CovenantAI - New Insights into Covenant Violations[*]

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Abstract

CovenantAI is an advanced artificial intelligence (AI)-based approach to identify loan covenant violations from SEC filings. It outperforms traditional keyword- and Dealscan-based approaches by reframing violations away from a binary (violation/no violation) flag, to precisely classifying complex renegotiation outcomes such as amendments (before or after violations), waivers, and technical defaults. Our analyses validate CovenantAI's higher accuracy and consistency against existing methods. We also document significant differences in the economic implications of covenant violations when using CovenantAI vis-a-vis traditional methods. By capturing nuanced creditor-borrower interactions, CovenantAI facilitates new academic research into the economic implications of covenant violations, and their severity in particular, for loan market investors.

JEL classification: G21, G32, G34

Keywords: Covenant violations, Loan amendments, Renegotiations, Large language models, 10-K/Q, GenAI

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1 Introduction

Prior research has established the pivotal role of covenants, and covenant violations in particular, for firms in different contexts. Table 1 catalogs this landscape across accounting and finance journals. The accounting literature, for example, documents managerial incentives to select accounting methods and accruals that reduce the probability of covenant violations (Bordeman and Demerjian [2022]; DeFond and Jiambalvo [1994]; Dichev and Skinner [2002]; Franz, HassabElnaby, and Lobo [2014]; Sweeney [1994]), the costs associated with covenant violations (Beneish and Press [1993,1995]) and management forecasts around breaches (Bourveau, Stice, and Wang [2022]). Chen and Wei [1993] study the creditors' decision to waive covenant violations. The finance literature highlights effects of covenant violations on firm-level outcomes such as investment and financing decisions (Chava and Roberts [2008]; Nini, Smith, and Sufi [2012]; Roberts and Sufi [2009b]), resource allocation within firms (Ersahin, Irani, and Le [2021]) or bank health propagation to the real economy (Chodorow-Reich and Falato [2022]).[1]

Interestingly, however, this literature mainly relies on two methods to identify covenant violations, either using reported data on financial covenants in Dealscan (e.g. Chava and Roberts [2008]) or using text searches on regulatory Securities and Exchange Commission (SEC) filings (e.g. Nini, Smith, and Sufi [2012]).[2] 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 a more up-to-date and inclusive analysis compared to traditional methods.[3] Unlike keyword-

[1] Table 1 provides a more comprehensive account of the literature on loan covenant violations in accounting and finance journals over the 1993 to 2025 period.

[2] A few other papers use confidential SNC data from the Federal Reserve Bank (e.g. 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] (e.g. Bushman et al. [2021]; Christensen et al. [2022]; Li, Wang, and Wruck [2020]).

[3] Chava et al. [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

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.

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 2.1). Our final dataset comprises 11,851 U.S. publicly listed, non-financial firms over the 1996 to 2022 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).[4] 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.[5]

Violations trend downward over the last two decades, consistent with Griffin, Nini, and Smith [2024], but remain strongly cyclical, spiking during the 2001–2003 dot-com bust, rising again in 2008-2009, and surging to nearly 20% during COVID-19. The long-run decline is largely

risks associated with covenant violations. Dyreng et al. [2025] document measurement error in violation and slack constructed from commercial data.

[4] 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.

[5] We use the pretrained MPNet Sentence Transformer model and fine-tune its parameters on our manually labeled 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%.

accounted for by loan amendments (defined to include pre- and post-violation changes and waivers), which mirror the violations time series, while technical defaults are rare and fall to about 1% by the end of the sample. Heterogeneity by credit quality shows investment-grade borrowers rely on preemptive amendments without violations (roughly 6% on average, with a temporary spike to about 20% in 2020) and rarely need waivers. For non-IG firms, amendment activity declines over time, remains procyclical, and exhibits a smaller pandemic jump; unrated firms face more severe violations, maintain 8% preemptive amendments, and show declining waivers with little COVID-related increase.

To interpret the secular decline in amendments, we examine covenant design as a channel: capital-based covenants continue to decline while performance-based covenants—used to address borrower–lender agency frictions Christensen and Nikolaev [2012]—have, if anything, increased, especially for Non-IG issuers. From 2000-2020, the share of performance-based covenants is negatively correlated with amendment activity, consistent with looser thresholds (Demerjian and Owens [2016]) or increasingly "weak" covenants (Ivashina and Vallee [2022]).

Next, we benchmark CovenantAI against existing approaches to identify covenant violations, particularly the (1) "Dealscan Approach" (Chava and Roberts [2008]) and (2) the "Keyword-Based Approach" (Griffin, Nini, and Smith [2024]; Nini, Smith, and Sufi [2012]; Roberts and Sufi [2009a]). Specifically, we ask: What are the differences w.r.t. violation rates in all three approaches? What can explain these differences? And, do they lead to economically different interpretations as to the implications of covenant violations?

Roberts and Sufi [2009a], Nini, Smith, and Sufi [2012], and Griffin, Nini, and Smith [2024] use a keyword-based approach on SEC filings in combination with a manual reclassification, which involves a substantial amount of manual effort to reduce false-positives or false-negatives. We thus replicate the keyword-based approach used in Nini, Smith, and Sufi [2012] to be able to compare the economic effects of covenant violations both with and without manual adjustments. Following Chava and Roberts [2008], we identify covenant violations using the Dealscan database as described in their paper.

We first compute annual violation rates for all approaches. We document that CovenantAI correlates highly with Griffin, Nini, and Smith [2024] ($\rho = 0.95$), Nini, Smith, and Sufi [2012] ($\rho = 0.78$ until 2009), and Roberts and Sufi [2009a] ($\rho = 0.83$ until 2010). All three approaches exhibit similar cyclicality, with violation rates declining over time. In contrast, the keyword-based method shows increasing violation rates over time, negatively correlating with all other approaches. The Dealscan approach has positive, but significantly smaller, correlations with the other methods (e.g., the correlation with CovenantAI is only $\rho = 0.26$). Strikingly, virtually all correlations become substantially smaller when the data are disaggregated to a quarterly level. At quarterly horizons, where event-timing (i.e., when the covenant breach occurs) matters, the correlations drop substantially ($\rho = 0.43$ with Roberts and $\rho = 0.47$ with Nini). This result indicates that small timing discrepancies (and thus measurement errors) are smoothed out in annual aggregates.

To better understand differences in identifying covenant violations, we analyze a random sample of 102 firm-quarters where CovenantAI's labeling of covenant violations *deviates* from that of Nini, Smith, and Sufi [2012] and Roberts and Sufi [2009a]. 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 [2009a] shows only 45.10% accuracy. Moreover and despite a manual adjustment on top of the keywords-based approach, Nini, Smith, and Sufi [2012] only finds 66.2% of the covenant violations that are correctly classified in CovenantAI. Roberts and Sufi [2009a], however, only identify 27.8% of these violations. Overall, this comparison underscores the advantages of using an LLM to accurately identify covenant violations in SEC filings.

Do methodological differences in identifying of covenant violations lead to different economic conclusions? We address this important question comparing the effects of covenant violation on a set of variables reflecting firm-level policies from the prior literature using the different approaches discussed above. More precisely, we proceed in three steps: (1) We compare CovenantAI and Nini, Smith, and Sufi [2012] using the original 1996 to 2007 sample period; (2) we then compare Nini, Smith, and Sufi [2012] to the keywords-based approach (which is Nini, Smith, and Sufi [2012] without the manual adjustment) using the original 1996 to 2007 sample period; (3) we compare CovenantAI to both the keywords-based approach and the Dealscan approach over the full 1996 to 2022 period.

Taken together, keyword-based approaches with and without manual reclassifications or the Dealscan approach yield different, and sometimes opposite, inferences of covenant violations compared to CovenantAI, highlighting possible measurement risk associated with these approaches (Dyreng et al. [2025]). CovenantAI addresses these issues, providing precise identification of covenant violations and, crucially, capturing their severity—an area previously underexplored in academic research. For both, the accounting and finance literature, CovenantAI enables new research that connects, for example, contract renegotiation, investor trading, and real outcomes.

In the final part of the paper, we outline two promising areas where the CovenantAI database facilitates new academic research that would not be possible with covenant violation data from the prior literature. First, we provide suggestions how to use CovenantAI to investigate investigate the economic implications of covenant violations focusing on their severity. We introduce the concept of violation severity by classifying covenant breaches according to their resolution—ranging from amendments without violation (least severe) to technical default (most severe). This distinction is crucial because the severity reflects the intensity of creditor intervention, the financial health of the borrower, and the likelihood of significant contract renegotiation.[6] By systematically incorporating severity, we uncover richer insights into the economic implications of covenant violations and creditor-borrower dynamics, addressing well-documented misclassification and slack measurement error in binary proxies (Dyreng et al. [2025]; Zhu [2024]). Empirical evidence shows that more severe outcomes lead to stricter covenant terms and greater operational constraints.

We provide initial evidence that the severity of covenant violations has a differential impact on firm policies. For example, firms with more severe violations reduce leverage and debt levels, and increase cash holdings more than firms with less severe covenant violations. This raises important questions. For example, understanding the determinants of violation severity appears crucial. Which firm-specific, bank-specific, or macroeconomic factors influence the outcomes firms experience? Importantly, along which margins do lenders intervene?[7] We use an LLM to extract covenants and covenant threshold dynamically over time. The availability of covenant

[6] This discussion relates to the literature on the debt covenant hypothesis, i.e., managers adjust accounting and sometimes real activities to avoid binding covenants, and to theories of state-contingent creditor remedies under renegotiation (DeFond and Jiambalvo [1994]; Dichev and Skinner [2002]; Roberts [2015]; Smith and Warner [1979]; Sweeney [1994]).

[7] Determinants plausibly include lender health and ownership structure, which affect enforcement intensity and access to credit after breaches (Chodorow-Reich and Falato [2022]; Haque and Kleymenova [2023]).

thresholds at the firm-quarter level allows us to observe the mechanics of renegotiation, i.e., tightening and relaxation of thresholds and the shifting mix of covenants, both in response to firm-specific shocks and broader macroeconomic conditions (Freudenberg et al. [2017]; Roberts [2015]). In particular, we analyze whether lenders systematically adjust covenant strictness in response to the severity of violations (Beneish and Press [1995]; Bird et al. [2022]). In summary, we show that leverage and coverage ratios are the most prevalent covenants, suggesting creditor focus on solvency and debt-servicing capacity. The data reveal that creditor interventions, such as through covenant modifications, intensifies with the severity of violations, while waivers tend to involve minimal contract changes.

A second promising avenue for future research using CovenantAI is to explore how loan market investors respond to covenant violations. Understanding how covenant structures influence corporate loan markets is crucial, particularly given the significant consequences of covenant violations for both borrowers and lenders. Covenant breaches can trigger credit downgrades, liquidity constraints, and even bankruptcy. Yet, the mechanisms by which institutional investors, such as Collateralized Loan Obligations (CLOs), anticipate and respond to potential covenant violations are not well understood. Advances in loan trading liquidity have enabled investors to strategically adjust their portfolios, potentially selling loans ahead of anticipated breaches. Further research can leverage CovenantAI to analyze how institutional investors trade around covenant violations and respond to different violation severity.

Information flow around breaches, including management forecasts and disclosure changes, can shape how fast prices incorporate covenant news (Bourveau, Stice, and Wang [2022]). Our initial analysis, merging CovenantAI data with daily secondary loan market quotes, shows distinct trading patterns in the period leading up to covenant violations (Saunders, Steffen, and Verhoff [2025]).[8] Loan prices remain relatively stable when covenants are amended proactively before a breach occurs. However, significant price declines are observed when amendments occur only after violations, or when loans enter technical default. These preliminary findings suggest that investors are sensitive to the severity and timing of covenant breaches and might therefore strategically position their portfolios in anticipation of potential distress. Differential price paths are consistent with pre-emptive amendments dampening information

[8] Loan mid-quotes track transaction prices well and bid–ask spreads are standard proxies for loan market liquidity (Saunders et al. [2024]; Wittenberg-Moerman [2008]).

shocks, whereas post-breach amendments and technical default amplify them (Acharya et al. [2020]). The dynamics observed raise important questions about the determinants of investor behavior: Which CLOs are selling and buying during these periods, how do specific constraints such as leverage or portfolio concentration influence their trading decisions, and what role do amendments and waivers play in shaping these market dynamics? Addressing these questions will provide deeper insights into the strategic behavior of institutional investors in corporate loan markets. We make the dataset available for future research on these and other important topics.

The rest of this paper is organized as follows. In Section 2, we introduce CovenantAI, we provide a benchmarking against earlier literature in Section 3. Section 4 illustrates promising avenues for future research using CovenantAI, and Section 5 concludes.

2 CovenantAI - A Machine Learning Approach

2.1 Data Sources

To investigate the economic implications of covenant violations using our machine learning approach, we obtain data from different data sources.

2.1.1 Company and loan data

We utilize the Compustat database to select US companies for our study, focusing on the period from 1996 to 2022. Our criteria included companies with assets over USD 10 million, excluding those with missing or negative key financial metrics like total assets and sales. We limited our analysis to non-financial firms, omitting those with SIC codes 6000-6999. Firms without a CIK identifier were also excluded. Our final dataset includes 445,017 firm-quarter observations from 11,851 US non-financial companies.

We obtain quarterly information about the usage of credit lines of U.S. publicly listed firms from from the Capital IQ database. Compustat/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, and we transform the rating into a numerical scale.[9] Overall, 77.6% of our sample firms are unrated, 6.0% are investment-grade (IG) rated, and 16.4% are non-investment-grade (Non-IG) rated.

We use loan data at the deal and facility level from Refinitiv Dealscan. We extend the Chava and Roberts [2008] Dealscan-Compustat link to 2022. From our 11,851 US non-financial firms, we are able to match about 60%, i.e., 6,934 unique firms to Dealscan (which corresponds to 26,561 deals).[10] Dealscan provides us with terms *at origination* of the loan including spread, amount, lenders but also initial covenants.

2.1.2 SEC filings

This section outlines our method for processing regulatory 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. We combined 10-K and quarterly filings to ensure continuity in our dataset. Covenant violations appear in both annual and quarterly reports. Additionally, 8-K reports, issued for specific events like bankruptcy or CEO changes, provide further relevant data for shareholder analysis.

In total, we extract 132,591 10-K, 451,826 10-Q, and 1,285,768 8-K reports over the 1996 to 2022 period from the SEC Edgar database.[11] As we describe further below in this paper 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 with the term "covenant," including 700 characters surrounding it to gather relevant information for our model. The source files varied in format, with newer ones in HTML and older ones in txt. We rechecked HTML-based paragraphs to confirm adherence to the 700-character limit, as the model cannot process beyond this. To optimize paragraph labeling by our algorithm, we applied a filter to our dataset. This filter highlights paragraphs containing specific word combinations that suggest possible covenant violations and amendments.[12] To verify the

[9] We report the industry classification as well as the numerical mapping of the S&P Credit Ratings in Online Appendix A. If a company has a rating number 26 or 27, it means that it is rated as "D" or in a selective default (SD). In our empirical tests, we match our companies to the LoPucki bankruptcy database. Both approaches, however, identify similar corporate defaults.

[10] We provide a comparison of firms in the full as well as the matched sample in the Online Appendix Section A.

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

[12] 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",

accuracy, we randomly sampled a subset of our data, checking for correctly identified potential violations and amendments. Overall, this method yields 1,081,905 paragraphs containing the word "covenant". These paragraphs are subsequently processed and labeled by our model.

2.2 Algorithm

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 Sections B and C of the Online Appendix). We then compare our approach to those used in prior literature on covenant violations. Finally, we benchmark our measure to other approaches from the literature replicating the main results from this literature and highlighting differences and similarities.

A manual inspection of the SEC filings suggest that loan renegotiation outcomes are more complex than previous literature suggests. There are loan amendments without covenant violations, amendments after covenant violations, a combination of amendments and waivers (i.e., a situation in which a lender temporarily waives the compliance with a covenant), pure waivers or technical defaults (i.e., a situation after a covenant violation that does not lead to an amendment or waiver in the two quarters following a violation).[13]

CovenantAI can account for these different renegotiation outcomes. We provide a brief overview of the design of this new ML algorithm in the subsection 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 duplication and leakage concerns of the training and test dataset mentioned in Kapoor and Narayanan [2023], we implement a two-step approach on all paragraphs containing the word *covenant*. Firstly, we select only one paragraph per firm[14] out the whole sample of covenant paragraphs and apply in a second step the Jaccard Similarity Score to identify and remove duplicates within the sample

"violated".

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

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

of paragraphs. The Jaccard Similarity Index[15] is a statistical measure that helps understanding the similarity between finite sample sets that is particularly effective in comparing the presence of words in two sets Prakoso, Abdi, and Amrit 2021. This method reduces the dataset from 1,081,905 paragraphs to 14,335 unique paragraphs. [16].

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 of 4,184 observations, which are specific, balanced and unique ensuring a high quality dataset for training and testing our model. To ensure a consistent and high-quality manually labeled dataset, the labeling process was performed in two steps. First, it was carried out independently by two research professionals currently enrolled in a Master of Science program in their final semester and by one of the authors. The labeling was split in such a way that each of the 4,184 selected paragraphs was independently labeled by two different individuals to minimize individual bias and ensure consistency. Second, we calculated a disagreement score for the same paragraphs labeled by different individuals, which showed that disagreements occurred in less than 1% of the cases. This provides strong evidence that the dataset is correctly labeled and reliable.

[15] The Jaccard Index, defined as: $\frac{|A \cap B|}{|A \cup B|}$

[16] 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

To train our classification algorithm, optimize the model parameters and compute the model performance, we manually label a subset of paragraphs which serves as a ground truth. Our manual labeling process categorizes firm quarters into six groups: *No Violation* (label 0), *Amendment w/o Violation* (label 1), *Waiver*(label 2), *Amendment and Waiver* (label 3), *Amendment w/ Violation* (label 4) and *Technical Default* (label 5). No violation is assigned where there is no evidence of a covenant breach, an amendment with violation label indicates a loan modification to rectify a violation, and technical default is used when no amendment or waiver is present in the following two quarters. Section B of the Online Appendix provides examples from SEC filings for these categories. After applying the mentioned labels, the manually labeled dataset consists of the following distributions per category:

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.[17]

Step 2-Classification. We divide the labeled sentences into three datasets: training (70%), testing (15%), and validation (15%)[18]. These datasets include varying distributions of technical default, waiver, amendment with violation, amendment without violation and no-violation observations and are employed to calibrate and assess the model's performance. The test dataset is constructed solely from a fully random dataset to evaluate the model's performance on the true underlying distribution.

For our analysis, we use the MPNet Sentence Transformer[19], a type of advanced language

[17] 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.

[18] We tested the model for various combinations of test, training and validation data sizes. See Section C in the Online Appendix

[19] We choose the MPNet sentence transformer, since it performs efficiently in tasks like sentence similarity and classification, which are important for identifying covenant violations and it builds on the strengths of traditional BERT models. The MPNet represents an improvement over traditional transformers like BERT by combining masked language modeling with permutation modeling, as found in XLNet. This approach helps MPNet capture complex sentence dependencies more effectively. We integrated MPNet within the Sentence-BERT framework as a backbone model, which leverages MPNet's strengths to produce high-quality sentence embeddings. This combination makes it well-suited for our analysis of financial documents to identify covenant violations, as it captures sentence context and nuances effectively.

model. In simpler terms, this model takes complete sentences and transforms them into a format it can understand, like converting sentences into numerical code. It is particularly adept at recognizing and differentiating various types of data, such as distinguishing between different classes in our dataset, by focusing on the unique features of each class. What makes it special is its ability to learn from both similarities and differences in these categories, helping it make more accurate classifications. This technique is key to teaching the model to correctly identify and classify different types of data we are studying (such as technical default, amendments or no violations).

A key advantage of CovenantAI is its ability to understand complex language structures. We exploit this to look in more detail into our loan amendments. However, several consequences of violations might be feasible. For example, a violation may be waived, in which case there is no explicit consequence for the borrower, and the credit contract preserves its original terms and conditions. A waiver may last only for a limited period of time. Also, waivers tend to be given after a covenant violation has occurred, whereas amendments might be granted prior to the occurrence of a violation. We can thus classify amendments either directly associated with and following a violation or outside of a covenant violation. Finally, a borrower might obtain a waiver first, but might eventually be required to amend some of the loan terms after the waiver period has expired. These variations hold significant economic implications, as they embody scenarios of varying severity for companies. For instance, companies proactively negotiating amendments prior to any covenant violation are potentially in a more advantageous position. They have prepared ahead and may even secure more favorable terms compared to the previous contract. Conversely, firms that breach covenants and subsequently negotiate amendments might face stricter terms during negotiations.

The model learns by minimizing the loss on the training data and the optimizer updates the model weights based on the training data. During the training the validation set is used to monitor the model's performance with the primary purpose to track how well the model generalizes beyond the training data and to assist in hyperparameter tuning (e.g. deciding when to stop the training process to avoid overfitting). The test set is used after the training process is completed and provides an unbiased overview of the model's performance.

Our machine learning model's performance is illustrated in Figure 1, using two types of data: test (628 observations) and validation (628 observations). Using confusion matrices provides a clear overview of the model performances in labeling the different classes. In these matrices, we compare the model's predictions (horizontal axis) with the actual data (vertical axis). The model showed a high accuracy rate: about 92.17% for the test data and 90.95% for the validation data. Specifically, it correctly identified nearly 87% of violations, 93% of all amendments with violation, 89% of the waivers, 89% of all amendments without violations and 84% of non-violations in the test data.[20]

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%).[21]

[20] To further gauge the model's effectiveness, we calculate its 'precision' and 'recall'. Precision tells us how many of the model's identified violations were actual violations, aiming to minimize false positives. Recall, on the other hand, shows how many actual violations the model successfully identified, focusing on reducing false negatives. We use two methods to calculate these: 'macro average' (simple average across categories) and 'weighted average' (adjusting for category size). Our model achieves around 91% precision and 93% recall with the macro average and 94% for both precision and recall with the weighted average. These results, including recall, precision, and the f1-score for both datasets, are detailed in Section C of the Online Appendix.

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

2.3 Time-series of covenant violations

To inspect covenant violations generated by CovenantAI, we first plot the time-series of covenant violations annually in Figure 2 over the 1996 to 2022 period, defined as the number of covenant violations scaled by the total number of firm observations within a year for our full sample. The shaded areas represent the NBER recession periods.

Time-series of violations and amendments. Panel A shows a significant decline in covenant violations over the last twenty years, consistent with Griffin, Nini, and Smith [2024], but also a cyclicality of covenant violations during periods of economic downturns and recessions. For example, violations spike during the 2001-2003 period and the burst of the dotcom bubble. They also spiked during the global financial crisis (2008-09), albeit at a lower level compared to the 2001-2003 period. Most strikingly, however, is the increase in covenant violations reported during the COVID-19 pandemic. Violations rose to almost 20% (and almost to levels seen during the global financial crisis). Panel B shows that this decline is mainly driven by loan amendments, which exhibit the same time-series pattern observed in Panel A.[22] Interestingly, covenant violations only rarely result in technical default. In the early 2000s, around 5% of firms experienced a technical default, but this share declined to about 1% towards the end of our sample period. Panel C shows amendments with and without covenant violations over time. Evidently, the decline is driven by loan amendments with violations, while amendments without violations remain constant around 10% over the sample period.

Amendmenty by ratings. Next, we plot loan amendments without violations, waiver and amendments after violations separately and also by rating category in Figure 3. Panel A focuses on investment-grade (IG). Interestingly, we do not observe a decrease in amendments for these firms. Amendments without violations have been fairly constant around 6% with a temporary spike to about 20% in 2020. Amendments of waivers after violations are almost negligible. Thus, as expected, violations have overall been less severe for IG-rated firms.[23] Panel B shows the time-series of amendments for Non-IG firms. We find a decreasing trend of all amendment types, but amendments without violations are also most pronounced among Non-IG firms.

[22] Note that "amendments" here comprise amendments without violation, amendments with violations and waivers.

[23] While previous literature highlights that even a large number of IG-rated firms violate covenants, we show that these are not actually violations (or technical defaults) but that IG firms rather negotiate and amend loan contracts *before* a violation occurs.

They decline from more than 15% in 2000 / 2001 to less than 10% in 2022, are procyclical and jump during the pandemic in 2020, but less than IG-rated firms. Amendments after violations and waivers decline from about 5% in 2000 to 1% at the end of 2020. Interestingly, also amendments after violations exhibit a temporary jump during the COVID pandemic. Panel C shows the time-series of amendments for unrated firms. Consistent with the literature on the importance of financial constraints of unrated firms, covenant violations appear more severe for these firms. Amendments without violations are almost constant around 8% during our sample period. Amendments with violations and waivers decline from about 6% in 2000 to about 2% in 2022. Amendments do not exhibit the jump around the COVID-19 pandemic in 2020, and are overall less cyclical.

Understanding the decline in loan amendments. While we cannot offer a complete analysis of the decline in loan amendments in this paper, we provide suggestive evidence in this section. We focus on the the development of covenants as a main channel to explain the declining trend.[24] Christensen and Nikolaev [2012] provide a theory-driven, empirical analysis of the choice between performance-based and capital-based covenants.[25] They argue that performance-based covenants are used to address agency problems between borrowers and lenders (acting as so-called "trip-wires") and are therefore positively correlated with loan amendments over the 1993 to 2010 period. We show that (despite a brief increase in capital-based covenants) the declining trend in the usage of capital-based covenants continued. The use of performance-based covenants has, if anything, increased, particularly for Non-IG firms where agency problems are arguably more pronounced. Interestingly, we find a negative correlation between loan amendments and the ratio of performance-based covenants over the 2000 to 2020 period (using data obtained from Dealscan). Possible explanations are less strict covenants (based on the Demerjian and Owens [2016] measure) or the inclusion of "weak covenants" that can easily be manipulated to avoid violations and the need to amend a loan contract (Ivashina and Vallee [2022]).[26] We provide a more detailed discussion in Online Appendix C and leave

[24] Other (not mutually exclusive) arguments suggest an institutionalization of the loan market as explanation for this trend (Becker and Ivashina [2016]). While Griffin, Nini, and Smith [2024] investigate the decline in violations – which, as we show, are loan amendments rather than violations – some of their arguments apply also to the decline in amendments.

[25] Demerjian [2011] provides complementary evidence as to a decline in both types of covenants.

[26] We observe that amendments before violations are usually more pronounced for Non-IG-rated firms, suggesting that institutional investors and private equity firms (which frequently own these firms) have an advantage in renegotiating loan contracts early.

further analyses for future research.

3 Benchmarking CovenantAI

In a next step, we benchmark CovenantAI against existing approaches that identify covenant violations, particularly the (1) "Dealscan Approach" (Chava and Roberts [2008]) and (2) the "Text-Search-Based Approach" (Griffin, Nini, and Smith [2024]; Nini, Smith, and Sufi [2012]; Roberts and Sufi [2009a]). What are the differences w.r.t. violation rates in all three approaches? What can explain these differences and what do they lead to economically different interpretations as to the implications of covenant violations?

3.1 Benchmark approaches

3.1.1 Dealscan approach

We follow the approach used in Chava and Roberts [2008] and first restrict the Dealscan sample to contracts containing at least one of the following three covenants: *Current Ratio*, *Net Worth* and *Tangible Net Worth*. We then map borrowers in Dealscan and Compustat using the linking table provided by Chava and Roberts [2008]. Next, we create facility quarter observations for all quarters in between the facility start and end date. We map this dataset based on the Compustat gvkey and year-quarter to our financial data obtained from Compustat. The matched sample on a facility (borrower) level contains 136,154 (70,839) quarterly observations. We calculate quarterly values for (1) *Current Ratio*, which is the ratio of current assets to current liabilities, (2) *Net Worth*, which is calculated as the difference between total assets and total liabilities, and (3) *Tangible Net Worth*, which is the sum of current assets, property, plant and equipment net and other assets minus total liabilities. The calculation follows the definition in Chava and Roberts [2008] and is reported in detail in Table A1. We mark the quarter as a violation, if the quarterly value is below the reported threshold for all three covenants. To make it comparable, we construct the variable *new*, a dummy variable equal to 1 if the firm was in violation of one of the three covenants and did not report a violation in the previous four quarters (Nini, Smith, and Sufi [2009]). The sample on the facility level contains 25,741 (18.91%) violation observations and 7,211 (5.30%) *new* violations. The firm level data contains

14,134 (19.95%) violations and 4,392 (6.20%) *new* violations.

3.1.2 Text-search-based approach

Roberts and Sufi [2009a], Nini, Smith, and Sufi [2012], and Griffin, Nini, and Smith [2024] use a keyword-based approach on SEC filings in combination with a *manual reclassification*, which involves a substantial amount of manual effort to reduce false-positives or false-negatives. We thus replicate the keyword-based approach used in Nini, Smith, and Sufi [2012] to be able to compare the economic effects of covenant violations both with and without manual adjustments.

As in Nini, Smith, and Sufi [2012], we first search for the keywords "waiv", "viol","in default","modif" and "not in compliance" within 10-K and 10-Q filings in the seven lines surrounding the word *covenant*. We then reclassify violation observations as no violation if we do not have information about the previous four quarters. We further generate the variable *new*, which is 1 if the firm violated a quarter in the respective period but did not violate a covenant in the previous four quarters. The final dataset consists of 435,323 firm quarter observations with 91,773 (21.08%) covenant violations and 28,319 (6.51%) *new* violations over the 1996 to 2022 period.

We obtain the data from the original papers from the authors' websites. The Nini, Smith, and Sufi [2012] dataset spans the 1996 to 2007 period including 225,451 firm quarter observations with 37,612 (16.68%) violations and 12,767 (5.66%) *new* violations. We also add the covenant violation data from Roberts and Sufi [2009a]. This dataset consists of 7,431 covenant violations from 1995 to 2011 for 2,729 unique U.S. firms. We match this data with our dataset (on a firm-quarter level) and label all quarters that remain unmatched as no violation.[27] The annual covenant violation data from Griffin, Nini, and Smith [2024] is provided in their Appendix Table I.

3.2 Comparing covenant violation rates

We first compare covenant violation rates of the approaches in Roberts and Sufi [2009a], Nini, Smith, and Sufi [2012], and Griffin, Nini, and Smith [2024], the keyword-based and Dealscan approach and CovenantAI. We follow Nini, Smith, and Sufi [2012] and Griffin, Nini, and Smith

[27] Because the data only contains the violation cases, it is difficult to say if Roberts and Sufi [2009a] did not include some companies or if the violations within these firms were not detected.

[2024] and calculate annual violation rates as the number unique firms, who violate covenants in a given year, divided by the total number of firms in the respective year.

Correlation analysis. Figure 4 shows the violation rates of the different approaches. Panel A shows the annual violation rates from CovenantAI in comparison with the violation rates in Roberts and Sufi [2009a], Nini, Smith, and Sufi [2012], and Griffin, Nini, and Smith [2024]. Panel B of Figure 4 shows the annual violation rates of CovenantAI, the keywords-based and the Dealscan approach.

We compute the correlations of the violation rates obtained by various approaches and report them in Table 2. We observe a high correlation of violation rates from CovenantAI with those in Griffin, Nini, and Smith [2024] ($\rho = 0.95$) as well as with Nini, Smith, and Sufi [2012] ($\rho = 0.78$) until 2009. We observe a correlation of $\rho = 0.83$ with the violation rates of Roberts and Sufi [2009a] until 2010 (Panel A of Table 2). As the figure suggests, the violation rates of Griffin, Nini, and Smith [2024], Nini, Smith, and Sufi [2012] and CovenantAI are very similar in terms of the level and cyclicality. All three approaches show a decrease in violation rates over time. The violation rates of (Roberts and Sufi [2009a]) have level differences, but show the same cyclicality in economic downturns.

These correlations, however, change substantially when we compare our violation rates to those from Griffin, Nini, and Smith [2024] but without manual adjustments. Panel B of Figure 4 shows that violation rates of the keywords-based approach (*without* the manual adjustments) are very different compared to the manually adjusted violation rates in e.g. Griffin, Nini, and Smith [2024] and are increasing (rather than decreasing) over time. Panel A of Table 2 consistently reports negative correlations between the covenant violation rates of the keywords-based approach with violation rates from all other approaches. Violation rates from the Dealscan approach are positively correlated with those obtained from other approaches.

Annual vs. quarterly violation rates. Different methods of calculating covenant violation rates often yield similar results when aggregated annually, as possible measurement errors on a quarterly basis might be smoothed out when aggregating to annual violation rates (Dyreng et al. [2025]). Therefore, we expect to see high correlations in Panel A of Table 2. Moreover, annual violation rates might be substantially larger as the nominator increases with each quarter while the denominator (the total number of firms) might stay constant.

As a next step, we thus compute quarterly violation rates and compare them across the different approaches. We report these correlations in Panel B of Table 2. Indeed, comparing the quarterly correlations of covenant violation rates, we find much lower correlations. For example, the correlation of violation rates from CovenantAI with those from Roberts and Sufi [2009a] are $\rho = 0.43$ and with those from Nini, Smith, and Sufi [2012] are $\rho = 0.47$.[28]

Event-level analysis. To compare the performances of the three models and emphasize the identification differences, we take a random sample of 102 firm quarters where the labeling of CovenantAI *disagrees* with the labeling of either of the Nini, Smith, and Sufi [2012] or the Roberts and Sufi [2009a] approach. Therefore, the confusion matrices are not representative of the overall performance of the respective model and only give us an indication how the models perform when we apply them to more complex paragraphs.

To make the labeling comparable to the other approaches, we simply divide the firm quarters into *Violation* and *No Violation*. The *Violation* is assigned with 1 if the firm either obtained a waiver, an amendment with violation or was in a technical default. The *Violation* is assigned with 0 if the firm was not in violation or obtained an amendment without violation. Panel A shows the confusion matrix of CovenantAI, which outperforms the other approaches with an accuracy of 79.41%. Panel B shows the confusion matrix of the Nini, Smith, and Sufi [2012] data, being constructed by additional manual adjustments on top of a simple keyword search. Panel C shows the performance on a simple keyword based approach build on the approach by Nini, Smith, and Sufi [2012].

In Appendix Table A2 we show examples of paragraphs where CovenantAI does not agree with the labeling of the keyword based approach. It highlights the shortcomings of keyword based approaches and the advantages of using a large language model in the task of identifying covenant violations in SEC filings. The Roberts and Sufi [2009a], using Dealscan data, performs worst in identifying covenant violations with an accuracy of 45.10%.

3.3 Economic Implications - Replication Exercise

Do methodological differences in identifying of covenant violations lead to different economic conclusions? In this section, we address this important question comparing the effects of

[28] We do not include the correlation with the Griffin, Nini, and Smith [2024] violation rates, because covenant violations are not available on a firm-quarter level.

covenant violation on a set of economic outcomes from the prior literature for the different approaches discussed above. More precisely, we proceed in three steps: (1) We compare results using violations rates from CovenantAI and Nini, Smith, and Sufi [2012] during the original 1996 to 2007 sample period; (2) we then compare Nini, Smith, and Sufi [2012] to the keywords-based approach (which is Nini, Smith, and Sufi [2012] minus the manual adjustment) using the original 1996 to 2007 sample period; (3) we compare CovenantAI to both the keywords-based approach and the Dealscan approach over the full 1996 to 2022 period.

Table 3 provides summary statistics of our sample for the two time periods. Panel A shows the summary statistics for the time period from 1996-2007 for all 8,839 non-financial U.S. companies. Panel B consists of 11,864 non-financial U.S. companies over the 1996 to 2022 period. All quarterly variables are annualized. All variables are defined in the Appendix A. Note that we do not aim for perfect identification of economic effects. Instead, our goal is to apply an approach consistent with prior literature to benchmark our covenant violation rates.

3.3.1 Methodology

We investigate the impact of covenant violations on investment and employment, financial policies as well as operational and financial performance using a "quasi-regression discontinuity design" (RDD) that is common in the literature (Nini, Smith, and Sufi [2012]; Roberts and Sufi [2009a]).[29]

We estimate the following regression model using OLS:

$$y_{i,t+4} - y_{i,t} = \alpha + \beta \times Violation_{i,t} + \theta \times X_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \quad (1)$$

The dependent variable $y_{i,t+4} - y_{i,t}$ is the change in our proxies for (1) Investment & Employment; (2) Financial Policies and (3) Operational & Financial Performance over the four quarters following a covenant violation. These are: (1) Δ *Ln (Assets)*; (2) Δ *CapEx/ Assets*;

[29] 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.

(3) Δ *CashAcq/ Assets*; (4) Δ *Ln(Debt)*; (5) Δ *Cash/Assets)*; (6) Δ *Ln(Shareholder Payout)*; (7) Δ *Ln(Sales)* and (8) Δ *Ln(Cost)*. $Violation_{i,t}$ is an indicator variable that is one if firm i has a covenant violation in quarter t. We do not differentiate by renegotiation outcome and drop all amendments that occur without covenant violations.

$X_{i,t}$ 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 $Violations_{i,t-4}$. Standard errors are clustered at the firm level.

3.3.2 Results

Nini, Smith, and Sufi [2012] vs. CovenantAI. We first investigate the differences in regression results when investigating the implications of covenant violations using the covenant violations from Nini, Smith, and Sufi [2012] vs. the covenant violations identified by CovenantAI over the 1996 to 2007 period (the same as in the original paper). Panel A of Table 4 shows the results using the Nini, Smith, and Sufi [2012] and Panel B the results using the CovenantAI data. The last line compares the coefficients of the regression results of both approaches. We use a ✓ to mark similar economic implications of both approaches, (✓) to mark a similar direction of the effect but a difference in economic magnitudes of more than 10%, and × to mark differences.

As expected because of the high correlations, both approaches provide similar economic implications in terms of the *direction* of the effect for most outcome variables except *Shareholder Payout*. While Nini, Smith, and Sufi [2012] find that covenant violations reduce shareholder payouts, CovenantAI does not find a statistical or economical meaningful relationship. For other outcome variables, CovenantAI suggests significantly larger effects. For example, firms reduce assets, capital expenditures and debt after covenant violations and the effect is about one-third larger compared to Nini, Smith, and Sufi [2012]. In other words, while broadly consistent in the direction of the effect over the 1996 to 2007 period, CovenantAI provides more precise points estimates as to the effect of covenant violations on economic outcomes compared to Nini, Smith, and Sufi [2012].

Nini, Smith, and Sufi [2012] vs. keyword-based approach. Table 5 compares the regression results using covenant violations obtained from Nini, Smith, and Sufi [2012] and the keyword bases approach used by Nini, Smith, and Sufi [2012] but *without* the manual adjustments. We compare the results for the time period from 1996-2007, over which the Nini, Smith, and Sufi [2012] data is available on a quarterly basis.

Only for 2 out of 8 outcomes, both approaches lead to similar conclusions ($\Delta CashAqu/Assets$ and $\Delta Cash/Assets$). For three other outcome variables ($\Delta Ln(Assets)$, $\Delta CapEx/Assets$, $\Delta Ln(Sales)$), effects of the keyword-based approach go into the same direction but are economically significantly smaller. For three other outcome variables ($\Delta Ln(Debt)$, $\Delta Ln(Payout)$, $\Delta Ln(Cost)$) the effects are significantly different. Overall, using the keywords-based approach (as in Nini, Smith, and Sufi [2012]) without adjusting covenant violations manually results in economically different conclusions for a large number of possible economic outcomes.

CovenantAI vs. keyword-based approach & Dealscan approach. Table 6 compares the regression results using violations from Covenant AI (Panel A) to those obtained from the keyword-based approach (Panel B) and the Dealscan approach (Panel C) over the full sample period (1996-2022). Comparing Panel A and B, we document that the results overlap only w.r.t 1 outcome variable (changes in shareholder payouts) for which both suggest an insignificant effect of covenant violations. The effects on $\Delta Ln(Assets)$ and $\Delta CapEx/Assets$ go into the same direction but are several orders of magnitude larger when using violations from CovenantAI. All other economic interpretations are different. Comparing the results using CovenantAI (Panel A) and Dealscan (Panel C) shows even larger differences in the economic conclusions based on both approaches, which are different for 7 out of the 8 outcomes that we analyzed.

Taken together, keyword-based approaches with and without manual reclassifications or the Dealscan approach yield different, and sometimes opposite, inferences of covenant violations compared to CovenantAI, highlighting possible measurement risk associated with these approaches (Dyreng et al. [2025]). CovenantAI reduces measurement risk and, importantly, is able to identify the severity of covenant violations (based on their outcomes such as amendment, waiver or technical default), which has been understudied in the academic literature this far. In the following section, we briefly outline two economic questions to demonstrate how

CovenantAI can be used in empirical research. These are explicitly descriptive rather than full applications and we make the dataset available for future research on these and other important topics.

4 Promising Areas for Future Research

As demonstrated in the previous discussion, CovenantAI is uniquely positioned to accurately identify covenant violations among publicly listed U.S. firms. In this section, we outline two promising areas where the CovenantAI database can enable further research: (1) the economic implications of covenant violation severity; and (2) loan trading dynamics surrounding covenant violations. We discuss each of these research areas and outline possible questions and analyses but leave a thorough investigation of these topics for future research.

4.1 Economic implications of covenant violation severity

4.1.1 Covenant severity and policy adjustments

We outline potential approaches to applying CovenantAI for exploring the economic consequences of covenant violations, particularly by emphasizing the severity of these breaches. We conceptualize severity by categorizing covenant violations based on how they are resolved, spanning cases from preemptive amendments without formal breach (least severe) to instances of unresolved technical defaults (most severe). This categorization is important as it captures variations in creditor intervention intensity, borrower financial distress, and the potential scope for substantial contract renegotiations. By explicitly integrating this severity measure, researchers can gain deeper insights into the economic effects of covenant breaches and better understand the nuances in creditor-borrower interactions.

As explained in section 2 above, CovenantAI has been trained not only to identify covenant violations but also the specific resolutions employed to address these breaches. The primary resolution mechanisms typically include waivers, amendments to loan agreements, and in some severe cases, acceleration or termination of the loan. Our analysis in Panel A of Table 8 using CovenantAI reveals notable variation in the relative occurrence of these resolutions. *Amendments* and *Waivers* emerge as the most frequent resolutions. 36% of all firms obtain an amendment (without a covenant violation), 23% obtain waivers and 21% amendments following a covenant breach indicating lenders' preference for flexibility and continued engagement with borrowers, whereas acceleration or *Technical Default* is comparatively rarer outcome, likely reflecting heightened borrower distress.

As noted in prior studies (e.g., Roberts and Sufi [2009a] or Chava and Roberts [2008]), covenant violations often serve as a mechanism through which lenders actively intervene to influence borrower policy decisions, including financing and investment strategies. CovenantAI's data supports these findings, as illustrated by Figure 6. Importantly, however, our investigation using CovenantAI allows exploration into firm policy adjustments associated with different levels of severity of covenant violations. We provide initial evidence that it matters. For example, firms with more severe violations reduce leverage and debt levels, and increase cash holdings more than firms with less severe covenant violations.

Overall, our initial evidence suggests that firm policies adjust differently depending violation severity, which raises important research questions. For example, understanding the determinants of violation severity appears crucial. Which firm-specific, bank-specific, or macroeconomic factors influence the outcomes firms experience. Importantly, along which margins do lenders intervene? We turn to this question in the next subsection.

4.1.2 Covenant severity - Changes in loan terms

Covenants are formulated in terms of a variety of accounting ratios (Dichev and Skinner [2002]; Leftwich [1983]). An important margin through which lenders can thus intervene are loan terms, for example, by adjusting the underlying covenants. We employ a large language model (LLM) to dynamically identify covenants and their corresponding thresholds over time. Having covenant threshold data at the firm-quarter level enables us to examine how covenant structures adapt throughout the duration of a loan, responding to both idiosyncratic firm-level shocks and general macroeconomic changes. Specifically, this granularity allows us to investigate if lenders systematically tighten or relax covenants in relation to the severity of prior covenant violations.

Obtaining covenant information from SEC filings. Modifications to covenant types or thresholds are typically not included in commercial databases such as Dealscan. We thus obtain these from SEC filings. To identify covenants and covenant thresholds within a large corpus of exhibits, we use a Generative AI methodology leveraging GPT-4O Mini, a large language model. Our methodology is in detail described in the Appendix A.3.

We start with the extraction of covenant thresholds by s metadata extraction, filtering, retrieval of relevant content, and data cleaning to ensure precise and scalable extraction of covenant-related information. The corpus of data is based on all loan contracts from SEC 10-K filings and the final dataset is firm-quarter panel dataset with covenants and covenant thresholds. We use this firm quarter panel dataset as the basis for tracing changes in covenant thresholds. Building on this corpus, we take all SEC filings that CovenantAI has flagged under any amendment type (*Amendment w/o Violation*, *Amendment and Waiver* and *Amendment w/ Violation*. For each firm quarter we retrieve the associated 8-K exhibits and, when additional context is needed, the relevant 10-Q and 10-K filings. For each document we perform preprocessing steps, including the removal of standardized disclosures, stripping of HTML markup, and elimination of footnote markers, all of which are detailed hereafter. The remaining narrative is then segmented into discrete paragraphs in original order, and character encoding, whitespace, and special symbols are normalized to produce a structured repository of amendment related filings. Within this repository we identify paragraphs most likely to contain covenant amendments by requiring both amendment cues such as amend, waive, eliminate, or violation and patterns indicating numerical transitions in covenant thresholds. Our natural language processing routines then detect explicit ratio names such as Leverage Ratio or Interest Coverage as well as implicit formula descriptions like total debt divided by EBITDA. We extract the original covenant value, the amended value, and any effective date mentioned, and assign each record a classification corresponding to the type of amendment. To guarantee accuracy we randomly sample approximately six hundred amendment events for manual annotation by expert coders who verify covenant classification, date spans, and before and after values. The resulting standard dataset is used to train and calibrate our supervised extraction model, which is then deployed across the full sample. A key benefit of our database is that it captures not only the covenant thresholds but also the exact definitions of each financial covenant and the dates of their amendments. This level of precision allows accurate identification of covenant breaches when comparing firms' actual performance to the relevant thresholds at each point in time.

Summary statistics The summary statistics in Panel A of Table 7 provide an overview of key financial covenants and their prevalence across firms subject to covenant agreements. The data is extracted at the firm-quarter level from SEC filings and then aggregated to the firm level. The leverage ratio is the most commonly applied covenant (associated with 72.49% of firms), followed by the fixed charge coverage ratio (44.42%) and the interest coverage ratio (41.99%). Liquidity-based metrics such as the current ratio and quick ratio are less frequently included, available only for 8.34 and 4.43% of firms, respectively. Overall, the widespread inclusion of leverage and coverage ratios suggests that creditors primarily target solvency and debt-servicing capacity, while liquidity measures play a more limited role in covenant structures.

Covenant modifications around breaches. Panel A of Table 8 shows creditor intervention intensifies with the severity of renegotiation outcomes. Waivers involve minimal adjustments, indicating temporary relief without significant contract changes. Technical defaults lead creditors to impose more notable changes, such as reducing the current ratio (-0.03, $p < 0.001$) and slightly increasing the quick ratio (0.01, $p < 0.05$). Amendments without violations show modest tightening, evidenced by an increased debt-to-cashflow ratio (0.01, $p < 0.001$). Amendments with violations reflect the most substantial creditor interventions, significantly decreasing the current ratio (-0.02, $p < 0.001$) and increasing leverage (0.05, $p < 0.001$), highlighting heightened risk management.

Panel B of Table 8 focuses on recalibrations of covenant thresholds post-renegotiation, also aligning with outcome severity. Waivers exhibit minimal threshold adjustments, such as a slight decrease in the interest coverage ratio (-0.18, $p < 0.01$). Technical defaults prompt significant tightening: an increased current ratio threshold (0.13, $p < 0.001$) and sharply reduced debt-to-cashflow ratio threshold (-0.30, $p < 0.001$). Amendments without violations show moderate tightening, including increased thresholds for debt-to-cashflow (0.07, $p < 0.01$) and leverage (0.03, $p < 0.05$). Amendments with violations entail the most stringent recalibrations, such as a substantial increase in debt-to-cashflow (0.15, $p < 0.01$) and reduced debt service coverage (-0.11, $p < 0.001$), emphasizing creditors' rigorous risk control.

Future research. Overall, these first insights suggest that creditor interventions escalate with the severity of renegotiation outcomes. Waivers involve minor covenant adjustments, while technical defaults and amendments with violations trigger significant tightening in both covenant likelihood and threshold recalibrations.

One important research direction involves examining whether looser covenant thresholds are associated with lower interest spreads, upfront fees or commitment fees, and conversely, whether tighter thresholds reflect increased lender concern about borrower risk. By linking covenant threshold differences to firm characteristics such as leverage, profitability, asset tangibility, growth opportunities and ownership structure, researchers can better understand which borrowers secure more favorable covenants and why. A second promising path involves using the firm quarter covenant thresholds to analyze whether lenders systematically adjust covenant strictness in response to the severity of violations (Beneish and Press [1995]; Bird et al. [2022]). The data allow for tracking how covenant thresholds change across the life of a loan, both in response to firm-specific shocks and broader economic developments. This perspective helps to shed light on how lenders reassess and renegotiate contract terms as borrower conditions evolve and how covenant strictness adapts to changing risk environments. It also allows to observe broader trends over time, such the number of covenants and the strictness of covenant thresholds. A third area for future research relates to the characteristics and market position of the lending banks. Why do otherwise similar borrowers receive different covenant packages, either in the number or strictness of covenants, from different lenders? Investigating whether lender specific attributes such as market power, bank capitalization, lending relationships, or overall bank strategy influence covenant structure could provide valuable insights into the borrower lender bargaining process.

In sum, there is ample scope for future research. How do other loan contract terms adjust (such as fees) following covenant violations, and how do covenant and other contract modifications interact? How do contracts adjust dynamically? The CovenantAI database provides an ideal foundation for exploring these open questions and deepening our understanding of covenant negotiation dynamics and their broader economic implications.

4.2 How do loan market investors respond to covenant violations?

A second promising avenue for future research using CovenantAI is to explore loan trading dynamics around covenant violations. Over the past two decades, there has been a noticeable decrease in covenant violations among leveraged loans (compare Figure 3 above). Despite this trend, each year, about 15% of borrowers with non-investment grade ratings or unrated borrowers still breach their covenants, significantly raising the odds of borrower downgrades or eventual bankruptcy. Regulatory requirements for bank and non-bank institutional investors, including the largest institutional investors such as Collateralized Loan Obligations (CLOs), may compel them to divest from these loans, potentially even before a breach occurs.

Over the past three decades, the market for trading syndicated corporate loans has become more liquid, with a trading volume exceeding USD 820 billion in 2022, allowing institutional investors to trade loans more easily. It is an interesting question, therefore, whether institutional investors strategically offload loans in anticipation of covenant violations and to examine the timing of their sales in relation to these potential breaches.[30]

CovenantAI & investor trading data. CovenantAI provides data on covenant breaches across a broad range of publicly listed U.S. companies and over an extended time-period covering various economic downturns and as well as in-depth details about the nature of these breaches. Are breaches addressed through amendments to loan agreements (either before or after a breach), do borrowers secure waivers, or do they remain in technical default? These variations are vital because they indicate different levels of severity and, consequently, different impacts on companies. As a result and anticipating possible covenant breaches, investors might be motivated to offload these loans.

To get an understanding how institutional investors might trade around covenant violations, we merge CovenantAI with data on daily secondary market trading of corporate loans obtained from LSEG Refinitiv. 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, Wittenberg-Moerman [2008] and Saunders et al. [2024]). Loan information is sourced from LSEG Refinitiv Dealscan via the Loan Information Number (LIN). To ensure that loans are owned by institutional investors, we restrict our sample to loans included in CLO portfolios. We obtain this information from LPC Collateral.

Loan prices before covenant violations. We focus on the 100 days before a covenant

[30] Bushman, Smith, and Wittenberg-Moerman [2010], for example, investigate price discovery in the secondary loan market and argue that covenant violations trigger immediate and extensive communications between borrowers and lenders through which lenders obtain information.

breach and plot daily mid-quotes for loans grouped by violation outcome, (1) Amendment w/o violation, (2) Amendment w/ violation (here we include also waivers) and (3) technical default (Figure 7).[31] We find that prices of loans that are eventually amended before a covenant violation exhibit minimal price fluctuation before the event. A notable decline in loan prices is predominantly attributed to two factors: firms that secure amendments subsequent to a violation (represented on the left y-axis) and loans linked to firms that persist in technical default (shown on the right y-axis). Although the price patterns are strikingly similar in both categories, the overall decrease in prices tends to be more pronounced when investors anticipate difficulties in amending loans that are in violation.

Future research. Figure 7 provides only initial evidence that institutional investors trade before covenant violation occur and it might be that loan prices drop simply because of deteriorating firm fundamentals. More detailed analysis could center on how institutional investors such as CLOs rebalance portfolios around violations of varying violation severity. Researchers can exploit a matched CovenantAI–CLO holdings panel dataset to test whether tighter portfolio-quality tests (e.g., Minimum Weighted Average Rating Factor (WARF), Junior Overcollateralization (OC) triggers) force certain CLO cohorts to act as "forced sellers" even before a default event. And, do unconstrained CLOs act as buyers, possibly attenuating some of the downward pressure on loan prices? More research can shed light on whether regulatory capital rules generate similar pressure for banks. Difference in difference designs that compare trades in loans on either side of covenant thresholds can quantify the causal impact of regulatory frictions on loan market prices and market liquidity.

With borrower–lender contract amendments now observable at high frequency, CovenantAI makes it possible to model the renegotiation game in which lenders choose between waivers, amendments, or accelerating the loan, while investors price these options in secondary trading. Future work can embed these micro findings in structural models to estimate (i) the option value of covenant clauses, (ii) how ex ante covenant tightness trades off against ex post amendment flexibility, or (iii) the welfare consequences for non bank investors who lack formal control rights but can exit the position. Such estimates would speak to ongoing policy discussions on whether the rise of covenant-lite loans has shifted monitoring costs from arrangers to dispersed investors.

[31] In a companion paper (Saunders, Steffen, and Verhoff [2025]) we provide initial evidence as to the implications of covenant violations on institutional investor behavior.

These are some of the underexplored questions in the literature and we look forward to more research in this area.

5 Conclusion

Our paper introduces CovenantAI, an advanced AI-driven methodology that substantially enhances the identification and classification of loan covenant violations using SEC filings. Prior literature primarily relies on either manually adjusted keyword-based methods or Dealscan-based approaches, each with inherent limitations such as inaccuracies, timing discrepancies, and overlooking nuanced renegotiation outcomes. CovenantAI overcomes these shortcomings by leveraging context-aware language models, providing a precise and comprehensive classification of covenant violations and their severity.

Our correlation analyses demonstrate that CovenantAI aligns closely with established manual adjustment methods from prior research, confirming its reliability for empirical studies under some constraints. However, CovenantAI notably outperforms keyword-based and Dealscan approaches, especially in terms of accuracy and consistency at the event-level, highlighting the advantages of employing advanced language models in financial research going forward.

Finally, to clarify how the data can be used, the Online Appendix outlines two brief illustrations. First, we show descriptive "first facts" that enforcement severity (pre-emptive amendment, waiver, amendment after breach, technical default) maps into sharper deleveraging, higher cash accumulation, and tighter financial thresholds (Online Appendix Section D). Second, we sketch loan-price dynamics that differ systematically by severity in the 100 days before violation. These are intentionally illustrative rather than a full empirical treatment, but are promising avenues for future research enabled by this novel dataset. We encourage subsequent research to leverage CovenantAI's granularity to deepen our understanding of creditor-borrower dynamics and their broader financial implications and look forward to researchers using CovenantAI in their projects going forward.

A Appendix

A.1 Variable Definition

Table A1: 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$_t$

A.2 Labeling Disagreement

Table A2: **Examples for Labeling Disagreement**

This table presents examples of paragraphs for which the labeling of CovenantAI and the keyword-based approach, based on Nini, Smith, and Sufi [2012], disagrees. The complete filing link can be constructed using "https://www.sec.gov/Archives/edgar/data/" + Link. Column (3) represents the label assigned by the keyword-based approach, while column (4) contains the label assigned by CovenantAI. Column (5) shows an example paragraph, and column (6) lists the keywords used to determine the label.

(1) **Link**	(2) **Reporting Date**	(3) **Nini**	(4) **CovenantAI**	(5) **Paragraph**	(6) **Keywords**
1060801/000095014903001934/*f92308e10vq.htm*	30.06.2003	0	1	The credit facility was amended on March 25, 2003 and again on July 18, 2003, as a result of non-compliance with the financial covenants of the facility.	
1086939/000095013102001978/*d10q.txt*	31.03.02	1	0	We amended our credit agreement on February 5, 2002 to include additional covenants. We will be in default if our cash expenditures incurred in connection with the Plan (including, without limitation, the costs of structuring and negotiating the divestiture transactions, terminating employees and closing facilities), exceeds by $10 million the sum of EBITDA from the discontinued management services operations plus the cash proceeds from these transactions. As of March 31, 2002, we were in compliance with all our credit agreement covenants [...]	in deafault
701345/000119312504040367/*d10k.htm*	31.12.03	1	0	Effective March 12, 2004, US Airways obtained covenant relief for the measurement periods beginning June 30, 2004 through December 31, 2005. If the Company is unable to meet these financial covenants, as amended, the Company would be in default under the ATSB Loan and the Stabilization Board would have the right to accelerate the ATSB Loan and exercise other remedies against the Company.	in default
912241/000119312505051263/*d10k.htm*	31.12.04	1	0	We maintain a $17.5 million working capital revolving line of credit facility with Foothill Capital Corporation. We have not drawn on this credit facility, but any borrowing will also increase our indebtedness and the related risks we currently face. We may not be in compliance with quarterly financial covenants to be able to borrow under this credit facility should it be deemed necessary.	not in compliance
930735/000110465903005515/$j8935_10k.htm$	21.12.02	1	0	If we fail to comply with these covenants, and if our lenders do not agree to waive the covenants, then we would be in default under our debt agreements. If we are in default under our debt agreements, our lenders can request immediate repayment of all outstanding principal balances. We would not have sufficient liquidity to repay our indebtedness under these circumstances without substantial asset sales, and if we were unable to refinance our borrowings at that time, we would need to seek protection from our creditors	waiv, in default
931948/000103570404000120/*d12924e10vk.htm*	31.12.03	1	0	Events of default in the credit facility include: (1) a cross-default to other indebtedness of the company [...] (5) any breach or modification of any of the sales contracts. The company anticipates it will refinance the credit facility during 2004. The company is in compliance with its debt covenants at December 31, 2003.	modif

(1) **Link**	(2) **Reporting Date**	(3) **Nini**	(4) **CovenantAI**	(5) **Paragraph**	(6) **Keywords**
931948/000103570404000120/*d12924e10vk.htm*	31.12.03	1	0	Events of default in the credit facility include: (1) a cross-default to other indebtedness of the company; (2) any material modification to the life-of-mine plans [...] The company anticipates it will refinance the credit facility during 2004. The company is in compliance with its debt covenants at December 31, 2003.	modif
1132809/0000950148 − 03 − 001269.*txt*	31.03.03	0	1	Under the Agreement, Bam may obtain advances, subject to the finance company discretion and Bams compliance with certain liquidity covenants, in the form of cash or as collateral for letters of credits, up to a maximum of 75% of outstanding domestic receivables at any point in time. At March 31, 2003 Bam did not meet the Agreementś liquidity covenants and had no sums advanced under the Agreement. Bam may not be able to obtain further advances until it is in compliance with the liquidity covenants.	
802492/0000802492 − 98 − 000018.*txt*	31.08.98	1	0	During fiscal years 1998, 1997, and 1996, the Company was either in compliance or had obtained waivers on all covenants related to these and prior related arrangements.	waiv
929994/000089102002001129/*v83521e10vq.htm*	30.06.02	1	0	In May 2002, the Company amended its existing agreement with U.S. Bank, establishing new covenants, with which the Company was in compliance as of June 30, 2002. Failure to comply with these covenants would constitute an event of default, which would allow U.S. Bank to declare any amounts outstanding under the loan documents to be due and payable. Certain of the Company's leases and loan agreements contain covenants and cross-default provisions such that a default on one of those agreements could cause the Company to be in default [...]	in default
1060801/000095014903001934/*f92308e10vq.htm*	30.06.03	0	1	The credit facility was amended on March 25, 2003 and again on July 18, 2003, as a result of non-compliance with the financial covenants of the facility	
1086939/000095013102001978/*d10q.txt*	31.03.02	1	0	We amended our credit agreement on February 5, 2002 to include additional covenants. We will be in default if our cash expenditures incurred in connection with the Plan (including, without limitation, the costs of structuring and negotiating the divestiture transactions, terminating employees and closing facilities), exceeds by $10 million the sum of EBITDA from the discontinued management services operations plus the cash proceeds from these transactions. As of March 31, 2002, we were in compliance with all our credit agreement covenants.	in default

A.3 Identiying Covenants and Covenant Thresholds

We extract metadata from the first section of each exhibit, where critical details such as the type of exhibit and its report date typically appear. Using GPT-4O Mini, we generate the report date and exhibit type for each document through tailored prompts. This initial step creates a structured foundation for subsequent filtering.

To focus only on relevant exhibits, we filter out documents that do not contain information on covenant thresholds, such as purchase or employment agreements. We extract agreement names, count occurrences of the term "credit," and manually review exhibits with low relevance. This process ensures that our dataset retains only those exhibits likely to include financial covenant information.

Next, we retrieve the specific sections most relevant to covenant thresholds. These include sections explicitly referencing financial covenants and tables reporting ratio thresholds while excluding rate-related data. For structured filings, we identify headings related to financial covenants. For unstructured filings, we rely on a keyword-based search to locate relevant paragraphs. Using GPT-4O Mini, we apply tailored prompts depending on the context. For amendment-related filings, we focus on extracting amended ratios, thresholds, and effective dates, while for non-amendment filings, we extract agreed-upon financial covenant thresholds.

We separately process tables containing ratio thresholds, identifying them through keyword filtering for terms associated with financial ratios. For these tables, we extract ratio thresholds, effective dates, and their contextual alignment with the exhibit type, ensuring comprehensive coverage of the data.

In the final step, we consolidate and clean the extracted data to ensure consistency. We standardize ratios for comparability across filings and map effective dates carefully. When effective dates are not explicitly mentioned, we infer the report date of the exhibit as the effective date, relying on contextual cues. This step ensures the data is accurate and ready for subsequent analysis.[32]

[32] The RAG methodology offers significant advantages. By iteratively narrowing the scope of information retrieval and tailoring prompts to specific exhibit types, we achieve high accuracy and relevance. The approach also handles both structured and unstructured filings efficiently, making it scalable and cost-effective. This comprehensive method produces a reliable dataset of covenant thresholds, enabling robust empirical analysis.

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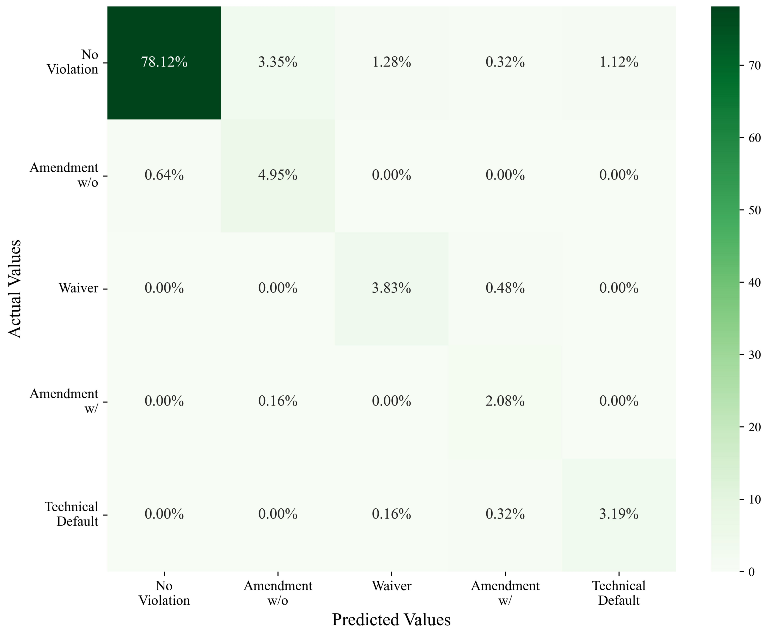
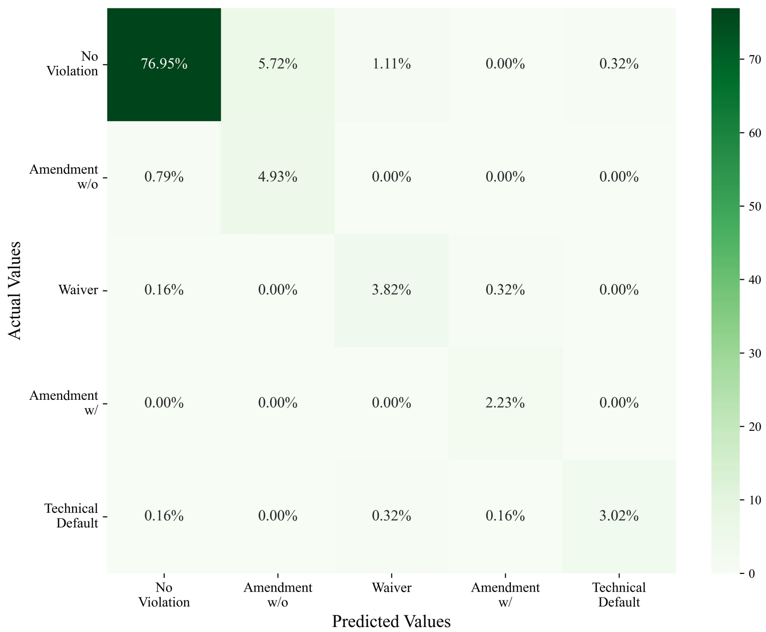
Figures and Tables

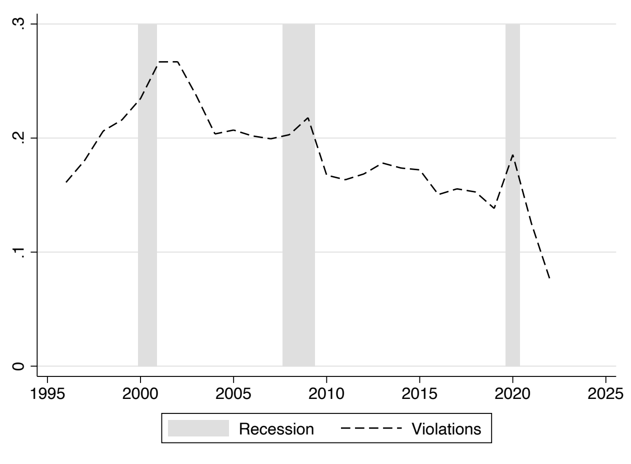


(a) Confusion matrix of the Test Data

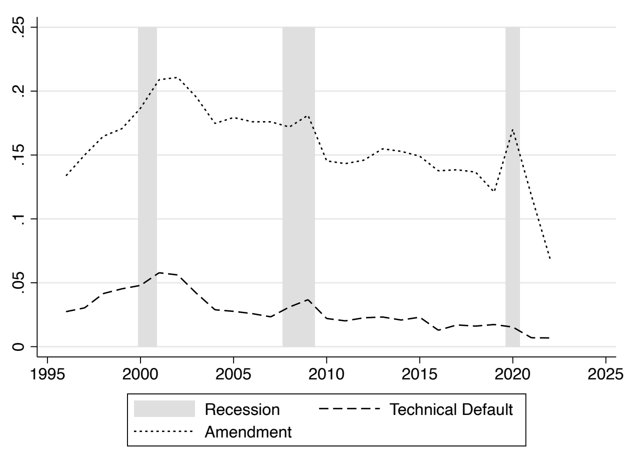


(b) Confusion matrix of the Validation Data

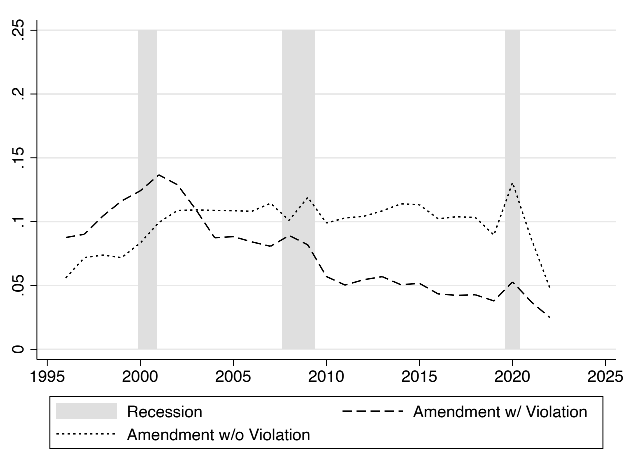
Figure 1: **Confusion Matrix**
This figure plots the accuracy of our machine learning algorithm. The true value is displayed on the vertical axis, and the value predicted by our model is on the horizontal axis. Panel A uses the test data to show model performance and Panel B the validation dataset.



(a) Covenant violations

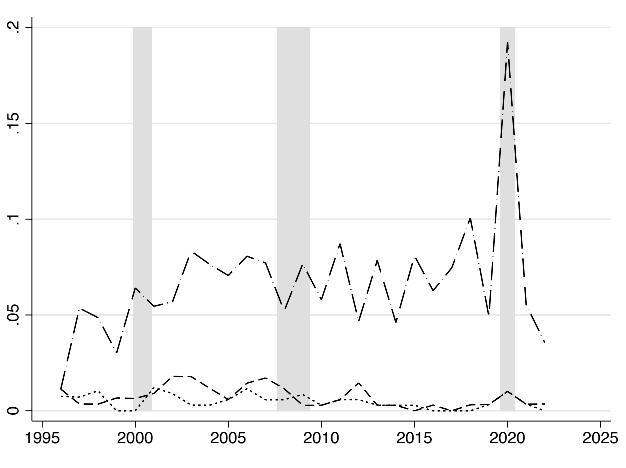


(b) Technical defaults and loan amendments

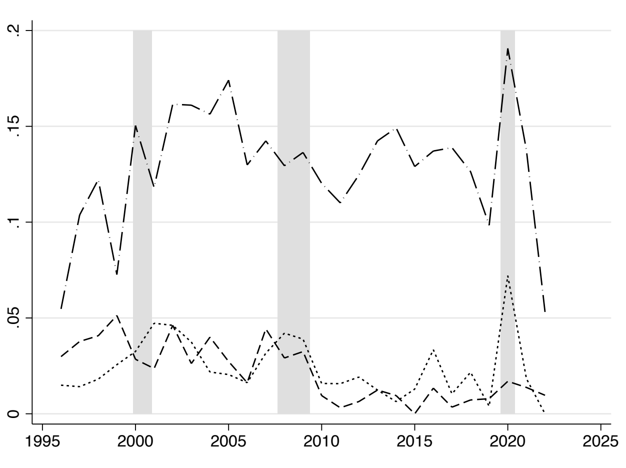


(c) Loan amendments with or without covenant violation

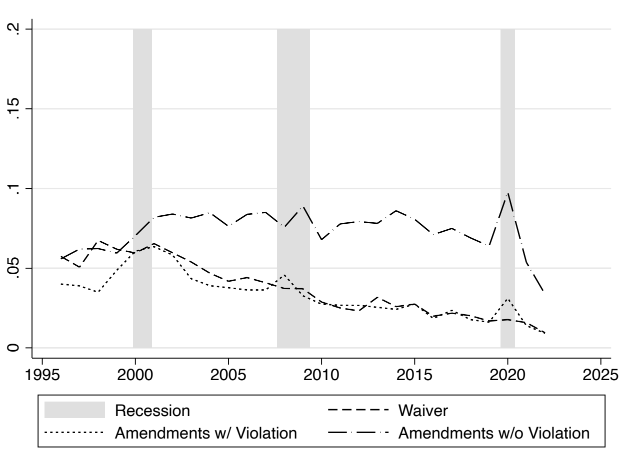
Figure 2: **Time-series of covenant violations**
This figure plots the annual share of technical defaults and loan amendments for the full sample of U.S. publicly listed, non-financial firms. The shaded areas represent the NBER recession periods (Panel A). Panel B plots the combined share of technical defaults and amendments and the proportion of technical defaults and amendments.



(a) IG rated firms

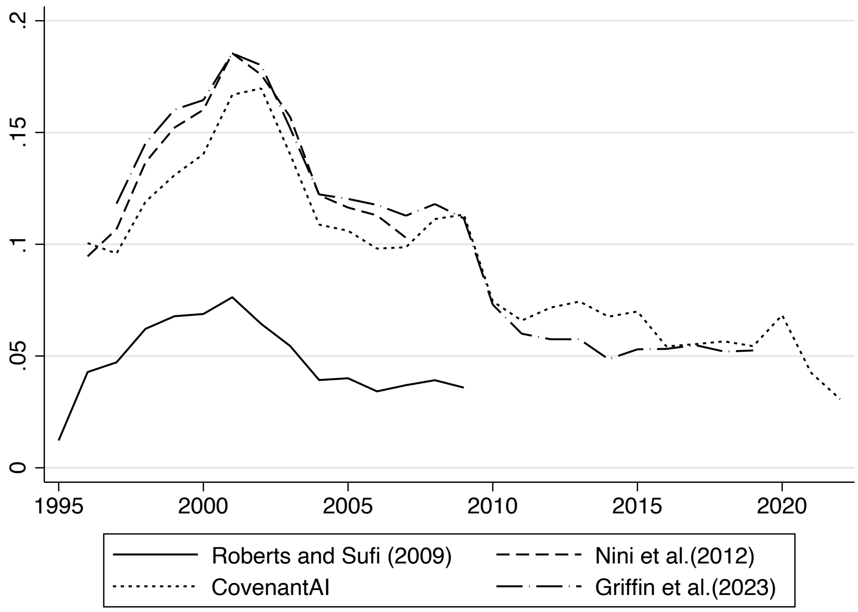


(b) Non-IG rated firms

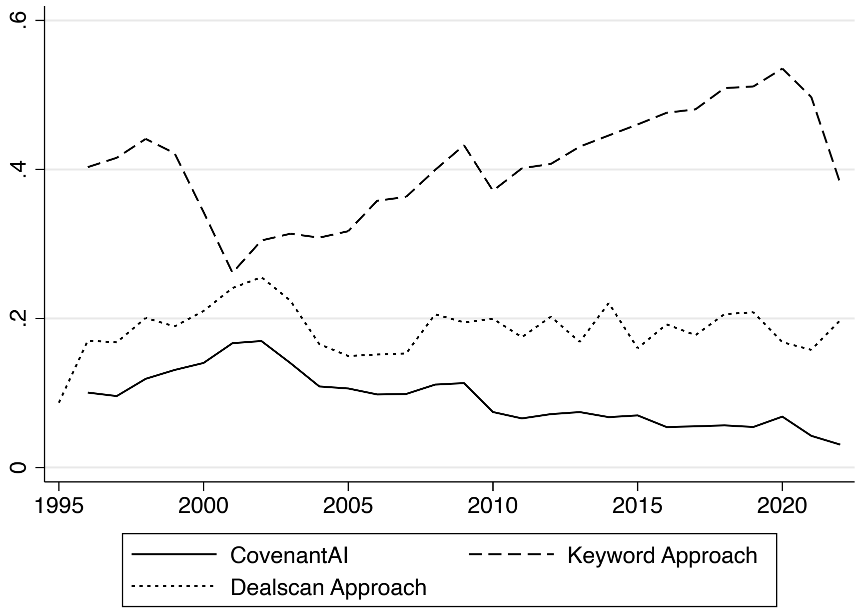


(c) Unrated firms

Figure 3: **Time-series of covenant violation outcomes by credit rating**
This figure plots the time-series of *Amendments w/o Violation*, *Amendments w/ Violation* and *Waiver* over the 1996 to 2022 period for different rating classes, IG, Non-IG and unrated firms.

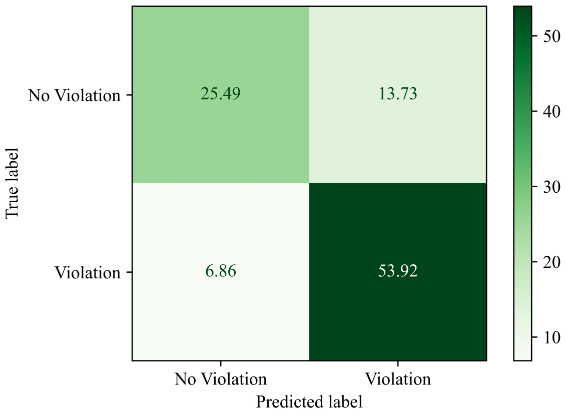


(a) Benchmarking against violations rates in published papers

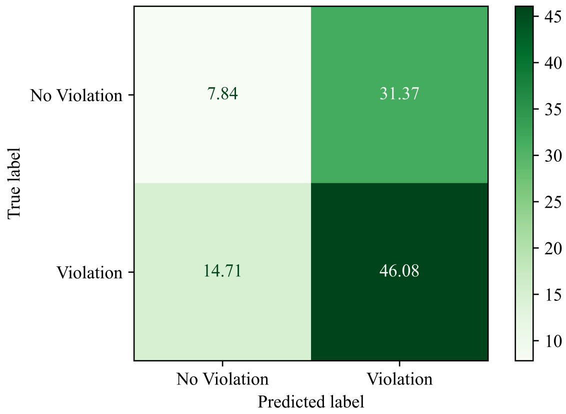


(b) Benchmarking against violation rates in different approaches

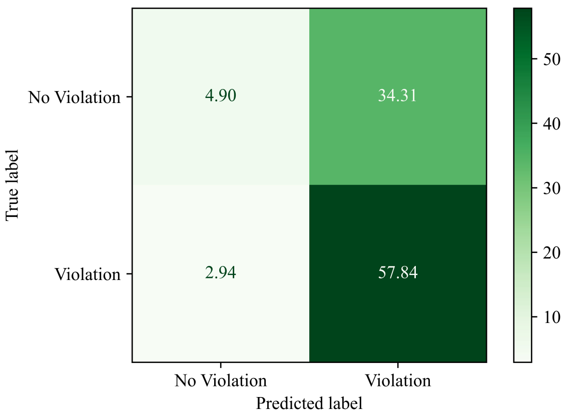
Figure 4: **Comparison of covenant violation rates**
This figure shows covenant violation rates of different approaches used in the literature. The data for the time-series of Roberts and Sufi [2009a] and Griffin, Nini, and Smith [2024] are from Appendix I in Griffin, Nini, and Smith [2024]. The data for Nini, Smith, and Sufi [2012] are from their Appendix. The Keyword Approach data represent the violations labeled by the approach used in Nini, Smith, and Sufi [2012] without manual adjustments. "CovenantAI" are violations obtained from our model.



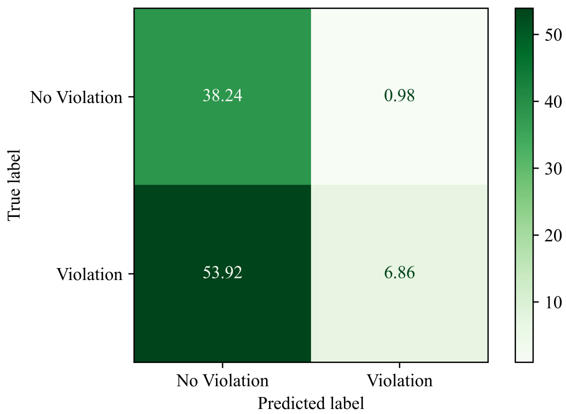
(a) CovenantAI Labeling



(b) Nini et al. (2012) Labeling

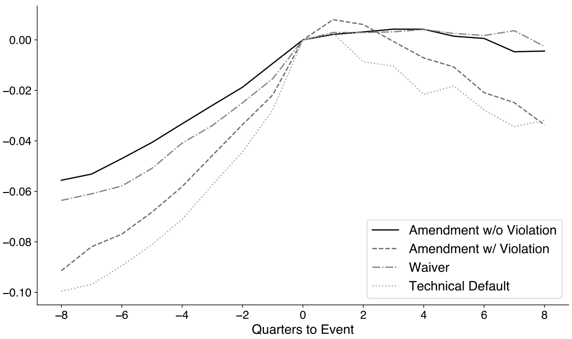


(c) Keyword Approach Labeling

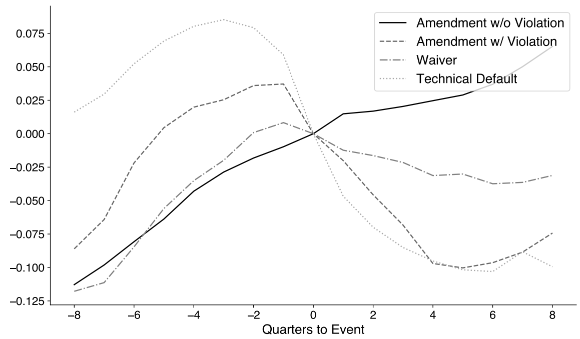


(d) Roberts and Sufi (2009) Labeling

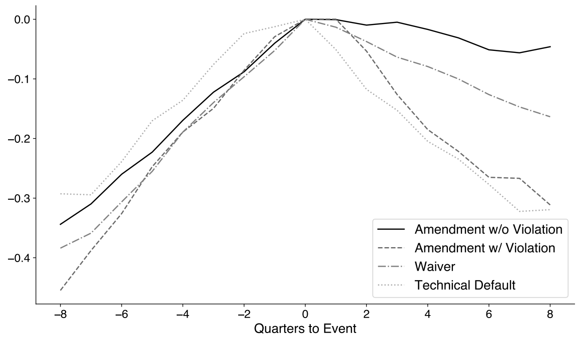
Figure 5: **Confusion matrices of the different approaches.**
This figure plots the confusion matrices of the different approaches for two categories *No Violation* and *Violation*. The true value is displayed on the vertical axis, and the value predicted by the respective model is on the horizontal axis. Panel A shows the performance of CovenantAI, where we created the "Violation" class by adding up *Waiver*, *Amendment w/ Violation* and *Technical Default* cases. Panel B shows the performance of the labeling by Nini, Smith, and Sufi [2012] and Panel C the replication of the approach by Nini, Smith, and Sufi [2012] without manual adjustments. Panel D plots the performance of the Roberts and Sufi [2009a] approach using the Dealscan data. 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.



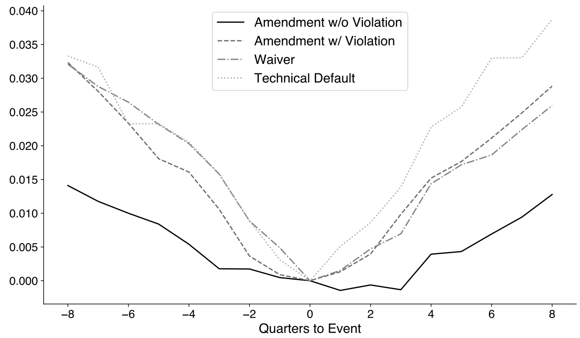
(a) Leverage Ratio



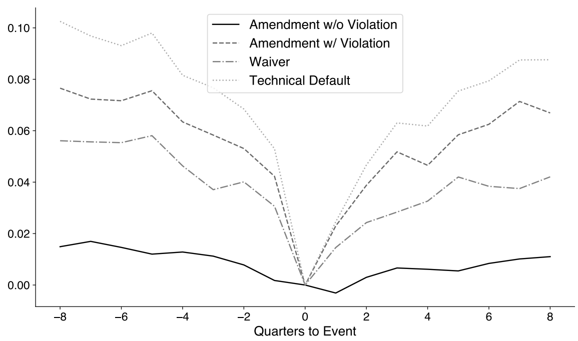
(b) Ln(Assets)



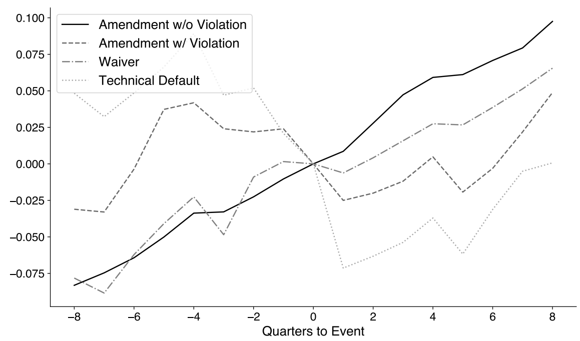
(c) Ln(Debt)



(d) Cash / Assets



(e) Operating Income / Assets



(f) Ln(Sales)

Figure 6: **Firm-specific changes around violations and amendments**
This figure plots the pre and post event performance as a change to the time of the event (t = 0) of the leverage ratio (a), the Ln(Assets) (b), the Ln(Debt) (c), the Cash/Assets (d), the Operating Income/Assets (e) and the Ln(Sales) (f) for the five violation and amendment categories.

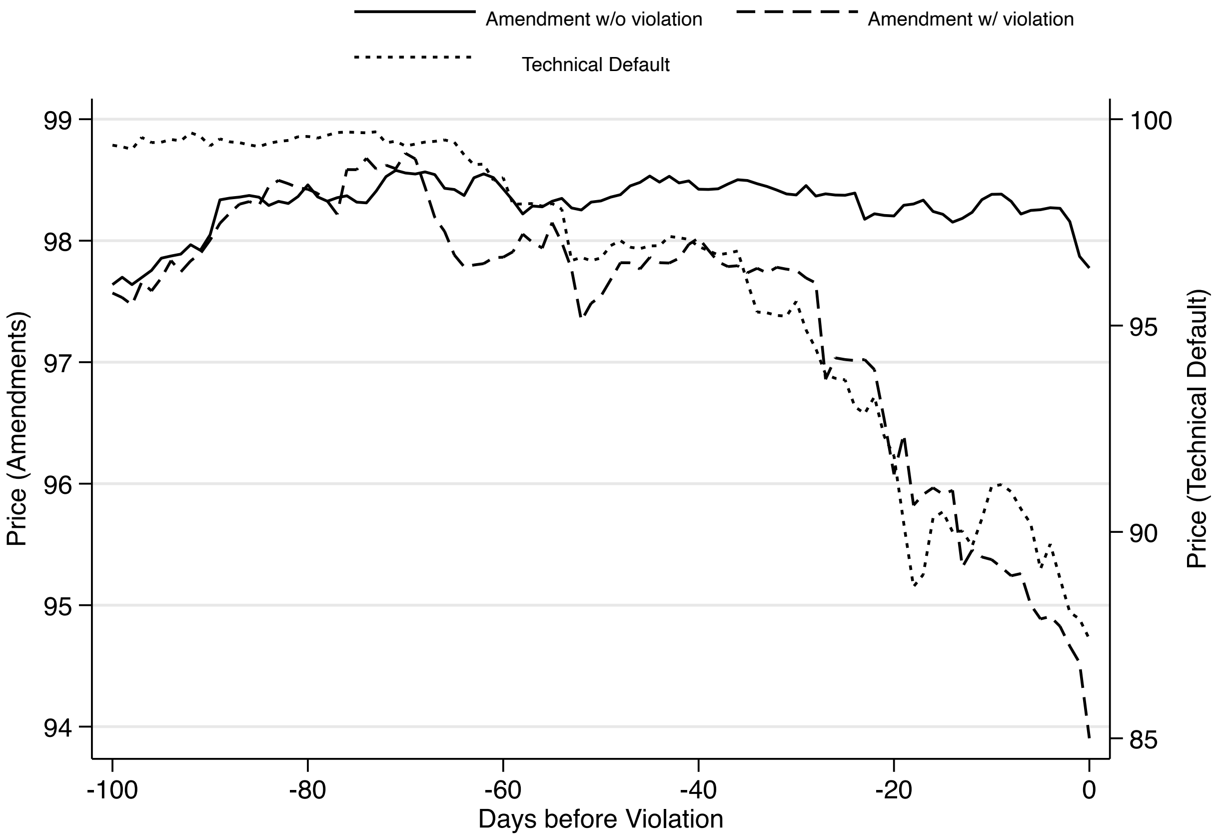


Figure 7: **Prices (mid-quotes) of loans in CLOs (by violation severity)**
This figure plots the prices (mid-quotes) of loans in CLO portfolios before a violation by violation severity (i.e., amendment w/o violation, amendment w/ violation and those that remain in technical default. The *Amendment w/ violation* category includes both amendments that were obtained after a violation and waivers.

Table 1: **Prior Research**

This table shows papers focusing on *loan* covenant violations in top accounting and finance journals.

Authors	**Title**	**Journal**	**Focus**	**Time period**	**Data Source**	**ML/AI**
Smith and Warner [1979]	On Financial Contracting: An Analysis of Bond Covenants	JFE	Production and investment policies; dividends and financing policies	1974-1975	Bond contracts (Commentaries)	No
Beneish and Press [1993]	Costs of Technical Violation of Accounting-Based Debt Covenants	TAR	Refinancing and restructuring costs and performance after covenant violations	1983-1987	10-K	No
Chen and Wei [1993]	Creditors' decisions to waive violations of accounting-based debt covenants	TAR	Creditor's decision: wave or not waive a violation; determinants of waiver decision	1985-1988	10-K	No
DeFond and Jiambalvo [1994]	Debt covenant violation and manipulation of accruals	JAE	Accruals around covenant violations	1985-1988	10-K	No
Sweeney [1994]	Debt covenant violations and managers' accounting responses	JAE	Income-increasing accounting changes prior to covenant violations	1980-1989	10-K	No
Beneish and Press [1995]	The Resolution of Technical Default	TAR	The Resolution of Technical Default	1983-1987	10-K	No
DeAngelo, DeAngelo, and Wruck [2002]	Asset liquidity, debt covenants, and managerial discretion in financial distress: the collapse of L.A. Gear	JFE	Operational and financial flexibility	Case Study	Compustat	No
Dichev and Skinner [2002]	Large–Sample Evidence on the Debt Covenant Hypothesis	JAR	Accounting choices by managers to avoid covenant violations	1989-1999	Dealscan	No
Chava and Roberts [2008]	How Does Financing Impact Investment? The Role of Debt Covenants	JF	Capital investment	1994-2005	Dealscan	No
Nini, Smith, and Sufi [2009]	Creditor Control Rights and Firm Investment Policy	JFE	Capital expenditure (restrictions)	1996-2005	Dealscan; 10-K / 10-Q	No
Roberts and Sufi [2009a]	Control Rights and Capital Structure: An Empirical Investigation	JF	Net debt issuance activities; Contracts after violation; switching of lenders	1996-2005	10-K / 10-Q	No
Sufi [2009]	Bank Lines of Credit in Corporate Finance: An Empirical Analysis	RFS	Access to credit lines	1996-2003	10-K	No
Bushman, Smith, and Wittenberg-Moerman [2010]	Price discovery and dissemination of private information by loan syndicate participants	JAR	Price discovery in debt and equity markets	1996-2005	10-K / 10-Q	No
Nini, Smith, and Sufi [2012]	Creditor Control Rights, Corporate Governance, and Firm Value	RFS	Firm investment policies, financial policies, CEO turnover, operating and stock price performance	1997-2008	10-K / 10-Q	No
Ozelge and Saunders [2012]	The Role of Lending Banks in Forced CEO Turnovers	JMCB	CEO Turnover	1992-2000	10-K / 10-Q	No
Franz, HassabElnaby, and Lobo [2014]	Impact of proximity to debt covenant violation on earnings management	RAS	Accounting earnings management around covenant violations	1992-2007	Dealscan	No

Authors	Title	Journal	Focus	Time period	Data Source	ML/AI
Denis and Wang [2014]	Debt Covenant Renegotiations and Creditor Control Rights	JFE	Impact of violations on CapEx restrictions, Debt/EBITDA restrictions, CapEx and Leverage	1996-2005	10-K / 10-Q	No
Roberts [2015]	The role of dynamic renegotiation and asymmetric information in financial contracting	JFE	Frequency of renegotiations; changes in contract terms (amount, pricing, maturity, covenant structure)	1991-2011	10-K	No
Demerjian and Owens [2016]	Measuring the probability of financial covenant violation in private debt contracts	JAE	Measuring covenant violation probability	1987-2004	Dealscan and Tearsheets	No
Falato and Liang [2016]	Do Creditor Rights Increase Employment Risk? Evidence from Loan Covenants	JF	Employment	1994-2010	Dealscan	No
Chava, Nanda, and Xiao [2017]	Lending to Innovative Firms	RCFS	Innovation	1987-2011	Dealscan	No
Freudenberg et al. [2017]	Covenant Violations and Dynamic Loan Contracting	JCF	Dynamic effect of violations on contract terms and covenant structure	1996-2010	10-K / 10-Q	No
Gu, Mao, and Tian [2017]	Banks' Interventions and Firms' Innovation: Evidence from Debt Covenant Violations	JLE	Innovation	1996-2008	10-K / 10-Q	No
Balsam, Gu, and Mao [2018]	Creditor Influence and CEO Compensation: Evidence from Debt Covenant Violations	TAR	CEO compensation and risk-taking incentives	1997-2008	10-K / 10-Q	No
Ferreira, Ferreira, and Mariano [2018]	Creditor Control Rights and Board Independence	JF	Firms appoint outside directors after covenant violations	1994-2008	Dealscan	No
Chava, Wang, and Zou [2019]	Covenants, Creditors' Simultaneous Equity Holdings, and Firm Investment Policies	JFQA	Dual holdings and firms' investment policies	1996-2010	10-K / 10-Q	No
Cohen et al. [2019]	Do Debt Covenants Constrain Borrowings Prior to Violation? Evidence from SFAS 160	TAR	Covenants constrain leverage for borrowers close to violation	2007-2009	Dealscan	No
Shan, Tang, and Winton [2019]	Do banks still monitor when there is a market for credit protection?	JAE	Strictness of covenants after trading in the CDS market	2002-2011	Dealscan	No
Acharya et al. [2020]	Bank lines of credit as contingent liquidity: Covenant violations and their implications	JFI	Credit line contract terms	2002-2011	10-K	No
Ersahin, Irani, and Le [2021]	Creditor control rights and resource allocation within firms	JFE	Creditor control rights influence resource allocation	1996-2009	10-K / 10-Q	No
Becher, Griffin, and Nini [2021]	Creditor Control of Corporate Acquisitions	RFS	Covenant violations and lender bargaining power	1997-2015	10-K / 10-Q	No
Bird et al. [2022]	Lender Forbearance	JFQA	Determinants of violation; Contract enforcement (fees and renegotiations)	1996-2008	10-K / 10-Q	No
Bordeman and Demerjian [2022]	Do borrowers intentionally avoid covenant violations? A reexamination of the debt covenant hypothesis	JAR	Accounting choices by managers to avoid covenant violations	2000-2019	Dealscan	No
Bourveau, Stice, and Wang [2022]	Strategic disclosure and debt covenant violation	JMAR	Managment forecasts around covenant violations	1996-2009	10-K / 10-Q	No

Authors	Title	Journal	Focus	Time period	Data Source	ML/AI
Chodorow-Reich and Falato [2022]	The Loan Covenant Channel: How Bank Health Transmits to the Real Economy	JF	Credit reduction upon covenant violation; real effects	2006-2011	Shared National Credit (SNC) program	No
Haque and Kleymenova [2023]	Private Equity and Debt Contract Enforcement: Evidence from Covenant Violations	WP	Access to credit for PE vs non-PE owned firms	2012-2021	Shared National Credit (SNC) program	No
Zhu [2024]	Treatment of Accounting Changes and Covenant Violation Errors	JAR	False positives and false negatives in identifying covenant violations	1994-2017	10-K	No
Griffin, Nini, and Smith [2024]	Losing Control? The Two-Decade Decline in Loan Covenant Violations	JF	Ex-ante covenant design	1997-2019	10-K	No
Dyreng et al. [2025]	Measurement Error when Estimating Covenant Violations	TAR	Measurement error when calculating slack using commerical data bases	2000-2016	10-K / 10-Q	No
Teoh [2025]	Anticipating binding constraints: An analysis of debt covenants	JFI	Anticipation can affect severity of covenant violations	2002-2016	10-K / 10-Q	No
Saunders, Steffen, and Verhoff [2025]	Do Institutional Investors Trade on Covenant Violations?	WP	Trading behavior around covenant violation and severity	1996-2022	10-K / 10-Q	Yes (CovenantAI)

Table 2: **Correlation Matrix Different Approaches**

This table shows the correlation in violation rates of the different approaches. Panel A compares the yearly violation rates of the four different approaches. Panel B shows the correlations based on firm quarter observations. It does not include the Griffin, Nini, and Smith [2024], because we do not have the violation on the firm quarters available.

Panel A: Correlation Matrix Yearly Violation Rates

	Roberts and Sufi [2009a]	Nini, Smith, and Sufi [2012]	Griffin, Nini, and Smith [2024]	Keyword	Dealscan	CovenantAI
Roberts and Sufi [2009a]	1.0000					
Nini, Smith, and Sufi [2012]	0.8322	1.0000				
Griffin, Nini, and Smith [2024]	0.9161	1.0000	1.0000			
Keyword	-0.1861	-0.4825	-0.8550	1.0000		
Dealscan	0.6593	0.8951	0.2908	-0.1240	1.0000	
CovenantAI	0.8956	0.9510	0.9395	-0.7921	0.2588	1.0000

Panel B: Correlation Matrix Firm Quarter Observations

	Roberts and Sufi [2009a]	Nini, Smith, and Sufi [2012]	Keyword	Dealscan	CovenantAI
Roberts and Sufi [2009a]	1.0000				
Nini, Smith, and Sufi [2012]	0.4743	1.0000			
Keyword	0.2239	0.4790	1.0000		
Dealscan	0.1446	0.2476	0.1528	1.0000	
CovenantAI	0.4548	0.7225	0.3455	0.2092	1.0000

Table 3: **Summary Statistics**

This table provides summary statistics of important firm characteristics. All absolute values are given in USD millions. All variables are defined in the Appendix (Table A1) Pane A shows the summary statistics for the period from 1996-2007 based on Nini, Smith, and Sufi [2012] and Panel B shows the summary statistic for the full sample from 1996-2022. All variables are winsorized at the 1% and 99% levels.

Panel A: Summary Statistics 1996-2007

	Mean	p25	Median	p75	SD
Violation	0.38	0.00	0.00	1.00	0.48
Control Variables					
Operating Income/ Assets	0.01	-0.04	0.09	0.15	0.26
Leverage Ratio	0.25	0.06	0.20	0.37	0.23
Interest Expenses/ Assets	0.03	0.01	0.02	0.04	0.03
NWA/ Assets	0.47	0.32	0.50	0.69	0.31
Current Ratio	3.25	1.39	2.21	3.70	3.34
MTB	2.40	1.22	1.70	2.76	2.04
Dependent Variables					
Ln(Assets)	5.00	3.66	4.78	6.14	1.82
CapEx/ Assets	0.07	0.02	0.04	0.08	0.09
CashAcqui/ Assets	0.03	0.00	0.01	0.04	0.08
Ln(Debt)	2.92	1.05	2.86	4.89	2.68
Cash/ Assets	0.22	0.04	0.11	0.33	0.24
Ln(Payout)	0.54	0.00	0.06	0.51	1.06
Ln(Sales)	3.35	2.01	3.33	4.74	2.13
Ln(Costs)	3.38	2.08	3.21	4.58	1.88
Observations	8,826				

Panel B: Summary Statistics 1996-2022

	Mean	p25	Median	p75	SD
Violation	0.37	0.00	0.00	1.00	0.48
Control Variables					
Operating Income/ Assets	-0.04	-0.12	0.07	0.13	0.29
Leverage Ratio	0.25	0.07	0.21	0.38	0.23
Interest Expenses/ Assets	0.03	0.01	0.02	0.03	0.03
NWA/ Assets	0.46	0.30	0.49	0.68	0.32
Current Ratio	3.64	1.42	2.31	4.14	3.93
MTB	2.43	1.24	1.74	2.83	1.98
Dependent Variables					
Ln(Assets)	5.28	3.83	5.10	6.53	1.89
CapEx/ Assets	0.06	0.02	0.04	0.07	0.08
CashAcqui/ Assets	0.03	0.00	0.01	0.04	0.06
Ln(Debt)	3.26	1.32	3.16	5.26	2.69
Cash/ Assets	0.25	0.04	0.14	0.39	0.26
Ln(Payout)	0.63	0.00	0.08	0.68	1.16
Ln(Sales)	3.45	2.00	3.50	4.97	2.26
Ln(Costs)	3.50	2.13	3.35	4.75	1.93
Observations	11,851				

Table 4: **Firm Adjustments to Covenant Violations (Nini Data vs. CovenantAI Database)**

This table relates covenant violations to financial and real adjustments of firms and the access to credit. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2007. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A shows the effect of covenant violations to firm adjustments over a period of four quarters $(t+4)$ after a covenant violation using the violation data from Nini, Smith, and Sufi [2012]. Panel B shows the regression results for the same variables using covenant data identified by CovenantAI. The lower row compares the coefficient of both approaches. Ln(Δ Assets) is the natural logarithm of the change in total assets (column 1), $\Delta\frac{CapEx}{Assets}$ is the change in capital expenditures over assets (column 2), $\Delta\frac{CashAcq}{Assets}$ is the change in cash acquisitions over assets (column 3), $Ln(\Delta Debt)$ is the natural logarithm of the change in total debt (column 4), $\Delta\frac{Cash}{Assets}$ is the change of cash over average assets (column 5), $\Delta Ln(Payout)$ the change in the natural logarithm of shareholder payouts (column 6), $Ln(\Delta Sales)$ is the natural logarithm of the change in sales (column 7) and $Ln(\Delta Cost)$ is the natural logarithm of operating costs (column 8). 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. $\Delta Employment$ and $\Delta\frac{EBIT}{Assets}$ are only available annually; 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: Nini Database

	(1) Δ Ln(Assets)	(2) $\Delta\frac{CapEx}{Assets}$	(3) $\Delta\frac{CashAcq}{Asset}$	(4) Δ Ln(Debt)	(5) $\Delta\frac{Cash}{Asset}$	(6) Δ Ln(Payout)	(7) Δ Ln(Sales)	(8) Δ Ln(Cost)
Violation	-0.027***	-0.003***	-0.002*	-0.078***	0.002	-0.022**	-0.044***	-0.045***
	(-4.583)	(-3.247)	(-1.979)	(-6.018)	(1.036)	(-2.202)	(-5.939)	(-5.362)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.176	0.029	0.015	0.095	0.065	0.023	0.079	0.102
N	97,753	94,552	92,033	81,996	97,720	82,113	95,531	94,427
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: CovenantAI

	(1) Δ Ln(Assets)	(2) $\Delta\frac{CapEx}{Assets}$	(3) $\Delta\frac{CashAcq}{Asset}$	(4) Δ Ln(Debt)	(5) $\Delta\frac{Cash}{Asset}$	(6) Δ Ln(Payout)	(7) Δ Ln(Sales)	(8) Δ Ln(Cost)
Violation	-0.036***	-0.004***	-0.002**	-0.090***	0.003	-0.002	-0.047***	-0.047***
	(-5.653)	(-5.136)	(-2.273)	(-5.215)	(1.485)	(-0.168)	(-5.665)	(-5.106)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.179	0.029	0.015	0.095	0.065	0.023	0.080	0.104
N	92,766	90,091	87,675	77,533	92,733	78,235	90,667	89,558
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	($\checkmark$)	($\checkmark$)	$\checkmark$	($\checkmark$)	$\checkmark$	$\times$	$\checkmark$	$\checkmark$

Table 5: **Firm Adjustments to Covenant Violations (Nini Data vs. Keyword Based Approach)**

This table relates covenant violations to financial and real adjustments of firms and the access to credit. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2007. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A shows the effect of covenant violations to firm adjustments over a period of four quarters $(t+4)$ after a covenant violation using the violation data from Nini, Smith, and Sufi [2012]. Panel B shows the regression results for the same variables using the keyword based approach used in Nini, Smith, and Sufi [2012] without manual adjustments. The lower row compares the coefficient of both approaches. We use the same dependend variables and the same specifications as in Table 4. Standard errors are reported in parentheses (* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Panel A: Nini Database

	(1) Δ Ln(Assets)	(2) $\Delta \frac{CapEx}{Assets}$	(3) $\Delta \frac{CashAcq}{Asset}$	(4) Δ Ln(Debt)	(5) $\Delta \frac{Cash}{Asset}$	(6) Δ Ln(Payout)	(7) Δ Ln(Sales)	(8) Δ Ln(Cost)
Violation	-0.027***	-0.003***	-0.002*	-0.078***	0.002	-0.022**	-0.044***	-0.045***
	(-4.583)	(-3.247)	(-1.979)	(-6.018)	(1.036)	(-2.202)	(-5.939)	(-5.362)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.176	0.029	0.015	0.095	0.065	0.023	0.079	0.102
N	97,753	94,552	92,033	81,996	97,720	82,113	95,531	94,427
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Keyword Based Approach

	(1) Δ Ln(Assets)	(2) $\Delta \frac{CapEx}{Assets}$	(3) $\Delta \frac{CashAcq}{Asset}$	(4) Δ Ln(Debt)	(5) $\Delta \frac{Cash}{Asset}$	(6) Δ Ln(Payout)	(7) Δ Ln(Sales)	(8) Δ Ln(Cost)
Violation	-0.009**	-0.001**	-0.002***	-0.019	0.000	0.004	-0.011**	-0.007
	(-2.487)	(-2.659)	(-3.003)	(-1.608)	(0.100)	(0.307)	(-2.104)	(-1.473)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.176	0.029	0.015	0.094	0.065	0.023	0.078	0.102
N	97,753	94,552	92,033	81,996	97,720	82,113	95,531	94,427
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(✓)	(✓)	✓	×	✓	×	×	×

Table 6: **Firm Adjustments to Covenant Violations (Keyword Based Approach vs. CovenantAI)**

This table relates covenant violations to financial and real adjustments of firms and the access to credit. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2022. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A shows the effect of covenant violations to firm adjustments over a period of four quarters $(t+4)$ after a covenant violation using covenant data identified by CovenantAI. Panel B shows the regression results for the same variables using the keyword based approach used in Nini, Smith, and Sufi [2012] without manual adjustments and Panel C presents the regression results identifying covenant violations using the Dealscan data following the approach of Chava and Roberts [2008]. The last row compares the coefficient of both approaches. We use the same dependend variables and the same specifications as in Table 4. Standard errors are reported in parentheses (* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Panel A: CovenantAI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Ln(Assets)	$\Delta \frac{CapEx}{Assets}$	$\Delta \frac{CashAcq}{Asset}$	Δ Ln(Debt)	$\Delta \frac{Cash}{Asset}$	Δ Ln(Payout)	Δ Ln(Sales)	Δ Ln(Cost)
Violation	-0.054***	-0.006***	0.002	-0.104***	0.003*	-0.014	-0.064***	-0.060***
	(-8.767)	(-3.096)	(0.772)	(-6.483)	(1.876)	(-1.273)	(-7.387)	(-6.670)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.134	0.011	0.011	0.069	0.071	0.028	0.059	0.089
N	219,341	215,750	207,914	183,575	219,267	193,302	209,274	214,953
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Keyword Based Approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Ln(Assets)	$\Delta \frac{CapEx}{Assets}$	$\Delta \frac{CashAcq}{Asset}$	Δ Ln(Debt)	$\Delta \frac{Cash}{Asset}$	Δ Ln(Payout)	Δ Ln(Sales)	Δ Ln(Cost)
Violation	-0.006**	-0.002*	-0.005**	-0.006	-0.001	-0.008	-0.005	-0.005
	(-2.167)	(-1.931)	(-2.560)	(-0.833)	(-1.528)	(-0.744)	(-1.330)	(-1.367)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.140	0.011	0.013	0.068	0.068	0.030	0.061	0.095
N	206,946	203,614	196,051	174,550	206,899	182,754	199,009	202,928
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(✓)	(✓)	×	×	×	×	×	×

Panel C: Dealscan Data on Firm Level

	(1) Δ Ln(Assets)	(2) $\Delta \frac{CapEx}{Assets}$	(3) $\Delta \frac{CashAcq}{Asset}$	(4) Δ Ln(Debt)	(5) $\Delta \frac{Cash}{Asset}$	(6) Δ Ln(Payout)	(7) Δ Ln(Sales)	(8) Δ Ln(Cost)
Violation	-0.004	-0.006*	-0.005	-0.013	0.002	-0.104***	-0.006	0.011
	(-0.514)	(-1.747)	(-0.768)	(-1.086)	(1.385)	(-5.233)	(-0.558)	(1.118)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.245	0.026	0.033	0.103	0.065	0.045	0.134	0.211
N	34,258	33,754	32,660	31,597	34,250	30,512	34,172	33,322
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Benchmarking to CovenantAI	$\times$	($\checkmark$)	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$

Table 7: **Summary Statistics**

This table shows the distribution of the different violation outcomes (Panel A). The summary statistics of the covenants in our sample (Panel B) and definition of key financial covenants mentioned in SEC filings (Panel C). The definitions of covenant ratios are based on those provided in the Dealscan dataset. Covenant information is collected at the firm-quarter level and then aggregated to the firm level.

Panel A: Distribution of Violation Outcomes

	Mean	p25	Median	p75	SD
Amendment w/o Violation	0.36	0.00	0.00	1.00	0.48
Waiver	0.23	0.00	0.00	0.00	0.42
Amendment w/ Violation	0.21	0.00	0.00	0.00	0.41
Technical Default	0.17	0.00	0.00	0.00	0.38
Observations	11,851				

Panel B: Summary Statistics

	Mean	p25	Median	p75	SD	Observations	% Contracts
Current Ratio	1.21	1.00	1.00	1.30	0.40	254	8.34
Debt to Cashflow Ratio	3.29	2.50	3.14	4.00	1.20	348	11.42
Debt Service Coverage Ratio	1.55	1.20	1.25	1.50	0.75	254	8.34
Fixed Charge Coverage Ratio	1.40	1.10	1.25	1.50	0.54	1,353	44.42
Interest Coverage Ratio	2.83	2.32	3.00	3.11	0.80	1,279	41.99
Leverage Ratio	3.23	2.50	3.25	4.00	1.33	2,208	72.49
Quick Ratio	1.35	1.00	1.25	1.50	0.52	135	4.43

Panel C: Covenant Definitions

Covenant	Definition
Current Ratio	Current Assets / Current Liabilities
Debt to Cashflow Ratio	Outstanding Debt / (Net Income + Depreciation + Non-Cash Charges)
Debt Service Coverage Ratio	EBITDA / (Interest Expense + Amount of Principal Repayments)
Fixed Charge Coverage Ratio	EBITDA / (Interest Charges Paid + Long-term Lease Payments)
Interest Coverage Ratio	EBITDA / Interest Expense
Leverage Ratio	Total Debt / Capitalization or Equity
Quick Ratio	(Cash + Accounts Receivable + Marketable Securities) / Current Liabilities

Table 8: **Covenants Pre and Post Event**

This table shows the pre and post means for each violation outcome *Waiver*, *Technical Default*, *Amendment w/o Violation* and *Amendment w/ Violation* and the differences in pre- and post means. Panel A shows the likelihood of including the covenant and Panel B displays the comparison in covenant thresholds before and after the event (* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Panel A: Likelihood of including Covenants

	Waiver			**Technical Default**		
	Pre Event Mean	**Post Event** Mean	T-Test Difference	**Pre Event** Mean	**Post Event** Mean	T-Test Difference
Current Ratio	0.19	0.17	-0.02**	0.14	0.11	-0.03***
Debt to Cashflow Ratio	0.15	0.16	0.02**	0.14	0.14	-0.00
Debt Service Coverage Ratio	0.14	0.14	0.00	0.14	0.15	0.01
Fixed Charge Coverage Ratio	0.43	0.46	0.03***	0.48	0.49	0.00
Interest Coverage Ratio	0.31	0.31	-0.00	0.33	0.32	-0.02
Leverage Ratio	0.55	0.55	0.00	0.58	0.58	-0.00
Quick Ratio	0.07	0.08	0.01	0.04	0.06	0.01**
Number of Covenants	1.00	1.00	0.00	1.00	1.00	0.00
	Amendment w/o Violation			**Amendment w/ Violation**		
	Pre Event Mean	**Post Event** Mean	T-Test Difference	**Pre Event** Mean	**Post Event** Mean	T-Test Difference
Current Ratio	0.10	0.09	-0.00	0.14	0.13	-0.02***
Debt to Cashflow Ratio	0.11	0.12	0.01***	0.13	0.13	0.01
Debt Service Coverage Ratio	0.07	0.08	0.01***	0.12	0.11	-0.01
Fixed Charge Coverage Ratio	0.46	0.47	0.01**	0.49	0.52	0.02**
Interest Coverage Ratio	0.43	0.43	0.00	0.29	0.30	0.01
Leverage Ratio	0.69	0.70	0.01*	0.58	0.62	0.05***
Quick Ratio	0.05	0.04	-0.00	0.08	0.08	0.01
Number of Covenants	1.00	1.00	0.00	1.00	1.00	0.00

Panel B: Covenant Thresholds

	Waiver			**Technical Default**		
	Pre Event Mean	**Post Event** Mean	T-Test Difference	**Pre Event** Mean	**Post Event** Mean	T-Test Difference
Current Ratio	1.22	1.19	-0.03	1.27	1.40	0.13***
Debt to Cashflow Ratio	3.30	3.22	-0.08	3.63	3.33	-0.30***
Debt Service Coverage Ratio	1.61	1.55	-0.06	1.38	1.30	-0.07***
Fixed Charge Coverage Ratio	1.37	1.35	-0.02	1.35	1.33	-0.02
Interest Coverage Ratio	2.81	2.63	-0.18***	2.85	2.76	-0.09*
Leverage Ratio	3.00	2.93	-0.07*	3.27	3.21	-0.06
Quick Ratio	1.18	1.21	0.04	1.18	1.26	0.07**
Number of Covenants	1.89	1.93	0.04**	1.92	1.88	-0.04**
	Amendment w/o Violation			**Amendment w/ Violation**		
	Pre Event Mean	**Post Event** Mean	T-Test Difference	**Pre Event** Mean	**Post Event** Mean	T-Test Difference
Current Ratio	1.22	1.23	0.01	1.29	1.29	0.00
Debt to Cashflow Ratio	3.17	3.25	0.07**	3.12	3.26	0.15**
Debt Service Coverage Ratio	1.92	1.82	-0.10**	1.64	1.53	-0.11***
Fixed Charge Coverage Ratio	1.42	1.40	-0.01	1.32	1.33	0.01
Interest Coverage Ratio	2.84	2.80	-0.04***	2.76	2.70	-0.06*
Leverage Ratio	3.22	3.26	0.03*	3.26	3.28	0.02
Quick Ratio	1.33	1.37	0.04	1.25	1.23	-0.03
Number of Covenants	1.93	1.98	0.04***	1.86	1.94	0.08***