing and ramp-up period, as subsequent trading likely reflects firm-specific developments rather than relationship effects.

Table 5 presents the results. Column (1) includes CLO, firm, and year–quarter fixed effects. We include CLO and firm–by–year–quarter fixed effects in Column (2). These fixed effects ensure that the relationship effect is not driven by time periods with few managers and borrowing firms, or by the dominance of specific CLO managers or borrowers.

The estimated coefficients on *Firm–CLO Manager Relation* are positive and statistically significant. The estimate in Column (1) indicates that CLO managers are 8.82 times ($\frac{27.97}{3.17}$) as likely to purchase loans from firms in their past portfolios compared to an

[16] Bharath et al. (2011) adopt a similar look-back strategy to quantify bank-firm relationships. Our results are also robust to using the entire set of firms in the CLO database as the consideration set.

average firm in their consideration set. The estimate is similar in Column (2), where we control for firm–by–year–quarter fixed effects. Our results suggest a strong persistence in borrower–CLO manager relationships, which is also documented in a concurrent paper by Hinzen (2023).

Column (2) adds the interaction between *Firm–CLO Manager Relation* and *CLO Manager Exposure*, where the latter measures managers' exposure to insurer cash flows as defined in the previous section. The estimated coefficient on this interaction term is positive and statistically significant. This suggests that when managers experience higher insurer cash flows, they are even more likely to purchase loans from firms in their past portfolios. The magnitude suggests that when CLO managers' exposure to insurer cash flows increases by one standard deviation, the probability of including loans from relationship borrowers increases by an additional 0.38 percentage points (0.53×0.72), equivalent to 12% of the average probability.[17]

We examine how this persistence varies between public and private firms. In Column (3), we add the interaction between *Firm–CLO Manager Relation*$_{f,m,t-1}$ and *Public Firm*, an indicator variable for publicly traded firms. The coefficient on the interaction term is negative and statistically significant, suggesting that firm–manager relationships are less persistent for public firms. This finding aligns with the notion that public firms face less information asymmetry, although the economic magnitude of this difference is modest.

We explore banks' role in firm–CLO manager relationship persistence by examining their shared banking relationships. We interact *Firm–CLO Manager Relation*$_{f,m,t-1}$ with *Firm–Underwriter–CLO Manager Relation*$_{f,m,t-1}$, where the latter indicates whether a lead arranger bank of any of firm f's outstanding loans in quarter $t-1$ is also an underwriter of any of the outstanding CLOs by manager m at $t-1$. The positive and significant interaction coefficient reveals that firm–manager relationships are 16% more

[17] Although this incremental effect is modest, it supports our identification strategy: as long as manager–borrower relationships do not disappear when manager exposure is high, we can trace insurers' impact on firms through these established relationships. The positive interaction coefficient ensures that high exposure to insurer cash flows does not weaken the baseline relationship effect.

persistent ($\frac{3.93}{24.57}$) when mediated by a common bank, supporting banks' role in facilitating firm–manager matches.

8 Effects of Insurers' Capital Supply to CLOs on Firms

8.1 Effects on Firm Borrowing

Our analyses in Section 6 suggest that when investors' capital supply to CLOs increases, their relationship CLO managers respond by launching new deals. In this section, we examine how this capital supply affects firms' borrowing decisions. A naive approach would be to directly analyze the relationship between CLO launches and firm financing outcomes, assuming investor capital drives CLO creation. We begin with this naive approach before turning to an instrumental variable approach.

Building on the sticky relationship between CLO managers and borrowing firms, we hypothesize that when a firm's relationship managers launch new deals, the firm is more likely to take out new loans. We test this hypothesis by estimating the specification below.

$$1(\text{New Loan})_{f,t} = \beta \times \text{Relation Manager \# CLO}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{s,t} + \varepsilon_{f,t}.$$

$1(\textit{New Loan})_{f,t}$ is a binary indicator equal to one when firm f in industry j and state s obtains a new leveraged loan during year–quarter t. $\textit{Relation Manager \# CLO}_{f,t-1}$ is the relationship–weighted average number of funds launched by firm f's related CLO managers during quarter $t-1$. We control for firm, industry–by–year–quarter, and state–by–year–quarter fixed effects.

The result in Column (1) of Table 6 suggests that when relationship managers' CLO launches increase by one standard deviation (0.30), the probability of a firm obtaining a new leveraged loan increases by 0.26 percentage points (0.86×0.30). This represents a 7% increase relative to the unconditional probability of 3.5%. Figure 1(a) is a binned scatter plot of the outcome variable against the independent variable, both demeaned by taking out firm, state–by–year–quarter, and industry–by–year–quarter fixed effects. The plot confirms the positive correlation between CLO launches and firms' loan issuances.

8.1.1 Instrumental Variable Analysis

A key challenge in establishing causality between CLO funding and firm borrowing is endogeneity. For example, firms' credit demand could simultaneously drive both loan issuance and CLO formation, as managers launch new CLOs to meet the increased loan supply. This means that the OLS estimate would be upward biased. Conversely, when banks prefer to retain loans on their balance sheets, they may increase direct lending while reducing loan distribution to CLOs, creating a downward bias in our estimates.

To address these endogeneity concerns, we use an instrumental variable approach, which relies on two findings from our analysis thus far: (1) insurers' cash flows affect CLO formation of relationship CLO managers, and (2) the relationship between CLO managers and borrowing firms is sticky. We construct an instrument for the endogenous independent variable, $Relation\ Manager\ \#\ CLO_{f,t-1}$. The instrument measures each firm's exposure to insurers' cash flows, weighted by these two relationships as follows:

$$\text{Firm Exposure to Insurer CF}_{f,t-2} = \sum_m \left(\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}} \times \text{CLO Manager Exposure}_{m,t-2} \right)$$
$$= \sum_m \left[\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}} \times \sum_i \left(\frac{\text{Insurer's CLO Holding}_{i,m,t-6}}{\text{Outstanding CLO Liabilities}_{m,t-6}} \times \text{Insurer Operating CF}_{i,t-5 \text{ to } t-2} \right) \right]$$

$\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}}$ is the share of firm f's outstanding loans held by manager m in quarter $t-6$. The denominator is the total value of firm f's outstanding loans in the Creditflux CLO-i data during quarter $t-6$. $CLO\ Manager\ Exposure_{m,t-2}$ is manager m's exposure to insurers' cash flows, as defined in Section 6 and spelled out in the second line of the equation above. $CLO\ Manager\ Exposure_{m,t-2}$ depends on managers' relationship with insurers in quarter $t-6$ and insurers' cash flows between $t-5$ and $t-2$. A firm has a higher exposure to insurer cash flows if it has more relationships with managers that are exposed to insurer cash flows.

The exclusion restriction requires that insurers' operating performance affects firms' outcomes only through new CLO formations, conditional on firm, industry–year–quarter, and state–year–quarter fixed effects. Since life insurance companies' cash flows mainly depend on policy premiums, benefit payouts, and investment income, they are plausibly exogenous to borrowing firms' economic prospects and financing outcomes. This is especially the case since we exclude income related to insurers' CLO investments, and our fixed effects control for time-invariant firm characteristics, as well as industry- and state-level fluctuations. Section 9 conducts two sets of robustness tests. First, we exclude all investment income from insurer cash flows. Second, to alleviate concerns about endogenous matching among insurers, CLO managers, and borrowers, we present results where relationships are measured in quarter $t-10$ instead of $t-6$.

Column (2) of Table 6 presents the first-stage result. A one-standard-deviation increase in firms' exposure to insurer cash flows leads to a 0.14 (0.24×0.60) increase in the number of CLO deals launched by relationship managers, which is a large magnitude compared to the mean of 0.09. The F statistic is also high, suggesting a strong first stage. Figure 1(b) visualizes this relationship through a binned scatter plot between CLO launches and our instrument, after residualizing both variables with respect to our fixed effects. The plot reveals a strong positive correlation, supporting the instrument's relevance.

Column (3) reports the second-stage result. The estimated coefficient on the instrumented *Relation Manager # CLO* suggests that a one-standard-deviation increase (0.3) in relationship managers' CLO launches during the previous quarter increases the probability of a firm obtaining a leveraged loan by 0.34 (0.3×1.14) percentage points. This magnitude represents 10% of the average probability of taking out a leveraged loan. This magnitude is larger than the OLS estimate, likely due to endogeneity in the OLS specification. For example, when banks are more willing to hold loans on their balance sheets, they may originate more loans and sell fewer loans to CLOs, which discourages the launching of new CLOs. This introduces a downward bias in the OLS estimate, causing it to understate the causal effect of capital supply to CLOs on new loan issuances. Figure 1(c) provides complementary visual evidence through a binned scatter plot of the probability of loan issuance against instrumented CLO launches, after residualizing both variables with respect to our fixed effects. The positive slope evident in this graph corroborates our regression result.

The interpretation of our results rests on CLO managers having meaningful influence over firms' loan financing through substantial purchases of firms' loans. Figure A2 presents the distribution of CLO managers' holdings as a share of firms' total outstanding securitized loans. The data reveal that CLO managers are indeed significant stakeholders: on average, a manager holds 7% of a firm's leveraged loans, with the 85th percentile at 15% and the maximum reaching 57%. These substantial holdings support our premise that CLO managers are influential intermediaries in firms' access to leveraged loan financing.

We next conduct a falsification test exploiting the fact that CLOs generally do not purchase revolving credit lines. If the loan result above is explained by increased CLO capital supply, there should be no effect on revolvers. Column (4) tests this hypothesis by replicating the 2SLS analysis, using an indicator of revolver issuance as the dependent variable in the second stage. The coefficient on *Relation Manager # CLO* is statistically insignificant, consistent with our prediction. This result supports our identification strategy: firms likely increase borrowing across all facility types, including revolvers, when their financing needs rise,[18] the absence of an effect on revolver issuance suggests our instrument captures supply-side effects rather than firms' demand for credit.

[18] Lins et al. (2010) document that firms maintain credit lines for future investment opportunities based on a CFO survey. Acharya et al. (2014) emphasize credit lines' importance for firms with future opportunities. Sufi (2009) identifies credit lines as "an instrumental component of corporate liquidity management," though less accessible to low–cash–flow firms. Our firm fixed effects control for firm-level time-invariant determinants of credit line access.

8.1.2 Effects on Loan Spreads and Purposes

Next, we examine how idiosyncratic CLO investor shocks affect the spreads of new leveraged loans through CLO managers. Our analysis uses loan-level data to investigate how loan spreads vary with the instrumented number of new CLOs created by relationship managers. Table 7 follows the empirical approach of Table 6, replacing the dependent variable with loan spreads in both the OLS and 2SLS second-stage regressions. As in our previous analysis, we use *Relation Manager # CLO* as the endogenous independent variable and instrument this variable using firm exposure to insurer cash flows.

The estimated coefficient on *Relation Manager # CLO* is −14 in the OLS specification and −56 in the 2SLS regression. The larger magnitude in the 2SLS estimate likely reflects endogeneity bias in the OLS estimate. For example, banks may preferentially sell loans of firms with increased default probabilities. When banks have more such loans to sell, it could trigger additional CLO launches. Since increased default probabilities also lead to higher loan spreads, this endogeneity could create an upward bias in the relationship between CLO activities and loan spreads, compared to the true causal effect of CLO capital supply on spreads.

The magnitude of the 2SLS estimate suggests that when the instrumented *Relation Manager # CLO* increases by one standard deviation, new loan spreads decline by 20.81 basis points (0.37×56), corresponding to 5.4% of the mean. This result suggests that the influx of insurer capital has a substantial effect on lowering loan spreads, which can explain the results on firms' increased loan issuance.

Table A3 analyzes how capital shocks in the CLO market affect the purpose of new loans. Panel (A) employs our baseline 2SLS framework, examining whether new loans have the stated purpose of: (1) general purpose or investment, (2) refinancing or dividend payouts, (3) leveraged buyouts, or (4) other. In Panel (B), we use multinomial logit regressions. Due to the lack of a standard estimation procedure for instrumenting endogenous variables in a multinomial logit model, we use the instrument directly as the main independent variable in the regression rather than employing a 2SLS approach.

Given econometric problems associated with including a large number of fixed effects in nonlinear models, we only include year–quarter fixed effects. We report the marginal effects estimated at the mean of the independent variables.

Both panels reveal that capital supply to the CLO market shifts the purpose of new loans toward general purpose or investment and away from leveraged buyouts. The economic magnitude is substantial. Based on Column (1) of Panel (A), a one-standard-deviation increase in instrumented *Relation Manager # CLO* raises the probability of general purpose or investment by 9 percentage points (0.37×0.24), representing a 20% increase relative to the baseline probability of 45%.

8.2 Effects on Firm Employment and Expansion

Do idiosyncratic investor capital supply shocks to CLOs generate real economic effects? If credit supply through the CLO market simply substitutes alternative financing sources, such as banks' on–balance–sheet lending, we would observe minimal real effects. To address this question, we employ the same 2SLS structure used in our previous analysis. As we discuss later, we find that insurers' capital supply only influences loan issuance for private firms, but not public ones. Since conventional datasets on firm outcomes like Compustat exclude private firms (63% of our sample), we rely on D&B data to assess real outcomes. While this dataset provides information on employee and establishment counts, it lacks data on investments and other financial variables. Because D&B data are at an annual frequency, observations are at the firm–year level.

Table 8 reports our analysis of how CLO manager relationships affect firm operations. Panel (A) examines log employment, while Panel (B) studies log establishment counts. In each panel, we present the OLS estimates in Column (1) and the 2SLS results in Columns (2) and (3). Both the raw and instrumented *Relation Manager # CLO* show positive and statistically significant effects across the two panels. The 2SLS estimates indicate that a one-standard-deviation increase in *Relation Manager # CLO* (0.31), driven by insurers' capital supply shocks, leads to a 3.4% (0.31×0.11) increase in employment and a 4.7%

(0.31×0.15) rise in establishment counts.

The effects are smaller in the OLS estimates, likely due to endogeneity bias. For instance, banks may preferentially sell loans of firms with limited growth prospects to CLOs rather than retain them on their balance sheets. When banks have more such loans to sell, it could trigger additional CLO launches, creating a downward bias in the OLS estimate of the relationship between firm operations and CLO launches, compared to the true causal effect of CLO capital supply.

The results in this section suggest that when idiosyncratic shocks increase investor capital supply to CLOs, it does more than simply allowing banks to offload more loans. It expands credit access and drives real economic effects through employment and business expansion. To contextualize our results, we compare with studies examining idiosyncratic bank lending shocks. We exclude studies on major crisis periods with aggregate shocks, which make them less comparable to our setting. Amiti and Weinstein (2018) show that idiosyncratic shocks affect the investment of public Japanese firms and account for 30–40 percent of the total variation in aggregate lending and investment. Using Spanish data, Alfaro et al. (2021) find that a one-standard-deviation increase in firms' credit supply shock raises employment growth by 71% and firm investment by 13%. Also using Spanish data, Jiménez et al. (2020) estimate that a one-standard-deviation increase in banks' real estate exposure leads to 6.1 percentage points higher credit growth. Using German data, Rehbein and Ongena (2022) reveals that firms connected to disaster-exposed banks with low capitalization experience 6.6% lower borrowing and 6.9% lower tangible assets. In the U.S., Levine et al. (2018) find that one standard deviation of bank liquidity gain through shale boom decreases loan spread by 0.08, representing 5.2% of mean.[19]

8.3 Private vs Public Firms

Are financially constrained firms more affected by CLO investors' capital supply shocks? Because 63% of our sample firms are private, we cannot employ traditional

[19] Gilje et al. (2016) and Cortés and Strahan (2017) study the effect of shale boom and disasters on banks' mortgage lending in unaffected areas.

financial constraint measures based on public firm data. Instead, we designate public firms as less constrained. In Table 9, we examine how firm outcomes vary between public and private firms by augmenting our 2SLS specifications with an interaction between the instrumented *Relation Manager # CLO* and *Public Firm* indicator.[20] We present the second-stage results of the 2SLS regressions, which show effects of CLO capital supply on: (1) new loan probability at the firm–quarter level, (2) new loan spreads at the loan level, (3) log employment at the firm–year level, and (4) log establishment counts at the firm–year level.

The estimated coefficients on *Relation Manager # CLO* capture the effects for private firms. Relative to the average sample firm as shown in previous tables, private firms exhibit more than double the effects on loan issuance, employment, and establishment counts. For public firms, effects on these outcomes are negligible. However, the effects on loan spreads remain similar between private and public firms. The contrast between loan issuance and loan spreads aligns with Graham and Harvey (2001)'s survey finding that only 46% of respondents (mostly public firms) consider low interest rates "important or very important" for debt issuance. Public firms' muted loan issuance response likely reflects their lower ex-ante unmet financing needs.

9 Robustness

9.1 Using Longer–Lagged Relationships

Our findings in Section 6 indicate that CLO managers increase their deal launches following positive cash flow shocks to their relationship insurers. However, this correlation could be the result of endogenous matching rather than a causal relationship. For example, CLO managers who plan to launch new deals might strategically form relationships with insurers that are expected to experience favorable cash flows. Alternatively, insur-

[20] In this case, our simultaneous 2SLS regressions have two first-stage equations with two endogenous variables and two instruments. The added endogenous variable is the interaction between *Relation Manager # CLO* and *Public Firm*. The added instrument is the interaction between our aforementioned instrument and *Public Firm*.

ers anticipating future cash flow increases might proactively establish relationships with CLO managers who will launch more deals, intending to increase their CLO investments.

To address these endogeneity concerns, we present a robustness check in Table A4, which replicates the analysis in Table 4 using further lagged relationship measures. Specifically, we regress CLO manager outcomes in year–quarter t on an alternative measure of *CLO Manager Exposure* as specified below, where the relationship is measured in year–quarter $t-9$:

$$\sum_i \left(\frac{\text{Insurer's CLO Holding}_{i,m,t-9}}{\text{Outstanding CLO Liabilities}_{m,t-9}} \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} \right).$$

The results remain similar to those of Table 4.

One may be similarly concerned about our 2SLS analyses on firms' outcomes. For firms' outcomes in year–quarter t, the instrument uses CLO manager–firm relationships and CLO manager–insurer relationships. Both relationships are measured in $t-6$, prior to insurer cash flows measured from $t-5$ to $t-2$. Even with such lagged relationships, one may still be concerned that they are endogenous to the borrowing firms' demand for capital. Specifically, firms anticipating future borrowing needs in period t might strategically form relationships with certain CLO managers in $t-6$. If these managers are systematically matched with insurers in $t-6$ who subsequently experience positive cash flows from $t-5$ to $t-2$, our instrument could be correlated with firms' demand for capital.

To alleviate the concern above, we use longer lags between the measurement of the relationships and insurers' cash flows in robustness tests. In Table A5, we repeat our main 2SLS results on firm outcomes. We use an alternative instrument where both the CLO manager–firm and the CLO manager–insurer relationships are measured at $t-10$, five quarters before the insurer cash flows from $t-5$ to $t-2$.

The first-stage result in Table A5 suggests that this alternative instrument still predicts more CLO deals by firms' relationship managers. The second-stage results indicate that firms respond to an increase in CLO deals predicted by this alternative instrument.

They are more likely to take out new loans and increase their employment and establishment counts. These results are consistent with our main analyses. To the extent that it is hard to predict insurers' cash flows five quarters prior, this alternative instrument alleviates the concern regarding endogenous matching.

9.2 Using Insurers' Cash Flows Excluding Investment Income

While our insurer cash flow measure excludes CLO-related investment income, potential common factors could still link insurers' investment income to the capital needs of firms connected through CLO managers. Insurers may favor firms with specific characteristics across both their CLO and non-CLO investments. Strong recent performance by these firms could boost insurers' lagged investment income while simultaneously increase firms' financing needs in the CLO market, potentially creating an endogenous relationship between insurer cash flows and firm outcomes.

To address this concern, we repeat our main analyses using insurers' cash flows excluding all of their investment income. Our results remain robust. Table A6 suggests that higher non-investment operating performance continues to predict increased CLO investment by insurers, paralleling our baseline findings in Table 2. Similarly, Table A7 confirms that CLO managers launch more deals when their relationship insurers experience positive non-investment cash flow shocks, consistent with Table 4. Finally, Table A8 shows results on firms' financing and real outcomes, using an alternative instrument based on insurers' non-investment cash flows. Results maintain the same economic patterns: increases in CLO capital supply drive higher loan issuance, employment, and establishment growth.

10 Conclusion

The dramatic expansion of loan securitization over the past two decades raises important questions about how the CLO market affects credit provision. While securitization might insulate borrowers from bank-specific shocks by distributing loans across diverse investors, we show that firms become exposed to idiosyncratic shocks to CLO investors' capital supply.

Using detailed data on insurance companies, the largest class of CLO investors, we document three key findings. First, insurers' cash flows affect their CLO investments. Second, CLO managers respond to this increase in investor capital by launching more deals. Third, these capital supply-driven CLO formations lead firms to increase borrowing, grow employment, and expand operations. Private firms, which likely have larger unmet financing needs, drive the effects.

These findings have two critical implications for credit markets. While loan securitization may reduce firms' exposure to bank-specific shocks, it creates new exposure to non-bank investor shocks through the CLO market. Moreover, increased CLO investor capital does more than facilitate bank risk transfer—it expands credit access and drives real economic activity. Understanding these transmission channels from non-bank investors to borrowers is crucial for assessing financial stability in modern credit markets, where these investors increasingly provide the ultimate funding for bank loans.

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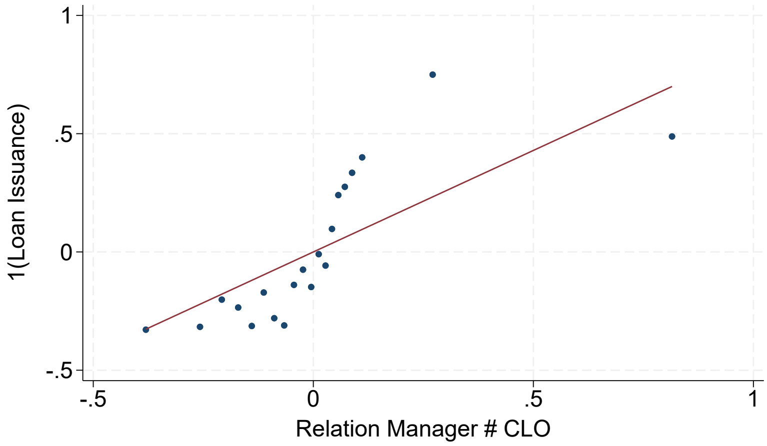
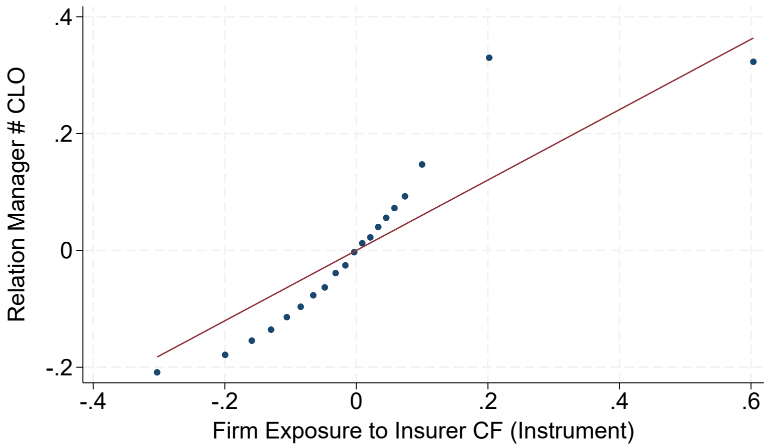
Figures and Tables

Figure 1. The Effect of Insurers' Capital Supply to CLOs on Loan Issuance

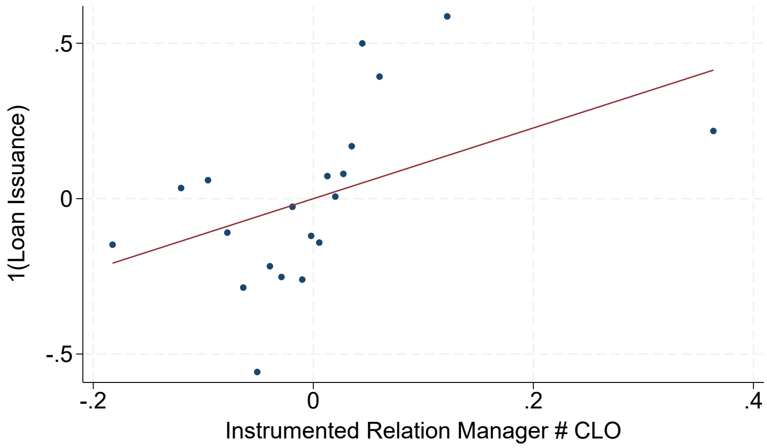
(a) 1(New Loan) vs Relation Manger # CLO



(b) Relation Manger # CLO vs Firm Exposure to Insurer CF (Instrument)



(c) 1(New Loan) vs Instrumented Relation Manger # CLO



Note: Figure 1 presents three binned scatter plots. Figure (a) is a scatter plot of the outcome variable, 1(New Loan) against the endogenous independent variable (Relation Manger # CLO). Figure (b) is a scatter plot of the endogenous variable against the instrument (Firm Exposure to Insurer CF). Figure (c) is a scatter plot of the outcome variable against the predicted endogenous variable. All the (predicted) variables in the three panels are demeaned by taking out firm, state–year–quarter and industry–year–quarter fixed effects.

Table 1. Summary Statistics

	(1) Mean	(2) SD	(3) 5%tile	(4) Median	(5) 95%tile
Insurance Companies					
Insurer Operating CF (scaled by Assets)	0.04	0.08	-0.07	0.04	0.17
1(CLO Purchase) (per Quarter)	0.38	0.49	0.00	0.00	1.00
# CLO Purchase (per Quarter)	1.00	1.50	0.00	0.00	4.00
Log(1+CLO Purchase) (per Quarter)	1.26	2.07	0.00	0.00	5.73
CLO Deals					
Deal Size ($ Millions)	507.04	197.75	303.09	468.87	814.88
Senior Tranche (% of Liabilities)	63.33	9.43	52.56	63.12	77.73
Mezzanine Tranche (% of Liabilities)	25.10	7.45	11.77	27.14	32.39
Tranche Coupon (pp, Wtd. Average)	1.73	0.67	0.55	1.82	2.60
No. of Portfolio Firms	192.72	91.86	62.70	187.53	333.89
Loan Spread (pp, Wtd. Average)	3.85	0.77	3.04	3.68	5.31
Insurer Holdings (%, Wtd. Average)	14.06	12.62	0.44	11.81	37.83
CLO Managers					
1(CLO Launched) (per Quarter) (×100)	15.10	35.81	0.00	0.00	100.00
# CLO Launched (per Quarter) (×100)	17.33	43.36	0.00	0.00	100.00
Log(1+Launched Volume) (per Quarter) (×100)	93.01	221.21	0.00	0.00	624.09
CLO Manager Exposure to Insurers	0.22	0.53	0.00	0.00	1.27
Manager Size ($ Billions)	2.31	3.47	0.07	0.91	9.03
Manager Age (in Quarters)	34.21	19.22	4.00	33.00	66.00
Borrowing Firms					
1(New Loan) (per Quarter)	3.50	18.38	0.00	0.00	0.00
Relation Manager # CLO (per Quarter)	0.09	0.30	0.00	0.00	0.88
Firm Exposure to Insurer CF	0.08	0.24	0.00	0.00	0.58
All In Spread Drawn (bps)	381.32	177.76	175.00	350.00	750.00
Employment	2278.94	5690.30	6.00	377.00	11436.00
# Establishments	38.01	107.06	1.00	6.00	187.00
Public Firm	0.37	0.48	0.00	0.00	1.00

Notes: Table 1 shows the summary statistics of key variables used in the empirical analysis.

Table 2. Effect of Insurers' Operating Cash Flows on Their CLO Investments

	(1) 1(CLO Purchase)	(2) # CLO Purchase	(3) Log(1+CLO Purchase)
Insurer Operating CF	0.20*** (0.06)	0.64*** (0.23)	1.09*** (0.31)
$\overline{y}$	.38	1	1.26
SD(x)	.08	.08	.08
Insurer FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	16,502	16,502	16,502
Adj. R-squared	0.39	0.47	0.51

Notes: Table 2 analyzes the relationship between insurers' CLO investments and their operating performance. The sample contains all insurers in the sample that had nonzero CLO holdings in the previous year. The specification is:

$$\text{Insurer CLO Investment}_{i,t} = \beta \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

$Insurer\ CLO\ Investment_{i,t}$ denotes outcomes for insurer i in year–quarter t: (i) $1(CLO\ Purchase)_{i,t}$ is an indicator for a CLO purchase transaction, (ii) $\#\ CLO\ Purchase_{i,t}$ is the number of CLOs purchased, and (iii) $Log(1 + CLO\ Purchase)_{i,t}$ is the dollar value of CLO tranches purchased, in natural logarithm. $Insurer\ Operating\ CF_{i,t-4 \text{ to } t-1}$ is insurer i's operating cash flows from year–quarter $t-4$ to $t-1$ scaled by assets. α_i and α_t denote insurer and year–quarter fixed effects, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Sticky Relationship Between Insurers and CLO Managers

	(1)	(2)	(3)	(4)
	1(Insurer Investment)×100			
CLO Manager–Insurer Relation	1.59***	1.32***	4.00***	4.11***
	(0.11)	(0.11)	(0.31)	(0.30)
CLO Manager–Insurer Relation × Insurer Operating CF		5.53***	5.34***	3.83***
		(0.86)	(0.85)	(0.89)
CLO Manager–Insurer Relation × Large Manager			-2.62***	-2.67***
			(0.36)	(0.35)
CLO Manager–Insurer Relation × Old Manager			-1.24***	-1.22***
			(0.31)	(0.31)
Insurer Operating CF		1.15***	1.17***	
		(0.15)	(0.15)	
$\overline{y}$	1.21	1.21	1.21	1.21
CLO FE	Y	Y	Y	Y
Insurer FE	Y	Y	Y	
Closing Year–Quarter FE	Y	Y	Y	
Insurer×Closing Year–Quarter FE				Y
Insurer×CLO Size Quartile FE				Y
Insurer×CLO Coupon Quartile FE				Y
Obs	1,211,775	1,211,775	1,211,775	1,211,295
Adj. R-squared	0.05	0.05	0.05	0.07

Notes: Table 3 analyzes how insurers' pre-existing relationships with CLO managers affect their decision to invest in new CLOs of those managers. The specification corresponding to Column (2) is:

$$1(\text{Insurer–CLO Pair Investment})_{i,c(m,t)} = \beta \times \text{CLO Manager–Insurer Relation}_{i,m,t-5} + \lambda \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \gamma \times \text{CLO Manager–Insurer Relation}_{i,m,t-5} \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_c + \alpha_t + \varepsilon_{i,c(m,t)}.$$

The dependent variable is an indicator for whether insurer i invested in CLO c launched by manager m in year–quarter t (multiplied by 100). We focus on investments made within one year of deal formation. For each CLO, the data contains one observation for each potential investor, where the set of potential investors are insurers with nonzero CLO holdings during the previous year. $\textit{CLO Manager–Insurer Relation}_{i,m,t-5}$ is an indicator that equals one if insurer i held a CLO by manager m in year–quarter $t-5$. $\textit{Insurer Operating CF}_{i,t-4 \text{ to } t-1}$ is insurer i's operating cash flows from year–quarter $t-4$ to $t-1$ scaled by assets. $\textit{Large Manager}_{m,t-1}$ and $\textit{Old Manager}_{m,t-1}$ are indicators for when manager m's CLO assets and age are higher than the sample median during year–quarter $t-1$. α_i, α_c, and α_t are insurer, CLO, and launch year–quarter fixed effects. $\overline{y}$ indicates the averages of the outcome variables. Standard errors are clustered at the CLO level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. CLO Manager Exposure to Insurer Cash Flows and New CLO Creation

	(1) 1(CLO Launched)×100	(2) # CLO Launched×100	(3) Log(1+Launched Volume)×100
CLO Manager Exposure to Insurer CF	3.81***	4.05***	23.53***
	(1.02)	(1.30)	(6.42)
$\overline{y}$	15.1	17.33	93.01
SD(x)	.53	.53	.53
Manager FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	13,418	13,418	13,418
Adj. R-squared	0.26	0.27	0.27

Notes: Table 4 analyzes the relation between CLO managers' exposure to relationship insurers' cash flows and their decision to launch a new CLO. The specification is:

$$\text{CLO Issuance}_{m,t} = \beta \times \text{CLO Manager Exposure to Insurer CF}_{m,t-1} + \alpha_m + \alpha_t + \varepsilon_{m,t}$$

$CLO\ Issuance_{m,t}$ denotes outcomes of manager m in year–quarter t: (i) $1(CLO\ Launched)_{m,t}$ is an indicator for CLO issuance (multiplied by 100), (ii) $\#\ CLO\ Launched_{m,t}$ is the number of CLOs launched (multiplied by 100), and (iii) $Log(1 + Launched\ Volume)_{m,t}$ is the CLO issuance volume (in logs, multiplied by 100). $CLO\ Manager\ Exposure_{m,t-1}$ is m's exposure to relationship insurers' cash flows in year–quarter $t-1$ as defined in Section 6. α_m and α_t are the manager and year–quarter fixed effects. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. Standard errors are clustered at the manager level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Sticky Relationship Between Borrowing Firms and CLO Managers

	(1)	(2)	(3)	(4)
	1(Loan Included in CLO)×100			
Firm–CLO Manager Relation	27.97***	27.47***	27.64***	24.57***
	(0.50)	(0.56)	(0.58)	(0.57)
× CLO Manager Exposure to Insurer CF		0.72*	0.72*	0.79*
		(0.43)	(0.43)	(0.45)
× Public Firm			-0.38*	
			(0.20)	
× Firm–Underwriter–CLO Manager Relation				3.93***
				(0.54)
Firm–Underwriter–CLO Manager Relation				3.90***
				(0.17)
$\overline{y}$	3.17	3.17	3.17	3.17
CLO FE	Y	Y	Y	Y
Firm×Year–Quarter FE	Y	Y	Y	Y
Obs	3,531,707	3,531,707	3,531,707	3,531,707
Adj. R-squared	0.37	0.37	0.37	0.37

Notes: Table 5 examines the degree of relationship stickiness between fund managers and borrowing firms at the inception of new CLOs. The specification in column (1) is:

$$1(\text{Loan Included in CLO})_{f,c(m,t)} = \beta_1 \times \text{Firm–CLO Manager Relation}_{f,m,t-1} + \alpha_c + \alpha_{f,t} + \varepsilon_{f,c(m,t)}$$

$1(\textit{Loan Included in CLO})_{f,c(m,t)}$ is an indicator that equals one if loans taken by firm f are included in a new CLO c launched by the manager m in year–quarter t, and zero otherwise (multiplied by 100). $\textit{Firm–CLO Manager Relation}_{f,m,t-1}$ is an indicator that equals one if loans from firm f were also held by existing CLOs by manager m during year–quarter $t-1$. $\textit{CLO Manager Exposure}_{m,t-1}$ is m's exposure to relationship insurers' cash flows in year–quarter $t-1$. We define public firms as those with publicly-listed equity or bonds. $\textit{Firm–Underwriter–CLO Manager Relation}_{f,m,t-1}$ is an indicator for when a bank has simultaneous relationships with firm f and manager m during year–quarter $t-1$. This implies that a bank that is a lead arranger on (one or more) outstanding loans of f is also an underwriter of (one or more) outstanding CLOs of m at time $t-1$. α_c, α_f, and α_t are CLO, firm, and launch year–quarter fixed effects, respectively. $\overline{y}$ indicates the averages of the outcome variables. Standard errors are clustered at the CLO level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Effect of Insurers' Capital Supply to CLOs on Loan Issuance

	OLS	2SLS: 1st Stage	2SLS: 2nd Stage	(Falsification) 2SLS: 2nd Stage
	(1) 1(New Loan) ×100	(2) Relation Manager # CLO	(3) 1(New Loan) ×100	(4) 1(New Revolver) ×100
Relation Manager # CLO	0.86***		1.14***	-0.28
	(0.13)		(0.26)	(0.23)
Firm Exposure to Insurer CF (Instrument)		0.60***		
		(0.01)		
$\overline{y}$	3.5	.09	3.5	3.71
SD(x)	.3	.24	.3	.3
Firm FE	Y	Y	Y	Y
Industry×Year–Quarter FE	Y	Y	Y	Y
State×Year–Quarter FE	Y	Y	Y	Y
Kleibergen-Paap Wald rk F			6,078	6,078
Obs	535,952	535,952	535,952	535,952

Notes: Table 6 suggests that firms take out new loans when their relationship CLO managers launch new CLOs. The OLS specification is:

$$1(\text{New Loan})_{f,t} = \beta \times \text{Relation Manager \# CLO}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{s,t} + \varepsilon_{f,t}$$

The two stages of the 2SLS regressions are estimated simultaneously. The first stage of the 2SLS specification is:

$$\text{Relation Manager \# CLO}_{f,t-1} = \beta \times \text{Firm Exposure to Insurer CF}_{f,t-2} + \alpha_f + \alpha_{j,t} + \alpha_{s,t} + \varepsilon_{f,t}$$

The second stage of the 2SLS specification is:

$$1(\text{New Loan})_{f,t} = \beta \times \text{Relation } \widehat{\text{Manager}} \text{ \# CLO}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{s,t} + \varepsilon_{f,t}$$

$1(New\ Loan)_{f,t}$ is an indicator for when firm f in industry j and state s obtains a new leveraged loan during year–quarter t (multiplied by 100). $Relation\ Manager\ \#\ CLO_{f,t-1}$ is the relationship–weighted–average number of CLO deals launched by f's relationship managers during year–quarter $t-1$. It is calculated as:

$$\text{Relation Manager \# CLO}_{f,t-1} = \sum_m \left(\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}} \times \text{\# New CLO}_{m,t-1} \right)$$

$\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}}$ is the share of firm f's outstanding loans held by manager m during year–quarter $t-6$. Relation $\widehat{\text{Manager}}$ # $\text{CLO}_{f,t-1}$ denotes the predicted value estimated in the first-stage regression corresponding to year–quarter $t-1$. The instrument, $Firm\ Exposure\ to\ Insurer\ CF_{f,t-2}$, is firm f's exposure to insurers' cash flows. It is calculated as:

$$\text{Firm Exposure to Insurer CF}_{f,t-2} = \sum_m \left(\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}} \times \text{CLO Manager Exposure}_{m,t-2} \right)$$

$$= \sum_m \left[\frac{\text{Manager's Firm Holding}_{f,m,t-6}}{\text{Outstanding Firm Loan}_{f,t-6}} \times \sum_i \left(\frac{\text{Insurer's CLO Holding}_{i,m,t-6}}{\text{Outstanding CLO Liabilities}_{m,t-6}} \times \text{Insurer Operating CF}_{i,t-5 \text{ to } t-2} \right) \right]$$

In Column (4), we do a falsification test where the outcome variable is an indicator for when firm f takes a new revolver loan during year–quarter t (multiplied by 100). α_f, $\alpha_{j,t}$, and $\alpha_{s,t}$ denote fixed effects at firm, industry–year–quarter, and state–year–quarter level, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Effect of Insurers' Capital Supply to CLOs on Loan Spreads

	OLS	2SLS: 1st Stage	2SLS: 2nd Stage
	(1) Loan Spread	(2) Relation Manager # CLO	(3) Loan Spread
Relation Manager # CLO	-14.05*		-56.25***
	(8.27)		(16.69)
Firm Exposure to Insurer CF (Instrument)		0.64***	
		(0.04)	
$\overline{y}$	381.32	.17	381.32
SD(x)	.37	.27	.37
Firm FE	Y	Y	Y
Industry×Year–Quarter FE	Y	Y	Y
State×Year–Quarter FE	Y	Y	Y
Kleibergen-Paap Wald rk F			222
Obs	34,492	34,492	34,492

Notes: Table 7 studies how the spreads of new loans change following new CLO launches of relationship managers. Each observation corresponds to a leveraged loan in our sample and the 2SLS estimation follows the analysis in Table 6. The two stages are estimated simultaneously. The outcome variable is the loan spread expressed in bps. We employ firm, industry–year–quarter, and state–year–quarter fixed effects and cluster standard errors at the firm level. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Effect of Insurers' Capital Supply to CLOs on Firms' Real Outcomes

Panel (A): Employment

	OLS	2SLS: 1st Stage	2SLS: 2nd Stage
	(1) Log(Employment)	(2) Relation Manager # CLO	(3) Log(Employment)
Relation Manager # CLO	0.05**		0.11***
	(0.02)		(0.04)
Firm Exposure to Insurer CF (Instrument)		0.68***	
		(0.01)	
$\overline{y}$	5.81	.16	5.81
SD(x)	.31	.26	.31
Firm FE	Y	Y	Y
Industry×Year FE	Y	Y	Y
State×Year FE	Y	Y	Y
Kleibergen-Paap Wald rk F			2,838
Obs	35,266	35,266	35,266

Panel (B): Number of Establishments

	OLS	2SLS: 1st Stage	2SLS: 2nd Stage
	(1) Log(Establishments)	(2) Relation Manager # CLO	(3) Log(Establishments)
Relation Manager # CLO	0.07***		0.15***
	(0.02)		(0.03)
Firm Exposure to Insurer CF (Instrument)		0.68***	
		(0.01)	
$\overline{y}$	2.02	.16	2.02
SD(x)	.31	.26	.31
Firm FE	Y	Y	Y
Industry×Year FE	Y	Y	Y
State×Year FE	Y	Y	Y
Kleibergen-Paap Wald rk F			2,838
Obs	35,266	35,266	35,266

Notes: Table 8 analyzes how borrowing firms' employment and establishment counts respond when their related CLO managers launch new CLO funds. The 2SLS specification is analogous to that in Table 6. The two stages are estimated simultaneously. For this analysis, we aggregate the data at the firm-year level since the outcome variables are only available at an annual frequency. The outcome variables in the OLS regressions and the second-stage of the 2SLS regressions are total employment in Panel (A) and number of establishments in Panel (B), expressed in natural logarithms at the firm-year level. The independent variable in the second stage regression is the predicted value of number of CLOs launched by relationship managers in the previous year. We employ fixed effects at the firm, industry–year, and state–year level, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Effect of Insurers' Capital Supply to CLOs on Firm Outcomes: Private vs Public Firms

	2SLS: 2nd Stage			
	(1) 1(New Loan)	(2) Loan Spread	(3) Log(Employment)	(4) Log(Establishments)
Relation Manager # CLO	3.03***	-53.71**	0.27***	0.31***
	(0.55)	(25.95)	(0.06)	(0.04)
Relation Manager # CLO × Public Firm	-2.93***	-4.52	-0.28***	-0.28***
	(0.70)	(30.08)	(0.08)	(0.05)
$\overline{y}$	4.2	381.32	1	1
SD(x)	.31	.37	.31	.31
Firm FE	Y	Y	Y	Y
Industry×Time FE	Y	Y	Y	Y
State×Time FE	Y	Y	Y	Y
Kleibergen-Paap Wald rk F	1,059	66	698	698
Obs	305,672	34,492	35,266	35,266

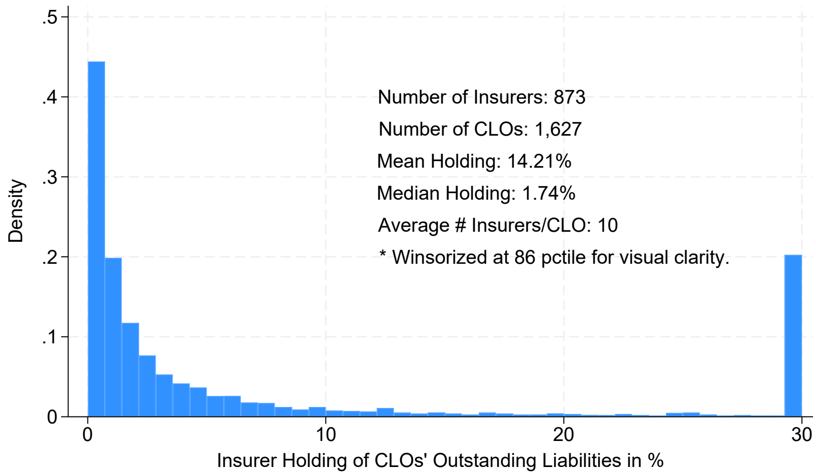
Notes: Table 9 analyzes how new CLO launch by relationship managers affect firm outcomes. The 2SLS specification is analogous to that in Table 6. Our simultaneous 2SLS regressions here have two first-stage equations with two endogenous variables and two instruments. The added endogenous variable is the interaction between *Relation Manager # CLO* and *Public Firm*. The added instrument is the interaction between our original instrument and *Public Firm*. Columns (1) and (2) examine borrowing outcomes whereas columns (3) and (4) examine real outcomes. For real outcomes, we aggregate the data at the firm-year level since the outcome variables are only available at an annual frequency. We define public firms as those with publicly-listed equity or bonds. We employ fixed effects at the firm, industry–time, and state–time level, respectively. "Time" in fixed effects denotes quarter in Columns (1) and (2) and year in (3) and (4). $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable, *Relationship Manager # CLO*. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendices

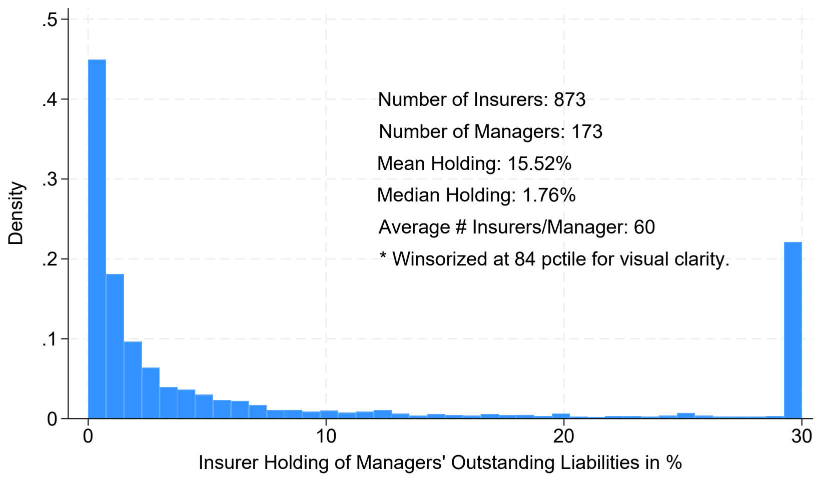
A Additional Figures and Tables

Figure A1. Histogram: Percent of CLO Liabilities Held by Each Insurer

(a) Deal level (Per Insurer)

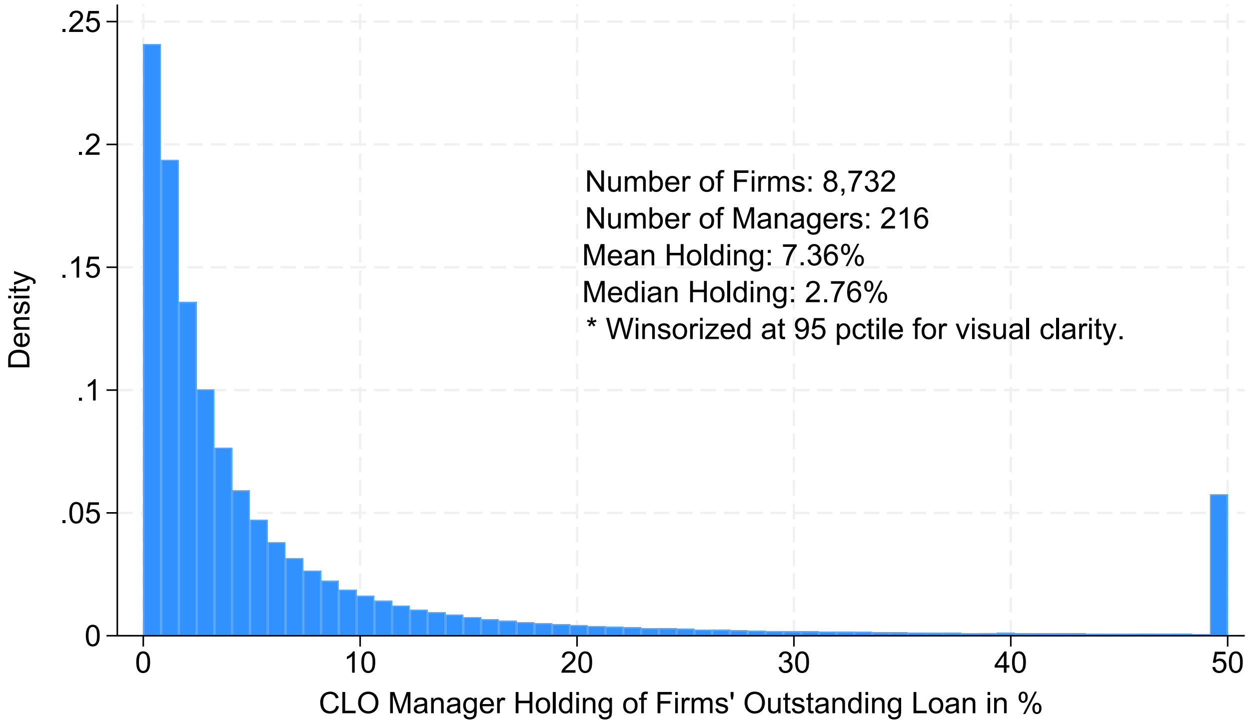


(b) Manager level (Per Insurer)



Note: Figure A1 shows the fraction of CLO liabilities held by each insurer in our sample. Figure (a) shows deal-level holding for each insurer and (b) manager-level holding for each insurer.

Figure A2. Histogram: Percent of Firm Loans Held by Each CLO Manager



Note: Figure A2 plots the distribution of the percent of firms' outstanding securitized loans held by each CLO manager.

Table A1. Effect of Insurers' Cash Flows on Their CLO Investments (All Insurers)

	(1) 1(CLO Purchase)	(2) # CLO Purchase	(3) Log(1+CLO Purchase)
Insurer Operating CF	0.02***	0.06***	0.10***
	(0.01)	(0.02)	(0.02)
$\overline{y}$	.03	.09	.1
SD(x)	.11	.11	.11
Insurer FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	233,190	233,190	233,190
Adj. R-squared	0.30	0.32	0.32

Notes: Table A1 analyzes the relationship between insurers' CLO investments and their operating performance. The sample contains all insurers. The specification is:

$$\text{Insurer CLO Investment}_{i,t} = \beta \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

$Insurer\ CLO\ Investment_{i,t}$ denotes outcomes for insurer i in year–quarter t: (i) $1(CLO\ Purchase)_{i,t}$ is an indicator for a CLO purchase transaction, (ii) $\#\ CLO\ Purchase_{i,t}$ is the number of CLOs purchased, and (iii) $Log(1 + CLO\ Purchase)_{i,t}$ is the dollar value of CLO tranches purchased, in natural logarithm. $Insurer\ Operating\ CF_{i,t-4 \text{ to } t-1}$ is insurer i's operating cash flows from year–quarter $t-4$ to $t-1$ scaled by assets. α_i and α_t denote insurer and year–quarter fixed effects, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Effect of Insurers' Cash Flows on Their Bond Investments

	(1)	(2)
	Log(1+Bond Purchase)	
	Industrial	Government
Insurer Operating CF	0.67***	0.37**
	(0.21)	(0.18)
$\overline{y}$	2.18	.95
SD(x)	.08	.08
Insurer FE	Y	Y
Year–Quarter FE	Y	Y
Obs	16,502	16,502
Adj. R-squared	0.89	0.72

Notes: Table A2 analyzes the relationship between insurers' bond investments and their operating performance. The sample contains all insurers in the sample that had nonzero CLO holdings in the previous year. The specification is:

$$\text{Y}_{i,t} = \beta \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

$Y_{i,t}$ denotes outcomes for insurer i in year–quarter t. In Column (1), it is the dollar value of industrial and miscellaneous bonds purchased minus CLO purchases, in natural logarithm. In Column (2), it is the dollar value of government bonds purchased, in natural logarithm. $Insurer\ Operating\ CF_{i,t-4 \text{ to } t-1}$ is insurer i's operating cash flows from year–quarter $t-4$ to $t-1$ scaled by assets. α_i and α_t denote insurer and year–quarter fixed effects, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Effect of Insurers' Capital Supply to CLOs on Purpose of New Loans

	(1) General Purpose/ Investments	(2) Refinance/ Payouts	(3) LBO	(4) Others
Panel (A): 2SLS 2nd-Stage				
Relation Manager # CLO	0.24***	0.02	-0.17***	-0.09***
	(0.06)	(0.03)	(0.06)	(0.03)
$\overline{y}$	.45	.09	.39	.07
SD(x)	.37	.37	.37	.37
Firm FE	Y	Y	Y	Y
Industry×Year–Quarter FE	Y	Y	Y	Y
State×Year–Quarter FE	Y	Y	Y	Y
Kleibergen-Paap Wald rk F	256	256	256	256
Obs	38,084	38,084	38,084	38,084
Panel (B): Multinomial Logit—Marginal Effect at Mean				
Firm Exposure to Insurer CF	0.17***	0.05***	-0.20***	-0.01
	(0.02)	(0.01)	(0.02)	(0.01)
$\overline{y}$	0.45	0.09	0.39	0.07
SD(x)	0.27	0.27	0.27	0.27
Year–Quarter FE	Y	Y	Y	Y

Notes: Table A3 analyzes the purpose of new loans when their relationship CLO managers launch new CLOs. The 2SLS specification in Panel (A) is analogous to that in Table 6. The outcome variables are indicator variables that equal one if the firm obtained a leveraged loan with a stated purpose of General or Capital Investment in Column (1), Refinance in Column (2), LBO in Column (3), or Others in Column (4). In Panel (B), we use a multinomial logit model for estimation and report the marginal effects at mean. α_f and $\alpha_{j,t}$ denote fixed effects at firm and industry–year–quarter level, respectively. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4. CLO Manager Exposure to Insurer Cash Flows and New CLO Creation, Using Longer–Lagged Relationships

	(1) 1(CLO Launch)×100	(2) # CLO Launched×100	(3) Log(1+Launched Volume)×100
CLO Manager Exposure to Insurer CF	2.97***	3.78**	18.47***
(Using Long–Lagged Relationships)	(1.12)	(1.46)	(7.05)
$\overline{y}$	15.07	17.31	92.8
SD(x)	.51	.51	.51
Manager FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	13,418	13,418	13,418
Adj. R-squared	0.26	0.27	0.27

Notes: Table A4 analyzes the relation between CLO managers' exposure to relationship insurers' cash flows and their decision to launch a new CLO. The specification is the same as in Table 4. However, we use longer lags on insurer–manager relationship when constructing the CLO Manager Exposure variable. The specification is:

$$\text{CLO Issuance}_{m,t} = \beta \times \text{CLO Manager Exposure to Insurer CF}_{m,t-1} + \alpha_m + \alpha_t + \varepsilon_{m,t}$$

$CLO\ Issuance_{m,t}$ denotes outcomes of manager m in year–quarter t: (i) $1(CLO\ Launched)_{m,t}$ is an indicator for CLO issuance (multiplied by 100), (ii) $\#\ CLO\ Launched_{m,t}$ is the number of CLOs launched (multiplied by 100), and (iii) $Log(1 + Launched\ Volume)_{m,t}$ is the CLO issuance volume (in logs, multiplied by 100). $CLO\ Manager\ Exposure\ to\ Insurer\ CF_{m,t-1}$ is m's exposure to relationship insurers' cash flows in year–quarter $t-1$ as specified below, where the relationship is measured in year–quarter $t-9$:

$$\sum_i \left(\frac{\text{Insurer's CLO Holding}_{i,m,t-9}}{\text{Outstanding CLO Liabilities}_{m,t-9}} \times \text{Insurer Operating CF}_{i,t-4 \text{ to } t-1} \right).$$

α_m and α_t are the manager and year–quarter fixed effects. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. Standard errors are clustered at the manager level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Effect of Insurers' Capital Supply to CLOs on Firm Outcomes, Using Longer–Lagged Relationships

	(1)	(2)	(3)	(4)
	2SLS: 1st Stage	2SLS: 2nd Stage		
	Relation Manager # CLO	1(New Loan)×100	Log(Employment)	Log(Establishments)
Relation Manager # CLO		0.90***	0.18***	0.19***
		(0.32)	(0.05)	(0.03)
Firm Exposure to Insurer CF (Instrument Using Longer–Lagged Relationships)	0.71***			
	(0.01)			
$\overline{y}$	.09	3.5	5.81	2.02
SD(x)	.17	.3	.32	.32
Firm FE	Y	Y	Y	Y
Industry×Time FE	Y	Y	Y	Y
State×Time FE	Y	Y	Y	Y
Kleibergen-Paap Wald rk F		6,536	2,624	2,624
Obs	535,952	535,952	35,266	35,266

Notes: Columns (1) and (2) of Table A5 analyze firms' new loan issuance when their relationship CLO managers launch new CLOs. We use the 2SLS specification in Table 6. We use longer lags on insurer–manager and manager–firm relationships when constructing the instrument, *Firm Exposure to Insurer CF*. $Relation\ Manager\ \#\ CLO_{f,t}$ is the relationship–weighted–average number of CLO deals launched by f's relationship managers during t. Column (1) presents the first-stage results corresponding to Column (2). In columns (3) and (4), we use Log(Employment) and Log(Establishments) as outcome variables. The specification follows the 2SLS in Table 8. In (1) and (2), observations are at the firm–quarter level; "Time" in fixed effects denotes year–quarter. In (3) and (4), observations are at the firm–year level; "Time" in fixed effects denotes year. We use insurer–manager and manager–firm relationships 8-quarters before the insurer CF. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Effect of Insurers' Cash Flows on Their CLO Investments, Excluding Investment Income from Insurer Cash Flows

	(1) 1(CLO Purchase)	(2) # CLO Purchase	(3) Log(1+CLO Purchase)
Insurer CF Excluding Investment Inc	0.18***	0.57**	1.00***
	(0.06)	(0.23)	(0.30)
$\overline{y}$	.38	1	1.26
SD(x)	.08	.08	.08
Insurer FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	16,539	16,539	16,539
Adj. R-squared	0.39	0.47	0.51

Notes: Table A6 analyzes the relationship between insurers' CLO investments and their operating performance excluding insurers' net investment income. The sample contains all insurers in the sample that had nonzero CLO holdings in the previous year. The specification is:

$$\text{Insurer CLO Investment}_{i,t} = \beta \times \text{Insurer CF Excluding Investment Inc}_{i,t-4 \text{ to } t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

$Insurer\ CLO\ Investment_{i,t}$ denotes outcomes for insurer i in year–quarter t: (i) $1(CLO\ Purchase)_{i,t}$ is an indicator for a CLO purchase transaction, (ii) $\#\ CLO\ Purchase_{i,t}$ is the number of CLOs purchased, and (iii) $Log(1 + CLO\ Purchase)_{i,t}$ is the dollar value of CLO tranches purchased, in natural logarithm. $Insurer\ CF\ Excluding\ Investment\ Inc_{i,t-4 \text{ to } t-1}$ represents insurer i's operating cash flows after adding back policyholder dividends and netting out investment income from year–quarter $t-4$ to $t-1$ scaled by assets. α_i and α_t are insurer and year–quarter fixed effects. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7. CLO Manager Exposure to Insurer Cash Flows and New CLO Creation, Excluding Investment Income from Insurer Cash Flows

	(1) 1(CLO Launched)×100	(2) # CLO Launched×100	(3) Log(1+Launched Volume)×100
CLO Manager Exposure to Insurer CF	5.29**	5.56**	30.25**
(Excluding Investment Income)	(2.18)	(2.64)	(13.63)
$\overline{y}$	15.11	17.35	93.09
SD(x)	.2	.2	.2
Manager FE	Y	Y	Y
Year–Quarter FE	Y	Y	Y
Obs	13,416	13,416	13,416
Adj. R-squared	0.26	0.27	0.27

Notes: Table A7 analyzes the relation between CLO managers' exposure to relationship insurers' cash flows and their decision to launch a new CLO, excluding insurers' net investment income. We calculate manager exposure using insurer operating CF after adding back policyholder dividends and netting out investment income. The specification is:

$$\text{CLO Issuance}_{m,t} = \beta \times \text{CLO Manager Exposure}_{m,t-1} + \alpha_m + \alpha_t + \varepsilon_{m,t}$$

$CLO\ Issuance_{m,t}$ denotes outcomes of manager m in year–quarter t: (i) $1(CLO\ Launched)_{m,t}$ is an indicator for CLO issuance (multiplied by 100), (ii) $\#\ CLO\ Launched_{m,t}$ is the number of CLOs launched (multiplied by 100), and (iii) $Log(1 + Launched\ Volume)_{m,t}$ is the CLO issuance volume (in logs, multiplied by 100). $CLO\ Manager\ Exposure_{m,t-1}$ is m's exposure to relationship insurers' cash flows (after adding back policyholder dividends and netting out investment income) in year–quarter $t-1$. α_m and α_t are the manager and year–quarter fixed effects. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. Standard errors are clustered at the manager level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8. Effect of Insurers' Capital Supply to CLOs on Firm Outcomes, Excluding Investment Income from Insurer Cash Flows

	(1)	(2)	(3)	(4)
	2SLS: 1st Stage	2SLS: 2nd Stage		
	Relation Manager # CLO	1(New Loan) × 100	Log(Employment)	Log(Establishments)
Relation Manager # CLO		2.94***	0.23***	0.23***
		(0.71)	(0.08)	(0.05)
Firm Exposure to Insurer CF (Excluding Investment Income)	0.54***			
	(0.01)			
$\overline{y}$	.09	3.5	5.81	2.02
SD(x)	.09	.3	.32	.32
Firm FE	Y	Y	Y	Y
Industry×Time FE	Y	Y	Y	Y
State×Time FE	Y	Y	Y	Y
Kleibergen-Paap Wald rk F		1,512	682	682
Obs	535,952	535,952	35,266	35,266

Notes: Columns (1) and (2) of Table A8 analyze firms' loan issuance when their relationship CLO managers launch new CLOs, excluding insurers' net investment income in the construction of the instrument. We use the 2SLS specification similar to Table 6. $1(Loan\ Issuance)_{f,t}$ is an indicator for when firm f in industry j and state s takes a new leveraged loan during year–quarter t (multiplied by 100). $Relation\ Manager\ \#\ CLO_{f,t}$ is the relationship–weighted–average number of CLO deals launched by f's relationship managers during time t. Column (1) presents the first-stage results corresponding to Column (2). In columns (3) and (4), we use Log(Employment) and Log(Establishments) as outcome variables. The specification follows the 2SLS in Table 8. We add back policyholder dividends and exclude net investment income from insurer operating CF when constructing the instrument, *Firm Exposure to Insurer CF*. In (1) and (2), observations are at the firm–quarter level; "Time" in fixed effects denotes year–quarter. In (3) and (4), observations are at the firm–year level; "Time" in fixed effects denotes year. $\overline{y}$ indicates the averages of the outcome variables. SD(x) indicates the standard deviation of the main independent variable. We cluster standard errors at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.