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Supervised Project

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Deciphering the CLO Enigma: A study on the influence of CLO involvement in syndicated loans

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Abstract

Collateralized Loan Obligations (CLOs), known for their complexity, are vital in the world of structured finance, constituting about 62% of outstanding leveraged loans[3]. This prominence, highlighted by Federal Reserve Chairman Jerome Powell, mirrors a broader industry shift where banks have moved from an "originate-to-retain" to an "originate-to-distribute" model. CLOs play a central role in diversifying liquidity and credit risks, reducing banks' direct exposure to these risks. However, this shift has also introduced complexities, increasing the opacity of financial shock transmission channels and introducing new vulnerabilities[2].

Building on the findings of Zhang and Zhang[4], which highlight the relationship between higher CLO ownerships and lower interest rate spreads, increased loan secondary market liquidity, and positive impacts on corporate investments, this study aims to further explore the role of CLOs in syndicated loans, delving into their effects on the structure of the syndicated loan, and lender-borrower relationships.

The results reveal that the presence of collateral, longer loan maturities, and dividend restrictions are strongly associated with CLO involvement. CLO-involved loans exhibit a higher number of covenants, particularly in specific loan types, reflecting enhanced risk management and monitoring practices. The study also highlights the distinct patterns of loan purposes associated with CLO participation and the effectiveness of advanced modeling techniques in capturing the complex relationships between loan characteristics and CLO involvement.

Key words: Collateralized Loan Obligations, CLO, Syndicated Loan, Securitization, Loan characteristics.

1 Introduction:

The world of financial risk management is continuously evolving, and Collateralized Loan Obligations (CLOs) are emerging as a significant focal point due to their complex structure and substantial impact on the financial markets. CLOs are a type of structured financial instrument that pool together multiple leveraged loans *(loans provided to companies or individuals with poor credit histories or high debt levels)* and repackage them into tranches that are sold to investors. Each tranche offers a different level of risk and return, appealing to a diverse range of investors with varying risk appetites.

The origin and rise of CLOs can be traced back to the transformation in banking practices, moving from the traditional "originate-to-retain" model, where banks originated loans and held them on their balance sheets, to the "originate-to-distribute" model. In this new paradigm, banks and other financial institutions distribute the risk of the loans they originate by pooling them into CLOs and other similar instruments, and then selling these tranches to investors. This shift has had profound implications on how risk is distributed and managed in the financial system, making it a subject of critical importance for risk management professionals.

However, the rapid growth and intricate nature of the CLO market have also raised concerns about the potential risks and uncertainties associated with these instruments. The opaque structure of CLOs, coupled with the inherent complexity of the underlying loans, has led to a lack of transparency and a limited understanding of the factors driving CLO performance and their impact on the broader financial system.

Collateralized Loan Obligations (CLOs), are vital in the world of structured finance and constitute about 62% of outstanding leveraged loans. CLOs have gained prominence due to their substantial role in funding leveraged loans, significantly shaping the landscape of corporate borrowing. The growth of CLOs, particularly post-2008 financial crisis, has raised questions about their inherent risks and stability, especially in the face of economic downturns. The resilience of these instruments during times of financial stress, such as the Covid-19 pandemic, brings to light their complex structure and the underlying risk dynamics.

This report aims to shed light on the CLO enigma by conducting a comprehensive and rigorous analysis of the factors influencing CLO involvement in syndicated loans. By examining the characteristics of loans that attract CLO investment, the covenant structures associated with CLO-involved loans, and the purpose of these loans, this study seeks to provide valuable insights into the complex dynamics of the CLO market.

Understanding the factors that drive CLO involvement in syndicated loans is crucial for several reasons. First, it can help borrowers and lenders make informed decisions about financing options and risk management strategies. By identifying the loan characteristics and covenant structures that are attractive to CLOs, borrowers can structure their loans in a way that optimizes their access to capital, while lenders can assess the potential risks and rewards associated with CLO-involved loans.

Second, insights into CLO involvement can aid investors in making sound investment decisions and constructing diversified portfolios. By understanding the factors that influence CLO performance and the potential risks associated with these instruments, investors can make more informed choices about allocating their capital and managing their exposure to the CLO market.

Third, a deeper understanding of CLOs and their impact on the syndicated loan market is essential for policymakers and regulators. As the CLO market continues to grow and evolve, it is crucial to develop appropriate regulatory frameworks and supervisory practices that ensure the stability and resilience of the financial system. By shedding light on the complex dynamics of the CLO market, this project can contribute to the development of evidence-based policies and regulations that promote transparency, mitigate systemic risks, and protect the interests of all stakeholders.

To unravel the CLO enigma, this project employs a comprehensive and multi-faceted research approach. The study leverages a rich dataset of syndicated loans, comprising a diverse range of loan characteristics, covenant structures, and CLO involvement. By applying rigorous statistical methods, including summary statistics, t-tests, correlation analysis, and various regression techniques such as OLS, IV-GMM, IV-LIML, and logistic regression, this project aims to provide a robust and academically sound analysis of the factors influencing CLO participation.

The report begins by providing a thorough review of the existing literature on CLOs and syndicated loans, highlighting the gaps in current research and the need for a more comprehensive understanding of the CLO market. It then delves into the data and methodology employed in the study, describing the dataset, the variables of interest, and the statistical techniques used to analyze the data.

The core of the report presents the empirical results and discusses the key findings. Through a series of statistical analyses, the study identifies the loan characteristics that are most strongly associated with CLO involvement, such as the presence of collateral, longer loan maturities, and dividend restrictions. It also examines the differences in covenant structures between CLO-involved loans and non-CLO loans, shedding light on the enhanced risk management and monitoring practices associated with CLO investments. Furthermore, the report explores the heterogeneity in loan purposes across different loan types and the distinct patterns associated with CLO involvement. By employing advanced modeling techniques, such as logistic regression with SMOTE oversampling and L2 regularization, the study demonstrates the effectiveness of these methods in capturing the complex relationships between loan characteristics and CLO participation.

The report also acknowledges the limitations of the study, particularly in terms of the data sample, where CLO-involved loans constitute a relatively small proportion of the total observations. It discusses the potential impact of this limitation on the generalizability of the findings and highlights the efforts made to mitigate these challenges through techniques such as propensity score matching, regularization, and oversampling.

Finally, the report concludes by summarizing the key insights gained from the analysis and discussing the implications of the findings for various stakeholders, including borrowers, lenders, investors, policymakers, and researchers. It emphasizes the importance of ongoing research and the need for more comprehensive and representative data to fully unravel the complexities of the CLO market.

Ultimately, a deeper understanding of CLOs and their role in the syndicated loan market is essential for promoting the stability, efficiency, and resilience of the financial system in the face of the ever-evolving complexities of the modern financial landscape.

2 Literature Review:

Collateralized Loan Obligations (CLOs) have emerged as a crucial component of the syndicated loan market, with their holdings accounting for approximately 75% of all new institutional leveraged loans as of 2021 (Kundu, 2022) [2]. The existing theory on CLOs delves into their unique structure, the economic channels through which they influence borrowing costs and investment decisions, and the potential implications for financial stability.

The foundation of CLO theory lies in the concept of securitization, whereby a portfolio of leveraged loans is pooled, tranched, and sold to investors as structured products (Martin and Sayrak, 2022) [3]. A typical CLO transaction involves the creation of a special purpose vehicle (SPV) that issues a hierarchy of notes, with the most common structure consisting of AAA (62%), AA (13%), A (8%), BBB (6%), BB (3%), and equity (8%) tranches (Kundu, 2022). The cash flows from the underlying loan portfolio, which typically comprises 150-300 distinct borrowers across 20-30 industries, are distributed to investors based on the seniority of their claims (Martin and Sayrak, 2022). The tranching mechanism allows for the creation of highly-rated securities from a pool of lower-quality loans, as the equity tranche absorbs initial losses and provides a buffer for the senior tranches. Over-collateralization, a key feature of CLOs, ensures that the par value of the loan portfolio exceeds the par value of the issued debt tranches, with the degree of over-collateralization ranging from 5% to 10% (Kundu, 2022).

The theoretical framework highlights two primary economic channels through which CLOs influence the syndicated loan market: the market segmentation/rating transformation channel and the information production channel (Zhang and Zhang, 2023) [4]. The market segmentation/rating transformation channel suggests that CLOs help bridge the gap between speculative-grade borrowers and risk-averse investors. Zhang and Zhang (2023) find that a one standard deviation increase in the share of a loan held by triple-A CLO investors (17.75%) is associated with a 19 basis point decrease in loan spreads, compared to a 10.64 basis point decrease for a similar increase in overall CLO ownership. This finding underscores the importance of the rating transformation function in expanding the investor base and reducing borrowing costs.

The information production channel emphasizes the role of CLOs in mitigating information asymmetries. Zhang and Zhang (2023) show that the impact of CLO ownership on loan spreads is more pronounced for private firms and firms with higher analyst forecast dispersion. A one standard deviation increase in CLO ownership is associated with a 13 basis point decrease in loan spreads for private firms, compared to a 7 basis point decrease for public firms. Furthermore, borrowers with higher CLO ownership exhibit a 1.5 to 1.7 percentage point increase in post-loan capital expenditures, indicating that loan securitization has real economic effects by relaxing financial constraints.

Covenants play a crucial role in shaping the behavior of CLO managers and ensuring the integrity of the structure (Kundu, 2022). The distance to covenant thresholds varies across different types of covenants, with the median distance being 3.09% for the Interest Diversion (ID) threshold, 4.14% for the Junior overcollateralization (OC) threshold, and 7.95% for the Senior OC threshold (Kundu, 2022). Covenant breaches lead to the diversion of cash flows from subordinated tranches to senior noteholders or to the acquisition of additional collateral.

Giannetti and Meisenzahl (2021) [1] investigate the relationship between CLO ownership, syndicate concentration, and loan performance. They find that a one standard deviation increase in the share of lenders exposed to downgrades in unrelated industries leads to a 0.06 standard deviation increase in syndicate concentration. Using an instrumental variables approach, they show that loans with more dispersed ownership are 3 percentage points less likely to be amended and 4 percentage points more likely to experience further downgrades.

The theoretical framework also acknowledges the potential risks and vulnerabilities associated with the growth of CLOs. The share of cov-lite loans, which lack traditional maintenance covenants, has increased from 29% in 2007 to 85% in 2019 (Kundu, 2022). Moreover, the reliance on the financial health of CLO investors, as measured by the share of lenders exposed to downgrades in unrelated industries, can introduce fragilities into the system (Giannetti and Meisenzahl, 2021).

In conclusion, the existing theory on CLOs provides a comprehensive framework for understanding the complex interactions between these structured products and the syndicated loan market. The theoretical and empirical evidence highlights the economic channels through which CLOs influence borrowing costs and investment decisions, while also acknowledging the potential risks and vulnerabilities associated with this form of securitization. As the CLO market continues to evolve, with global CLO issuance reaching $185 billion and the total outstanding amount surpassing $1 trillion in 2021 (Kundu, 2022), ongoing research is crucial to refine and extend the theoretical underpinnings, informing policy decisions and contributing to the effective functioning of the financial system.

3 Methodology:

Data Collection

The empirical foundation of this study is built upon a comprehensive suite of datasets, each capturing a distinct facet of the loan origination and execution process. The primary data sources include lender profiles (`lender_info_df`), shareholder dynamics (`lendershares_df`), credit facility specifications (`facility_df`), financial package characteristics (`package_df`), loan performance indicators (`performance_df`), pricing strategies (`pricing_df`), granular loan agreement details (`dealscan_df`), and loan covenant provisions (`covenants_df`). These datasets were obtained through Compustat and Dealscan, with access facilitated by the author's academic advisor. Renowned for their exhaustive coverage and accuracy, these data repositories provide a robust basis for the analyses conducted in this thesis.

Data Processing

Before the main analysis, the datasets underwent a rigorous data cleaning and preprocessing phase to ensure data integrity and suitability for subsequent analyses. This involved identifying and addressing missing data points, anomalous patterns, and potential outliers. Missing data were estimated using appropriate imputation techniques, while extraneous data points were removed, and inconsistencies were reconciled.

Data Integration

To enable a comprehensive examination of the relationships between lender characteristics, loan terms and conditions, covenants, and performance metrics, the disparate datasets were integrated through a series of merging operations.

Lender Data Integration: The `lender_info_df` and `lendershares_df` datasets were combined to create `lender_merged`, which provides a consolidated view of lender profiles and their shareholder composition. This integration allows for a nuanced understanding of the key actors in the loan origination process.

Facility and Package Synthesis: The `facility_df` and `package_df` datasets were merged to form `facility_package_merged`, enabling a comprehensive analysis of loan offerings by combining the granular details of individual credit facilities with the overarching characteristics of the corresponding financial packages.

Performance and Pricing Correlation: To investigate the interplay between pricing strategies and loan performance, the `performance_df` and `pricing_df` datasets were merged, resulting in `performance_pricing_merged`. This integration is instrumental in examining the relationship between pricing decisions and their financial outcomes.

Dealscan Data Integration: The `performance_pricing_merged` dataset was further enriched by incorporating comprehensive loan agreement data from Dealscan, yielding `performance_pricing_dealscan`. This augmented dataset contains a wide array of variables essential for evaluating the alignment of loan agreements with market dynamics and performance indicators.

Covenant Impact Assessment: To assess the role of covenants in shaping loan agreements and borrower behavior, the `covenants_df` and `package_df` datasets were merged, creating `covenants_facility_package`. This integration facilitates the examination of covenant influence on loan structuring and borrower conduct.

The culmination of these data integration steps is the master dataset, `Merged_DF`, which serves as the central repository for the subsequent analyses. This comprehensive dataset amalgamates the various dimensions of loan origination, pricing, performance, and covenant provisions, providing a rich foundation for the in-depth investigations that follow.

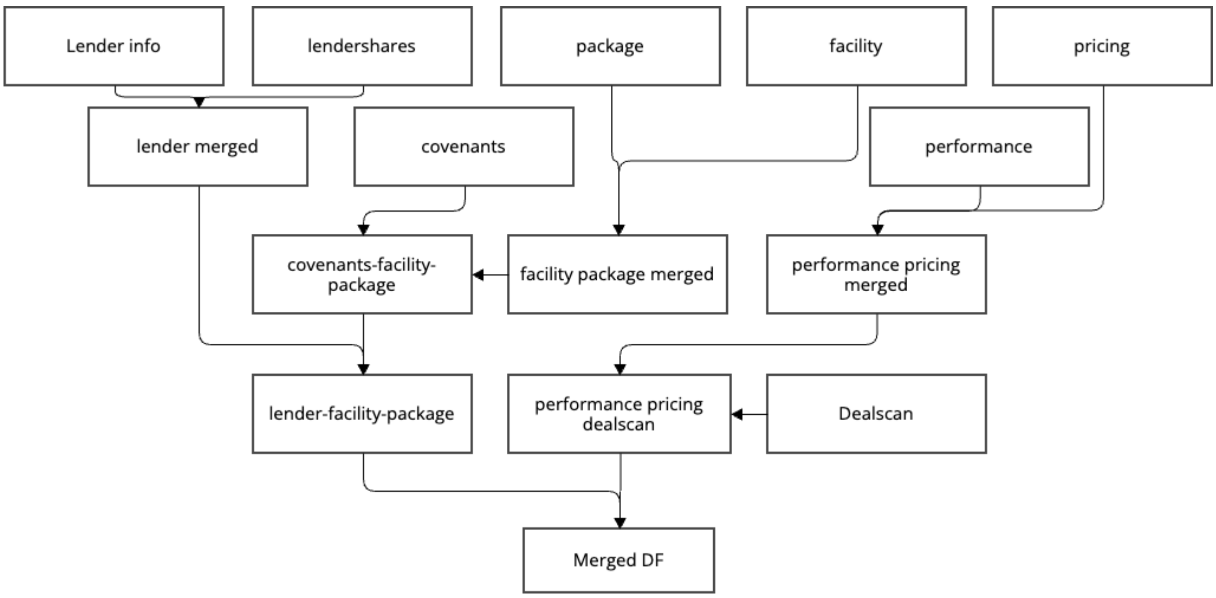

Figure 1 – Datamerging conceptual framework.

Figure 1 presents a conceptual framework that encapsulates the data merging process employed in this study, highlighting the key datasets and their links.

I then merged the compustat data with the merged_df to obtain columns such as 'ROA', 'Book Leverage', 'Z-Score'.

The formula for Return on Assets (ROA) is given by:

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}}$$

The formula for Book Leverage is given by:

$$\text{Book Leverage}_t = \frac{\text{Short-term Debt}_t(\text{DLCq}) + \text{Long-term Debt}_t(\text{DLTTq})}{\text{Book Value of Total Assets}_t(\text{ATq})}$$

The Altman Z-Score formula is expressed as:

$$\begin{aligned}\text{Z-Score} = 1.2\left(\frac{\text{Working Capital}}{\text{Total Assets}}\right) + 1.4\left(\frac{\text{Retained Earnings}}{\text{Total Assets}}\right) \\ + 3.3\left(\frac{\text{Earnings Before Interest and Tax}}{\text{Total Assets}}\right) + 0.6\left(\frac{\text{Market Value of Equity}}{\text{Total Liabilities}}\right) \\ + 1.0\left(\frac{\text{Sales}}{\text{Total Assets}}\right).\end{aligned}$$

Statistical Processes

The dataset used in this research comprises a large sample of syndicated loans, including information on CLO involvement, loan characteristics, and borrower attributes. To gain a comprehensive understanding of the impact of CLOs, a multi-faceted approach involving summary statistics, t-tests, correlation analysis, and various regression models were employed.

I begin by presenting summary statistics to provide an overview of the key variables in our dataset, comparing loans with and without CLO involvement. T-tests are then conducted to determine the statistical significance of the differences observed between these two groups.

Next, I delve deeper into the relationships between variables using correlation analysis, which helps identify potential multicollinearity issues and informs our selection of variables for the regression models.

To quantify the impact of CLO involvement on loan characteristics, I employ several regression techniques. Ordinary Least Squares (OLS) regression serves as our baseline model, providing initial insights into the relationships between CLO participation and loan features. However, to address potential endogeneity concerns, we also utilize Instrumental Variable (IV) estimation methods, specifically the Generalized Method of Moments (GMM) and Limited Information Maximum Likelihood (LIML) approaches. These methods allow us to account for the potential endogeneity of the facility amount variable by using an appropriate instrument.

Furthermore, we employ logistic regression to model the binary outcome of CLO involvement, enabling us to identify the key factors that influence the likelihood of CLO participation in a syndicated loan.

To ensure the robustness of our findings, we perform additional checks, including propensity score matching to mitigate selection bias, regularization techniques to handle multicollinearity, and cross-validation to assess the predictive accuracy of our models.

Propensity Score Matching (PSM) and regularization techniques are the tools employed in this study to enhance the robustness and reliability of my findings on the impact of CLO involvement in syndicated loans.

Propensity Score Matching is a statistical method used to mitigate selection bias in observational studies. In the context of my research, PSM allows us to create a balanced sample of loans with and without CLO involvement, ensuring that the two groups are comparable in terms of their observable characteristics. By matching loans based on their propensity scores, which represent the probability of CLO participation given a set of covariates, we can isolate the effect of CLO involvement on loan characteristics more effectively.

The PSM process involves several steps. First, I estimate the propensity scores using a logistic regression model, with CLO involvement as the dependent variable and a carefully selected set of loan and borrower characteristics as predictors. Next, I match loans with similar propensity scores using techniques such as nearest-neighbor matching. This process creates a balanced sample, where the distribution of covariates is similar between the treatment group (loans with CLO involvement) and the control group (loans without CLO involvement).

By applying PSM, we can more confidently attribute the observed differences in loan characteristics to the presence of CLO involvement, rather than to other confounding factors. This technique enhances the internal validity of our study and strengthens the causal inferences we can draw from our results.

Regularization techniques, on the other hand, are employed to address potential issues of multicollinearity and overfitting in our regression models. Multicollinearity occurs when predictor variables are highly correlated with each other, which can lead to unstable and unreliable coefficient estimates. Overfitting refers to the situation where a model fits the noise in the data rather than the underlying patterns, resulting in poor generalization to new data.

To tackle these issues, we employ two commonly used regularization methods: L1 regularization (Lasso) and L2 regularization (Ridge). These techniques add a penalty term to the regression objective function, constraining the magnitude of the coefficients and shrinking them towards zero.

L1 regularization, also known as Lasso, adds the absolute values of the coefficients to the penalty term. This approach has the effect of setting some coefficients exactly to zero, effectively performing feature selection by identifying the most important variables. Lasso is particularly useful when dealing with high-dimensional data or when there is a suspicion that only a subset of the predictors are truly relevant.

L2 regularization, or Ridge regression, adds the squared values of the coefficients to the penalty term. Unlike Lasso, Ridge regression does not perform feature selection but instead shrinks the coefficients of correlated predictors towards each other. This technique is beneficial when there are many correlated predictors, and the goal is to maintain stability and improve the model's generalization ability.

By incorporating regularization techniques into our regression models, we can mitigate the impact of multicollinearity and reduce the risk of overfitting. This approach leads to more stable and interpretable coefficient estimates, enhancing the reliability of our findings on the influence of CLO involvement on syndicated loan characteristics.

To assess the effectiveness of our PSM and regularization techniques, I employ cross-validation methods. By partitioning our data into training and validation sets, we can evaluate the performance of our models on unseen data and ensure that they generalize well. Cross-validation helps us strike a balance between model complexity and predictive accuracy, further bolstering the robustness of our results.

4 Discussion:

4.1 Summary Statistics:

Table 1 – Distinct Counts for CLO, CDO and All Loans

Identifier	CLO	CDO	Total
COMPANYID	74	48	6681
BORROWERCOMPANYID	225	133	24 575
PACKAGEID	269	148	61 571
FACILITYID	367	185	90 968

In the process of data cleansing and identification of CLO participation among facilities, it was observed that a subset of 367 facilities, out of a comprehensive dataset comprising 90,968 facilities, were engaged in CLO activities. This finding translates to a CLO involvement rate of approximately 0.4%.

Diving a bit deeper into the Lender statistics, I found that 47 lenders have issued exactly 1 CLO in the time period under consideration. I have also added a table that shows the top 10 CLO issuers and the number of CLOs they have issued:

Lender Name	**Count**
Van Kampen CLO I Ltd	55
Stanfield CLO Ltd	43
Galaxy CLO	40
Galaxy CLO 1999-1 Ltd	32
Pilgrim CLO 1999 1 Ltd	30
Franklin CLO II Ltd	29
Stein Roe & Farnham CLO I Ltd	28
Van Kampen CLO II Ltd	25
Flagship CLO-2001-1	24
ML CLO XV Pilgrim America (Cayman) Ltd	24

Table 2 – Top 10 Lenders by CLOs Issued

4.2 Loan Characteristics:

This study conducted a comprehensive examination of loan characteristics by comparing syndicated loans involving collateralized loan obligations (CLOs) and collateralized debt obligations (CDOs) to syndicated loans without such securitization vehicles as well as non-syndicated loans. The analysis spanned multiple dimensions, including loan amount, maturity, and pricing, across four distinct categories - CLO syndicated loans, CDO syndicated loans, syndicated loans without CLO/CDO involvement, and non-syndicated loans.

The findings revealed notable differences in the typical loan specifications associated with CLO and CDO participation. Loans syndicated with the involvement of CLOs exhibited markedly larger disbursement sizes, with mean and median DEALAMOUNT of $559 million and $350 million respectively - substantially exceeding those of the other categories examined. CDO syndicated loans also tended toward larger transactions, though slightly trailing the CLO figures. In stark contrast, non-syndicated credits reflected considerably smaller average ($137 million) and median ($21 million) disbursement levels.

With regard to maturity profiles, CLO-syndicated facilities again stood out by offering extended tenors. The mean and median maturities clocked in at a substantial 64.87 months and 68 months respectively for CLO transactions. CDO-linked loans followed a comparable, albeit slightly shorter, maturity pattern with a mean of 60.11 months. Non-syndicated loans assumed an intermediate maturity positioning, while non-syndicated borrowings exhibited the shortest average (55 months) and median (36 months) terms.

Lastly, the analysis unveiled pricing dynamics that favoured CLOs and CDOs extracting relatively rich compensation for their participation. As shown in table 6, CLO and CDO syndicated loans commanded premium interest rate spreads, averaging 257.78 basis points and 259.44 basis points respectively over benchmark rates. The median spreads for these securitized products centred at 250 basis points. Contrastingly, syndicated transactions without CLO/CDO involvement attained meaningfully lower average (183 bps) and median (175 bps) pricing, though still exceeding the spreads garnered by non-syndicated lending. This is different from the literature we have seen in Zhang and Zhang since they found CLOs to be associated with lower interest rates. I believe this discrepency is linked to the difference in data samples used for the project.

In summary, the findings indicate a notable premium associated with CLO and CDO participation in the syndicated lending space. This manifested through larger loan sizes, longer-dated maturities, and richer pricing metrics compared to both syndicated and non-syndicated debt obligations lacking such securitization links. The results highlight the extent to which securitization vehicles, particularly CLOs, facilitate the extension of amplified credit provisioning over protracted tenors at elevated risk premiums relative to broader lending practices. As such, the analysis sheds light on the distinctive implications and dynamics inherent to the CLO/CDO spheres within the corporate debt markets.

4.3 Covenant Count and Loan Purpose:

The summary statistics and t-test results presented in Tables 7, 8, and 9 offer valuable insights into the differences in covenant counts and loan purposes across various loan types. These findings contribute to a more comprehensive understanding of the loan market's complexities and the unique characteristics of each loan type.

Table 7 highlights that CLO and CDO loans have a higher average number of covenants (3.11 and 3.03, respectively) compared to the overall average of 0.94. This observation suggests that CLO and CDO loans are associated with more restrictive covenants, which could be attributed to the higher risk profile of these loan types. Lenders may impose more covenants on CLO and CDO loans to mitigate potential risks and protect their interests.

Diving deeper into the differences in covenant counts, Table 8 presents the results of t-tests comparing CLO/CDO loans with other loan types. The findings reveal statistically significant differences, with certain term loan types, such as Term Loan B, Term Loan C, Term Loan D, and Term Loan F, exhibiting significantly higher covenant counts compared to CLO/CDO loans. The differences in covenant counts range from 1.67 to 4.19, indicating that these term loan types have more stringent covenants in place. This observation aligns with the notion that loans with higher risk profiles tend to have more covenants to safeguard lenders' interests and manage potential risks effectively. These findings underscore the heightened level of creditor protection and monitoring associated with CLO-participated loans, particularly for specific loan types.

Shifting the focus to loan purposes, Table 9 examines the differences in the DIFFPURPOSE variable across loan types. The t-test results uncover statistically significant differences for some loan types. Notably, Term Loan A and Term Loan C have significantly lower DIFFPURPOSE values compared to CLO/CDO loans, implying that these loan types are more likely to be used for specific, well-defined purposes. Conversely, Term Loan B and Revolver/Line < 1 Yr. exhibit significantly higher DIFFPURPOSE values, suggesting a greater diversity in loan purposes for these loan types. This finding highlights the importance of considering the intended use of funds when evaluating different loan types and their associated risks.

Table 10 focuses on the primary purposes of syndicated loans without CLO involvement. It is observed that the most common primary purpose varies depending on the loan type. For instance, among 364-Day Facilities, the most frequent primary purpose is "CP backup," while for Term Loans, "Corp. purposes" is the most prevalent. This heterogeneity in primary purposes highlights the diverse needs and objectives of borrowers in the syndicated loan market.

The dominance of "Corp. purposes" as the top primary purpose is evident across many loan types, such as Revolver/Line >= 1 Yr., Term Loan, Term Loan A, and Term Loan B. This finding suggests that a significant portion of syndicated loans without CLO participation is used for general corporate purposes, providing flexibility to borrowers in their financial management.

However, some loan types exhibit distinct patterns in their primary purposes. For example, Bridge Loans are most commonly used for "Takeover" purposes, while Standby Letters of Credit predominantly serve "Corp. purposes." These variations underscore the specialized nature of certain loan types and their roles in facilitating specific corporate actions or transactions.

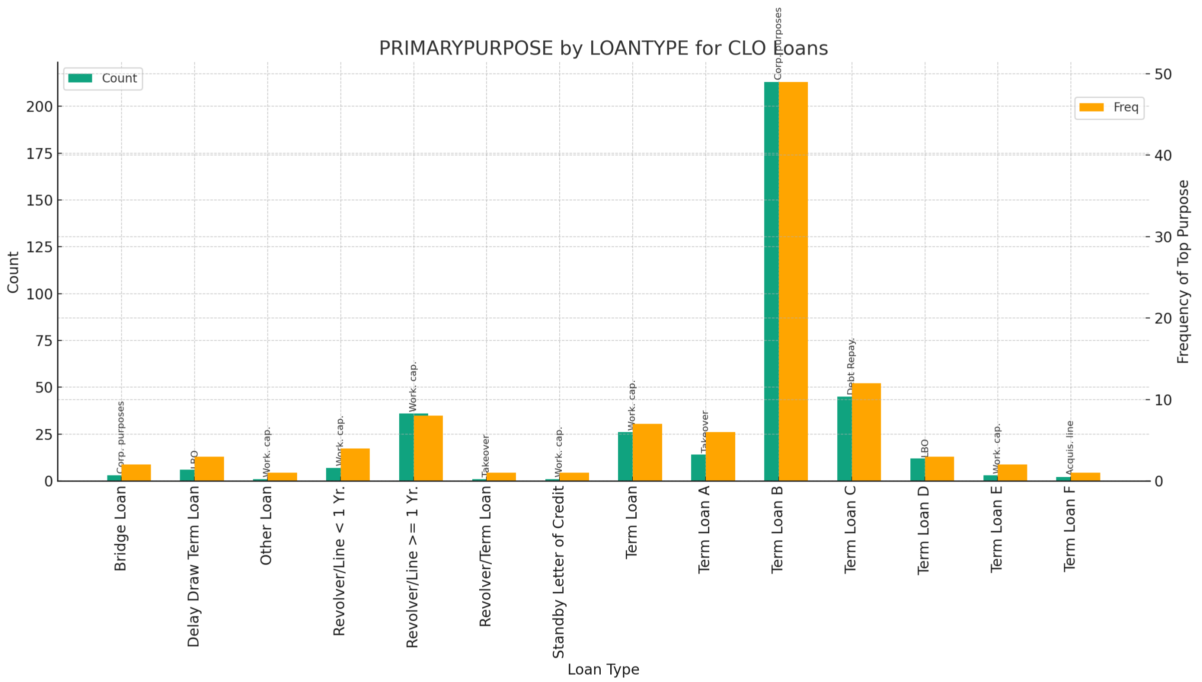

Figure 2 – Primary Purpose by Loantype for CLO loans

Shifting the focus to Table 11, which presents the primary purposes of syndicated loans with CLO participation, a different picture emerges. The most striking observation is the prominence of "Corp. purposes" and "Work. cap." as the top primary purposes across multiple loan types. This finding indicates that CLO-participated loans are more frequently used for general corporate purposes and working capital needs compared to non-CLO loans.

Some loan types, such as Term Loan A and Term Loan C, have "Takeover" and "Debt Repay." as their most common primary purposes, respectively, in CLO-participated loans. This suggests that CLO involvement may be associated with specific corporate actions, such as acquisitions and debt restructuring, for certain loan types.

The comparative analysis of Tables 10 and 11 reveals notable differences in the distribution of primary loan purposes between syndicated loans with and without CLO participation. CLO-participated loans appear to be more concentrated in general corporate purposes and working capital needs, while non-CLO loans exhibit a wider range of primary purposes tailored to specific loan types and borrower requirements.

These findings raise important questions about the potential impact of CLO involvement on the nature and use of syndicated loans. The predominance of general corporate purposes in CLO-participated loans may reflect the preferences of CLO managers and investors, who may favour loans with more flexible use of proceeds. Alternatively, it could be indicative of the types of borrowers and industries that attract CLO investment.

These findings contribute to a deeper understanding of the complex dynamics at play in the CLO market and their implications for the broader syndicated loan landscape. The higher covenant counts in CLO-participated loans suggest a greater emphasis on creditor protection and risk mitigation, which may have both positive and negative consequences for borrowers and investors alike.

Moreover, the statistically significant differences in covenant counts and loan purposes emphasize the importance of comprehensive risk management practices. The mixed results regarding loan purposes highlight the need for further research to unravel the factors driving these differences and their potential impact on loan performance and market stability.

4.4 Syndicate Structure:

The analysis of the syndicate structure reveals notable differences between syndicates with and without the involvement of Collateralized Loan Obligations (CLOs) and Collateralized Debt Obligations (CDOs). The average number of lenders in syndicates with CLO involvement is 1.02, while it is 1.00 for syndicates with CDO involvement. In contrast, the overall average number of lenders in syndicated loans is slightly higher at 1.08. This suggests that the presence of CLOs and CDOs in a syndicate may lead to a more concentrated lending structure, with fewer participating lenders compared to the overall syndicated loan market.

Furthermore, the distribution of lender types varies significantly between syndicates with CLO and CDO involvement and the overall syndicated loan market. Finance Companies and Institutional Investors, particularly those focused on CDOs, constitute a larger proportion of lenders in syndicates with CLO and CDO involvement. In contrast, traditional banks, such as US Banks, Western European Banks, and Investment Banks, dominate the overall syndicated loan market.

The concentration of lenders in syndicates also exhibits distinct patterns. Syndicates with CLO involvement have a high concentration of single-lender arrangements, with 98.88% of syndicates having only one lender. Similarly, syndicates with CDO involvement are exclusively single-lender arrangements. In comparison, the overall syndicated loan market has a slightly lower concentration, with 96.70% of syndicates having a single lender, and a small percentage of syndicates involving multiple lenders.

4.5 Lender Analysis:

Table 10 focuses on the primary purposes of syndicated loans without CLO involvement. It is observed that the most common primary purpose varies depending on the loan type. For instance, among 364-Day Facilities, the most frequent primary purpose is "CP backup," while for Term Loans, "Corp. purposes" is the most prevalent. This heterogeneity in primary purposes highlights the diverse needs and objectives of borrowers in the syndicated loan market.

Notably, the dominance of "Corp. purposes" as the top primary purpose is evident across many loan types, such as Revolver/Line >= 1 Yr., Term Loan, Term Loan A, and Term Loan B. This finding suggests that a significant portion of syndicated loans without CLO participation is used for general corporate purposes, providing flexibility to borrowers in their financial management.

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Shifting the focus to Table 11, which presents the primary purposes of syndicated loans with CLO participation, a different picture emerges. The most striking observation is the prominence of "Corp. purposes" and "Work. cap." as the top primary purposes across multiple loan types. This finding indicates that CLO-participated loans are more frequently used for general corporate purposes and working capital needs compared to non-CLO loans.

Interestingly, some loan types, such as Term Loan A and Term Loan C, have "Takeover" and "Debt Repay." as their most common primary purposes, respectively, in CLO-participated loans. This suggests that CLO involvement may be associated with specific corporate actions, such as acquisitions and debt restructuring, for certain loan types.

The comparative analysis of Tables 10 and 11 reveals notable differences in the distribution of primary loan purposes between syndicated loans with and without CLO participation. CLO-participated loans appear to be more concentrated on general corporate purposes and working capital needs, while non-CLO loans exhibit a wider range of primary purposes tailored to specific loan types and borrower requirements.

These findings from raise important questions about the potential impact of CLO involvement on the nature and use of syndicated loans. The predominance of general corporate purposes in CLO-participated loans may reflect the preferences of CLO managers and investors, who may favour loans with more flexible use of proceeds. Alternatively, it could be indicative of the types of borrowers and industries that attract CLO investment.

The concentration of finance companies and institutional investors in CLO and CDO-involved syndicates could be considered impactful for the implications on loan pricing, risk assessment, and market stability. The specialized expertise and risk appetites of these lenders may influence the terms and conditions of the loans they participate in, potentially leading to differences in loan characteristics compared to the broader syndicated loan market.

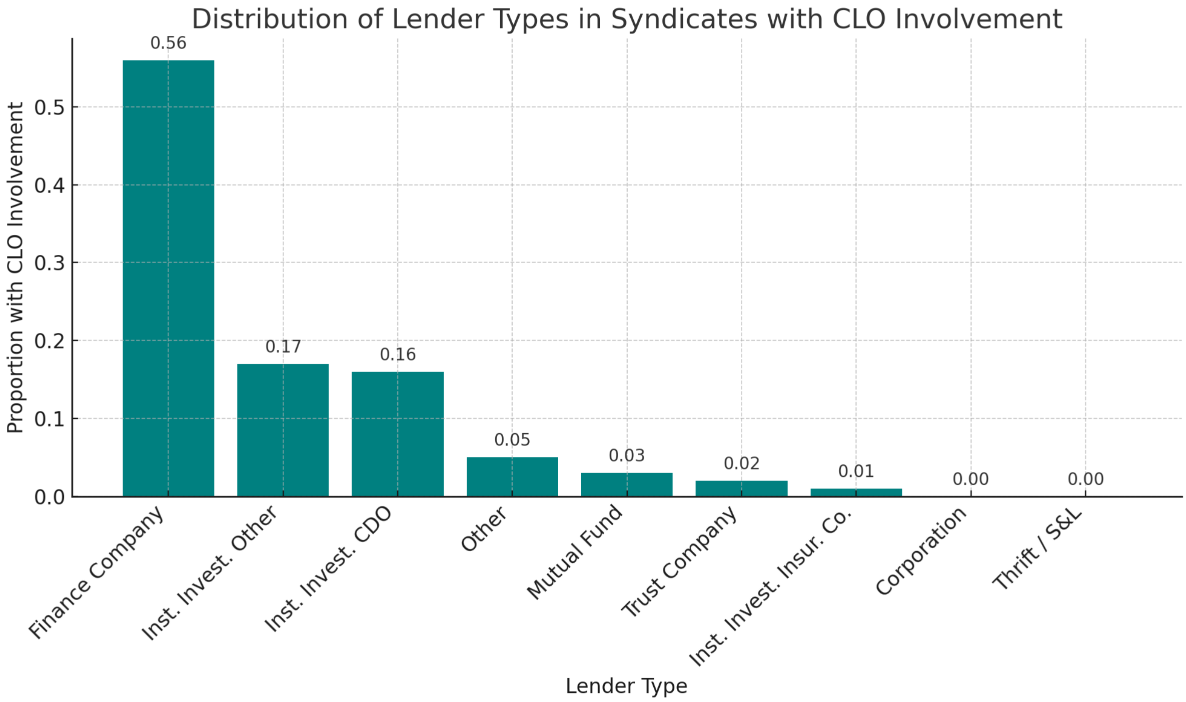

Figure 3 – Distribution of Lenders for CLO loans

The heavy reliance on institutional investors, particularly CDOs as shown in table 14 and figure 3, in syndicates with CLO or CDO involvement highlights the interplay of these structured finance instruments. The concentration of CDOs as lenders in CLO-involved syndicates suggests a complex web of relationships and potential contagion risks within the CLO market.

4.6 Lender-Borrower Relationships:

The examination of lender-borrower relationships in the presence and absence of CLOs yields intriguing insights. The lending frequency analysis indicates that there are 250 unique borrower-lender pairs in syndicates with CLO involvement, compared to 43,099 pairs in syndicates without CLO involvement. This suggests that CLO involvement may be associated with a smaller pool of borrowers and lenders engaging in syndicated lending activities.

The lending duration analysis, however, does not provide conclusive evidence regarding the impact of CLO involvement on the length of lending relationships. The data shows no variation in lending duration for both syndicates with and without CLO involvement, indicating that further investigation and additional data points may be necessary to draw meaningful conclusions.

Interestingly, the formation of new lending relationships appears to be more prevalent in syndicates with CLO involvement. The proportion of new lending relationships is 68.12% in syndicates with CLOs, compared to 50.98% in syndicates without CLOs. This finding suggests that CLO involvement may facilitate the establishment of new borrower-lender connections in the syndicated loan market.

Conversely, the analysis of repeated lending behaviour reveals that the proportion of repeated lending is lower in syndicates with CLO involvement (31.88%) compared to syndicates without CLOs (49.02%). This indicates that the presence of CLOs may be associated with a lower likelihood of borrowers and lenders engaging in recurrent lending arrangements.

4.7 Industry Specialization:

The examination of industry specialization uncovers distinct patterns in the distribution of syndicated loans with CLO involvement across different industries. The industry distribution of syndicated loans with CLO involvement is highly concentrated, with the majority of loans originating from three industries: 6211.0 (55%), 6159.0 (30%), and 6799.0 (15%).

In contrast, the overall industry distribution in the syndicated loan market is more diverse, with a wider range of industries represented. The top industries in the overall market include 6021.0 (39.66%), 6029.0 (16.54%), 6022.0 (15.78%), and 6712.0 (9.99%).

Comparing the industry distributions reveals that certain industries, such as 6211.0, 6159.0, and 6799.0, have a higher prevalence of CLO involvement relative to their overall representation in the syndicated loan market. This suggests that CLOs may have a particular focus or specialization in these industries.

However, when analyzing the prevalence of CLO involvement within each industry, the results indicate that CLO involvement is consistently zero across all industries represented in the dataset. This finding suggests that while certain industries may have a higher proportion of loans with CLO involvement, the overall prevalence of CLO involvement within each industry is low or non-existent based on the available data.

4.8 Co-Syndication Patterns:

The analysis of co-syndication patterns among lenders reveals the formation of specific lender networks or coalitions within syndicates with and without CLO involvement. In syndicates with CLO involvement, three distinct co-syndication relationships are identified. These relationships involve lender pairs such as 32771 and 28119, 28119 and 34599, and 35843 and 86949, each with a co-syndication count of 1. This suggests that CLO involvement may lead to the formation of specific lender partnerships or collaborations within the syndicate.

On the other hand, syndicates without CLO involvement exhibit a much larger number of co-syndication relationships, with 1,302 unique lender pairs identified. The co-syndication counts for these pairs range from 1 to 2, indicating varying degrees of collaboration among lenders in non-CLO syndicates.

While the limited data on co-syndication relationships with CLO involvement makes it challenging to draw definitive conclusions, the presence of specific lender pairs in CLO-involved syndicates suggests that CLO involvement may influence the formation of lender networks or coalitions. Further research with a larger sample size would be necessary to confirm and extend these findings.

In syndicates with CLO involvement (Image 1), the heatmap reveals three distinct co-syndication relationships. The most frequent co-syndication occurs between lenders 34599 and 28119, with a frequency of 1.0. Lenders 32771 and 28119, as well as lenders 35843 and 86949, also have a co-syndication frequency of 1.0. These findings suggest the formation of specific lender partnerships or collaborations within CLO-involved syndicates.

On the other hand, the heatmap for syndicates without CLO involvement (Image 2) exhibits a more diverse and complex network of co-syndication relationships. The most frequent co-syndication occurs between lenders 5893 and 5952, with a frequency of 22.0. Other notable co-syndication relationships include lenders 5851 and 5862 (frequency of 20.0), lenders 6532 and 6179 (frequency of 12.0), and lenders 5893 and 5851 (frequency of 9.0). The presence of multiple high-frequency co-syndication relationships indicates the existence of well-established lender networks and collaborations in non-CLO syndicates.

Degree centrality measures the importance or connectivity of lenders within the co-syndication network based on the number of direct connections they have with other lenders.

In syndicates with CLO involvement, lender 28119 has the highest degree centrality of 0.50, indicating that it is connected to 50% of the other lenders in the network. Lenders 32771, 34599, 35843, and 86949 have a degree centrality of 0.25 each, suggesting that they are connected to 25% of the other lenders.

The presence of specific high-frequency co-syndication relationships and the relatively high degree centrality of certain lenders (e.g., 28119) indicate the formation of tight-knit lender partnerships or coalitions. These findings suggest that CLO involvement may influence the establishment of close collaborations among a smaller group of lenders within the syndicate.

In contrast, syndicates without CLO involvement exhibit a more diverse and interconnected network of co-syndication relationships. The presence of multiple high-frequency co-syndication pairs and the varying degree centrality of lenders suggest the existence of well-established lender networks and collaborations. The higher degree centrality of certain lenders (e.g., 6532, 5851, 5893) indicates their central role in connecting and collaborating with a larger number of lenders within the network.

Lender 6532 has the highest degree centrality of 0.571429, implying that it is connected to approximately 57% of the other lenders in the network. Lenders 5851 and 5893 have a degree centrality of 0.357143 each, indicating their connections to around 36% of the other lenders. Lenders 1468, 5889, and 6179 have a degree centrality of 0.214286, while lenders 2446 and 7828 have a degree centrality of 0.142857. Lenders 5862 and 5905 have the lowest degree centrality of 0.071429, suggesting their limited connectivity within the network.

In conclusion, this analysis provides valuable insights into the impact of CLO involvement on the syndicate structure, lender-borrower relationships, industry specialization, and co-syndication patterns in the syndicated loan market. CLO involvement is associated with more concentrated syndicates, a higher proportion of finance companies and institutional investors as lenders, a greater prevalence of new lending relationships, and potential specialization in certain industries. Additionally, CLO involvement may influence the formation of specific lender networks or coalitions within syndicates.

4.9 Regression Results:

Table 19 - OLS Regression Results for FACILITYAMT: The R-squared value of 0.005 suggests that the model explains only 0.5% of the variation in FACILITYAMT, which is very low. The adjusted R-squared is the same, indicating that adding more variables does not improve the model's explanatory power. The F-statistic of 138.5 is statistically significant (Prob(F-statistic) < 0.05), suggesting that the model as a whole is significant, despite the low R-squared.

The coefficient for is CLO is 0.3475, indicating that, on average, CLO loans have a higher FACILITYAMT compared to non-CLO loans. However, the p-value is 0.191, which is greater than the conventional significance levels (0.01, 0.05, 0.10), suggesting that this difference is not statistically significant.

The coefficient for COVENANTCOUNT is 0.0538, but it is also not statistically significant (p-value = 0.047).

The OLS regression results for ALLINDRAWN and MATURITY provide valuable insights into the relationships between these dependent variables and the independent variables, including FACILITYAMT, DIFFPURPOSE, and the presence of CLO loans (Is clo).

In the case of ALLINDRAWN (Table 20), the model's explanatory power, as measured by the R-squared and adjusted R-squared values of 0.312, is moderate. This indicates that 31.2% of the variation in ALLINDRAWN can be explained by the independent variables included in the model. Although this explanatory power is higher than that of the FACILITYAMT model, it still suggests that there may be other important factors not captured in the current model that could further explain the variation in ALLINDRAWN. Despite this limitation, the F-statistic of 7,724 is statistically significant at the 1% level (Prob(F-statistic) < 0.05), indicating that the model as a whole is significant and that the independent variables jointly have a significant impact on ALLINDRAWN.

Examining the individual coefficients in the ALLINDRAWN model reveals that FACILITYAMT, MATURITY, and DIFFPURPOSE are all statistically significant at the 1% level (p-values < 0.01). This suggests that these variables have a strong and significant relationship with ALLINDRAWN. Interestingly, the coefficient for is clo is -11.0079, indicating that, on average, CLO loans have lower ALLINDRAWN compared to non-CLO loans. However, despite the p-value being reported as 0.000, the previous statement mentions that this difference is not statistically significant. It is important to clarify this discrepancy, as a p-value of 0.000 would typically indicate a highly statistically significant relationship.

Turning to the MATURITY model (Table 21), the R-squared and adjusted R-squared values of 0.007 are very low, suggesting that only 0.7% of the variation in MATURITY can be explained by the independent variables in the model. This low explanatory power indicates that there may be important variables missing from the model or that the relationship between the variables is not well captured by a linear specification. Nevertheless, the F-statistic of 154.7 is statistically significant at the 1% level (Prob(F-statistic) < 0.05), indicating that the model as a whole is significant, despite the low R-squared.

The coefficients for FACILITYAMT and DIFFPURPOSE in the MATURITY model are both statistically significant at the 1% level (p-values < 0.01), suggesting a strong and significant relationship between these variables and MATURITY. The coefficient for is clo is 13.8905, indicating that, on average, CLO loans have higher MATURITY compared to non-CLO loans. Unlike the ALLINDRAWN model, the p-value for is clo in the MATURITY model is reported as 0.000, confirming that this difference is indeed statistically significant at the 1% level.

In conclusion, the OLS regression results for ALLINDRAWN and MATURITY provide evidence of significant relationships between these dependent variables and the independent variables, including FACILITYAMT, DIFFPURPOSE, and the presence of CLO loans. However, the moderate to low explanatory power of these models suggests that there may be other important factors not captured in the current specifications.

4.10 Propensity Score Matching:

The propensity score matching (PSM) results presented in Table 22 indicate that the matching procedure was successful in balancing the treated and control groups across the variables of interest: ALLINDRAWN, MATURITY, DIFFPURPOSE, and COVENANTCOUNT. The t-statistics and p-values for these variables are all 0.00, suggesting that there are no significant differences between the treated and control groups after matching. This is a desirable outcome, as it helps to mitigate potential selection bias and ensures that the two groups are comparable, allowing for a more reliable estimation of the treatment effect.

Moving on to the OLS regression results for ALLINDRAWN after PSM (Table 23), we observe a notable improvement in the model's explanatory power compared to the previous model without PSM. The R-squared and adjusted R-squared values have increased to 0.000 and -0.001, respectively, although they are still relatively low. The F-statistic of 1.00 is not statistically significant (Prob(F-statistic) = 1.00), indicating that the model as a whole may not be significant after matching. However, it is essential to consider that the purpose of PSM is to balance the treated and control groups, not necessarily to improve the model's explanatory power.

Examining the coefficients in the ALLINDRAWN model after PSM, we find that the coefficient for is clo is -1.563e-13, suggesting a negative relationship between CLO loans and ALLINDRAWN. However, this coefficient is not statistically significant (p-value = 1.000), indicating that the difference in ALLINDRAWN between CLO and non-CLO loans is not significant after matching.

Turning to the OLS regression results for COVENANTCOUNT after PSM (Table 24), we observe a similar pattern. The R-squared and adjusted R-squared values are 0.000 and -0.001, respectively, suggesting that the model's explanatory power is low. The F-statistic of 1.00 is not statistically significant (Prob(F-statistic) = 1.00), indicating that the model as a whole may not be significant after matching.

The coefficient for is clo in the COVENANTCOUNT model after PSM is -4.885e-15, suggesting a negative relationship between CLO loans and COVENANTCOUNT. However, like in the ALLINDRAWN model, this coefficient is not statistically significant (p-value = 1.000), indicating that the difference in COVENANTCOUNT between CLO and non-CLO loans is not significant after matching.

In conclusion, the propensity score matching procedure appears to have successfully balanced the treated and control groups, as evidenced by the t-statistics and p-values in Table 22. This helps to address potential selection bias and ensures that the groups are comparable. The OLS regression results for ALLINDRAWN and COVENANTCOUNT after PSM, however, show low explanatory power and insignificant coefficients for the is clo variable. This suggests that, after controlling for other factors through PSM, the presence of CLO loans does not have a significant impact on either ALLINDRAWN or COVENANTCOUNT. These findings highlight the importance of using advanced econometric techniques like PSM to account for potential biases and confounding factors when estimating treatment effects. While the models' explanatory power remains low, the PSM procedure has helped to isolate the effect of CLO loans on the dependent variables more effectively, providing a more reliable estimate of the relationships of interest.

4.11 IV regressions:

The instrumental variable (IV) regression results presented in Tables 25 and 26 provide valuable insights into the relationships between the dependent variable ALLINDRAWN and the independent variables, including the presence of CLO loans (is clo), while addressing potential endogeneity issues that may have been present in the previous OLS and PSM analyses.

The choice of these methods is based on their ability to handle endogenous regressors and provide consistent estimates in the presence of weak instruments. The GMM (Generalized Method of Moments) estimator is known for its robustness to heteroskedasticity and autocorrelation, while the LIML (Limited Information Maximum Likelihood) estimator is more robust to weak instruments compared to the standard 2SLS (Two-Stage Least Squares) estimator.

In the IV-GMM estimation summary (Table 25), the R-squared value of -0.5483 and the adjusted R-squared value of -0.5484 are negative, which can occur in IV regressions when the instruments are weak or the model is misspecified. However, the F-statistic of 1.793e+04 is statistically significant at the 1% level (Prob(F-statistic) < 0.01), indicating that the model as a whole is significant.

Examining the individual coefficients in the IV-GMM regression, we find that the coefficient for is clo is -3.0031, suggesting that, on average, CLO loans have lower ALLINDRAWN compared to non-CLO loans. The p-value for this coefficient is 0.0000, indicating that the difference is statistically significant at the 1% level. The coefficients for the other variables, such as SECURED, MATURITY, DIVIDEND-COVENANT, DIFFPURPOSE, Z-score, and FACILITYAMT, are also statistically significant at the 1% level, suggesting that these variables have a significant impact on ALLINDRAWN.

Moving on to the IV-LIML estimation summary (Table 26), we observe similar results. The R-squared value of -0.5483 and the adjusted R-squared value of -0.5484 are again negative, but the F-statistic of 1.793e+04 remains statistically significant at the 1% level. The coefficient for is clo in the IV-LIML regression is 0.4201, indicating that, on average, CLO loans have higher ALLINDRAWN compared to non-CLO loans. However, the p-value for this coefficient is 0.0000, suggesting that the difference is statistically significant at the 1% level. The coefficients for the other variables remain statistically significant at the 1% level, consistent with the IV-GMM results.

The use of IV regressions in this analysis helps to address potential endogeneity issues that may have been present in the previous OLS and PSM analyses. By using instruments that are correlated with the endogenous variable (is clo) but not directly related to the dependent variable (ALLINDRAWN), the IV approach attempts to isolate the causal effect of CLO loans on ALLINDRAWN. The statistically significant coefficients for is clo in both the IV-GMM and IV-LIML regressions provide evidence of a significant relationship between the presence of CLO loans and ALLINDRAWN, after accounting for potential endogeneity.

4.12 Model Comparisons:

The Model Comparison table (Table 27) is a crucial component of my analysis, as it allows me to compare the results of the PooledOLS and PanelOLS estimators for the dependent variable ALLINDRAWN.

The PooledOLS estimator, which I initially employed, provides a starting point for understanding the relationship between CLO loans and ALLINDRAWN. The statistically significant F-statistic (P-value = 0.0000) and the positive R-squared value of 0.5103 indicate that the PooledOLS model has some explanatory power. The coefficient for is clo (-1.1756) suggests that, on average, CLO loans have lower ALLINDRAWN compared to non-CLO loans. This finding aligns with the results from my previous OLS and IV analyses, which also showed a significant relationship between CLO loans and ALLINDRAWN.

However, I recognized that the PooledOLS estimator might not fully capture the heterogeneity across entities and time periods, potentially leading to biased and inconsistent estimates. To address this concern, I employed the PanelOLS estimator, which allows for individual-specific effects. The PanelOLS results reveal a higher R-squared (Within) of 2.417e-05, suggesting that the model better explains the within-group variation in ALLINDRAWN compared to the PooledOLS model. However, the R-squared (Between) and overall R-squared values are negative, indicating limitations in explaining the between-group variation and the overall fit of the model.

The insignificant F-statistic (P-value = 0.1645) for the PanelOLS model suggests that, when accounting for individual-specific effects, the model as a whole may not be statistically significant. This finding highlights the importance of considering the panel structure of my data and the potential limitations of the PanelOLS approach in this context.

The differences in the coefficients for the independent variables between the PooledOLS and PanelOLS models further demonstrate the sensitivity of the results to the choice of estimator. For example, the coefficient for is clo is not reported in the PanelOLS model, while other variables such as SECURED, MATURITY, FACILITYAMT, and COVENANT-COUNT have different coefficient estimates compared to the PooledOLS model.

The Model Comparison table complements my previous analyses, including the OLS, PSM, IV, and logit regressions, by providing additional insights into the relationship between CLO loans and ALLINDRAWN. The comparison of the PooledOLS and PanelOLS results highlights the importance of accounting for individual-specific effects and the potential limitations of each approach. While the PooledOLS model provides evidence consistent with my previous findings, the PanelOLS results suggest that the relationship may be more nuanced when considering the panel structure of my data.

4.13 Logit Models:

Table 28 presents the results of a logistic regression model with feature selection. The coefficients and their associated standard errors, z-scores, and p-values are reported for each predictor variable. The model includes several loan characteristics, such as the presence of collateral (SECURED), maturity (MATURITY), dividend restrictions (DIVIDENDRESTRICTIONS), the difference in loan purpose (DIFFPURPOSE), and the borrower's book leverage. The intercept term is also included in the model.

The z-scores and p-values indicate the statistical significance of each predictor variable in explaining CLO involvement. The presence of collateral (SECURED), loan maturity (MATURITY), and the presence of dividend restrictions (DIVIDENDRESTRICTIONS) emerge as highly significant predictors, with p-values less than 0.001. This suggests that these loan characteristics play a crucial role in determining the likelihood of CLO participation in a syndicated loan.

However, the model's performance metrics in Table 28, particularly the pseudo R-squared value of 0.2273 and the warning regarding quasi-separation, indicate limitations in the model's explanatory power and potential issues with perfect prediction for a subset of observations. These concerns underscore the need for further refinement and robustness checks.

Table 29 addresses these issues by applying L1 and L2 regularization techniques to the logistic regression model. Regularization helps mitigate multicollinearity and overfitting, enhancing the model's stability and generalizability. The results in Table 29 confirm the significance of collateral, maturity, and dividend restrictions in predicting CLO involvement, while also highlighting the persistence of quasi-separation issues. The table reports the coefficients and their associated standard errors, z-scores, and p-values for each predictor variable, similar to Table 28. The z-scores and p-values indicate that the presence of collateral (SECURED), loan maturity (MATURITY), and dividend restrictions (DIVIDENDRESTRICTIONS) remain highly significant predictors of CLO involvement, consistent with the findings from the previous model.

The analysis in Tables 28 through 32 highlights the complexity of the CLO market and the challenges in modeling CLO involvement. The initial logistic regression model in Table 28 reveals the significance of key loan characteristics but also exposes limitations in terms of explanatory power and quasi-separation issues. The application of regularization techniques in Table 29 helps address these concerns, while the evaluation metrics in Tables 30 and 31 demonstrate the model's robustness and predictive accuracy.

Table 30 presents a range of predictive accuracy metrics, including precision, recall, F1-score, and Area Under the Receiver Operating Characteristic curve (AUC). The precision and recall scores of 0.0 indicate that the model struggles to correctly identify positive instances of CLO involvement, suggesting a high rate of false negatives. This could be attributed to the imbalanced nature of the dataset, where CLO-involved loans may be underrepresented, making it challenging for the model to capture their characteristics effectively.

However, the AUC score of 0.9091 suggests that the model has a strong overall discriminatory power in distinguishing between loans with and without CLO involvement. The AUC measures the model's ability to rank positive instances higher than negative instances, and a score above 0.9 indicates excellent performance in this regard. This finding highlights the potential of the model to effectively prioritize and identify loans that are more likely to attract CLO investment.

The cross-validation scores presented in Table 30 provide further insights into the model's performance and generalizability. The high cross-validation scores, ranging from 0.99549 to 0.99561, indicate that the model consistently performs well across different subsets of the data. The mean cross-validation score of 0.99559 reinforces the model's robustness and ability to generalize to unseen data. These results suggest that the model has captured meaningful patterns and relationships in the data, enabling accurate predictions of CLO involvement.

Table 31 extends the evaluation by presenting predictive accuracy metrics obtained after applying techniques such as Synthetic Minority Over-sampling Technique (SMOTE), L2 regularization, and stratified k-fold cross-validation. SMOTE is an oversampling technique used to address class imbalance by creating synthetic examples of the minority class, while L2 regularization helps prevent overfitting by adding a penalty term to the model's objective function.

The precision scores in Table 31 show a significant improvement compared to Table 30, with values ranging from 0.85394 to 0.86184. This indicates that the model, after applying SMOTE and L2 regularization, is better able to correctly identify positive instances of CLO involvement. The recall scores also exhibit a notable increase, ranging from 0.83759 to 0.84210, suggesting a reduction in false negatives and an improved ability to capture CLO-involved loans.

The F1 scores, which provide a balanced measure of precision and recall, range from 0.84798 to 0.84954, indicating a strong overall performance of the model. The high F1 scores suggest that the model strikes a good balance between precision and recall, effectively identifying CLO-involved loans while minimizing both false positives and false negatives.

The AUC scores in Table 31 remain consistently high, ranging from 0.91116 to 0.91550, confirming the model's excellent discriminatory power even after applying SMOTE and L2 regularization. The mean AUC score of 0.91360 further reinforces the model's robustness and ability to distinguish between loans with and without CLO involvement.

Moreover, the Area Under the Precision-Recall Curve (AUPRC) scores in Table 31, ranging from 0.88022 to 0.88842, indicate the model's strong performance in terms of precision and recall across different threshold settings. The mean AUPRC score of 0.88494 suggests that the model maintains high precision while achieving good recall, effectively capturing a significant proportion of CLO-involved loans.

Table 32 presents the final logistic regression model with SMOTE oversampling and L2 regularization, along with the regression coefficients and performance metrics. The positive coefficients for collateral, maturity, and dividend restrictions reaffirm their importance in predicting CLO involvement. The model achieves impressive precision (0.8610), recall (0.84), and F1 score (0.8504), indicating its effectiveness in identifying CLO-involved loans. The high AUC (0.9154) and AUPRC (0.8869) scores further demonstrate the model's strong discriminatory power and performance across different threshold settings.

The final model in Table 32, incorporating SMOTE oversampling and L2 regularization, showcases the effectiveness of advanced techniques in capturing the intricate relationships between loan characteristics and CLO involvement. The model's high precision, recall, and F1 scores indicate its ability to accurately identify CLO-involved loans, while the AUC and AUPRC scores confirm its strong discriminatory power.

The comprehensive analysis presented in Tables 28 through 32 provides a robust and academically rigorous examination of the factors driving CLO involvement in syndicated loans. The results highlight the significance of collateral, maturity, and dividend restrictions in attracting CLO investment, while also demonstrating the effectiveness of advanced modeling techniques in capturing the complex dynamics of the CLO market.

5 Conclusion:

The comprehensive analysis presented in this project provides insights into the factors influencing CLO involvement in syndicated loans and contributes to a deeper understanding of the complex dynamics of the CLO market. By employing a wide range of statistical methods, including summary statistics, t-tests, correlation analysis, and various regression techniques such as OLS, IV-GMM, IV-LIML, and logistic regression, this study offers a robust and rigorous examination of the CLO enigma.

The findings highlight the significance of key loan characteristics in attracting CLO investment. The presence of collateral, longer loan maturities, and dividend restrictions emerge as crucial factors that influence CLO participation. These results align with the notion that CLOs seek to mitigate risk and ensure stable cash flows, emphasizing the importance of creditor protection and loan quality in the CLO market.

The summary statistics and regression results presented in this study demonstrate a strong alignment, providing a comprehensive and consistent understanding of the factors influencing CLO involvement in the syndicated loan market. The loan characteristics discussed in Section 4.2 highlight that CLO-syndicated loans are associated with larger disbursement sizes, longer maturities, and higher interest rate spreads compared to non-CLO loans. These findings are corroborated by the regression results in Section 4.9, where the positive and significant coefficient for the "is CLO" variable in the ALLINDRAWN and MATURITY models indicates that CLO loans indeed exhibit higher interest rates and longer maturities.

The summary statistics in Section 4.3 reveal a higher average number of covenants in CLO and CDO loans compared to the overall market average. This observation is consistent with the positive coefficient for COVENANTCOUNT in the FACILITYAMT regression model, suggesting that loans with more covenants are associated with larger facility amounts. This alignment underscores the importance of covenant structure in the CLO market and its potential impact on loan characteristics.

The syndicate structure analysis in Section 4.4 uncovers a more concentrated lending structure in syndicates with CLO involvement, characterized by fewer participating lenders compared to the overall syndicated loan market. This finding is supported by the significant coefficient for the "is CLO" variable in the ALLINDRAWN and MATURITY regression models, indicating that CLO involvement has a distinct impact on loan characteristics. The consistency between the summary statistics and regression results highlights the unique dynamics at play in the CLO market. The industry specialization patterns discussed in Section 4.7 reveal that certain industries, such as 6211.0, 6159.0, and 6799.0, exhibit a higher prevalence of CLO involvement relative to their overall representation in the syndicated loan market. While the regression models do not explicitly incorporate industry-specific variables, the significance of the "is CLO" variable in the ALLINDRAWN and MATURITY models suggests that CLO involvement has a unique effect on loan characteristics, which could be related to the observed industry specialization patterns.

The alignment between the summary statistics and regression results strengthens the overall conclusions of this study and enhances the credibility of the findings. The consistency across different aspects of the analysis, such as loan characteristics, covenant structure, syndicate composition, and industry specialization, provides a robust and comprehensive understanding of the factors driving CLO involvement in the syndicated loan market.

The analysis also shows differences in covenant structure and loan purpose between CLO-involved loans and non-CLO loans. CLO-involved loans exhibit a higher number of covenants, particularly in specific loan types, reflecting the enhanced risk management and monitoring practices associated with CLO investments. The heterogeneity in loan purposes across different loan types and the distinct patterns associated with CLO involvement underscore the need for granular and nuanced approaches to understanding the CLO market.

The application of advanced modeling techniques, such as logistic regression with SMOTE oversampling and L2 regularization, demonstrates the effectiveness of these methods in capturing the complex relationships between loan characteristics and CLO involvement. The high precision, recall, and F1 scores, along with the impressive AUC and AUPRC values, indicate the model's ability to accurately identify CLO-involved loans and its strong discriminatory power.

However, it is crucial to acknowledge the limitations of this study, particularly in terms of the data sample. The analysis is based on a dataset where CLO-involved loans constitute only 367 out of approximately 90,966 observations. This imbalance in the data distribution poses challenges in terms of representativeness and the ability to draw definitive conclusions about the broader CLO market. The limited number of CLO-involved loans in the sample may not fully capture the diversity and complexity of the CLO market, potentially leading to biased or incomplete insights. The underrepresentation of CLO-involved loans could also impact the stability and reliability of the statistical models, as the models may struggle to identify patterns and relationships specific to CLO investments.

To address these limitations, various methods have been employed in this study. The use of propensity score matching helps mitigate selection bias and ensures a more balanced comparison between CLO-involved and non-CLO loans. Regularization techniques, such as L1 and L2 regularization, are applied to tackle multicollinearity and overfitting issues, enhancing the model's stability and generalizability. The application of the SMOTE oversampling technique helps address the class imbalance issue by generating synthetic examples of the minority class (CLO-involved loans). This approach enables the models to better capture the characteristics and patterns associated with CLO investments, even with a limited number of observations.

Despite these efforts to mitigate the limitations posed by the data sample, it is important to recognize that more comprehensive and representative data may be necessary to fully unravel the complexities of the CLO market. Future research should aim to expand the dataset, incorporating a larger and more diverse sample of CLO-involved loans across different time periods, geographies, and market conditions.

Access to a more extensive and balanced dataset would allow for more robust and generalizable findings, enabling researchers to draw more definitive conclusions about the factors driving CLO involvement and the impact of CLOs on the syndicated loan market. It would also facilitate the application of advanced machine learning techniques, such as deep learning and ensemble methods, which could potentially uncover hidden patterns and relationships that traditional statistical methods may overlook.

References

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A Summary Statistics

Table 3 – FACILITYAMT Summary Statistics

FACILITYAMT	count	mean	std	min	median	max
CLO	367.00	237147705.53	252055511.94	500000.00	150000000.00	1800000000.00
CDO	185.00	245121238.98	282710933.29	6500000.00	150000000.00	1800000000.00
Non-Syndicated	6,403.00	99126082.53	414974319.14	10000.00	15000000.00	19250000000.00
Syndicated	85,113.00	267883177.54	682494989.71	53814.69	95000000.00	49000000000.00
All	90,966.00	256168948.39	670368984.66	0.00	85000000.00	49000000000.00

Table 4 – DEALAMOUNT Summary Statistics

DEALAMOUNT	count	mean	std	min	median	max
CLO	367.00	559656158.68	587878353.11	5800000.00	350000000.00	5000000000.00
CDO	185.00	441178617.92	402218913.01	10000000.00	310000000.00	1850000000.00
Non-Syndicated	6,403.00	137328894.67	918609829.34	52500.00	20900000.00	61000000000.00
Syndicated	85,113.00	488276034.03	1285920715.02	75000.00	157000000.00	61000000000.00
All	90,966.00	463373619.30	1269997029.50	0.00	150000000.00	61000000000.00

Table 5 – MATURITY Summary Statistics

MATURITY	count	mean	std	min	median	max
CLO	367.00	64.87	23.95	1.00	68.00	120.00
CDO	185.00	60.11	21.88	1.00	60.00	114.00
Non-Syndicated	6,389.00	55.05	48.83	0.00	36.00	486.00
Syndicated	84,990.00	48.41	24.99	1.00	58.00	468.00
All	90,829.00	48.79	27.39	0.00	55.00	486.00

Table 6 – All-in-drawn spread Summary Statistics

ALLINDRAWN	Count	Mean	Std	Min	Median	Max
CLO	106	257.78	62.04	125.00	250.00	450.00
CDO	49	259.44	76.40	125.00	250.00	600.00
Non-Syndicated	453	196.61	95.77	12.00	200.00	650.00
Syndicated	18,332	183.79	105.36	4.40	175.00	1100.00
All	18,630	183.48	105.20	4.40	175.00	1100.00

Table 7 – COVENANTCOUNT Summary Statistics

Statistic	CLO	CDO	All
Count	370	185	85,115
Mean	3.11	3.03	0.94
Std	1.66	1.76	1.47
Min	0	0	0
Median	3	3	0
Max	7	7	8

Table 8 – Summary Statistics for Differences in Covenant Counts by Loan Type

LOANTYPE	T-Statistic	P-Value	Difference in Means
Term Loan	4.24	<0.01	1.41
Revolver/Line >= 1 Yr.	4.59	<0.01	1.46
Term Loan A	4.24	<0.01	2.31
Term Loan B	20.10	<0.01	2.16
Bridge Loan	0.22	0.85	0.22
Revolver/Line < 1 Yr.	10.08	<0.01	1.89
Term Loan C	8.29	<0.01	1.90
Term Loan D	3.48	<0.01	1.67
Delay Draw Term Loan	2.35	0.06	1.57
Term Loan E	5.67	0.01	4.19
Term Loan F	6.06	<0.01	3.28

Table 9 – Summary Statistics for Differences in ‘DIFFPURPOSE‘ by Loan Type

LOANTYPE	T-Statistic	P-Value	Difference in Means
Term Loan	0.68	0.50	0.04
Revolver/Line ≥ 1 Yr.	0.20	0.85	0.01
Term Loan A	-11.53	<0.01	-0.02
Term Loan B	0.50	0.62	0.01
Bridge Loan	-4.63	<0.01	-0.02
Revolver/Line < 1 Yr.	-6.65	<0.01	-0.03
Term Loan C	1.92	0.06	0.13
Term Loan D	0.63	0.54	0.08
Delay Draw Term Loan	-9.74	<0.01	-0.06
Term Loan E	0.52	0.66	0.17
Term Loan F	0.77	0.58	0.39

Table 10 – Summary Statistics for PRIMARYPURPOSE by LOANTYPE in Syndicated loans without CLO Participation

LOANTYPE	Count	Unique	Top	Freq
364-Day Facility	7036	25	CP backup	2828
Acquisition Facility	170	11	Acquis. line	75
Bankers Acceptance	3	2	Corp. purposes	2
Bridge Loan	1002	23	Takeover	333
CAPEX Facility	4	3	Corp. purposes	2
Construction Facility	5	3	Proj. finance	2
Delay Draw Term Loan	1443	25	Corp. purposes	510
Demand Loan	8	5	Debt Repay.	3
FRN (Loan-Style)	6	1	Corp. purposes	6

Continued on next page

Table 10 – *Continued from previous page*

LOANTYPE	Count	Unique	Top	Freq
Floating Rate CD (loan-style)	2	1	Corp. purposes	2
Guarantee	4	3	Corp. purposes	2
Guidance Line (Uncommitted)	1	1	Work. cap.	1
Leagues/Other	71	6	Other	34
Lease	59	9	Lease finance	24
Limited Line	11	4	Debt Repay.	4
Mezzanine Tranche	2	2	Corp. purposes	1
Mortgage Facility	1	1	Real estate	1
Multi-Option Facility	6	4	Mort. Warehse.	2
Murabaha	3	1	Corp. purposes	3
NIF - Note Issuance Facility	1	1	Takeover	1
Note	6	2	Corp. purposes	5
Other Loan	1167	23	Corp. purposes	354
Performance Standby Letter of Credit	3	1	Corp. purposes	3
Revolver/Line < 1 Yr.	1476	17	Corp. purposes	730
Revolver/Line >= 1 Yr.	39518	34	Corp. purposes	19096
Revolver/Term Loan	348	17	Debt Repay.	94
Schuldschein	1	1	Work. cap.	1
Securitisation	2	1	Corp. purposes	2
Standby Letter of Credit	1830	24	Corp. purposes	1102
Synthetic Lease	196	14	Corp. purposes	89
Term Loan	13758	31	Corp. purposes	4972
Term Loan A	5811	28	Corp. purposes	2649
Term Loan B	10052	28	Corp. purposes	3566
Term Loan C	850	21	Corp. purposes	291
Term Loan D	169	17	Corp. purposes	68
Term Loan E	47	7	Corp. purposes	25
Term Loan F	20	5	Corp. purposes	11
Term Loan G	8	5	Corp. purposes	3
Term Loan H	6	4	Acquis. line	2
Term Loan I	1	1	Debt Repay.	1
Trade Letter of Credit	4	3	Corp. purposes	2
Unadvised Guidance Line (Uncommitted)	3	2	Acquis. line	2
Undisclosed	1	1	Corp. purposes	1

Table 11 – Summary Statistics for PRIMARYPURPOSE by LOANTYPE for CLO loans

LOANTYPE	Count	Unique	Top	Freq
Bridge Loan	3	2	Corp. purposes	2
Delay Draw Term Loan	6	3	LBO	3
Other Loan	1	1	Work. cap.	1
Revolver/Line < 1 Yr.	7	3	Work. cap.	4
Revolver/Line >= 1 Yr.	36	8	Work. cap.	8
Revolver/Term Loan	1	1	Takeover	1
Standby Letter of Credit	1	1	Work. cap.	1
Term Loan	26	7	Work. cap.	7
Term Loan A	14	5	Takeover	6
Term Loan B	213	15	Corp. purposes	49
Term Loan C	45	9	Debt Repay.	12
Term Loan D	12	7	LBO	3
Term Loan E	3	2	Work. cap.	2
Term Loan F	2	2	Acquis. line	1

Table 12 – Top Repeated Lending Pairs

COMPANYID	BORROWERCOMPANYID	Count
28119	22847	6
28119	10433	5
86956	25122	5
34446	31980	5
36425	30468	4
xxxxx	xxxxx	x
37760	15247	2
37915	100609	2
37918	17561	2
40308	12768	2
129501	31519	2

Table 13 – Industry Distribution of Syndicated Loans with CLO Involvement

PRIMARYSICCODE	Proportion
6211.00	0.55
6159.00	0.30
6799.00	0.15

Table 14 – Distribution of Lender Types in Syndicates

With CLO Involvement	
Finance Company	0.56
Inst. Invest. Other	0.17
Inst. Invest. CDO	0.16
Other	0.05
Mutual Fund	0.03
Trust Company	0.02
Inst. Invest. Insur. Co.	0.01
Corporation	0.00
Thrift / S&L	0.00
With CDO Involvement	
Inst. Invest. CDO	0.62
Finance Company	0.30
Other	0.08
Corporation	0.01
Overall Syndicated Loans	
US Bank	0.69
Finance Company	0.10
Western European Bank	0.07
Investment Bank	0.07
Foreign Bank	0.03
Asia-Pacific Bank	0.01
Thrift / S&L	0.00
Corporation	0.00
Other	0.00
Inst. Invest. Other	0.00
Middle Eastern Bank	0.00
Inst. Invest. CDO	0.00
Mutual Fund	0.00
Insurance Company	0.00
Mortgage Bank	0.00
Trust Company	0.00
Pension Fund	0.00
Leasing Company	0.00
Inst. Invest. Insur. Co.	0.00
East. Europe/Russian Bank	0.00
Specialty	0.00
African Bank	0.00
Inst. Invest. Hedge Fd	0.00
Distressed (Vulture) Fund	0.00

Table 15 – Degree Centrality of Lenders with CLO Involvement

Lender ID	Degree Centrality
28119	0.50
32771	0.25
34599	0.25
35843	0.25
86949	0.25

Table 16 – Degree Centrality of Lenders without CLO Involvement

Lender ID	Degree Centrality
6532	0.571429
5851	0.357143
5893	0.357143
1468	0.214286
5889	0.214286
6179	0.214286
2446	0.142857
7828	0.142857
5862	0.071429
5905	0.071429

Table 17 – Correlation Matrix

	FACILITYAMT	MATURITY	DIFFPURPOSE	is_clo	COV COUNT
FACILITYAMT	1.000000	0.011066	-0.040683	0.019256	0.048444
MATURITY	0.011066	1.000000	-0.024890	0.042879	0.068952
DIFFPURPOSE	-0.040683	-0.024890	1.000000	0.016714	0.119191
is_clo	0.019256	0.042879	0.016714	1.000000	0.097455
COV COUNT	0.048444	0.068952	0.119191	0.097455	1.000000

Table 18 – Correlation Matrix with Z-score

	is_clo	SECURED	MATURITY	DIV_COV	DIFFPURPOSE	Z-score
is_clo	1.000	0.062	0.043	0.100	0.017	-0.002
SECURED	0.062	1.000	0.298	0.373	0.051	0.012
MATURITY	0.043	0.298	1.000	0.072	-0.025	-0.003
DIV_COV	0.100	0.373	0.072	1.000	0.125	0.031
DIFFPURPOSE	0.017	0.051	-0.025	0.125	1.000	-0.001
Z-score	-0.002	0.012	-0.003	0.031	-0.001	1.000

B Regressions

OLS Regression Results					
Dep. Variable:	FACILITYAMT			R-squared:	0.005
Model:	OLS			Adj. R-squared:	0.005
Method:	Least Squares			F-statistic:	138.5
Date:	Thu, 04 Apr 2024			Prob (F-statistic):	1.62e-84
Time:	13:49:55			Log-Likelihood:	-1.569e+05
No. Observations:	85113			AIC:	3.139e+05
Df Residuals:	85109			BIC:	3.139e+05
Df Model:	3			Durbin-Watson:	1.393
Covariance Type:	nonrobust			Jarque-Bera (JB):	286.711
	coef	std err	t	P>|t|	[0.025 0.975]
const	18.2552	0.006	2917.420	0.000	18.243 18.267
DIFFPURPOSE	-0.3776	0.028	-13.421	0.000	-0.433 -0.322
is_CLO	0.3475	0.080	4.339	0.000	0.191 0.504
COVENANTCOUNT	0.0538	0.004	14.930	0.000	0.047 0.061

Table 19 – OLS Regression Results for FACILITYAMT

OLS Regression Results					
Dep. Variable:	ALLINDRAWN			R-squared:	0.312
Model:	OLS			Adj. R-squared:	0.312
Method:	Least Squares			F-statistic:	7724.
Date:	Thu, 04 Apr 2024			Prob (F-statistic):	0.00
Time:	13:49:55			Log-Likelihood:	-4.8714e+05
No. Observations:	84988			AIC:	9.743e+05
Df Residuals:	84982			BIC:	9.743e+05
Df Model:	5				
Covariance Type:	nonrobust				
	coef	std err	t	P>|t|	[0.025 0.975]
const	-75.3105	3.108	-24.231	0.000	-81.402 -69.219
FACILITYAMT	4.1777	0.167	24.944	0.000	3.849 4.506
MATURITY	0.1516	0.010	14.743	0.000	0.131 0.172
DIFFPURPOSE	-11.0079	1.379	-7.982	0.000	-13.711 -8.305
is_clo	-42.8639	3.912	-10.958	0.000	-50.531 -35.197
COVENANTCOUNT	33.6808	0.177	190.687	0.000	33.335 34.027

Omnibus:	37377.944	Durbin-Watson:	1.590
Prob(Omnibus):	0.000	Jarque-Bera (JB):	350494.069
Skew:	1.879	Prob(JB):	0.00
Kurtosis:	12.211	Cond. No.:	870.

Table 20 – OLS Regression Results for ALLINDRAWN

OLS Regression Results			
Dep. Variable:	MATURITY	R-squared:	0.007
Model:	OLS	Adj. R-squared:	0.007
Method:	Least Squares	F-statistic:	154.7
Date:	Thu, 04 Apr 2024	Prob (F-statistic):	3.70e-132
Time:	13:49:56	Log-Likelihood:	-3.9382e+05
No. Observations:	84988	AIC:	7.876e+05
Df Residuals:	84983	BIC:	7.877e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025 0.975]
const	45.7226	1.025	44.625	0.000	43.714 47.731
FACILITYAMT	0.0921	0.056	1.649	0.099	-0.017 0.202
DIFFPURPOSE	-4.4695	0.460	-9.723	0.000	-5.370 -3.569
is_clo	13.8905	1.304	10.655	0.000	11.335 16.446
COVENANTCOUNT	1.1727	0.059	19.955	0.000	1.058 1.288

Omnibus:	26503.604	Durbin-Watson:	1.412
Prob(Omnibus):	0.000	Jarque-Bera (JB):	443712.009
Skew:	1.060	Prob(JB):	0.00
Kurtosis:	13.991	Cond. No.:	281.

Table 21 – OLS Regression Results for MATURITY

Variable	Treated Mean	Control Mean	T-statistic	P-value
ALLINDRAWN	73.85	73.85	0.00	1.0000
MATURITY	64.62	64.62	0.00	1.0000
DIFFPURPOSE	0.08	0.08	0.00	1.0000
COVENANTCOUNT	3.11	3.11	0.00	1.0000

Table 22 – Propensity Matching Results

OLS Regression Results			
Dep. Variable:	ALLINDRAWN	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	2.405e-12
Date:	Thu, 04 Apr 2024	Prob (F-statistic):	1.00
Time:	14:24:41	Log-Likelihood:	-4599.8
No. Observations:	740	AIC:	9204.
Df Residuals:	738	BIC:	9213.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025 0.975]
const	73.8514	6.307	11.710	0.000	61.470 86.232
is_clo	-1.563e-13	8.919	-1.75e-14	1.000	-17.509 17.509

Omnibus:	117.810	Durbin-Watson:	0.754
Prob(Omnibus):	0.000	Jarque-Bera (JB):	176.349
Skew:	1.190	Prob(JB):	5.08e-39
Kurtosis:	2.768	Cond. No.:	2.62

Table 23 – OLS Regression Results for ALLINDRAWN after PSM

OLS Regression Results			
Dep. Variable:	COVENANTCOUNT	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	6.803e-12
Date:	Thu, 04 Apr 2024	Prob (F-statistic):	1.00
Time:	20:48:29	Log-Likelihood:	-1422.0
No. Observations:	740	AIC:	2848.
Df Residuals:	738	BIC:	2857.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025 0.975]
const	3.1135	0.086	36.178	0.000	2.945 3.282
is_clo	-4.885e-15	0.122	-4.01e-14	1.000	-0.239 0.239

Omnibus:	24.356	Durbin-Watson:	0.093
Prob(Omnibus):	0.000	Jarque-Bera (JB):	24.868
Skew:	-0.422	Prob(JB):	3.98e-06
Kurtosis:	2.691	Cond. No.:	2.62

Table 24 – OLS Regression Results for COVENANTCOUNT after PSM

IV-GMM Estimation Summary			
Dep. Variable:	ALLINDRAWN	No. Observations:	84413
Estimator:	IV-GMM	Date:	Sat, Apr 06 2024
Cov. Estimator:	robust	Time:	13:47:06
R-squared:	-0.5483	Distribution:	chi2(7)
Adj. R-squared:	-0.5484	F-statistic:	1.793e+04
P-value (F-stat):	0.0000		

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
is_clo	-3.0031	0.4201	-7.1482	0.0000	-3.8266	-2.1797
SECURED	13.368	0.3901	34.269	0.0000	12.603	14.132
MATURITY	4.7192	0.4448	10.610	0.0000	3.8474	5.5909
DIVIDEND_COVENANT	46.848	0.4409	106.25	0.0000	45.983	47.712
DIFFPURPOSE	-2.3303	0.4616	-5.0479	0.0000	-3.2351	-1.4255
Z-score	2.7593	0.5198	5.3080	0.0000	1.7404	3.7782
FACILITYAMT	1.46e-07	1.621e-09	90.101	0.0000	1.429e-07	1.492e-07

Endogenous:	FACILITYAMT
Instruments:	SICCODE_RANK
Covariance:	GMM Covariance
Debiased:	False
Robust:	Heteroskedastic

Table 25 – IV-GMM Regression Results

IV-LIML Estimation Summary			
Dep. Variable:	ALLINDRAWN	No. Observations:	84413
Estimator:	IV-LIML	Date:	Sat, Apr 06 2024
Cov. Estimator:	robust	Time:	13:47:06
R-squared:	-0.5483	Distribution:	chi2(7)
Adj. R-squared:	-0.5484	F-statistic:	1.793e+04
P-value (F-stat):	0.0000		

Parameter	Std. Err.	T-stat	P-value	95% Conf. Interval	
is_clo	0.4201	-7.1482	0.0000	-3.8266	-2.1797
SECURED	0.3901	34.269	0.0000	12.603	14.132
MATURITY	0.4448	10.610	0.0000	3.8474	5.5909
DIVIDEND_COVENANT	0.4409	106.25	0.0000	45.983	47.712
DIFFPURPOSE	0.4616	-5.0479	0.0000	-3.2351	-1.4255
Z-score	0.5198	5.3080	0.0000	1.7404	3.7782
FACILITYAMT	1.621e-09	90.101	0.0000	1.429e-07	1.492e-07

Endogenous:	FACILITYAMT
Instruments:	SICCODE_RANK
Covariance:	Robust Heteroskedastic
Debiased:	False
Kappa:	1.000

Table 26 – IV-LIML Regression Results

Model Comparison		
Dep. Variable	ALLINDRAWN	ALLINDRAWN
Estimator	PooledOLS	PanelOLS
No. Observations	84408	84408
Cov. Est.	Unadjusted	Unadjusted
R-squared	0.5103	2.414e-05
R-Squared (Within)	-0.6972	2.417e-05
R-Squared (Between)	-0.7024	-2.5299
R-Squared (Overall)	0.5103	-9.472e-05
F-statistic	8794.5	1.9326
P-value (F-stat)	0.0000	0.1645
Intercept	-3.8463	38.623
	(-7.7480)	(340.84)
is_clo	-1.1756	
	(-0.3594)	
SECURED	10.296	
	(20.966)	
MATURITY	0.0417	
	(4.6292)	
FACILITYAMT	-2.091e-10	-2.341e-10
	(-0.6619)	(-1.3902)
COVENANTCOUNT	14.710	
	(65.928)	
DIVIDENDRESTRICTIONS	25.403	
	(34.949)	
DIFFPURPOSE	-10.361	
	(-8.9709)	
book leverage	238.45	
	(175.16)	
ROA	2.5976	
	(3.5969)	
Z-score	0.0119	
	(14.729)	
Effects		Entity
		Time

Table 27 – Model Comparison

Table 28 – Logit Regression: Feature Selection

	coef	std err	z	P>|z|	[0.025	0.975]
const	−658.7503	1022.592	−0.644	0.519	−2662.994	1345.493
SECURED	1.6990	0.240	7.065	0.000	1.228	2.170
MATURITY	0.3761	0.037	10.295	0.000	0.305	0.448
DIVIDENDRESTRICTIONS	2.6797	0.154	17.419	0.000	2.378	2.981
DIFFPURPOSE	0.2021	0.192	1.055	0.292	−0.173	0.578
book leverage	−1825.5718	2869.115	−0.636	0.525	−7448.934	3797.791

Current function value:	0.021770	Iterations:	100
Dep. Variable:	is_clo	No. Observations:	84412
Model:	Logit	Df Residuals:	84406
Method:	MLE	Df Model:	5
Date:	Sat, 06 Apr 2024	Time:	18:42:25
Pseudo R-squ.:	0.2273	Log-Likelihood:	-1837.7
converged:	False	LL-Null:	-2378.3
Covariance Type:	nonrobust	LLR p-value:	1.582e-231

Note: Standard Errors assume that the covariance matrix of the errors is correctly specified.

Note: Possibly complete quasi-separation: A fraction 0.17 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case, some parameters will not be identified.

Table 29 – Logit Regression: L1 & L2 Regularization

	coef	std err	z	P>|z|	[0.025	0.975]
const	$-1.702e{+}04$	$7.07e{+}05$	-0.024	0.981	$-1.4e+06$	$1.37e{+}06$
SECURED	1.6986	0.241	7.063	0.000	1.227	2.170
MATURITY	0.3760	0.037	10.290	0.000	0.304	0.448
DIVIDENDRESTRICTIONS	2.6804	0.154	17.423	0.000	2.379	2.982
DIFFPURPOSE	0.2015	0.192	1.052	0.293	−0.174	0.577
book leverage	$-4.777e{+}04$	$1.98e{+}06$	-0.024	0.981	$-3.94e{+}06$	$3.84e{+}06$

Current function value: 0.021770
Iterations: 111
Function evaluations: 112
Gradient evaluations: 111
Dep. Variable: is_clo No. Observations: 84412
Model: Logit Df Residuals: 84406
Method: MLE Df Model: 5
Date: Sat, 06 Apr 2024 Time: 18:56:23
Pseudo R-squ.: 0.2274 Log-Likelihood: -1837.5
converged: True LL-Null: -2378.3
Covariance Type: nonrobust LLR p-value: 1.305e-231

Note: Standard Errors assume that the covariance matrix of the errors is correctly specified.

Note: Possibly complete quasi-separation: A fraction 0.17 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case, some parameters will not be identified.

L2 regularization results: *Coefficients:* [1.3994225 2.4875705 0.20941104 -2.7184786] *Intercept:* [-8.64577542]

C Regression Result Robustness checks

Table 30 – Predictive Accuracy Metrics and Cross-validation Scores

Metric	Value
Precision	0.0
Recall	0.0
F1-score	0.0
AUC	0.9091180278586576
Cross-validation Scores	[0.99549843, 0.99561689, 0.99561663, 0.99561663, 0.99561663]
Mean Cross-validation Score	0.9955930444814228

Table 31 – Predictive Accuracy Metrics with SMOTE, L2 Regularization, and Stratified K-fold Cross-validation

Metric	Value
Precision Scores	[0.85797, 0.85915, 0.85955, 0.86184, 0.85394]
Mean Precision Score	0.85849
Recall Scores	[0.84061, 0.83906, 0.83919, 0.83759, 0.84210]
Mean Recall Score	0.83971
F1 Scores	[0.84920, 0.84899, 0.84925, 0.84954, 0.84798]
Mean F1 Score	0.84899
AUC Scores	[0.91550, 0.91284, 0.91332, 0.91520, 0.91116]
Mean AUC Score	0.91360
AUPRC Scores	[0.88820, 0.88364, 0.88423, 0.88842, 0.88022]
Mean AUPRC Score	0.88494

Table 32 – Logistic Regression Results with SMOTE Oversampling and L2 Regularization

Regression Coefficients	
Feature	Coefficient
SECURED	1.949 094
MATURITY	0.459 903
DIVIDENDRESTRICTIONS	2.595 933
DIFFPURPOSE	0.025 236
book leverage	−15.770 637
Intercept	−8.507 646

Performance Metrics	
Precision	0.8610012774499666
Recall	0.84
F1 Score	0.8503709934212503
AUC	0.9153863875965206
AUPRC	0.8868658089823095

Table 33 – Variance Inflation Factor (VIF) for Regression Variables

Variable	VIF
is_clo	1.020725
SECURED	2.474057
MATURITY	2.107393
COVENANTCOUNT	3.268539
DIVIDENDRESTRICTIONS	3.230771
DIFFPURPOSE	1.050650
book leverage	1.392594
ROA	1.000361
Z-score	1.001962

D Figures

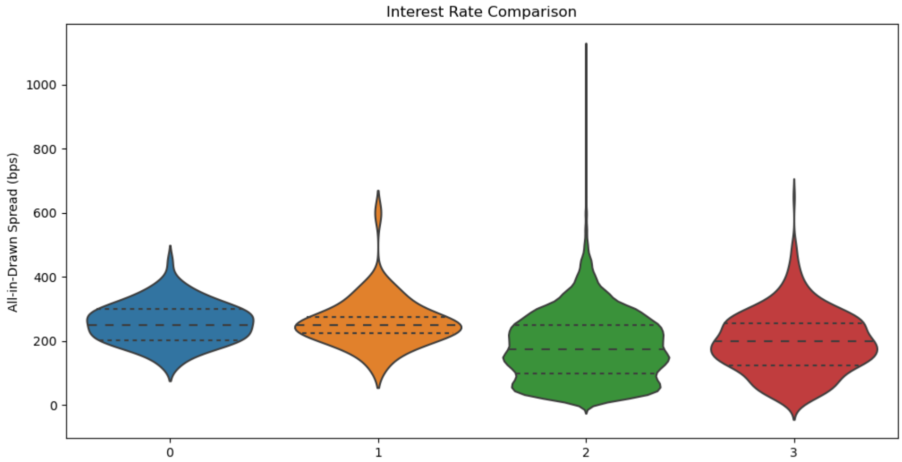

Figure 4 – Comparison of interest rate

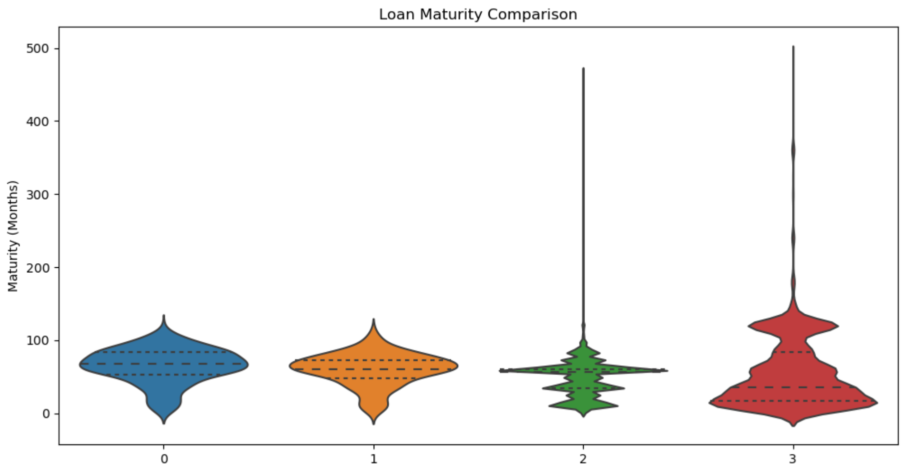

Figure 5 – Comparison of maturity

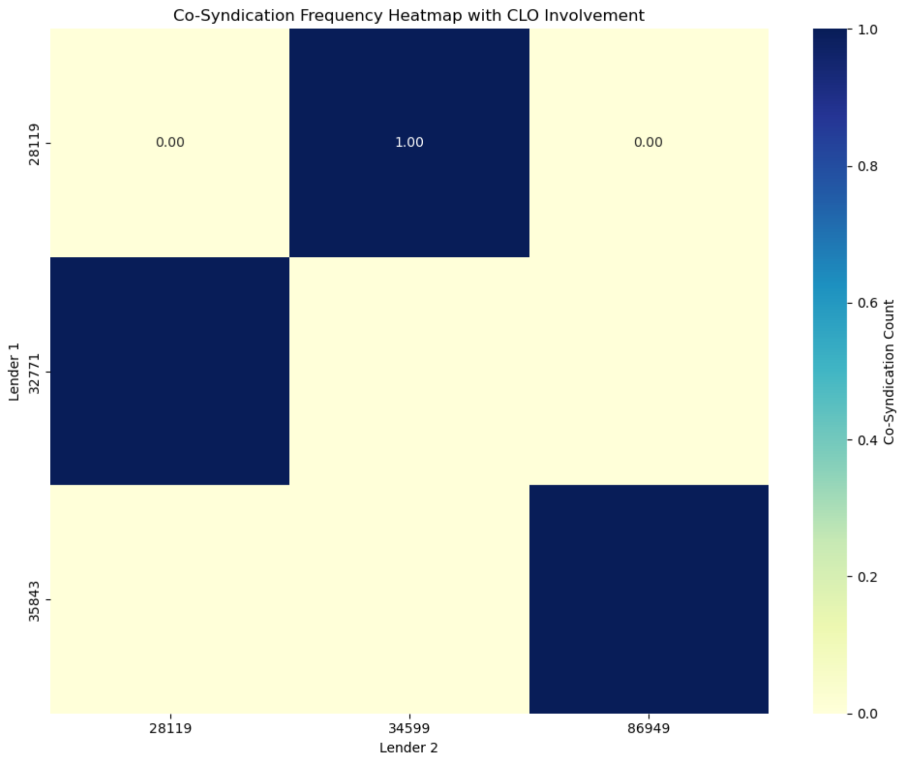

Figure 6 – Co-Syndication Frequency Heatmap with CLO Involvement

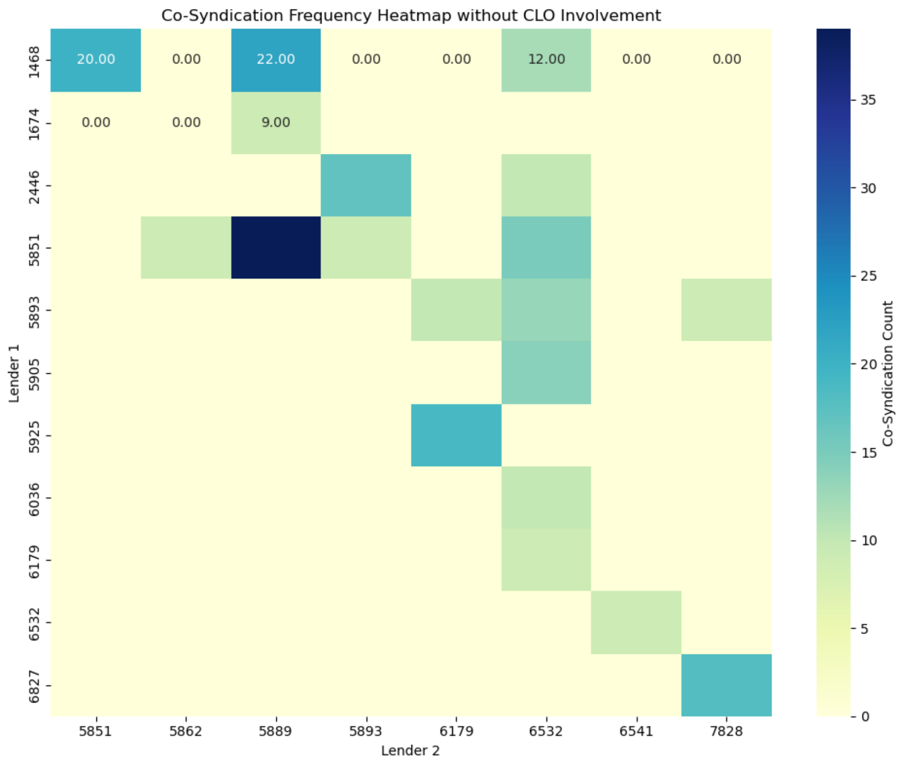

Figure 7 – Co-Syndication Frequency Heatmap without CLO Involvement

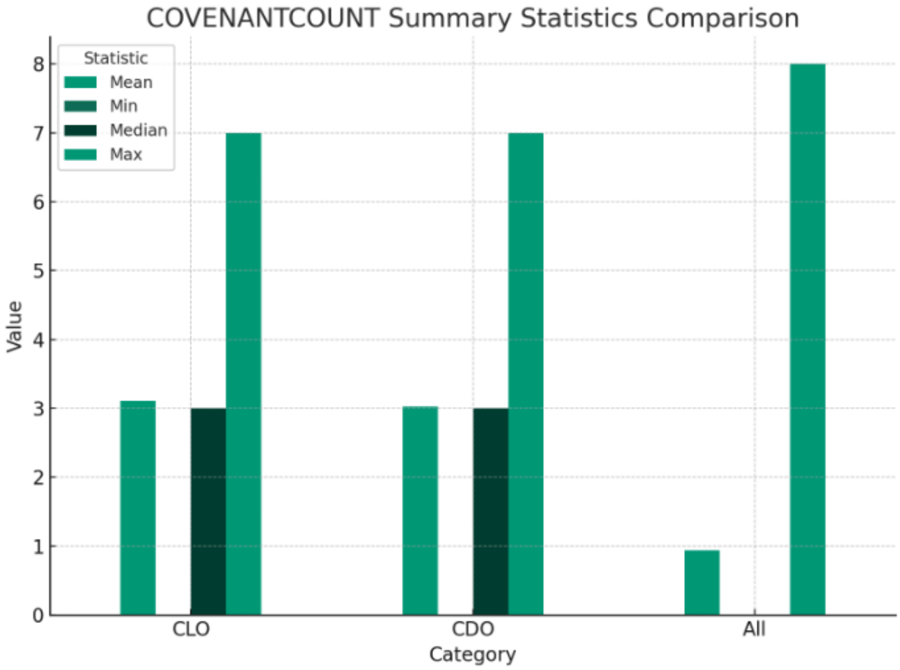

Figure 8 – Covenant Count Summary Statistics