Do Institutional Investors Trade on Covenant Violations?*

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Abstract

We develop CovenantAI, an artificial intelligence-powered covenant monitoring methodology, to examine whether institutional investors strategically trade around covenant violations in leveraged loan markets. We document a persistent decline in loan prices during the 100 days preceding violations, with a most pronounced drop 80 days prior to the violation: for example, we find cumulative abnormal returns of -6.39% during the [-80,-60] event window. Price effects are most severe for loans amended post-violation or those that remain in technical default. Covenant violations significantly increase the likelihood that the firm's credit rating is downgraded or the company enters bankruptcy, particularly among non-investment-grade loans held by Collateralized Loan Obligations (CLOs). We document substantial cross-sectional heterogeneity in CLO constraints driven by overcollateralization ratios and CCC-rated loan holdings. Loans predominantly owned by constrained CLOs exhibit steeper pre-violation price declines and significantly more negative abnormal returns. Our evidence demonstrates that constrained institutional investors preemptively divest loan positions in anticipation of covenant violations, with trading intensity reflecting both violation severity and investor-specific portfolio constraints.

JEL classification: G21, G32, G34

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1 Introduction

Covenant violations in leveraged loans play a central role in shaping risk and trading behavior in modern credit markets. Despite a general decline in observed violation rates over recent decades (Griffin, Nini, & Smith, 2021), covenant breaches remain frequent among non-investment-grade and unrated borrowers. These events trigger a range of contractual responses, from amendments and waivers to technical defaults, each carrying different economic and market consequences. Importantly, such violations raise firms' likelihood of downgrades and bankruptcy, especially for the leveraged loans most commonly held by Collateralized Loan Obligations (CLOs).

For CLOs and other major institutional investors, regulation and portfolio constraints often require loan sales ahead of or immediately after a covenant breach. Combined with the growing liquidity of the secondary loan market, already exceeding USD 800 billion in annual trading in 2022, these frictions create ample opportunity and incentive for anticipatory trading before borrowers violate covenants. Yet, despite their importance, our understanding of whether and how institutional investors trade in advance of anticipated covenant violations, and how these actions interact with contract outcomes, remains limited.

A key barrier is data: The literature mainly relies on two methods to identify covenant violations, either using reported data on financial covenants in Dealscan (Chava & Roberts, 2008) or using text searches on regulatory Securities and Exchange Commission (SEC) filings (Nini, Smith, & Sufi, 2012).[1] Both approaches have shortcomings. While the thresholds of covenants frequently change until the loan matures making it difficult to identify covenant violations using the originally reported thresholds in Dealscan, a text-search approach on SEC filings has limitations, for example, because of the complex language structure in regulatory filings. Importantly, both approaches overlook the adjustments and creditor interventions tied to different loan renegotiation outcomes, which is a key innovation of our approach.

"CovenantAI" is an advanced artificial intelligence (AI)-based methodology to identify covenant violations that offers several key advantages for academic research. It generates a comprehensive, time-series dataset of covenant violations covering all SEC filings, providing

[1] A few other papers use confidential SNC data from the Federal Reserve Bank Chodorow-Reich and Falato (2022); Haque and Kleymenova (2023). Other papers identify covenant violations by calculating violation probabilities using the approach outlined in Demerjian and Owens (2016), Li, Wang, and Wruck (2020), Bushman, Gao, Martin, and Pacelli (2021),or Christensen, Macciocchi, Morris, and Nikolaev (2022).

a more up-to-date and inclusive analysis compared to traditional methods.[2] Unlike keyword-based approaches, CovenantAI interprets the *context* within regulatory filings, enhancing both accuracy and consistency in identifying covenant violations. Additionally, it can exploit complex language structures to identify nuanced situations, such as pre- and post-violation loan amendments and waivers. Its adaptability and scalability allow it to easily incorporate new data and adjust to changes in financial reporting standards, making it a highly flexible tool for ongoing research. Leveraging this new dataset, we study whether constrained institutional investors, particularly CLOs, strategically divest in anticipation of covenant violations and assess how these trading patterns are linked to subsequent loan price dynamics, abnormal returns, and firm outcomes.

Our initial contribution is methodological, as we present CovenantAI, a tool that enables researchers to extract quarterly information on covenant violations for nearly all U.S. firms directly from their 10-K and 10-Q SEC filings. The model is calibrated using over 580,000 filings, identified through the CIK numbers of the full range of Compustat firms. We apply a small set of filters (as described in detail in Section 3). Our final dataset comprises 11,851 U.S. publicly listed, non-financial firms over the 1996 to 2024 period.

A manual inspection of SEC filings reveals that loan renegotiation outcomes are more complex than previously recognized in the literature. These outcomes include amendments without covenant violations, amendments following violations, combinations of amendments and waivers (where lenders temporarily waive covenant compliance), pure waivers, and technical defaults (where a covenant violation occurs without an amendment or waiver within two quarters).[3] These distinct outcomes reflect varying levels of covenant violation severity that must be carefully accounted for in the analysis. We train a Large Language Model (LLM) to classify our data into categories of covenant violation severity. This is a new lens through which to analyze covenant breaches and reframes violation away from a binary flag to a taxonomy of creditor-borrower renegotiation states, precisely the margin on which theory and empirical literature predicts heterogenous interventions.[4]

[2] Chava, Fang, Kumar, and Prabhat (2019) highlight that difficulty in data collection is an important factor impeding research on debt contracts and covenants. Zhu (2024) shows the relevance of accounting changes and misclassification risks associated with covenant violations. Dyreng, Ferracuti, Hills, and Kubic (2025) document measurement error in violation and slack constructed from commercial data.

[3] Chen and Wei (1993) and Beneish and Press (1993, 1995), for example, study how technical defaults are resolved, waiver decisions and the determinants of creditor forbearance.

[4] We use the pretrained MPNet Sentence Transformer model and fine-tune its parameters on our manually la-

To validate the reliability of CovenantAI for this purpose, we benchmark its classification accuracy against widely used approaches by Nini et al. (2012) and Roberts and Sufi (2009), focusing on a random sample of 102 firm-quarters where the models disagree. Using confusion matrices to compare a binary classification of violation versus no violation, our results show that CovenantAI achieves a much higher accuracy of 79.41%, outperforming both manually adjusted and simple keyword-based methods. In contrast, the approach by Roberts and Sufi (2009) shows only 45.10% accuracy. Moreover and despite a manual adjustment on top of the keywords-based approach, Nini et al. (2012) only finds 66.2% of the covenant violations that are correctly classified in CovenantAI. Roberts and Sufi (2009), however, only identify 27.8% of these violations. Overall, this comparison underscores the advantages of using a LLM to accurately identify covenant violations in SEC filings.

Violations trend downward over the last two decades, consistent with (Griffin et al., 2021), but remain strongly cyclical, spiking during the 2001-2003 dot-com bust, rising again in 2008-2009, and surging by about 50% during COVID-19. The long-run decline is largely accounted for by loan amendments after covenant violations, waivers and technical default, while amendments before violations remain surprisingly persistent.

With CovenantAI at its centre, we construct a novel data set using different sources, which we explain in detail in Section 3. We obtain daily secondary loan market data for U.S. firms from LPC Refinitiv from 1999 until today. While this dataset does not obtain transaction data, it comprises bid, ask and mid-quotes as well (for a subset of loans) the dealer banks providing quotes on any given day. Prior literature uses these mid-quotes as a proxy for transaction prices and bid-ask spreads as a measure of loan liquidity (see, for example, Saunders, Spina, Steffen, and Streitz (2024) and the literature cited therein). To study loan level transactions (buying and selling) around covenant violations, we turn to CLOs.

CLOs are actively managed closed-end funds and the largest investors in leveraged loans, which are syndicated term loans to large speculative-grade companies. We obtain data about portfolio holdings of CLOs as well as actual loan transaction data from LPC Collateral. The organizational structure of CLOs results in noticeable differences in the level of discretion

beled dataset. As robustness checks, we compare its performance to large language models such as ChatGPT, where our model achieves higher accuracy and more consistent classification results. We also run similarity tests to ensure the qualitative representativeness of the training data and cross-labeling consistency checks (each paragraph labeled independently by at least two people), with disagreement rates below 1%.

managers have to trade portfolio assets. Specifically, this discretion for CLO managers to make trades is confined primarily to the initial reinvestment period set at the CLO's issuance, typically lasting around 5 years. Beyond this period, their trading discretion is significantly limited, transforming CLOs into largely passive entities.

Our sample statistics reveal systematic institutional investor concentration in covenant-violation-prone loans: CLOs hold predominantly below-investment-grade borrowers with leverage ratios 2.1 times higher than the broader syndicated loan market, and 16.0 percentage points higher violation frequency. Critically, within violating loans, CLO portfolios show markedly different resolution patterns, 44% involve pre-violation covenant amendments compared to 33% in the full sample, suggesting CLOs preferentially hold loans where renegotiation precedes formal breaches. This composition difference reflects CLOs' strategic portfolio positioning around covenant violation risk. Moreover, loans held by constrained CLOs (45% of sample holdings) experience substantially worse credit fundamentals conditional on violation: firms experiencing technical defaults show ROA of -0.28 and interest coverage of -1.94, yet these distressed loans are substantially smaller (USD 201.3 million) and concentrated among fewer lenders (6.13), limiting borrower flexibility for proactive covenant renegotiation and are consistent with loan divestment incentives for constrained CLOs.

We first document a persistent decline in loan prices in the 100 days prior to a covenant violation using our secondary loan market data and mid-quotes (Section 5). There are noticeable drops in loan prices specifically around 80 days before a covenant violation occurs. We then compute abnormal returns using the same secondary loan market data data for different time windows. As benchmark returns we use (a combination of) the ICE BofA US Corporate Index, the ICE BofA US High Yield Index, the yield on a 3-month Treasury Bill, the change in the S&P 500 Index and the change in the LSTA index (constructed from daily prices of loans in the LSTA Morningstar Leveraged Loan Index). Consistent with the price drop around 80 days before covenant violations, we find the largest (and statistically most significant) cumulative abnormal returns of -6.39% for the [-80,-60] window. This effect is also economically large.

Do CARs increase with the severity of the covenant violation? We address this question in Section 5.3 in the paper. The literature has largely focused on the "event" covenant violation but not on how they are resolved. Yet, outcomes like waivers, which temporarily maintain original contract terms without penalties, are possible. Notably, waivers usually follow violations, whereas amendments can occur before. This allows us to categorize amendments as either violation-related or independent. Additionally, firms might initially receive waivers, later leading to mandatory loan term adjustments post-waiver. This differentiation is economically significant. Proactively negotiating amendments before violations can place companies in a stronger position, possibly gaining better terms. In contrast, firms amending post-violation may confront tougher negotiation conditions.

We first plot the daily average price of loans that record a covenant violation by violation outcome. As expected, prices of loans that are amended before a violation show hardly any price movement. Price drops of loans that experience covenant violations and are either amended or remain in technical default, however, show noticeable price declines. While loan prices of firms in technical default show the most pronounced decline before the covenant violation, the CARs are larger but statistically insignificant specifically in the [-80, -60] and [-60, -40] windows, suggesting that loan performance is driven by deteriorating fundamentals. Loans with amendments post covenant violations exhibit the most negative significant CARs throughout most event windows. For example, during the [-80,-60] event window, the CAR is approximately -6.283%. Amendments before violations show much smaller CARs, though these remain statistically significant.

Overall, these results suggests that investors trade out of loan positions for which they anticipate future covenant violations. We obtain detailed data for loan portfolio holdings and loan trades for the largest group of institutional investors, CLOs, that allows us to explore the motivation for these investors in more detail.

We first ask why CLOs might care about covenant violations. One primary rationale stems from regulatory obligations. To protect senior tranche investors in CLOs from default risks, there are several portfolio constraints, such as portfolio diversification and, importantly, leverage restrictions, particularly maintaining certain Over-Collateralization (OC) ratios. Managers are required to keep these ratios above specific thresholds to mitigate insolvency risks. The OC ratios are regularly monitored, and failing to meet them can have severe consequences for CLO managers, like not receiving fees and damaging their reputation.

Thus, as a first step, we show that covenant violations increase the likelihood that borrowers are downgraded or file for Chapter 7 or 11 bankruptcy. We use our quarterly information about covenant violations from CovenantAI and investigate the impact of covenant violations on firm default and downgrades using a "quasi-regression discontinuity design" (RDD) that is common in the literature (Roberts & Sufi, 2009; Nini et al., 2012). We find that IG-rated firms do not experience an increase in either the likelihood to file for bankruptcy or to be downgraded. There is a sizeable economic effect among Non-IG firms, though, exactly in those loan purchased by CLOs. In the four (eight) quarters after a covenant violation, these firms are 4.2% (6%) more likely to default and about 1.8% more likely to be downgraded. The effect of violations on bankruptcy risk among unrated firms is much smaller. Consistent with our hypothesis that different violation outcomes represent also scenarios of varying severity for companies, we find that non-IG rated firms, those that secure amendments before the violation occurs experience a lower likelihood of default compared to firms that obtain amendments or waivers post-violation or remain in technical default. For example, the likelihood that a firms files for bankruptcy after a technical default is between 17.6% and 19% higher, the likelihood to experience a downgrade is about 5% to 6% higher. Overall, our results suggest that there is a significant increase in both downgrade and bankruptcy likelihood particularly among the leveraged (Non-IG rated) loans usually purchased by CLOs. In other words, CLOs, especially those already constrained with regard to their leverage, might need to offload these loan before a violation occurs.

We then measure CLO leverage constraints using data on monthly OC ratio tests obtained from Creditflux. Following earlier literature (Elkamhi and Nozawa (2022); Fleckenstein (2022); Kundu (2023)) we restrict our sample to those CLOs still in their reinvestment period and compute slack in the OC ratio as the difference between reported OC ratios and the threshold value and use a simple average to compare CLOs across the years. As expected, leverage constraints are more likely for junior tranches. The average CLO has an OC ratio slack for junior traches ranges from 1.87% to 5.87%. Slack is lower during periods of widespread economic stress, e.g. in the GFC or COVID-19 period. Also the percentage of CCC rated loans relative to CLO assets is very cyclical and likely affects CLO decision to buy and sell loans. During periods of economic stress (such as the GFC or COVID-19) the ratio of CCC loans increases substantially and above the regulatory threshold of 7.5%. In fact,since 2016, CLOs have, on average, exceeded this threshold in every single year. Relative to the share of these risky loans, the junior OC ratio slack is thin, which may constrain CLOs' portfolio choice once hit by adverse events.

In Section 6.3, our focus shifts to examining the influence of constrained CLOs on the CARs surrounding covenant violations. Our findings confirm their significant impact. Initially, we plot the mid-quotes of loans for the 100 days leading up to covenant violations, distinguishing between those held by constrained and unconstrained CLOs. Our analysis reveals that loans in the portfolios of constrained CLOs experience earlier and more pronounced price declines prior to the violation, particularly around 80 days before the violation.

We test this more formally and regress the CARs in the [-80,-60] event window on a measure of CLO portfolio constraints. We initially categorize the loans into two groups: constrained and unconstrained. A loan is classified as constrained if its slack is below the median slack observed among all CLOs on that specific date. Conversely, if the slack exceeds the median, the loan is considered not constrained. We then compute the weighted percentage of constrained CLOs in a loan. This is calculated by dividing the total deal amounts of the constrained CLOs by the aggregate deal amount for that loan. Consistent with our hypothesis, we find that if the share of the loan owned by constrained CLOs is higher, CARs before covenant violations are more negative.[5]

2 CovenantAI

In this section, we develop our new machine learning (ML) algorithm to identify covenant violations, which we call "CovenantAI" (a detailed technical discussion is relegated to the Online Appendix).

[5] There is a growing literature on the importance of non-bank intermediaries and in particular CLOs. In particular,the rise of CLOs has led to lower credit spreads and more credit for firms during booms (Ivashina & Sun, 2011; Shivdasani & Wang, 2011; Nadauld & Weisbach, 2012), but also a stronger reduction of credit and a larger increase in credit spreads during busts (Fleckenstein, 2022; Fleckenstein, Gopal, Gutierrez Gallardo, & Hillenbrand, 2020). Other papers on CLOs have studied the adverse selection of loans into CLOs (Benmelech, Dlugosz, & Ivashina, 2012; Bord & Santos, 2015) and CLO performance (Cordell, Roberts, & Schwert, 2023; Fabozzi, Klingler, Mølgaard, & Nielsen, 2021). Others find that trading can be value destroying because CLO managers sell risky loans at fire-sale prices to avoid OC test failures (Loumioti & Vasvari, 2019; Elkamhi & Nozawa, 2022; Kundu, 2024) – in particular loans of firms they have no relationship with (Bhardwaj & Mukherjee, 2022) – which has real effects for affected firms (Kundu, 2023).

2.1 SEC filings

The main datasource to develop CovenantAI are regulatory (SEC) filings. Companies issue 10-K reports annually at fiscal year-end, and 10-Q reports for the first three quarters. If a firm reports only three quarters, its 10-K includes the fourth quarter data, and we combine 10-K and quarterly filings to ensure continuity in our dataset. Covenant violations appear in both annual and quarterly reports. 8-K reports, issued immediately following specific events including covenant violations, provide further relevant information such as the timing of the violation.

In total, we extract 132,591 10-K, 451,826 10-Q, and 1,285,768 8-K reports over the 1996 to 2024 period from the SEC Edgar database.[6] As we describe further below and in contrast to other machine learning models, we do not need to further clean these reports as our model interprets the *context* of complete sentences. We develop a data frame capturing paragraphs including 700 characters surrounding the term "covenant." The source files vary in format, newer ones are presented as HTML and older ones as txt filings. We confirm that HTML-based paragraphs adhere to the 700-character limit, as the model cannot process beyond this limit. To optimize labeling of paragraph by our algorithm, we apply a filter to our dataset that highlights paragraphs containing specific words or combinations of words that suggest possible covenant violations and amendments.[7] To verify its accuracy, we randomly sample a subset of our data and verify that violations and amendments are correctly classified. Overall, this method yields 1,081,905 paragraphs containing the word "covenant." These paragraphs are then processed and labeled as described below.

2.2 Algorithm

A manual inspection of the SEC filings suggest that loan renegotiation outcomes are more complex than the previous literature suggests. For example, there are loan amendments without covenant violations, amendments after covenant violations, waivers (i.e., a situation in which a lender temporarily waives covenant compliance), or technical defaults (i.e., when covenant

[6] In 2009, the XBRL filing program became mandatory for all companies. This filing program ensures a standardized structure for all reports.

[7] We flagged paragraphs as potential amendments or violations if they contained the following specific words: "amends", "waived", "amending", "violate", "amendment", "amended", "violations", "waiving", "violating", "violates", "waives", "amendments", "compliances", "compliance", "amend", "waive", "violation", "violated".

violations remain unresolved).[8] CovenantAI can account for these different renegotiation outcomes. We provide a brief overview of the design of this new ML algorithm below and refer the reader to Section B of the Online Appendix for an in-depth (technical) discussion.

Step 1-Labeling. Building a robust machine learning model to identify covenant violations requires a clean and representative dataset. Ensuring diversity while preventing duplication and data leakage is key to maintaining model integrity and reliability. To address possible duplication and leakage concerns of training and test datasets (Kapoor & Narayanan, 2023), we apply a two-step approach to all paragraphs containing the word *covenant*. We first select only one paragraph per firm out the whole sample of covenant paragraphs and then apply the "Jaccard Similarity Index" to identify and remove duplicates within the sample of paragraphs.[9] The Jaccard Similarity Index is a statistical measure that helps understanding the similarity between finite sample sets that is particularly effective in comparing the presence of words in both samples (Prakoso, Abdi, & Amrit, 2021). This method reduces the dataset from 1,081,905 paragraphs to 14,335 unique paragraphs.[10]

The final manual dataset consists of three parts, the first is a random selection of 2,000 paragraphs out of the previously created unique paragraphs sample. The second manual dataset is extracted quasi random. To make the training of the model more efficient for all classes, we select the other two parts of the dataset to make the sample more balanced to the different groups. The second sample consists of 2,084 paragraphs, which we balanced by adding more non-zero labeled paragraphs. We conduct a keyword search within the remaining paragraphs of the unique sample paragraphs to identify terms indicating potential violations or amendments, providing a preliminary basis for labeling. 21.35% of the data are labeled as technical defaults, 7.39% of the paragraphs are amendments after violation, 7.29% are waivers and 19.48% are amendments without violations.

Since these two datasets have only a few instances of the *Amendment w/ Violation* class, we add 100 artificially created paragraphs for this label to the manual dataset. This step ensures a more efficient training of the *Amendment w/ Violation* class. The final manual dataset consists

[8] We combine amendments after covenant violations and amendments and waivers as they are economically similar.

[9] We also ensure that for this selection underlies an equal distribution of years.

[10] To identify similar paragraphs, we start by converting the paragraphs into sets of words. We then calculate the Jaccard Similarity Index, where we use an threshold of 0.5 to eliminate similar paragraphs. After eliminating those paragraphs above the threshold leads to a dataset of 14,335 unique paragraphs that are dissimilar to each other

of 4,184 observations, which are specific, balanced and unique ensuring a high quality dataset for training and testing our model. To ensure a high-quality labeled dataset, each of the 4,184 selected paragraphs was independently labeled by two individuals: either one of the authors or a trained research assistant. Disagreements occurred in less than 1% of cases, providing strong evidence of accuracy and consistency in the labeling process.

To train the classification algorithm and evaluate model performance, we manually labeled a subset of paragraphs to serve as ground truth. Each paragraph was categorized into one of six groups: *No Violation* (label 0), *Amendment without Violation* (1), *Waiver* (2), *Amendment and Waiver* (3), *Amendment with Violation* (4), or *Technical Default* (5). *No Violation* is assigned when there is no evidence of a breach; *Amendment with Violation* indicates a loan modification to cure a violation; *Technical Default* applies when neither an amendment nor a waiver occurs within two subsequent quarters. Section B of the Online Appendix provides SEC filing examples for each category. The resulting manually labeled dataset has the following distribution across categories:

The random dataset represents the true distribution of the overall sample. There are 3.7% instances of *Technical Defaults*, 2.2% instances of *Amendments w/ Violation*, 4.3% instances of *Waivers* and we detect *Amendments w/o Violations* in 5.65% of the cases.

In our overall sample, there are 519 (12.71%) instances of *Technical Defaults*, 198 (4.85%) of *Amendments w/ Violation*, 238 (5.83%) of *Waivers*, and 519 (12.71%) of *Amendment w/o Violation*. This distribution results from our sampling method, which is designed to balance the dataset for training and validation.[11]

Step 2-Classification. We divide the labeled sentences into three datasets: training (70%), testing (15%), and validation (15%).[12] Each dataset reflects different proportions of technical default, waiver, amendment with violation, amendment without violation, and no-violation observations, and is used to calibrate and evaluate model performance. The test set is constructed solely from a fully random sample to assess accuracy on the true underlying distribution.

For our analysis, we use the MPNet Sentence Transformer, an advanced language model.[13]

[11] However, this sample is not fully representative of the five categories; a random sample from our full dataset indicates a mean technical default rate of about 3.7%, reflecting a more accurate distribution.

[12] We tested the model using various splits for test, training, and validation set sizes. See Section C in the Online Appendix.

[13] We choose the MPNet sentence transformer because it performs efficiently in sentence similarity and classification tasks, which are crucial for identifying covenant violations. Building on traditional BERT models, MPNet combines masked language modeling with permutation modeling (as in XLNet), allowing it to cap-

In short, this model transforms complete sentences into numerical representations, making them suitable for machine learning tasks. It excels at distinguishing between different classes in our dataset by capturing the unique characteristics of each type. Its ability to learn both similarities and differences among categories enables more accurate classifications, which is essential for identifying and categorizing different events, such as technical defaults, amendments, or no violations.

A key advantage of CovenantAI is its ability to interpret complex language structures, allowing us to distinguish between types of loan amendments and covenant outcomes. Violations can result in different resolutions: a waiver (typically granted after a violation and often temporary), an amendment (which may occur before or after a violation), or a sequence involving both. These distinctions matter economically: firms that secure amendments before breaching covenants are likely in a stronger negotiating position and may obtain better terms, while firms amending after a violation often face stricter conditions. During training, the model minimizes error on the training set, while validation data monitor performance and help tune hyperparameters to prevent overfitting. The test set, used only after training, provides an unbiased measure of model accuracy.

Model performance is shown in Panel A of Table 1 for our test data (628 observations). The confusion matrix summarizes how accurately the model assigns each class by comparing predicted versus actual outcomes. The model achieved 92.17% accuracy on the test set (and 90.95% on the validation set as shown in the Online Appendix), correctly identifying 87% of violations, 93% of amendments with violation, 89% of waivers, 89% of amendments without violation, and 84% of non-violations in the test data. We also report precision and recall in Panel B of Table 1. Precision measures the proportion of predicted violations that are correct, minimizing false positives, while recall measures the proportion of actual violations the model identifies, reducing false negatives. We calculate both macro averages (simple averages across categories) and weighted averages (accounting for category size). The model achieves approximately 91% precision and 93% recall using macro averages, and 94% for both using weighted averages. Additional details are provided in Section C of the Online Appendix.

ture complex sentence dependencies effectively. We integrate MPNet within the Sentence-BERT framework, leveraging its strengths to generate high-quality sentence embeddings. This combination is well-suited for analyzing financial documents, as it accurately captures sentence context and nuances important for classifying covenant violations.

Step 3-Full sample analysis. We merge the 10-K/10-Q data and the quarterly covenant violation data from our machine learning algorithm using the reporting date from the SEC filings. We extract the date that is mentioned within the 700 characters and calculate a difference column to check the distance between the reporting date of the SEC filing and the covenant violation date mentioned in the filing. If the difference between both is larger than 180 days, we do not count the observation as a violation, as it contains information about a previous violation that has already been reported (and recognized as such by our model). We apply the same machine learning algorithm to the 8-K filings to validate our results. 8-Ks give us real-time information because they need to be filed within four days after the event. In cases where a Technical Default is succeeded by an Amendment with Violation, an Amendment with Violation/Waiver, or a Waiver within the subsequent two quarters, it is not classified as a Technical Default.

Applying our algorithm using these criteria, we obtain 19,048 (3.36%) loan amendments without violation, 7,336 (1.26%) amendments after a violation, 7,536 waiver (1.33%) and 5,475 (0.97%) observations with firms in technical default for all firm quarters. The number of firm quarters in which we find a "new" technical default is 2,850 (0.50%), a "new" waiver is 4,425 (0.78%), a "new" amendment with violation is 3,844 (0.68%) and in which we find a "new" amendment without violation is 9,499 (1.68%).[14]

2.3 Benchmarking CovenantAI

Understanding when and how covenant violations occur is central to identifying periods of institutional trading pressure in loan markets. To validate the reliability of CovenantAI for this purpose, we benchmark its classification accuracy against widely used approaches by Nini et al. (2012) and Roberts and Sufi (2009), focusing on a random sample of 102 firm-quarters where the models disagree. For comparability, we collapse outcomes into a binary violation/no violation measure: Violation equals one if a waiver, an amendment with violation, or technical default is observed; otherwise, it is coded as zero.

Panel C of Table 1 presents the confusion matrices comparing CovenantAI, the Nini et al. (2012) approach, and the Roberts and Sufi (2009a) Dealscan labeling, based on the 102-sample

[14] We mark the variable as new if the respective outcome did not occur in the previous two quarters.

where methods disagree. CovenantAI achieves the highest classification accuracy at 79.41% (sum of true positives for No Violation and Violation: 25.49% + 53.92%), followed by Nini et al. with 53.92% accuracy (7.84% + 46.08%), and Roberts and Sufi (2009a) with 52.74% (4.9% + 47.84%). The keyword-based Roberts and Sufi approach yields the lowest accuracy at 45.10% (38.24% + 6.86%).[15] These results demonstrate that CovenantAI provides more reliable identification of covenant violations in challenging cases, which is critical for robust empirical analysis of trading around these events.[16]

2.4 Time-series of covenant violations

Figure 1 plots the annual incidence of each major covenant violation outcome (waiver, amendment with violation, amendment without violation, and technical default) as identified by CovenantAI during the 1996 to 20220242 period. The figure shows that amendments without violation are most frequent, while technical defaults and waivers occur less often. All violation types display clear cyclical fluctuations, with noticeable spikes around identified NBER recession periods (shaded), and an especially pronounced increase during the COVID-19 recession. This highlights substantial time-variation and economic sensitivity in both the frequency and type of covenant violations.

3 Data Sources

To investigate trading behavior of institutional investors around covenant violations, we obtain data from different data sources. Our main data set is the intersection of data on daily secondary loan market trading and firms that report covenant violations in their SEC filings (and which are identified using CovenantAI). While we do not observe actual trading of loans or the parties who are involved in these trades (except the dealer banks) in this data set, this is the most comprehensive source to identify trading patterns before or around covenant violations.

In a second step, we construct a novel data set at the intersection of secondary loan market data, covenant violations and holdings and trading data of Collateralized Loan Obligations (CLOs), who are the largest investors in leveraged loans. For a subset of our data, we can thus

[15] Online Appendix X shows examples of paragraphs where CovenantAI does not agree with the labeling of the keyword based approach.

[16] Dyreng et al. (2025) also highlight possible measurement risk associated with these alternative approaches.

observe trading (buying and selling) of a large group of investors in this market and exploit cross-sectional variation in our data to link the trades around covenant violations to investor characteristics.

3.1 Secondary loan market trading

Over the last two decades, the U.S. secondary market for corporate loans has developed into an active and liquid dealer-driven market, where loans are traded like debt securities. This allows the observation of daily price quotes even for private claims, which can be traded by institutional investors legally in possession of material non-public information. This market has developed into a liquid market for private debt claims since 1995, when the Loan Syndication and Trading Association (LSTA) standardized loan contracts and procedures. In 2022, the annual secondary market trading volume reached USD 824 billion (afterwards declined to USD 715 in 2023, though) and the underlying debt claims reached a notional volume of about USD 1.5 trillion at this time (Figure 2).

We use a novel dataset provided by Refinitiv comprised of daily secondary market quotes for corporate loans spanning December 1999 to March 2023. Loan sales are usually structured as assignments,[17] and investors trade through dealer desks at underwriting banks. The data contain daily bid and ask quotes from over 35 dealers that represent over 80% of the secondary market trading. A recent literature has shown that price quotes provide an accurate representation of prices in this market (Addoum & Murfin, 2020; Berndt & Gupta, 2009).[18]

The secondary loan market appears to be sufficient liquid for institutional investors to effectively trade their positions. Figure 3 plots the median bid-ask spread (scaled by the mid-quote) over the 1999-2023 period as well as the interquartile range (grey area). The median bid-ask spread in the 1999 to 2023 period is 87 bps. For comparison, (Feldhütter & Poulsen, 2018) report an average bid-ask spread for the U.S. bond market of 34 bps over the 2002 to 2015 period.

Loan origination data. We complement pricing data with information about the under-

[17] In assignments the buyer becomes a loan signatory. This facilitates trading as ownership is transferred from seller to buyer. In contrast, in participation agreements the lender retains official ownership.

[18] There is little public information about dealers who provide quotes. However, the data identifies dealer banks for a subsample of loans. We show a snapshot of the Top 10 dealer banks in Table A1. The top 25 dealers account for about 90% of all quotes. We rank dealers by their market share in the secondary loan market and underwriter market share in the primary loan market and find a correlation of 0.87.

lying loans from Refinitiv Dealscan. This includes information on various loan terms such as loan size, maturity and interest rates. The databases are merged using the Loan Identification Number (LIN), if available, or else a combination of the borrower name, dates, and loan characteristics.

Borrower information. We extend the Chava and Roberts (2008) Dealscan-Compustat link to 2022 and map Compustat firms to our secondary loan market data. Overall 54% (46%) of firms in the secondary loan market data are public (private) firms. We obtain quarterly information about our publicly listed from Computstat/CRSP (and Capital IQ) can be merged using the GVKEY-CIK identifier. Credit rating information is sourced from S&P. Our information contains the long-term issuer ratings as well as the rating data and unique company ID.

3.2 CLO loan holdings and trading

We obtain data on CLOs' security-level portfolio holdings and transactions from the LPC Collateral database provided by Refinitiv. These data are sourced from Trustee Report over the 2005 to 2023 period. If in a given quarter multiple reports are available for a CLO, we include only data from the last report. We restrict the sample to CLO predominantly invested in U.S. dollar denominated syndicated loans.

We also keep credit rating information from the rating agencies Moody's, S&P, and Fitch, which we convert to numerical scores following the classification in Becker and Milbourn (2011). For comparability, all rating references are translated to the S&P scale. Additionally, I collect information on a CLO's manager, issue date, reinvestment period and legal maturity date.

The LPC Collateral database covers about 80% of the market for our sample period.[19] On average, each issuer's loans are held in 250 CLOs. We limit the analysis to firms that received a syndicated loan, as indicated in Refinitiv DealScan, to ensure comprehensive coverage across datasets.

The trading data shows the individual transactions of the CLO within each month and provides information such as the activitiy itself (buy or sale), the transaction amount and price, trade as well as settlement date. We also compute a measure for loan market liquidity based

[19] We use the International Monetary Fund's figures on total outstanding US CLOs to compute this (International Monetary Fund (2020)).

on these transaction data and plot the Amihud (2002) illiquidity measure together with the bid-ask-spread in Figure 3. Noticeably, the Amihud measure based on transaction data exhibits higher volatility and spikes. The cross-sectional correlation, however, is high ($rho = 0.88$).

We can match the loan to the holdings data, Refinitiv Dealscan and the secondary loan market data via the LIN number. This allows us to broaden the scope of our analysis as we can, for example, compare the bid-ask quote provided by dealer banks to the transaction price at which it was executed and link the transaction to overall loan market liquidity.

CLO overcollateralization test. We augment our CLO holdings and trading data using collateralization (OC) test results of CLOs on a monthly basis from the Creditflux CLO-i database. CLO-i report the current OC ratio as well as the threshold level for each CLO. As there is no identifier of CLOs across both data providers, we use a fuzzy string match between the CLO names in LPC Collateral and Creditflux. We describe this more in detail in Section 6.1.2 below in this paper.

3.3 Sample construction

We employ multiple samples with increasing specificity depending on our analysis as shown in Table 2. Our foundation is the CovenantAI sample (14,792 firms, 537,804 firm-quarters) containing machine-learning-detected covenant violations for all U.S. public firms. We merge this with Dealscan syndicated loans (3,999 firms, 15,124 loans, 104,359 firm-quarters) to obtain loan information. For analyses of secondary market pricing effects around covenant violations including loan specific information, we further restrict to loans with available transaction-level prices (891 firms, 2,388 loans, 15,033 firm-quarters). However, for our primary analysis of CLO institutional investor trading behavior around covenant violations, we impose the most restrictive requirements: CLO holdings data from LPC (648 firms, 1,611 loans, 11,676 firm-quarters), CLO transaction records (598 firms, 1,476 loans, 10,624 firm-quarters), and CLO overcollateralization constraint metrics from Creditflux. This stringent subsample of 598 firms with 1,476 loans ensures we directly observe covenant violation events, CLO portfolio positions, actual buy-sell transactions, and investor-specific regulatory constraints, both essential elements for examining whether constrained institutional investors trade in anticipation of covenant violations.

3.4 Descriptive statistics

CovenantAI. Panel A of Table 3 shows statistics related to CovenantAI. In total, we obtain data on 11,428 publicly listed firms in the US via their regulatory filings. On average, about 47% of all firms in our sample violate a covenant at some point during our sample period. Firms might have multiple consecutive violations over time that result in different violation outcomes. 15%, on average, stay in technical default and 28% (33%) amend their contracts after (before) a covenant breach. While 2% of firms default during our sample period, about 87% experience a downgrade at some point during our sample period. The average credit rating is 12.26, which corresponds to a BBB- rating.

Secondary loan market sample. The sample contains 14,874 loans to U.S. non-financial firms. We exclude credit lines and special loan types (4,830 loans), i.e., we restrict our sample to term loans.[20] Term loans are fully funded at origination and typically mostly repaid at maturity, i.e., the cash-flow structure is similar to bonds. We require that loans can be linked to LPC's Dealscan and remove loans with a remaining maturity of less than one year. We further exclude loans to private firms resulting in a final sample of 6,782 loans. Panel B of Table 3 shows summary statistics of loans traded in the secondary loan market. The average number of loans traded in a given year is 905 with an average bid (ask) quote of 95.47 (96.59) and a midquote of 96.03, respectively. The midquote is our measure for the "price" at which a buy/sell is executed. Loans carry a loan spread (which is the All-In-Spread-Drawn from Dealscan) of 362.52bps and the average maturity is 4.31 years; the mean bid-ask-spread is 0.02.

CLO sample. We then construct a second sample at the intersection of our secondary loan market data, CLO holdings, trading and collateralization test information and CovenantAI. We start with merging the secondary loan market data to the LPC Collateral database using the LIN identifier. This process results in 8,734 loans. Overall, about 70% of loans available in LPC Collateral could be matched to the Refinitiv Secondary Loan Market database. Panel C of Table 3 shows summary statistics of overall 8,734 loans in CLO portfolios. The average number of loans (# Loans) in a CLO portfolio is 532 with a mean rating of 14.55. The average spread is 430bps. The panel also shows the share of loans by credit ratings. Only 0.72% are IG-

[20] The vast majority of loans traded in the secondary market are term loans, as (non-bank) institutional investors typically dislike the uncertain cash-flow structure of credit lines Gatev and Strahan (2006, 2009). About 90% of loans in our secondary market dataset are institutional term loans (term loan B). Only around 10% are term loan A.

rated, 16.31% are BB-rated, 67.78% are B-rated and almost 4% are CCC rated. About 50% of loans in CLO portfolios are originated by public (private) firms. We then use the GVKEY-CIK mapping to link this merged dataset to CovenantAI. We drop all loans to private borrowers as CovenantAI only comprises information about publicly-listed firms.

3.5 Characteristics by Sample

Table 4 shows firm and loan characteristics across the different sample (e.g., CovenantAI, after merging with Dealscan, after merging with secondary loan market data, etc.) as well as differences in means. Panel A shows firm characteristics. Firms in the CLO sample (Column 4) differ systematically from the full CovenantAI universe (Column 1), with substantially smaller market capitalizations and higher leverage ratios. CLOs concentrate holdings in below-investment-grade borrowers (Panel B): B-rated loans comprise 19.88% of CLO portfolios versus 5.96% of CovenantAI firms, while CCC-or-below loans increase from 2.32% to 7.13%.

Violation patterns differ markedly across samples (Panel C). The "ever violate" rate declines from 32.79% (CovenantAI) to 16.78% (CLO data), suggesting CLOs strategically avoid serial violators. More importantly, the composition of violation outcomes shifts: technical defaults decline from 15.30% to 7.87%, while amendments before violations increase from 32.55% to 43.36This composition shift indicates CLOs preferentially hold loans where proactive covenant renegotiation precedes formal violations, consistent with anticipatory divestment before technical defaults or post-violation amendments that trigger adverse price movements. CLO-held loans are also substantially larger and carry higher spreads (Panel D).

3.6 Violation outcomes, loan characteristics, and CLO ownership

Table 5 shows heterogeneity across firm and loan characteristics for different covenant violation outcomes. Panel A shows that firms experiencing technical defaults exhibit the weakest fundamentals one quarter before a covenant violation occurs: ROA of -0.28, interest coverage of -1.94, and Z-scores of 1.5, compared to ROA of 1.26 for firms receiving amendments before violations. Firms receiving waivers show intermediate credit quality (ROA of 0.21, interest coverage of -0.76), while firms obtaining post-violation amendments display ROA of 0.16. Firms that obtain amendments before a covenant violation exhibit the strongest fundamentals.

Panel B reveals systematic loan characteristic variation across violation types. Loans with no violations average 258.31 bps spreads and USD 421.25mfacility size, while technical defaults carry 327.77 bps spreads but are substantially smaller (USD 201.3m) with fewer lenders (6.13). Loans receiving amendments before violations are larger (USD 335.39m) with lower spreads (288.52 bps) and more lenders (8.08), suggesting stronger fundamentals (with less monitoring needs) already at the loan origination stage.

Panel C documents CLO ownership patterns. The average loan is held by 150.38 CLOs (median 109), with 50% held by at least one top-10 CLO manager. The HHI of CLO ownership averages 0.1 (median 0.01), indicating dispersed ownership. Critically, 45% of sample loan holdings are owned by constrained CLOs—those with binding overcollateralization ratios—with substantial cross-sectional variation (interquartile range: 0.39 to 0.54).

4 Methodology

As a first step, we use merged Secondary Loan Market and CovenantAI dataset to understand trading in loans around covenant violations. A group of institutional investors' (collective) action to buy or sell loans may lead to a temporary deviation of the price of the loan away from its fundamentals, if the group of investors has a large volume share in transacting the loan and arbitrage capital does not flow to the market soon enough. Therefore, we first examine whether or not we can observe abnormal returns around covenant violations and whether the price reaction is stronger if the (expected) violation outcome is more severe.

4.1 Measuring abnormal returns

To measure cumulative abnormal returns (CAR), we estimate regression (1) for each firm i (and each event window $[-t, +t]$ around a covenant violation) separately:

$$r_{i,t} = \alpha_i + \sum \beta_i \times I_{Vio=1} + \sum \gamma_i \times X_t \times I_{(0|Vio=1)} + \epsilon_{i,t} \tag{1}$$

where $I_{Vio=1}$ is an indicator variable equal to one for each trading day in the event window $[-t, +t]$, X_t is a vector of benchmark returns and $I_{(0|Vio=1)}$ is an indicator variable that is zero when $I_{Vio=1}$ equals one. This way, contemporaneous changes in the benchmark returns do not bias the point estimates of our CAR during the event window. $\sum \beta_i$ is our CAR estimate.

As benchmark returns we use (a combination of) the following returns:

- The ICE BofA US Corporate Index Effective Yield[21], which monitors the performance of IG corporate debt (in USD), publicly issued in the domestic US market.
- The ICE BofA US High Yield Index Effective Yield[22], which measures the performance of corporate debt rated below investment grade, publicly issued in the domestic US market.
- The Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity[23].
- The daily adjusted closing prices of the S&P500 Index, downloaded from Yahoofinance.
- The LSTA Index, which be calculate as a with the facility amount weighted average of the daily loan prices. We use the loan prices and amounts from the LPC Refinitiv. We compare our LSTA index to the Morningstar LSTA US Leveraged Loan Index for the same time period and observe a correlation of 86.5%.

Our approach differentiates from the traditional approach, which runs the regression on the pre-event window observations and applies the coefficients to the event window observation. This represents the expected returns in the event window period. The abnormal returns represent the difference between the actual returns and the expected returns. We calculate the cumulative abnormal returns using this traditional approach and show the results in the Online Appendix.

Covenant violations can appear repeatedly in short time intervals. Calculating the abnormal returns of an event window from [-80,-60] and using a minimum of 30 observations before an event means that a minimum of 120 business days have to be used to calculate the abnormal returns of one event. The advantage of our used model is that we just define the event window and use the remaining data to run the regression for each firm separately. Therefore, we have more data points for running the regression. The benchmark returns are set to zero for the event window so that we do not influence the regression by using the event window data. We

[21] Obtained from FRED using the following identification code: BAMLC0A0CMEY
[22] Obtained from FRED using the following identification code: BAMLH0A0HYM2EY
[23] Obtained from FRED using the following identification code: DGS3MO

present the cumulative returns for different event windows and for different combinations of these five benchmark returns in Table 6.

5 Price Impact of Covenant Violations

5.1 Loan prices before covenant violations

In a first step, we plot the daily average price of loans that record a covenant violation over the [-100,0] day period before a covenant violation occurs (Figure 4a). Loan prices have declined, on average, over the entire period. However, there are noticeable drops in loan prices, for example around 20 days before a covenant violation, and an even more pronounced decline in the window from 80 to 60 days *before* the violation. While we restrict our sample to borrowers experiencing covenant violations, there may be an overall market decline during these periods. Therefore, we compute abnormal returns to isolate the trading behavior of loans with covenant violations.

5.2 Cumulative abnormal returns

In a next step, we compute CARs using the methodology outlined above for the following event windows: [-80,-60]; [-80,-1]; [-60,-40]; [-60,-1]; [-20,-1]; [-1,+1]. Table 6 shows the results. We compute the CARs for the different event windows as well as for different combinations of benchmark returns to demonstrate the robustness of our results.

We do not find a significant abnormal return around the covenant violation itself ([-1,+1]), but we do find very significant negative CARs three to four months before the covenant violation, consistent with Figure 4a. In other words, investors trade out of these loans some time before the violation occurs. This is a key result of this table and is insensitive to the benchmark returns that are used in the model.

As we noticed in Figure 4a, the steepest price drop and, as we find, also largest negative abnormal return, is measurable in the 80 trading days before the violation; the CAR during this period is about -6.39 percentage points. The violating firms have over the whole time period an return of -0.02% while the firms that never violate a covenant have an average return of -0.008%.

5.3 Understanding CARs: The role of violation outcomes

Do CARs (in absolute terms) increase with the severity of the covenant violation? The literature has largely focused on the "event" covenant violation but not on how they are resolved. Yet, outcomes like waivers, which temporarily maintain original contract terms without penalties, are possible. Notably, waivers usually follow violations, whereas amendments can occur before. This allows us to categorize amendments as either violation-related or independent. Additionally, firms might initially receive waivers, later leading to mandatory loan term adjustments post-waiver. This differentiation is economically significant. Proactively negotiating amendments before violations can place companies in a stronger position, possibly gaining better terms. In contrast, firms amending post-violation may confront tougher negotiation conditions.

CovenantAI is proficient in handling complex language structures and differentiate between these possible outcomes. We thus create different indicator variables that we can summarize in the vector $Z_{Outcome}$, which denotes the respective outcome of the violation: (1) $Z_{Amendment(w/o)}$, (2) $Z_{Amendment(w)}$ (which we group together with waivers), and (3) $Z_{TechnicalDefault}$.

Descriptive evidence. We first plot the daily average price of loans that record a covenant violation over the [-100,0] day period before a covenant violation occurs by violation outcome (Figure 4b). As expected, prices of loans that are amended before a covenant violation show little movement, remaining between 95% and 96% over this period. In contrast, loans that experience covenant violations show substantial price declines. For example, loans receiving a waiver decline from 95% to 93%, loans amended after a violation fall from 91% to 88%, and loans issued by borrowers in technical default drop from 87% to 81% during the 100 days before the violation.

Methodology. To understand the drivers of CAR around covenant violations, we compute CARs for the different violation outcomes and event windows ([-80,-60]; [-80,-1]; [-60,-40]; [-60,-1]; [-20,-1]; [-1,+1]). Panel A of Table 7 reports the results. Loan prices of firms in technical default exhibit the most pronounced price declines and most negative CARs across all event windows. However, these CARs are statistically insignificant specifically in the [-80,-60] and [-60,-40] windows, consistent with broader deterioration in firm fundamentals rather than covenant-specific anticipation. Loans with amendments post covenant violations (*Amendment* *w/ violation*) exhibit the largest significant negative CARs throughout all event windows (except the [-60,-40] days before the violation, during which we did not find negative CARs in our analysis). For example, during the [-80,-60] event window, the CAR is about -6.28%. Loans obtaining waivers before the violation, show negative CARs across all event windows, but these are less pronounced and less statistically significant than those with amendments w/ violation. For example, during the [-80,-60] event window, the CAR is about -3.55%. Amendments before violations (*Amendment w/o violation*) significant but much much smaller CARs compared to all other violation outcomes.

In Panel B of Table 7, we report a differences-in-mean test. Importantly, we find significant differences between firms that obtain amendments *after* a violation relative to those that obtain amendments *before* a covenant violation for the event window [-80,-60]. Overall, investors appear to sell loans that obtain amendments (and thus contract adjustments) before the violation occurs.

6 Trading of CLOs Around Covenant Violations

6.1 Consequences of covenant violations

Why should CLOs care about covenant violations? In this subsection, we discuss possible concerns of CLOs that facilitate selling of loans prior or after covenant violations. To protect senior tranche investors in CLOs from default risks, there are several portfolio constraints. A key one is portfolio diversification; CLOs must calculate and maintain a "diversity score" to ensure diversification within and across industries. Additionally, CLOs face leverage restrictions, particularly maintaining certain Over-Collateralization (OC) ratios. The OC ratio compares a CLO's assets to its tranches' outstanding amounts. For instance, a CLO with USD 100 in assets and 65% senior and 25% junior tranches will have a senior OC ratio of approximately 154% and a junior OC ratio around 111%. Managers are required to keep these ratios above specific thresholds to mitigate insolvency risks.

The OC ratio fluctuates with changes in assets and liabilities. Assets can decrease in value if loans are downgraded or default, affecting the OC ratio. Managing assets to avoid downgrades below CCC is crucial. Liabilities change over the CLO's life cycle, which includes the ramp-up, reinvestment, and amortization periods. The OC ratios are regularly monitored, and failing to meet them can have severe consequences for CLO managers, like not receiving fees and damaging their reputation.

6.1.1 Defaults and downgrades after covenant violations

Thus, as a next step, we ask whether covenant violations have implications for the likelihood that a firms defaults or is downgraded. We use the same sample as in Saunders, Steffen, and Verhoff (2025), which is the intersection of quarterly observations for 11,432 firms for which we obtain SEC 10k and 10Q filings and the merged Compustat / CRSP database that provides firm control variables. We use the GVKEY-CIK match to map the SEC sample to Compustat. We obtain quarterly information about covenant violations from CovenantAI.

Methodology. We investigate the impact of covenant violations on firm default and downgrades using a "quasi-regression discontinuity design" (RDD) that is common in the literature (Roberts & Sufi, 2009; Nini et al., 2012).[24]

We estimate the following regression model using OLS:

$$y_{i,t+k} - y_{i,t} = \alpha + \beta \times Violation_{i,t} + \theta \times X_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \tag{2}$$

The dependent variable $y_{i,t+k} - y_{i,t}$ is the four ($k = 4$) or eight ($k = 8$) quarter ahead likelihood to file for Chapter 7 or Chapter 11 (*Default*) or likelihood to be downgraded (*Downgrade*). $Violation_{i,t}$ is an indicator variable that is one if firm i has a covenant violation in quarter t. $X_{i,t}$ is a vector of covenant control variables (operating cash flow scaled by assets, leverage ratio, the ratio of interest expense to assets, the ratio of net worth to assets, the current ratio, and the market-to-book ratio). We also add industry (γ_j) and quarter (δ_t) fixed effects. All regressions include higher-order covenant control variables, as well as the four-quarter lag of these variables. We also include a four-quarter lag of our covenant violation dummy $Violations_{i,t-4}$.

[24] This design is particularly useful in the context of covenant violations: (1) there is a sharp cutoff for comparison as firms either violate (treatment group) or not violate a covenant (control group); (2) we can control for unobserved heterogeneity between violating and non-violating firms using a first-difference specification; (3) we can control for confounding variables that are related to the likelihood of a covenant violation to isolate the effect of the violation itself on the firm's outcomes; (4) we can identify a causal effect related to covenant violations, separate from the trajectory a firm was already on due to its fundamentals; and (5) there is some flexibility in modeling as to how firm performance changes over time using higher-order controls and controlling for both current and lagged variables.

Standard errors are clustered at the firm level.

Table 8 reports the results. In Panel A, we show the results relating $Violation_{i,t}$ to corporate bankruptcy and downgrades by rating category. We thus interact $Violation_{i,t}$ with indicator variables for different rating categories, i.e., IG if a company is investment-grade rated, $Non-IG$ if a company is non-investment-grade rated, and $Unrated$ (if a firm is not rated). IG firms do not experience an increase in either the likelihood to file for bankruptcy or to be downgraded. There is a sizeable economic effect among Non-IG firms, though. In the four (eight) quarters after a covenant violation, these firms are 4.2% (6%) more likely to default and about 1.8% more likely to be downgraded. The effect of violations on bankruptcy risk among unrated firms is much smaller (about 0.3% to 0.6%).

The results in Panel B are consistent with our hypothesis that different violation outcomes represent also scenarios of varying severity for companies. Columns (1) and (2) indicate a lower likelihood of default within the set of firms that are IG rated (independent of violation outcome). However, among Non-IG rated firms, those that secure amendments before the violation occurs experience a lower likelihood of default compared to firms that obtain amendments or waivers post-violation or remain in technical default. For example, the likelihood that a firms files for bankruptcy after a technical default is between 17.6% and 19% higher, the likelihood to experience a downgrade is about 5% to 6% higher.

Overall, our results suggest that there is a significant increase in both downgrade and bankruptcy likelihood particularly among the leveraged (Non-IG rated) loans usually purchased by CLOs. In other words, CLOs, especially those already constrained with regard to their leverage, might need to offload these loan before a violation occurs.

6.1.2 CLO leverage constraints

In a next step, we directly measure CLO constraints using data from Creditflux. We obtain data for CLO OC ratio test over the 2007 to 2020 period and focus on in our analysis on CLOs with non-missing OC ratio test results. For each CLO, we compute slack in the OC ratio as the difference between reported OC ratios and the threshold value and use a simple average to compare CLOs across the years.[25]

[25] We follow the earlier literature to calculate OC ratio slack (Elkamhi and Nozawa (2022); Fleckenstein (2022); Kundu (2023)). The Creditflux data feature diverse test names for OC ratio and other tests, as each CLO has its own terminology. To pinpoint OC ratio test results, we look for "OC" and "Overcollateralization" in

The time series characteristics are reported in Table 9. The average CLO has an OC ratio slack for senior tranches ranging from 7.4% to 20.16% and for junior traches ranging from 1.87% to 5.87%. Slack is lower during periods of widespread economic stress, e.g. in the GFC period.

Also the percentage of CCC rated loans relative to CLO assets is very cyclical and likely affects CLO decision to buy and sell loans. During periods of economic stress (such as the GFC or COVID-19) the ratio of CCC loans increases substantially and above the regulatory threshold of 7.5%. In fact,since 2016, CLOs have, on average, exceeded this threshold in every single year. Relative to the share of these risky loans, the junior OC ratio slack is thin, which may constrain CLOs' portfolio choice once hit by adverse events. In contrast, the average CLO has ample slack for the senior OC ratio, and thus this ratio is less likely than the junior ratio to constrain CLOs.

In Panel C of Table 3 above we show the cross-sectional distribution of OC ratio slack averaged over time. The average CLO has a 4.7% slack against the junior OC ratio threshold with a cross-sectional standard deviation of 2.05%. Thus, there is significant variation across CLOs with respect to distance to OC ratio test failures.

6.2 Descriptive evidence of transaction prices

In this section, we delve into the trading behavior of the largest buyers of leveraged loans, CLOs, and use a subsample of our data that is the intersection of our secondary loan market data, loans that we can identify in CLO portfolios (sourced from LPC Collateral as described above) and covenant violation data from CovenantAI. In order to get a better understanding of the data and the trading of CLOs, we first provide descriptive evidence as to (1) whether quotes by dealers banks are different for loans bought by CLOs compared to other loans, (2) the development of transaction prices of loans traded by CLOs in the weeks before covenant violations as well as their selling and buying behavior, and (3) the development of transaction prices as a function of the violation outcome (such as amendment or technical default).

Prices (Mid-quotes) of loans traded in CLO portfolios. We first investigate prices of loans that are purchased by CLOs and those that are not purchased by CLOs in the 100

the data, then confirm these tests relate to OC ratios. For junior OC ratios, we search specifically for class D and E tests. When only one is present, it's used as the CLO's junior OC ratio. If both are available, the class E test is selected as the junior OC ratio. We drop all other tests, where CLOs fail the OC test and set negative slack to zero. To control for outliers, we winsorize at the 5% (95%) level.

trading days before a covenant violation. Both graphs are shown in Figure 5.

The trend is very similar while prices of loans in CLOs are usually somewhat higher. Around 80 days before the violation, both prices first drop and then diverge, with loans held in CLOs experiencing an earlier and sharper decline compared to loans not in CLOs. The price drop for CLO-held loans occurs earlier and their prices remain rather stable afterwards, while the loans not in CLOs show another, steeper decline beginning around 60 days before the covenant violation.

Transaction prices and CLO trading volume. We next focus on loans held in CLO portfolios and plot their transaction prices over the 40 weeks prior to covenant violations (Figure 6). Transaction prices are calculated as the mean of the bid and ask prices at each point in time.

We observe noticeable drops in loan prices around 40 weeks and again 15 weeks before the violation. For example, the price at which CLOs are selling loans drops, on average, from 97 to 96 cents on the dollar between weeks 40 and 30, recover to 95 cents by week 15, and then decline sharply to 93.5 cents thereafter.

The mean volume of loan sales shifts, starting at USD 490k in week -20, increasing to USD 1.5 million in week -19, and then slightly decreasing to USD 1.3 million in week -18 prior to a violation. The most significant CLO sale reached USD 4.5 million in week -20, escalated to USD 24 million in week -19, and then reduced to USD 18 million in week -18.

What factors contribute to this significant price decrease during these two weeks? One potential explanation is a decrease in market liquidity around this time, leading to a shift in prices (a point that requires further examination, even though a significant and simultaneous increase in the transaction volume of sell-side transactions suggest that liquidity is not a concern). Alternatively, it might be hypothesized that investor behavior changes in anticipation of loan amendments or when they foresee borrowers continuing in technical default. As a subsequent step, we will examine this hypothesis in more detail, considering different outcomes of the violation.

Transaction prices of loans traded by CLOs (by violation outcome). Finally, we zoom into the different violation outcomes and the respective implication for loan prices of those loans purchased by CLOs. We first plot the daily loan prices (mid-quotes) by violation outcome in Figure 7a. Consistent with the evidence from our full sample (Figure 4b), we find that prices of loans are eventually amended before a covenant violation (*Amendment w/o*) exhibit minimal fluctuation. The notable decline in prices is predominantly attributed to three factors: firms that secure amendments subsequent to a violation (*Amendment w/*), firms that obtain waiver (*Waiver*) and loans linked to firms that persist in technical default (*Technical Default*). Although price patterns are strikingly similar across all three categories, the overall decrease in prices tends to be more pronounced when investors anticipate difficulties by amending loans that are in violation.

Figure 7 shows transaction prices of CLO-held loans for different violation outcomes in the weeks before the violation. Loans with amendments *before* the violation remain stable and even rise, while the other three categories exhibit persistent declines. These declines are more pronounced for loans obtaining amendments *after* the violation (*Amendment w/ violation*) and those remaining in *technical default*.

6.3 CARs for constrained vs. unconstrained CLO ownership

We next test whether the abnormal returns are driven by CLOs that we can describe as "constrained", i.e. those that have junior OC ratios close to violation.

Descriptive evidence. We first plot the mid-quotes of loans in the 100 days prior to a covenant violation for loans that are owned by constrained or unconstrained CLOs in Figure 8. A CLO is constrained if the slack of the junior OC ratio is below the median on the date of the covenant violation. There is a noteable difference between both time-series. Consistent with the interpretation that CLOs that are constrained due to their junior low OC ratio, we find a similar trend while prices of loans in portfolios of constrained CLOs are usually higher. Around 80 days before the violation, both series start to fall. The decline is more pronounced for loans held by constrained CLOs, causing the two price paths to diverge around 60 days before the violation. After this divergence, both series continue to decrease as the violation approaches

Methodology.

$$CAR_{ij} = b_0 + b_1 \times Ownership_i + \gamma \times X_i + \eta_t + \epsilon_{ij} \tag{3}$$

where CAR_{ij} is the CAR of loan i and violation event j, $Ownership_i$ represents the weighted proportion of constrained CLOs within a given loan. To determine this, we initially categorize the loans into two groups: constrained and not constrained. A loan is classified as constrained if its slack is below the median slack observed among all CLOs on that specific date. Conversely, if the slack exceeds the median, the loan is considered not constrained. We then compute the weighted percentage of constrained CLOs in a loan. This is calculated by dividing the total deal amounts of the constrained CLOs by the aggregate deal amount for that loan. X_i are loan-level control variables such as the loan rating at time of the violation and the remaining time until the loan officially matures. We also include time fixed effects (η_t).

Results. Table 10 reports the results. We focus on the [-80,-60] event window which exhibits the largest negative CARs in our previous tests. In column (1), we simply include *Ownership*, in column (2), we add *Rating* and *Remaining Maturity* as control variables, and in column (3), we also add time fixed effects. In all specification, we find that $b_1 < 0$, i.e., if the share of the loan owned by constrained CLOs is higher, the CAR in the [-80,-60] window before a covenant violation is more negative.

7 Conclusion

In our paper, we utilize CovenantAI, an advanced Artificial Intelligence (AI)-powered tool for monitoring covenants, originally developed by Saunders et al. (2025). Our primary objective is to investigate whether institutional investors, notably Collateralized Loan Obligations (CLOs), engage in trading activities surrounding covenant violations. Our findings confirm this hypothesis, revealing a distinct pattern in loan pricing behavior.

Analyzing data spanning 100 days before a covenant breach, we observe a consistent downward trend in loan prices, with a particularly sharp decline occurring around 80 days prior to the violation. This trend is further quantified through the calculation of Cumulative Abnormal Returns (CAR), where the most notable impact, a decrease of -6.39%, is seen during the [-80,-60] event window. This effect is markedly more pronounced in loans that undergo amendments following a covenant violation or those that end up in technical default.

Furthermore, our research uncovers a substantial likelihood of downgrades and increased bankruptcy risks post-amendment, especially in the context of leveraged loans typically acquired by CLOs. This aspect is critical in understanding the broader economic implications of covenant breaches and subsequent institutional responses.

An intriguing aspect of our study involves the significant variation we document in the constraints faced by CLOs. These constraints arise from multiple factors, including the ownership of CCC-rated loans and results from overcollateralization tests conducted on junior tranches. This variability in constraints plays a pivotal role in influencing both loan prices and CARs in the period leading up to a covenant violation.

We find that loans predominantly held by constrained CLOs exhibit more pronounced price declines before a covenant violation. In line with this, the CARs in the [-80,-60] event window are significantly more negative for these constrained CLOs compared to their unconstrained counterparts.

In summary, our results paint a consistent picture: constrained institutional investors, specifically CLOs, tend to strategically exit loan positions when they anticipate upcoming covenant violations. This behavior is reflected in the observable pricing trends and abnormal returns in the loan market, underscoring the significant impact of covenant violations on institutional trading strategies.

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Figures and Tables

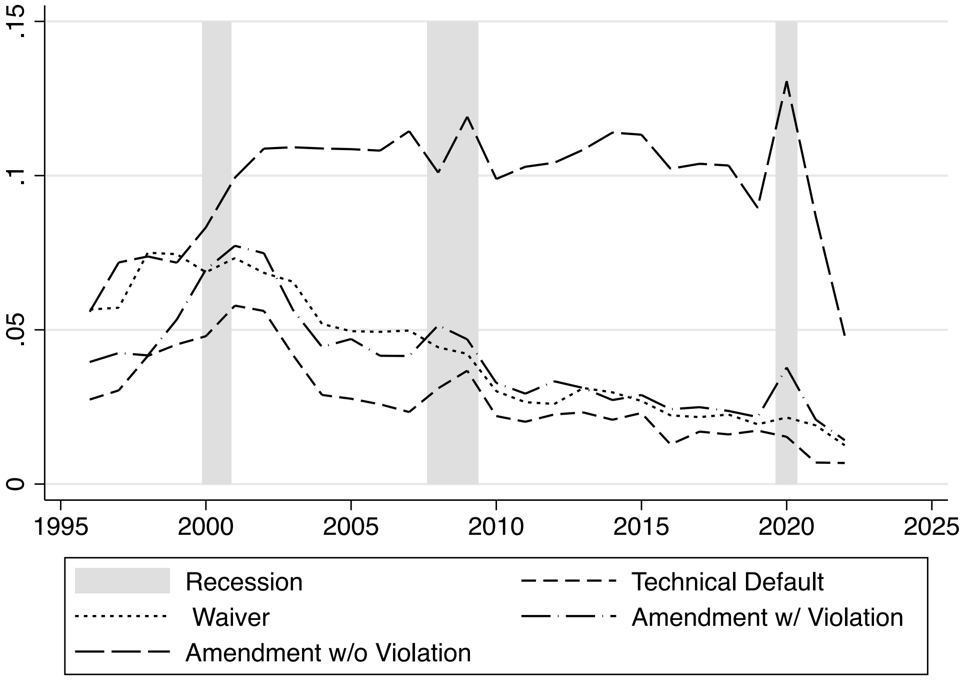
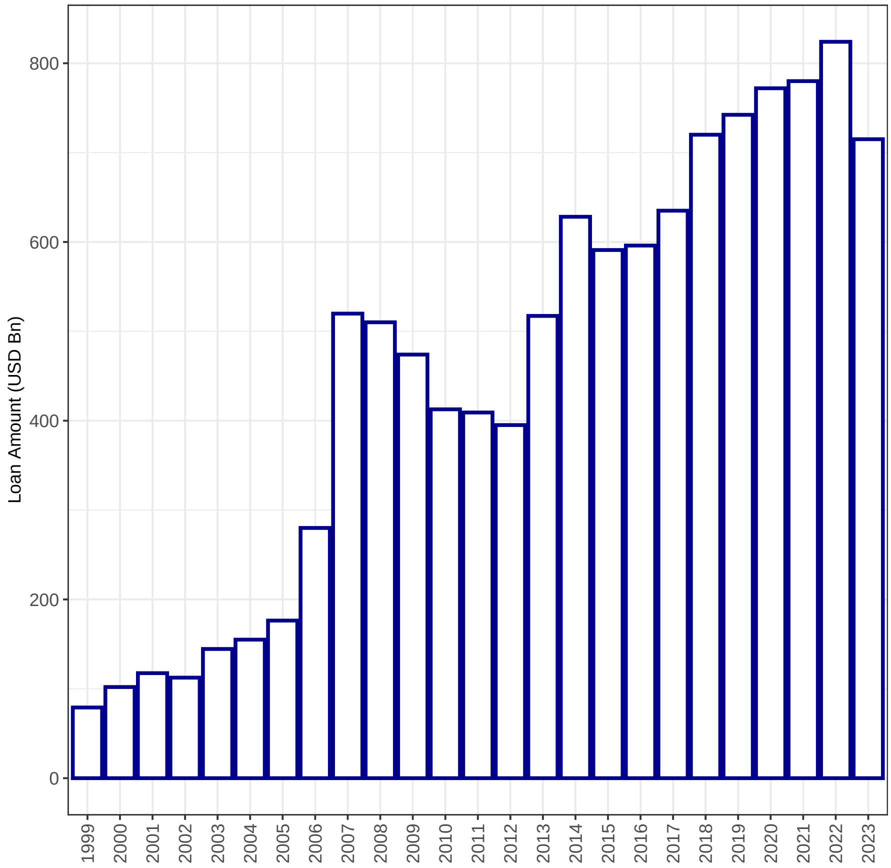
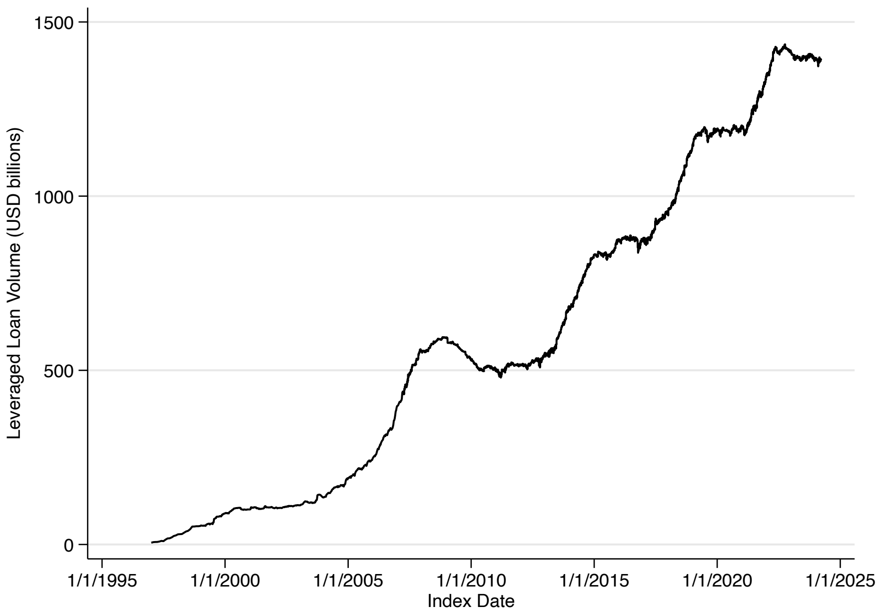


Figure 1: **Time-series of covenant violations**
This figure plots the annual share of the different violation outcomes for the full sample of U.S. publicly listed, non-financial firms. The shaded areas represent the NBER recession periods.



(a) Traded loan volume



(b) Notional amount of traded loans

Figure 2: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2023 period (Panel A) and the notional amount of loans traded in the Morningstar LSTA Leveraged Loan Index. Source: LSTA.

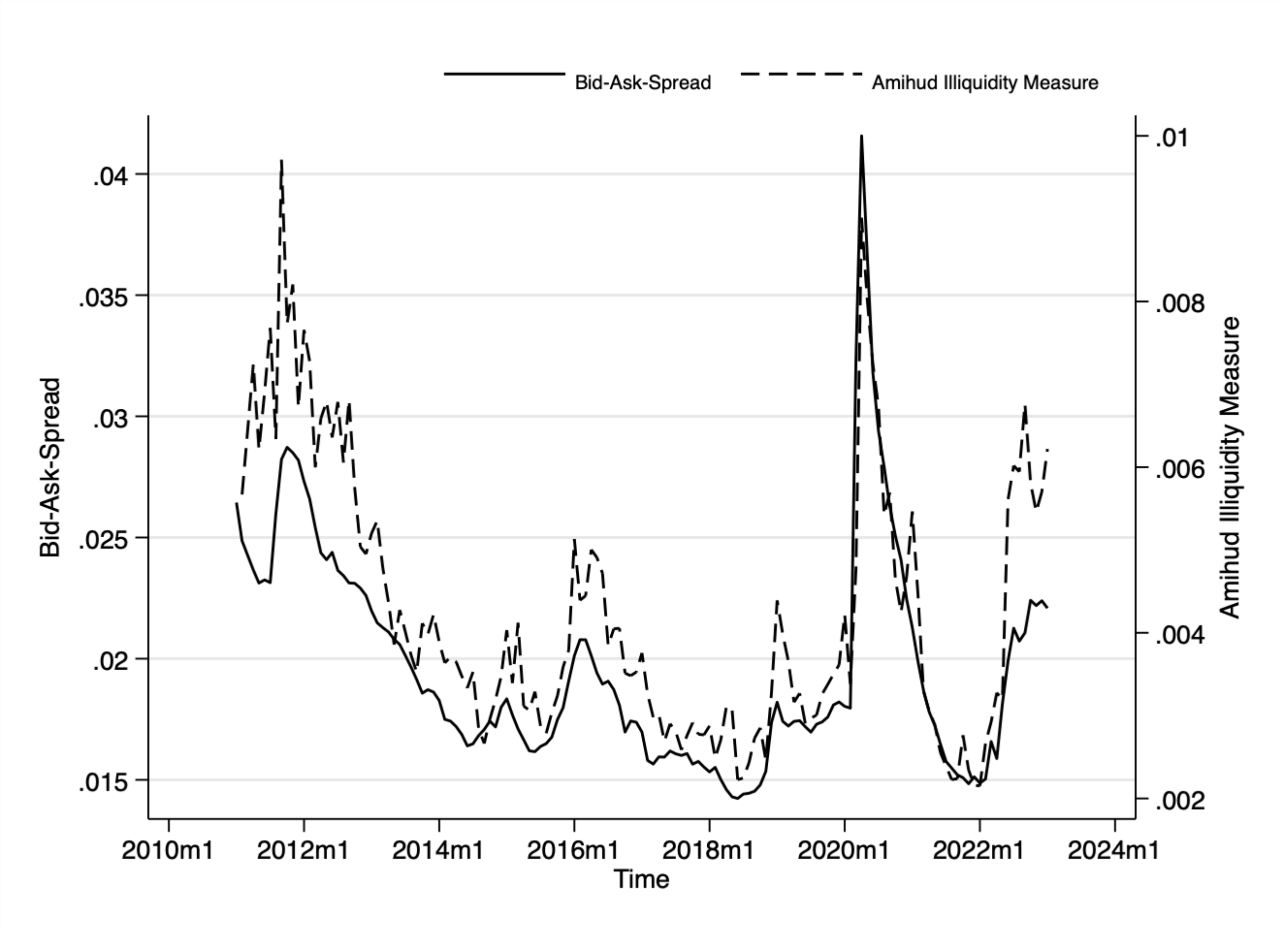
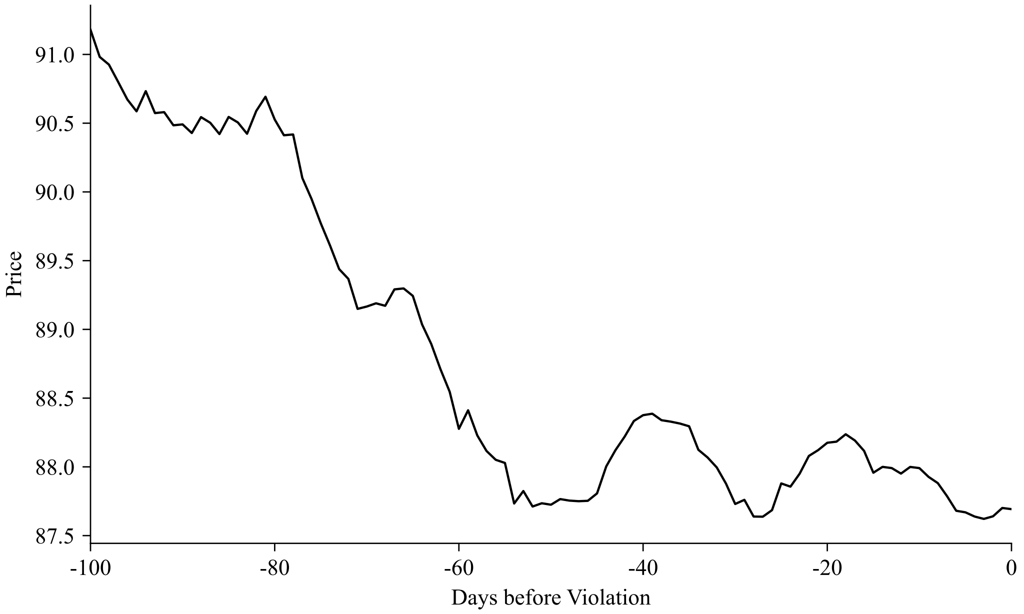


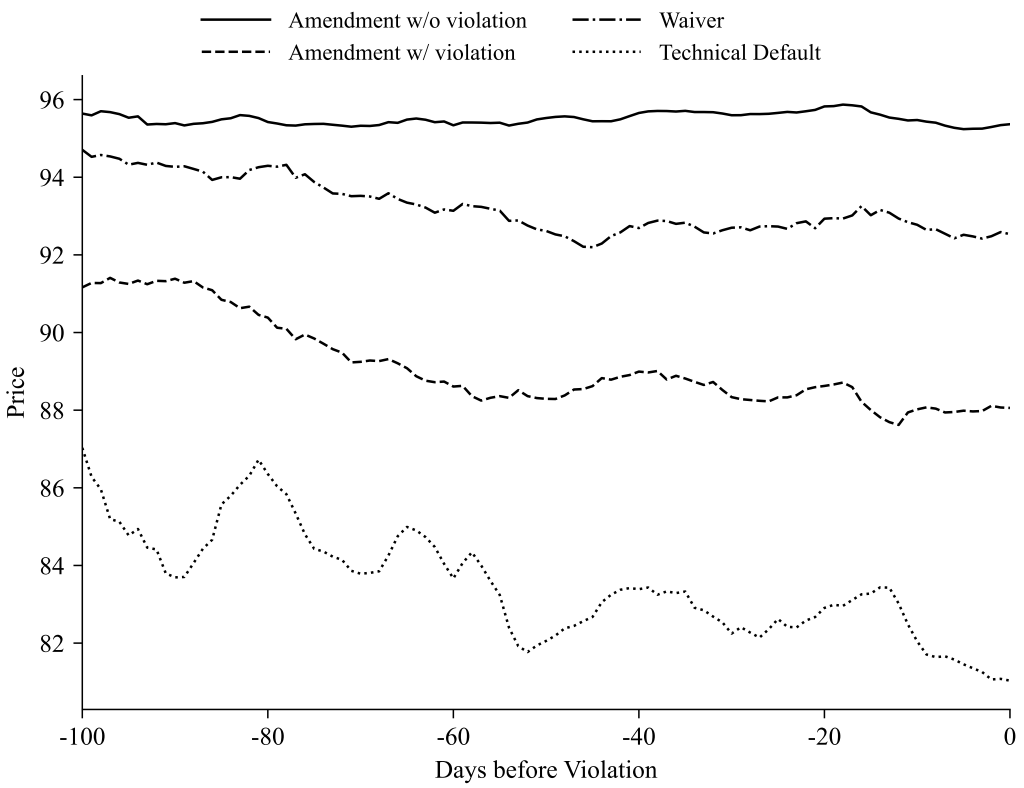
Figure 3: **U.S. secondary loan market liquidity.** This Figure plots the median bid-ask spread (scaled by the mid-quote) over the 1999-2023 period. It also plots (right y-axis) the Amihud Illiquidity Measure (*ILLIQ*) (Amihud, 2002), which is calculated as

$$ILLIQ_{im} = \frac{|r_{im}|}{VOL_{im}}$$

where instead of using the average daily measure, we use monthly loan market returns and monthly aggregated volume of buy and sale transactions (in million USD).



(a) All violation outcomes



(b) Loan prices by violation outcome

Figure 4: **Loan prices before a covenant violation**
This figure plots the (mean) price of loans trading in the secondary loan market and issued by publicly listed U.S. firms 100 trading days before a covenant violation. Panel (a) shows this for all loans with covenant violation, Panel (b) by violation outcome (i.e., amendment w/o violation, amendment w/ violation, waiver and those that remain in technical default.

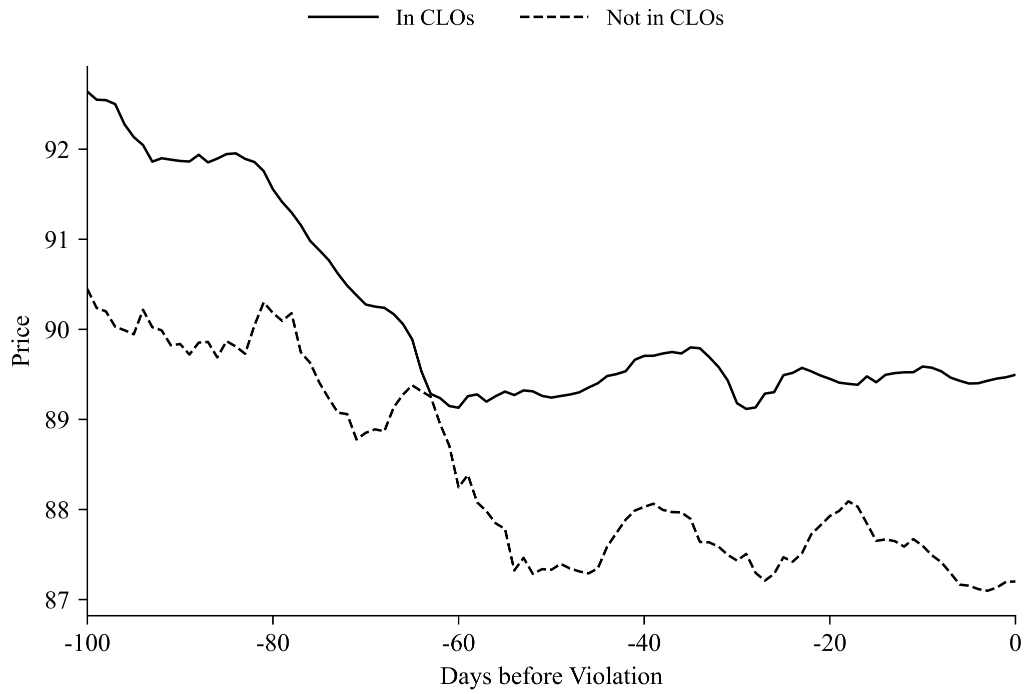


Figure 5: **Prices of loans (not) in CLO portfolios before covenant violations**
This figure plots the (mean) price of loans trading in the secondary loan market and issued by publicly listed U.S. firms 100 days before a covenant violation. We plot this time-series separately for loans that are (not) purchased by CLOs.

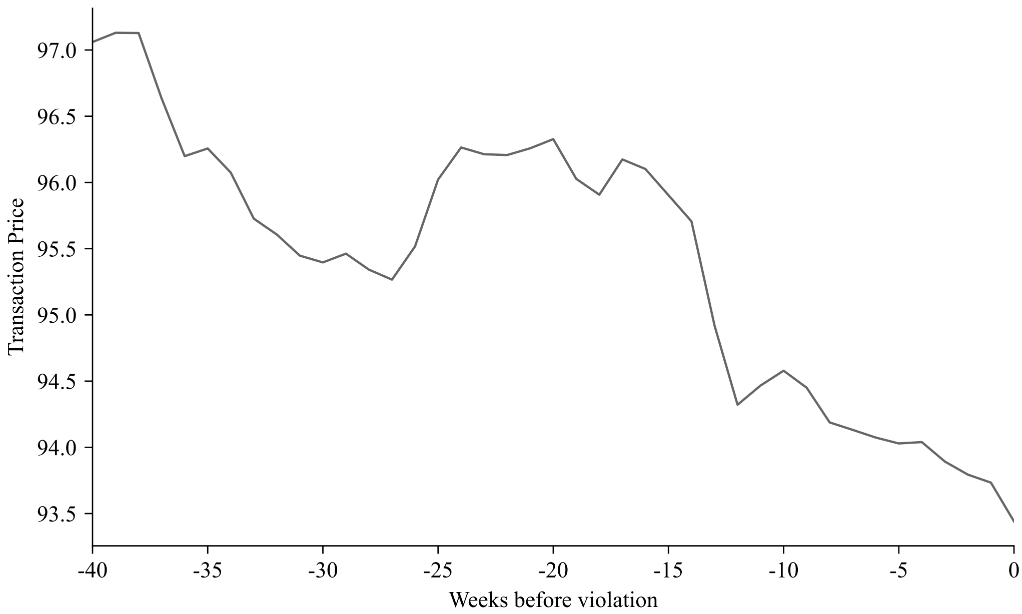
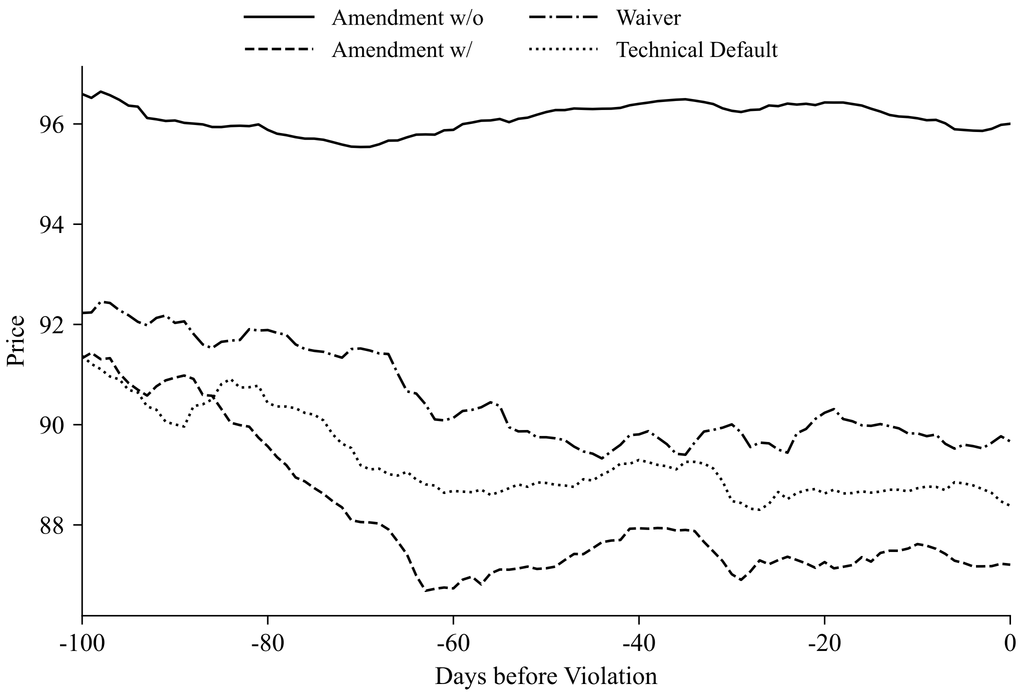
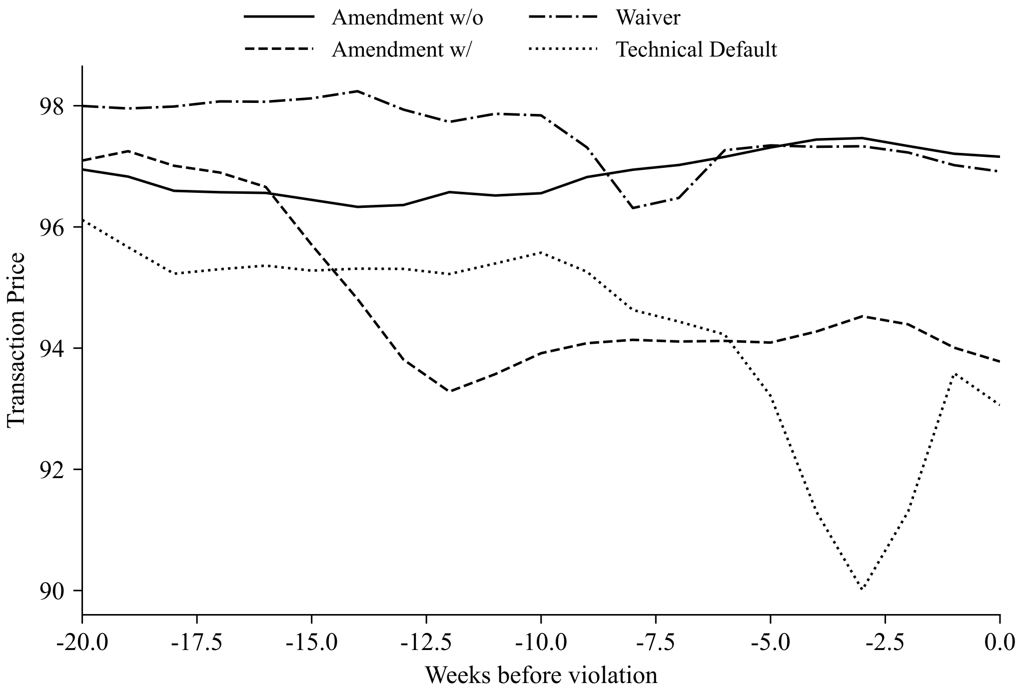


Figure 6: **CLO Transaction prices before covenant violations**
This figure plots the weekly transaction price in our sample of loans owned by CLOs in the 40 weeks prior to a covenant violation. The transaction price is measured as the average of the bid and ask prices.



(a) Prices (mid-quotes) of loans in CLOs (by violation outcomes)



(b) Transaction prices of loans traded by CLOs (by violation outcome)

Figure 7: **Prices of loans in CLO portfolios before a covenant violation**
This figure plots loan and CLO prices around covenant violations. Panel (a) shows loan prices by violation outcome (i.e., amendment without violation, amendment with violation, waiver, and loans remaining in technical default) in the 100 trading days before the violation. Panel (b) shows CLO transaction prices, computed as the mean of the bid and ask prices, over the 20 weeks before the violation.

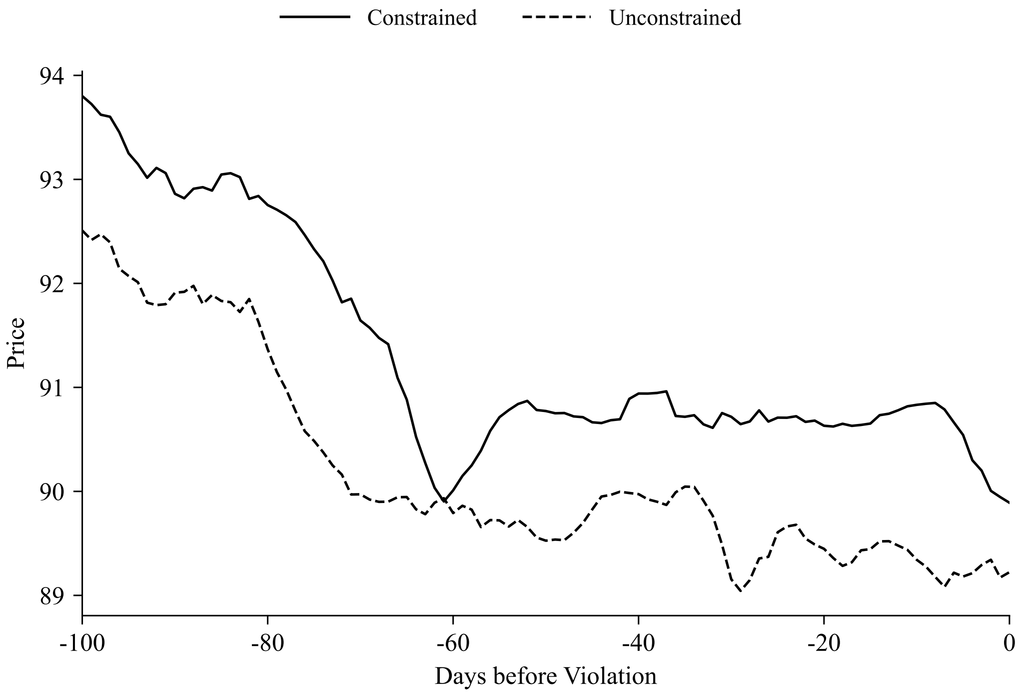


Figure 8: **Price of Loans in portfolios of constrained vs. unconstrained CLO**
This figure plots the (mean) price of loans trading in the secondary loan market and issued by publicly listed U.S. firms 100 days before a covenant violation. We plot this time-series separately for loans in portfolios of constrained vs. unconstrained CLOs.

Table 1: **CovenantAI Model Performance**

This figure plots the accuracy of our machine learning algorithm. The true value is displayed on the vertical axis, and the value predicted by our model is on the horizontal axis. Panel A uses the test data to show model performance and Panel B the validation dataset. Panel B shows the Precision, Recall and F1-Score for the test data, when splitting them only into three categories (No Violation, Amendment and Technical Default). Panel C compares the performances of the different approaches for two categories *No Violation* and *Violation*. We compare the performance of CovenantAI, where we created the "Violation" class by adding up *Waiver*, *Amendment w/ Violation* and *Technical Default* cases with the performance of the labeling by Nini et al. (2012), the replication of the approach by Nini et al. (2012) without manual adjustments and the performance of the Roberts and Sufi (2009) approach. The confusion matrices are constructed based on a random dataset of 102 firm quarters, where CovenantAI didn't agree with either of the approaches and it is therefore not representative for the full sample.

Panel A: Confusion Matrix of the Test Data

		Predicted Label				
		No Violation	Amendment w/o	Waiver	Amendment w/	Technical Default
True Label	No Violation	**78.12%**	3.35%	1.28%	0.32%	1.12%
	Amendment w/o	0.64%	**4.95%**	0.00%	0.00%	0.00%
	Waiver	0.00%	0.00%	**3.83%**	0.48%	0.00%
	Amendment w/	0.00%	0.16%	0.00%	**2.08%**	0.00%
	Technical Default	0.00%	0.00%	0.16%	0.32%	**3.19%**

Panel B: Precision, Recall, F1-score for Test Data

	Precision	Recall	F1-Score	Number
No Violation	0.99	0.93	0.96	529
Amendment w/o	0.58	0.89	0.70	35
Waiver	0.73	0.89	0.80	27
Amendment w/	0.65	0.93	0.76	14
Technical Default	0.74	0.87	0.8	23
Accuracy			0.92	628
Macro Average	0.74	0.90	0.80	628
Weighted Average	0.94	0.92	0.93	628

Panel C: Confusion Matrices of the Different Approaches

		Predicted Label	
		No Violation	Violation
	CovenantAI Labeling		
	No Violation	**25.49%**	13.73%
	Violation	6.86%	**53.92%**
	Nini et al. (2012)		
	No Violation	**7.84%**	31.37%
True Label	Violation	14.71%	**46.08%**
	Roberts and Sufi (2009)		
	No Violation	**4.9%**	34.31%
	Violation	2.94%	**47.84%**
	Roberts and Sufi Labeling		
	No Violation	**38.24%**	0.98%
	Violation	53.92%	**6.86%**

Table 2: **Sample Construction**

This table describes the progressive assembly of the analysis sample across multiple data sources. Panel A shows the filtering process beginning with the CovenantAI Full Sample of 14,792 U.S. public firms from SEC filings (1996–2024), comprising 537,804 firm-quarter observations. We sequentially impose data availability requirements: firms with syndicated term loans from Dealscan (3,999 firms, 15,124 loans, 104,359 firm-quarters), loans with available secondary market pricing (891 firms, 2,388 loans, 15,033 firm-quarters), loans held by CLOs with quarterly holdings data from LPC (Collateral) (648 firms, 1,611 loans, 11,676 firm-quarters), CLO transaction-level data availability (598 firms, 1,476 loans, 10,624 firm-quarters), and CLO overcollateralization ratio constraints measured via Creditflux (589 firms, 1,456 loans, 10,463 firm-quarters).

Panel A: Descriptives Datasets

	N (Firms)	N (Loans)	N (Firm-Quarters)	Description
CovenantAI Full Sample	14,792		537,804	All U.S. public firms in SEC filings, 1996-2024
Has syndicated loan (Dealscan)	3,999	15,124	104,359	Firms with syndicated term loans
Secondary market pricing available	891	2,388	15,033	Loans actively traded in secondary market
CLO holdings data (LPC Collateral)	648	1611	11,676	Loans held by CLOs with quarterly holdings
CLO transaction data available	598	1,476	10,624	Subset with actual buy and sell transactions
CLO OC ratio data (Creditflux)	589	1,456	10,463	CLOs with quarterly OC constraint measures

Table 3: **Descriptive Statistics**

This table provides summary statistics of important firm characteristics. Panel A shows the summary statistics for our CovenantAI dataset. *Violation* is an indicator variable that is one if a firm violates a covenant in a specific quarter. *Technical Default*, *Amendment w/ Violation* and *Amendment w/o Violation* represent the share of firms that reported a violation within these outcome-categories. *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period and *Downgrade* is an indicator that is one if the firm was downgraded over the whole period. *Credit rating* is a numerical translation of S&P rating information, where 1 is the best rating (AAA+). Panel B shows loan characteristics of the Secondary Loan market data for all *publicly listed* firms. The *# Loans* represents the average number of loans per year. The *Ask Price*, *Bid Price*, the *Midquote* and the *Spread* are reported as averages per loan. The *Maturity* is the average remaining maturity of the loan stated in years. The *Bid-Ask-Spread* is calculated by $\frac{AskPrice-BidPrice}{Midquote}$. Panel C shows the summary statistics of all publicly listed firms in the LPC Collateral (CLO) data. S&P Rating is the numeric translation of the rating symbol (Where AAA+ is 1). *Spread* is reported in basis points. The share of loans by credit ratings is reported in the bottom part of Panel C. *IG* includes all firms that are BBB- rated (equal to a numerical rating of 10) or better. The *BB* rating includes all loans that are rated BB+, BB and BB-.

Panel A: Summary Statistics: CovenantAI

	Mean	Median	Min	Max	SD
Violation	0.47	0.00	0.00	1.00	0.50
Technical Default	0.15	0.00	0.00	1.00	0.36
Amendment w/ Violation	0.28	0.00	0.00	1.00	0.45
Amendment w/o Violation	0.33	0.00	0.00	1.00	0.47
Default	0.02	0.00	0.00	1.00	0.13
Downgrade	0.87	1.00	0.00	1.00	0.33
Credit Rating	12.26	13.00	1.00	26.47	3.10
Observations	11,428				

Panel B: Summary Statistics Secondary Loan Market Data

	Mean	Median	Min	Max	SD
# Loans	904.76	852	325	1,453	320.37
Ask Price	96.59	100.03	2.27	155.22	10.66
Bid Price	95.47	99.33	1.11	150.05	11.41
Midquote	96.03	99.69	1.69	152.64	11.03
Spread	362.52	325.00	12.50	1,600.00	183.70
Maturity	4.31	4.36	0.17	9.15	1.57
Bid-Ask-Spread	0.02	0.01	0.00	1.00	0.05
Observations	6,782				

Panel C: Summary Statistics CLO Data

	Mean	Median	Min	Max	SD
OC ratio slack					
Slack(S) (%)	20.24	11.39	0.00	117.62	18.44
Slack(J) (%)	4.67	4.86	0.00	10.74	2.05
Loan Characteristics					
# Loans	531.94	484.50	1.00	2,346.00	355.48
S&P Rating	14.55	14.54	7.18	21.00	0.60
Spread	371.06	365.99	175.00	755.00	48.22
Share of loans by credit ratings (%)					
IG	1.04%	0.76%	0%	78.36%	2.14%
BB	18.75%	19.63%	0%	100%	8.84%
B	62.95%	68.44%	0%	100%	18.31%
CCC	2.24%	1.68%	0%	36.26%	2.97%
Observations	2,100				

Table 4: **Characteristics by Sample**

This table compares firm and loan characteristics across four samples: (1) the full CovenantAI universe of leveraged loans with covenant data, (2) loans merged with Dealscan data, (3) loans matched to the secondary market database, and (4) loans held by CLOs. Panel A reports firm fundamentals (total assets, market capitalization, leverage ratio, market-to-book, ROA, and sales growth). Panel B presents credit characteristics including ratings distribution and S&P numeric ratings. Panel C documents violation characteristics: the percentage of firms that ever violate covenants, incidence of technical defaults, amendments following or preceding violations, and waivers granted. Panel D provides loan-level characteristics including facility size, spread, maturity, and bid-ask spreads. Column (5) reports the differences between the CovenantAI sample and the CLO sample, with t-statistics testing equality of means.

Characteristics by Sample

Characteristic	(1) CovenantAI Only	(2) Dealscan Merge	(3) Secondary Market	(4) CLO Data	(1)-(4) Difference	t-stat
Panel A: Firm Fundamentals						
Total Assets ($M)	7,189.98	8,765.3	6,815.67	7,523.67	-333.69	-1.907
Market Cap ($M)	1,845.14	3,087.1	2936.59	3,338.58	-1493.44***	-43.991
Leverage Ratio	0.23	0.42	0.49	0.49	-0.26***	-163.479
Market-to-Book	1.31	0.89	0.73	0.74	0.56 ***	96.765
ROA (%)	0.87	2.86	3.05	3.05	-2.18***	-117.497
Sales Growth (%)	0.04	0.03	0.02	0.02	0.01***	9.365
Panel B: Credit Characteristics						
Investment Grade (%)		6.41	2.93	2.38	4.03***	8.857
BB (%)		6.37	9.80	13.83	-7.46***	-7.872
B (%)		5.96	13.95	19.88	-13.92***	-12.790
CCC or below (%)		2.32	4.96	7.13	-4.81***	-6.857
Unrated (%)		78.93	68.36	56.77	22.16***	16.170
Avg S&P Rating (numeric)		BB-	B+	B	-1.73***	-47.56
Panel C: Violation Characteristics						
Ever violate (%)	32.79	37.41	23.54	16.78	16.00***	9.944
Technical default (%)	15.30	16.08	9.91	7.87	7.43***	6.385
Amend after violation (%)	18.16	23.91	12.16	7.87	10.29***	8.800
Amend before violation (%)	32.55	48.54	45.27	43.36	-10.81***	-5.127
Waiver (%)	20.17	19.45	8.67	4.37	15.80***	17.246
Panel D: Loan Characteristics						
Loan Size ($M)		369.7	621.77	752.97	-383.27***	-49.296
Loan Spread (bps)		270.7	302.75	318.35	-47.65***	-36.098
Maturity (years)		5.63	6.1	6.1	-0.48***	-45.181
Bid-Ask Spread (bps)		0.21	0.0	0.0	0.21***	4.158

Table 5: **Firm, Loan and CLO Characteristics Around Covenant Violations**

Panel A reports firm financial metrics measured in the quarter preceding covenant violation (t–4), stratified by violation resolution: amendment before violation, amendment after violation, technical default, and waiver granted. Panel B presents loan-level characteristics conditional on violation outcomes, including pricing (spread), structure (maturity, size, number of lenders and covenants), and liquidity characteristics. Panel C documents CLO ownership concentration and constraint intensity for loans in the sample: number of CLOs per loan (count), concentration among top-10 CLO managers (percentage), ownership dispersion measured by Herfindahl-Hirschman Index (HHI), and measure of constraint intensity, the percentage of each loan held by CLOs with binding overcollateralization ratios (constrained CLOs).

Fundamentals Before Violation

Characteristic$_{t-4}$	Amendment Before	Amendment After	Technical Default	Waiver
Leverage	0.33	0.34	0.35	0.3
Interest Coverage	3.43	-0.78	-1.94	-0.76
Cash/Assets	0.12	0.1	0.11	0.12
ROA	1.26	0.16	-0.28	0.21
Z-Score	1.76	0.97	1.5	0.73

Loan Characteristics

Loan Characteristic	No Violation	Amendment Before	Amendment After	Technical Default	Waiver
Spread (bps)	258.31	288.52	318.11	327.77	297.01
Maturity (years)	4.89	5.32	5.16	5.36	5.23
Loan Size ($M)	421.25	335.39	159.7	201.3	161.71
#Lenders	7.69	8.08	6.4	6.13	5.88
#Covenants	2.37	2.81	3.01	3.01	3.02

CLO Characteristics

Ownership Measure	Mean	Median	SD	p25	p75
# CLOs per Loan	150.38	109.0	150.75	26.0	226.0
% Held by top 10 CLOs	0.5	1.0	0.5	0.0	1.0
HHI of CLO Ownership	0.1	0.01	0.24	0.0	0.04
% Held by constrained CLOs	0.45	0.47	0.2	0.39	0.54

Table 6: **Cumulative abnormal returns**

This table shows the estimates of our cumulative abnormal returns (CAR) for different event windows and benchmark returns. As event windows we use: [-80,-60]; [-80,-1]; [-60,-40]; [-60,-1]; [-20,-1]; [-1,+1]. To measure CARs, we estimate the following regression for each firm i (and each event window around a covenant violation) separately:

$$r_{i,t} = \alpha_i + \sum \beta_i \times I_{Vio=1} + \sum \gamma_i \times X_t \times I_{(0|Vio=1)} + \epsilon_{i,t}$$

where $I_{Vio=1}$ is an indicator variable equal to one for each trading day in the event window $[-t, +t]$, X_t is a vector of benchmark returns and $I_{(0|Vio=1)}$ is an indicator variable that is zero when $I_{Vio=1}$ equals one. This way, contemporaneous changes in the benchmark returns do not bias the point estimates of our CAR during the event window. $\sum \beta_i$ is our CAR estimate.
As benchmark returns we use (a combination of) the following returns: The ICE BofA US Corporate Index Effective Yield (*Corporate*), the ICE BofA US High Yield Index Effective Yield (*High-Yield*), the Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity (*T-Bill*), the daily prices of the S&P500 Index (*SP500*), and the LSTA Index (*LSTA*). T-statistics are in parentheses (significance levels are $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Benchmark Returns	[-80,-60]	[-80,-1]	[-60,-40]	[-60,-1]	[-20,-1]	[-1,+1]
LSTA, T-Bill, Corporate	-6.385%*	-2.668%***	-1.276%	-2.712%***	-2.185%**	0.185%
	(-1.695)	(-3.762)	(-0.863)	(-3.350)	(-2.000)	(0.064)
LSTA, T-Bill, Corporate, SP500, HY	-6.376%*	-2.812%***	-1.346%	-2.820%***	-2.296%**	0.134%
	(-1.693)	(-3.879)	(-0.909)	(-3.418)	(-2.096)	(0.046)
LSTA, T-Bill, SP500	-6.447%*	-2.574%***	-1.318%	-2.575%***	-2.113%*	0.284%
	(-1.713)	(-3.485)	(-0.894)	(-3.080)	(-1.918)	(0.098)
LSTA, T-Bill, Corporate, SP500	-6.405%*	-2.690%***	-1.278%	-2.719%***	-2.191%**	0.173%
	(-1.700)	(-3.736)	(-0.864)	(-3.316)	(-2.008)	(0.060)

Table 7: **Understanding CARs**

Panel A shows cumulative abnormal returns (CAR) for different covenant violation outcomes and event windows ([-80,-60]; [-80,-1]; [-60,-40]; [-60,-1]; [-20,-1]; [-1,+1]). As benchmark returns we use LSTA, T-Bill, Corporate, SP500 and High Yield. We show CARs separately for technical defaults (*CAR Technical Default*), amendments after covenant violations (*CAR Amendment w/ violation*), waiver (*CAR Waiver*) and amendments before covenant violations (*CAR Amendment w/o violations*). Panel B shows differences in mean tests between CARs associated with different outcomes. The difference-in-means tests include LIN fixed effects and cluster standard errors at the LIN level. T-statistics are in parentheses (significance levels are $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Mean Cumulative Abnormal Returns

Mean CAR	[-80,-60]	[-80,-1]	[-60,-40]	[-60,-1]	[-20,-1]	[-1,+1]
(1) CAR Technical Default	-9.454%	-3.605%**	-1.442%	-3.987%***	-3.504%*	-2.050%
	(-1.157)	(-2.424)	(-0.537)	(-2.770)	(-1.769)	(-0.267)
(2) CAR Amendment w/ violation	-6.283%*	-4.966%**	0.053%	-5.007%**	-1.755%	1.606%
	(-1.701)	(-2.064)	(0.027)	(-1.975)	(-1.526)	(0.494)
(3) CAR Waiver	-3.547%*	-1.755%**	-2.187%	-1.450%	-3.497%*	1.636%
	(-1.806)	(-2.023)	(-1.554)	(-1.355)	(-1.669)	(0.310)
(4) CAR Amendment w/o violation	-1.871%*	-1.462%**	-0.088%	-1.715%**	-2.240%***	3.136%*
	(-1.843)	(-2.371)	(-0.124)	(-2.447)	(-2.663)	(1.758)

Panel B: Differences in Mean Test

Comparison	[-80,-60]	[-80,-1]	[-60,-40]	[-60,-1]	[-20,-1]	[-1,1]
(1)-(2)	-0.136	0.180	0.101	0.205	-0.116*	-0.013
	(-1.272)	(0.832)	(1.063)	(0.949)	(-1.845)	(-0.101)
(1)-(3)	-0.236**	0.088	0.092	0.105	-0.094**	0.152
	(-2.361)	(0.655)	(1.568)	(0.778)	(-2.070)	(1.211)
(1)-(4)	-0.250**	0.094	0.076	0.124	-0.081*	-0.028
	(-2.349)	(0.689)	(1.470)	(0.909)	(-1.753)	(-0.264)
(2)-(4)	-0.114*	-0.086	-0.025	-0.081	0.035	-0.015
	(-1.692)	(-1.029)	(-0.467)	(-0.961)	(1.049)	(-0.211)
(3)-(4)	-0.014	0.006	-0.016	0.019	0.013	-0.180
	(-0.259)	(0.380)	(-0.681)	(0.987)	(0.557)	(-1.549)

Table 8: **Covenant Violations - Firm Default and Downgrades**

This table relates covenant violations to the financial performance of firms. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2024. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A relates covenant violations to *Default*, an indicator variable that is one if a firms files for Chapter 7 or Chapter 11 in the four $(t+4)$ or eight $(t+8)$ quarters after a violation, and *Downgrade*, an indicator variable equal to one if a company is downgraded in the four $(t+4)$ or eight $(t+8)$ quarters after a violation. Panel B relates the outcomes of covenant violations (interacted with credit rating categories) to *Default* and *Downgrade*, both four quarters $(t+4)$ to eight quarters after a covenant violation. The outcome variables are Amendments without Violations (*Amendment w/o Violation*), Amendments with Violations (*Amendment w/ Violation*), and *Technical Defaults*. *Amendment w/o Violation* is an indicator variable that is one if the firm obtained an amendment without being in violation of a covenant and *Amendment w/ Violation* is an indicator variable that is one if the firm obtained an amendment in combination with a covenant violation. *Technical Defaults* is an indicator variable equal to one if the firm remains in technical default. *IG* is an indicator that is one if the firm has an investment-grade rating. *Non-IG* is an indicator that is one if the firm has a non-investment-grade rating. *Unrated* is an indicator variable that is one if the firm is unrated. All regressions include the following firm characteristics as control variables that are frequently used as covenants in loan contracts (*Covenant Controls*): the ratio of operating income over average assets, leverage ratio, the ratio of net worth over assets, the market-to-book-ratio, the ratio of interest expenses and average assets, and the current ratio. Each specification includes a four-quarter lag of the covenant violation variable ($Violation_{t-4}$), four-quarter lags of *Covenant Controls*, and higher order terms of *Covenant Controls*. Each specification includes industry and quarter fixed effects (calendar and fiscal quarter) and we cluster standard errors at the firm and the reporting quarter level. We use industry fixed effects, and cluster standard errors at the industry level. Standard errors are reported in parentheses ($^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Default and Downgrade

	(1) Default_{t+4}	(2) Default_{t+8}	(3) Downgrade_{t+4}	(4) Downgrade_{t+8}
Violation x IG	0.004	0.005	0.010	0.008
	(0.006)	(0.010)	(0.017)	(0.021)
Violation x Non-IG	0.042***	0.060***	0.018**	0.012
	(0.005)	(0.007)	(0.008)	(0.008)
Violation x Unrated	0.003*	0.006**		
	(0.002)	(0.002)		
Observations	221,167	221,167	90,122	90,182
R^2	0.032	0.046	0.093	0.181
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES
Higher Order Controls	YES	YES	YES	YES
Lagged Covenant Controls	YES	YES	YES	YES

Panel B: Default and Downgrade & Rating Interaction

	(1) Default_{t+4}	(2) Default_{t+8}	(3) Downgrade_{t+4}	(4) Downgrade_{t+8}
Amend w/o violation x IG	-0.002	-0.003	0.008	-0.009
	(0.004)	(0.006)	(0.017)	(0.021)
Amend w/ violation x IG	0.026	0.029	0.041	0.114**
	(0.019)	(0.026)	(0.051)	(0.055)
Technical Default x IG	0.026	0.054	-0.045	-0.038
	(0.034)	(0.047)	(0.051)	(0.073)
Amend w/o violation x Non-IG	0.011***	0.025***	0.010	0.008
	(0.003)	(0.005)	(0.007)	(0.009)
Amend w/ violation x Non-IG	0.059***	0.085***	0.017	0.009
	(0.009)	(0.012)	(0.016)	(0.016)
Technical Default x Non-IG	0.176***	0.191***	0.059**	0.046*
	(0.025)	(0.026)	(0.023)	(0.025)
Amend w/o violation x Unrated	-0.001	0.005**		
	(0.001)	(0.002)		
Amend w/ violation x Unrated	0.002	0.005		
	(0.002)	(0.003)		
Technical Default x Unrated	0.014***	0.013**		
	(0.004)	(0.005)		
Observations	212,644	212,644	87,278	87,330
R^2	0.039	0.050	0.093	0.176
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES
Higher Order Controls	YES	YES	YES	YES
Lagged Covenant Controls	YES	YES	YES	YES

Table 9: **CLO Constraints**

This table shows time-series summary statistics related to CLO leverage constraints over the 2007 to 2020 period. It reports the number of CLOs, average size of the CLO (in USD millions), the slack in junior and senior OC ratios and the percentage of CCC-rated loans in the CLO.

Year	N(CLO)	CLO Amount ($ mil)	Slack (J) (%)	Slack (S) (%)	CCC (%)
2007	28	529	4.65	11.37	2.46
2008	190	497	4.04	10.89	4.54
2009	220	358	1.87	7.40	8.33
2010	275	413	2.82	10.08	5.50
2011	291	408	3.83	11.60	5.13
2012	232	375	4.36	12.69	5.45
2013	238	344	5.05	13.06	6.12
2014	350	358	5.49	15.59	4.15
2015	457	366	5.95	17.30	4.92
2016	544	358	5.22	18.11	8.42
2017	816	364	5.34	18.93	10.58
2018	983	392	5.87	20.16	11.69
2019	973	410	5.54	19.04	11.64
2020	984	415	3.87	7.47	13.63

Table 10: **Loan ownership - Constrained vs unconstrained CLOs**

This tables shows the results of OLS regression of CARs in the [-80,-60] window on CLO constraints and control variables. A loan is classified as constrained if the majority of its holdings are held by constrained CLOs during the day of the covenant violation. A CLO is defined as constrained if its junior oc slack is below the median of all CLOs in the same month-year. *Rating* is the numerical rating at the time of the covenant violation. *Remaining Maturity* is the time until the loan officially matures, measured in months. We use industry fixed effects and we cluster standard errors at the reporting quarter level. Standard errors are reported in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

	(1) CAR [-80,-60]	(2) CAR [-80,-60]	(3) CAR [-80,-60]
Ownership	-0.106*	-0.155**	-0.154**
	(0.034)	(0.038)	(0.047)
Rating		0.004	-0.004
		(0.009)	(0.012)
Remaining Maturity		-0.001*	-0.001
		(0.000)	(0.001)
Industry FE	No	No	Yes
Observations	334	221	213
R-squared	0.014	0.030	0.321

A Appendix

A.1 Dealer Banks in the Secondary Loan Market

Table A1: **Top 10 dealers in the secondary loan market**

This table shows the loan market lead arranger (underwriter) market share in the primary syndicated loan market as well as the dealer market share in the secondary market for syndicated loans for the top 10 dealers.

Name	Dealer Market Share (Secondary)	Underwriter Market Share (Primary)
Credit Suisse	9.0%	6.6%
Bank of America	8.3%	12.3%
Barclays	7.7%	7.7%
Citigroup	6.0%	7.3%
JP Morgan	5.8%	12.4%
Morgan Stanley	5.7%	6.4%
Deutsche Bank	5.2%	5.1%
BNP Paribas	3.9%	2.9%
Wells Fargo	3.5%	3.2%
Royal Bank of Canada	3.3%	1.8%

A.2 Variable Definition

Table A2: Compustat variables used for quarterly financial data

Variable Names	Variables	Compustat Variables/ Capital IQ
Assets	Total assets	= atq
$\overline{Assets}$	Average assets	= (atq$_t$ + atq$_{t-1}$) /2
MV	Market value	= Market value of equity – book value of equity + atq
MV Equity	Market value of equity	= prccq × cshoq
BV Equity	Book value of equity	= atq – ltq + txditcq
Debt	Total debt	= dltcq + dlttq
PPE / Assets	PPE scaled by assets	= ppentq / atq
Div	Dividends	= dv adjusted for dependend quarter accumulation
Stock purchased	Purchase of common and preferred stocks	= prstkc adjusted for dependend quarter accumulation
CapEx	Capital expenditures quarterly	= capxy adjusted for fiscal quarter accumulation
CashAcqui	Cash acquisitions quarterly	= aqcy adjusted for fiscal quarter accumulation
Sales	Sales	= saleq
Net Worth	Net Worth	= atq - ltq
Tangible Net Worth	Tangible Net Worth	= actq + ppentq + aoq - ltq
	Control Variables	
Operating Income/ Assets	Operating income scaled by average assets	= oibdpq / Average assets
Leverage Ratio	Leverage ratio	= Total debt / Total assets
Interest Expenses/ Asset	Interest expense scaled by average assets	= xintq / Average assets
NWA/ Assets	Net worth to assets ratio	= seqq / Total assets
Current Ratio	Current ratio	= actq / lctq
MTB	Market-to-book-ratio	= Market value / Total assets
	Dependent Variables	
Δ Ln(Assets)	Change in Ln(assets)	= Ln(Total assets$_{t+4}$)-Ln(Total assets$_t$)
Δ Ln(PPE)	Change in Ln(PPE)	= Ln(PPE$_{t+4}$)-Ln(PPE$_t$)
$\Delta\frac{CapEx}{Assets}$	Capital expenditures scaled by average assets	= Capital expenditures / Average assets
$\Delta\frac{CashAcq}{Assets}$	Cash acquisitions scaled by average assets	= Cash acquisitions / Average assets
Empl Growth	Relative change of employees	= (emp$_t$- emp$_{t-1}$) / emp$_{t-1}$
$\Delta\frac{NDI}{Assets}$	Net debt issuance scaled by average assets	= (Total debt$_t$ – Total debt$_{t-1}$) / Average assets$_t$
Δ Ln(Debt)	Change in Ln(total debt)	= Ln(total debt$_{t+4}$)-Ln(total debt$_t$)
$\Delta\frac{Cash}{Assets}$	Cash scaled by assets	= cheq /Total assets
Δ Ln(Payout)	Change in Ln(shareholder payout)	= Ln(shareholder payout$_{t+4}$)-Ln(shareholder payout$_t$)
$\Delta\frac{OpIncome}{Assets}$	Change Operating cash flow by average assets	= (OpIncome/Assets$_{t+4}$) - (OpIncome/Assets$_t$)
Δ Ln(Sales)	Change in Ln(sales)	= Ln(Sales$_{t+4}$)-Ln(Sale$_t$)
Δ Ln(Cost)	Change in Ln(Operating Costs)	= Ln(Operating Costs$_{t+4}$)-Ln(Operating Costs$_t$)
Δ Cash Ratio	Total assets	= cheq/ (undrawn_balance + cheq)
Δ Usage	change in usage	= usage$_{t+4}$-usage$_t$