

CovenantAI - New Insights into Covenant Violations

July 16, 2025

Online Appendix

Contents

A Data	3
Mapping of SIC Code to Industry classification	3
Mapping of Rating Symbol to Rating Number	4
B Covenant Violation Classification	8
Covenant Violation and Amendment Classification	8
Examples for Amendment Sub-Categories	14
C CovenantAI	16
MPNET Sentence Transformer Model	16
Comparison with the Nini et al. Algorithm	18
Comparison with the prediction of Chatgpt	19
D Additional Analyses	20
References	27

A Data

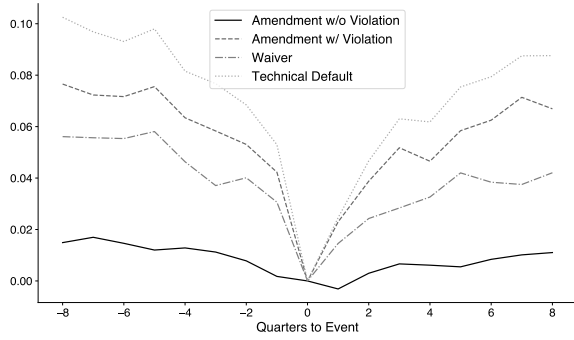
Mapping of SIC Code to Industry classification

SIC range	Industry classification ¹
0000-0999	Agriculture, Forestry, And Fishing
1000-1499	Mining
1500-1799	Construction
2000-3999	Manufacturing
4000-4999	Transportation, Communications, Electric, Gas, And Sanitary Services
5000-5199	Wholesale Trade
5200-5999	Retail Trade
6000-6799	Finance, Insurance, And Real Estate
7000-8999	Services
9100-9999	Public Administration

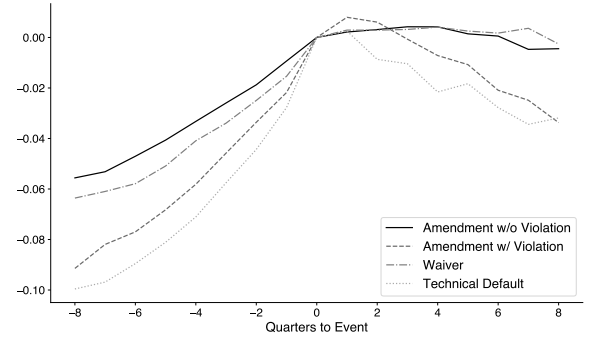
Mapping of S&P Rating Symbol to Rating Number

Rating Symbol	Rating Number
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC+	20
CC	21
CC-	22
C+	23
C	24
C-	25
SD	26
D	27

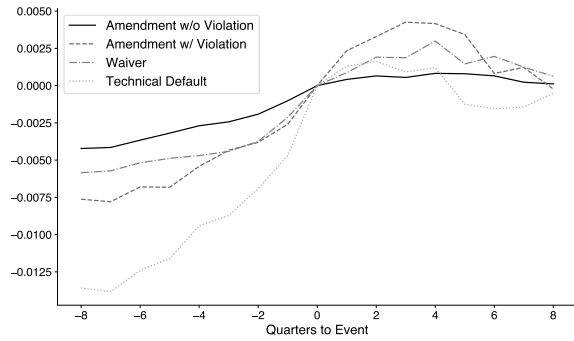
Control Variables and Dependent Variables in the Quarters before and after the Violation



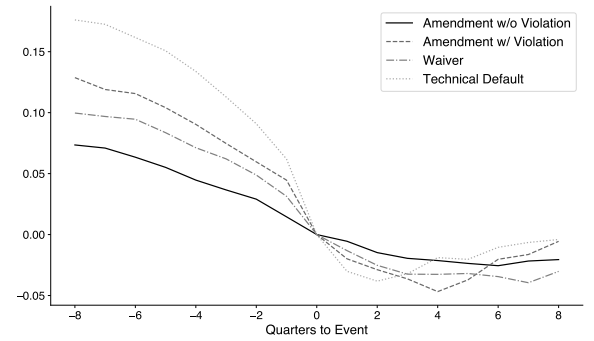
(a) Operating Income / Assets



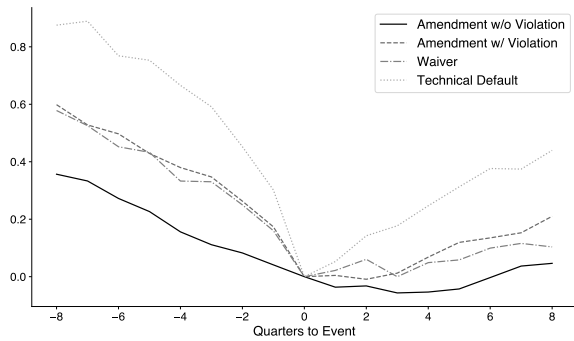
(b) Leverage Ratio



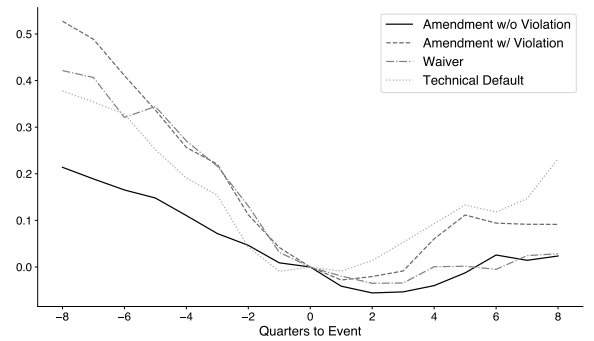
(c) Interest Expenses / Assets



(d) NWA / Assets



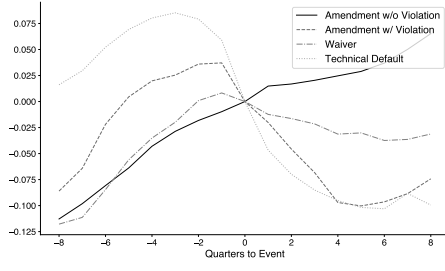
(e) Current Ratio



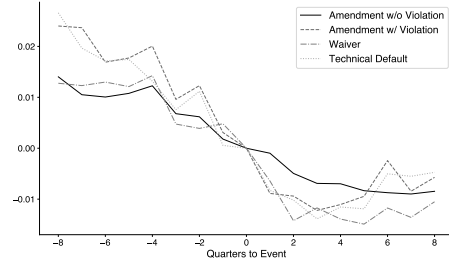
(f) MTB

Figure 1: Control Variables before/ after the Violation

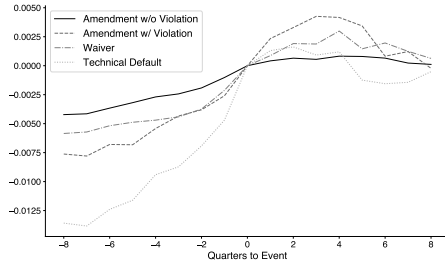
This figure plots the pre and post event performance as a change to the time of the event ($t = 0$) of the six covenant control variables (a) Operating Income/ Assets, (b) Leverage Ratio, (c) Interest Expenses / Assets, (d) NWA / Assets, (e) Current Ratio and (f) Market to Book Ratio for the four violation and amendment categories. The violations are identified by CovenantAI and use the time period 1996-2022



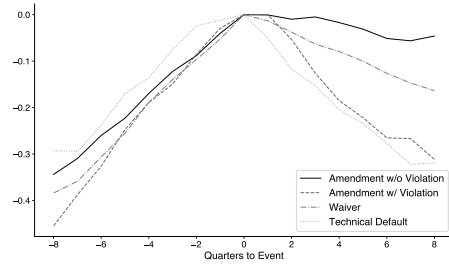
(a) $\text{Ln}(\text{Assets})$



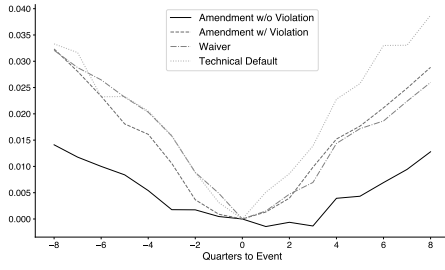
(b) $\text{CapEx} / \text{Assets}$



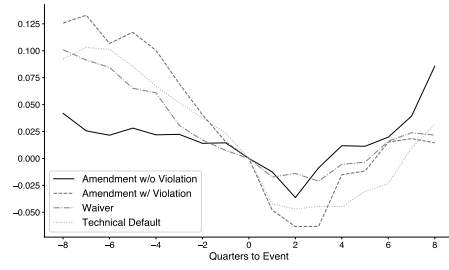
(c) $\text{CashAcqui} / \text{Assets}$



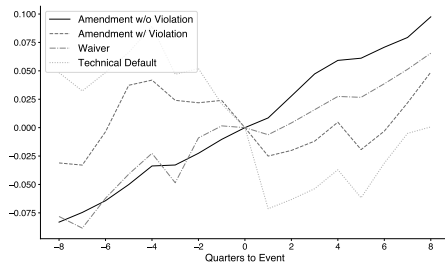
(d) $\text{Ln}(\text{Debt})$



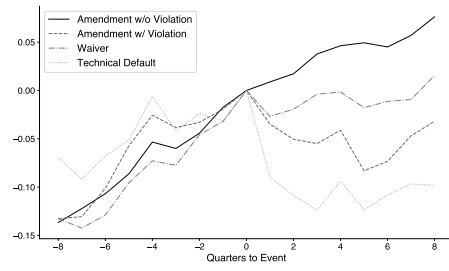
(e) $\text{Cash} / \text{Assets}$



(f) $\text{Ln}(\text{Payout})$



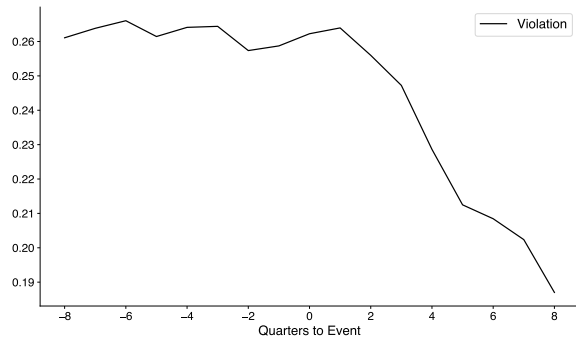
(g) $\text{Ln}(\text{Sales})$



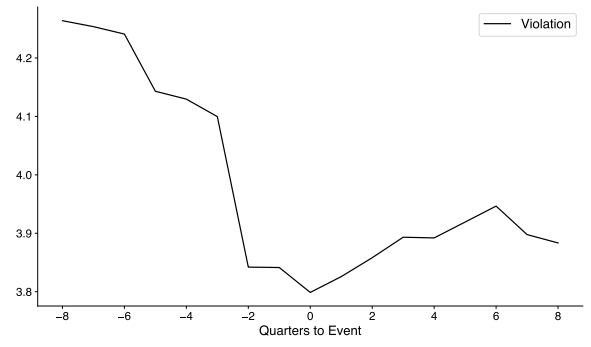
(h) $\text{Ln}(\text{Costs})$

Figure 2: Dependent Variables before/ after the Violation

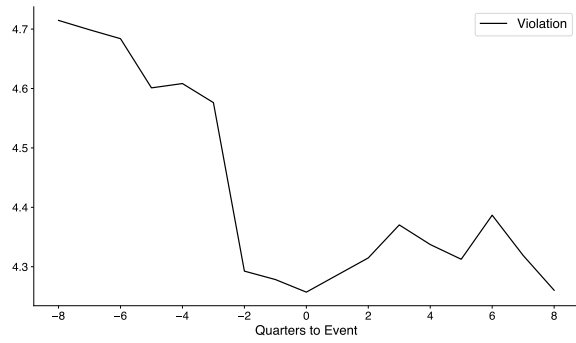
This figure plots the pre and post event performance as a change to the time of the event ($t = 0$) of the eight variables that we use as proxies in our regressions (a) $\text{Ln}(\text{Assets})$, (b) $\text{CapEx} / \text{Assets}$, (c) $\text{CashAcqui} / \text{Assets}$, (d) $\text{Ln}(\text{Debt})$, (e) $\text{Cash} / \text{Assets}$ (f) $\text{Ln}(\text{Payout})$ (g) $\text{Ln}(\text{Sales})$ and (h) $\text{Ln}(\text{Costs})$ for the four violation and amendment categories. The violations are identified by CovenantAI and use the time period 1996-2022



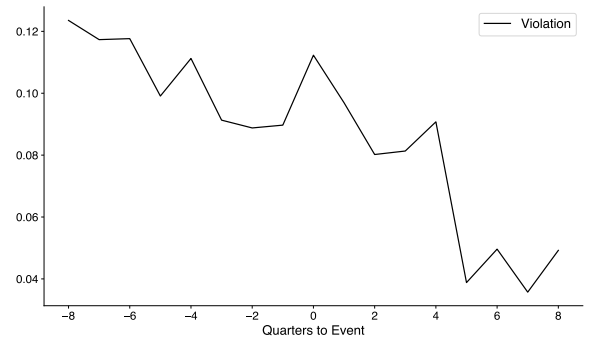
(a) Leverage Ratio



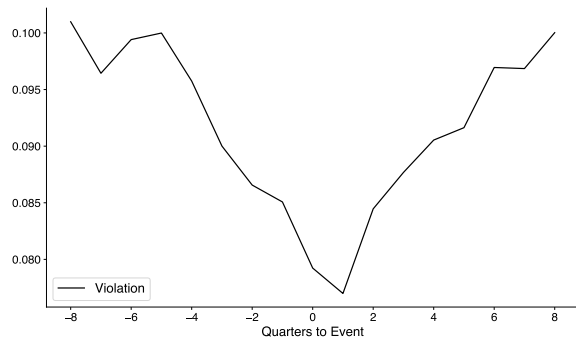
(b) LN(PPE)



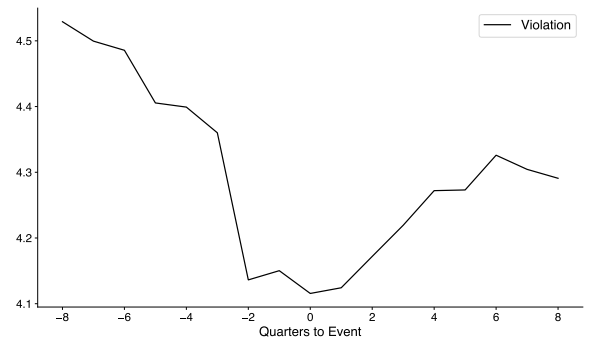
(c) Ln(Debt)



(d) CL Usage



(e) Operating Income/Assets



(f) Ln(Sales)

Figure 3: Change in Ratios for Violations identified by the Nini Keyword Approach
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(PPE) (b), the Ln(Debt) (c), the usage of credit lines (d), the operating income/ assets (e) and the Ln(Sales) (f) for the five violation and amendment categories.

B Covenant Violation Classification

Covenant Violation and Amendment Classification

In this section, we develop our machine learning algorithm to classify firm quarters into those in which a firm has violated a covenant and those in which no covenant violation occurs. We proceed in four steps: (1) We first manually classify firm-quarter observations into violation, amendments, or non-violation quarters based on a quasi-random subset of 10K/10Q observations; (2) we then build our machine learning (classification) model and calibrate the performance of the model; (3) we apply the model to the full dataset of firm-quarter observations; (4) finally, we compare our approach to a manual classification based on [Nini et al. \(2012\)](#).

Step 1: Labeling covenant violations and loan amendments

In order to train our classification algorithm, we need to specify a ground truth, i.e., a set of firms that have violated or not violated a covenant, that is used as a label in our classification algorithm. We thus select a (quasi) random sample of 3,991 firm-quarter observations containing the word “covenant” from the 10K and the 10Q reports. We construct this random sample by selecting one part completely random and another part based on whether the word “violation” is included in the sentence to increase the number of potential violations.

We then manually assign labels to these observations. Importantly, we not only assign firm quarters into violation and non-violation but also use a separate category for quarters in which a loan was amended. These amendments are used to either avoid a possible covenant violation or to cure an existing one. We thus observe whether a covenant violation was avoided/cured in the same quarter or in a subsequent quarter after a violation. We provide examples of SEC filings to demonstrate our labeling into covenant violations and amendments at the end of this section.

We label the observations such that the observations have a value of 0 if there is no violation in the specific quarter. It has a value of 1 if there is no violation, but the filings report an amendment of a loan. Finally, the observation is assigned a value of 2, if the firm has violated a covenant in the respective quarter. Consistent with this approach and to be able to recognize the extent to which loans are being amended, we train our model to reduce the so-called “false negatives”. False negatives are observations that our model predicts as non-violations but are actually violations. “False positives”, on the other hand, are observations that our model predicts as a violation but that are actually not violations (but, for example, could be amendments).

Overall, our manually labeled sample comprises 692 covenant violations and 606 amendments, which is almost 17,34%, respectively 15,18%, of the firm-quarter sample. The high number of violations and amendments is a mechanic, given our sampling procedure. We try to balance the number of violation and no-violation observations to have enough data to train and validate the model.² The MPNET sentence transformer is trained in a massive corpus and is automatically fine-tuned to extract of meaningful and context-aware representations of the text based on the training data. We checked a subsample with chatgpt to see if it agrees with the labeling.

Step 2: Classification algorithm

We split the sentences with our newly assigned labels into test, training, and validation data. The validation data account for 10% of the whole dataset. The remaining 90% is split into

² Therefore, the mean violation rate is not representative for covenant violations in our sample. When using a random sample from our full dataset, we find that the mean violation rate is 2.5%, which better represents the true distribution of the violation data.

the test data (25%) and training data (75%). The training dataset consists of 467 violations, 409 amendments, and 1,817 no-violation observations, while the test dataset is composed of 156 violations, 136 amendments, and 606 non-violations. The validation dataset consists of 69 violations, 61 amendments, and 270 non-violations. While the train data is used to calibrate the model, the test and validation datasets are both used to assess the model’s performance.

We obtained a sample of 4,184 observations and proceeded with training, ensuring that the test and validation sets accurately reflected the real distribution. We randomly selected 2,000 observations exclusively for the test and validation sets, while the training set contained a more balanced dataset, as described in the sample description document. [Xu and Set \(2018\)](#) emphasized the importance of determining an optimal dataset split, so we tested multiple configurations: 15% validation, 20% test, and 65% training; 20% validation, 25% test, and 55% training; 10% validation, 15% test, and 75% training; and finally, 70% training, 15% validation, and 15% test. The confusion matrix showed that the 70% training, 15% validation, and 15% test split produced the best accuracy, reaching 92% on the test set. We selected hyperparameters based on best practices and observed performance during training. We set the number of epochs to 40, allowing the model to converge, with the error stabilizing around the 30th epoch. We used the F1 score as the evaluation metric because it balances precision and recall, which is especially useful when working with imbalanced data. To enhance generalization, we chose the AdamW optimizer for its efficiency and built-in regularization. We set the batch size to 10, ensuring stable gradient updates while maintaining computational efficiency. We determined a learning rate of 0.01 to balance fast convergence with training stability. The model achieved 92% accuracy on both the validation and test sets, confirming its robustness across different datasets.

Date extraction and paragraph aggregation. We extract the date on which the amendment or violation occurred for the classified paragraphs. We use the Flan-T5 large model, which is known for its efficiency and compatibility with GPU, allowing for a faster computation. We then cleaned and parsed the extracted dates into a standardized date format. These dates are compared to the reporting dates in a next step. We sourced the reporting dates from an SEC document that cataloged all reporting dates for filings. However, some entries contained errors where they mistakenly listed the filing date instead of the reporting date. To correct these errors, we developed a custom NLP algorithm to accurately extract reporting dates for the affected filings. The algorithm analyzed the first 500 characters of each document, applying keyword searches, regular expressions, and context-based logic to identify and extract the correct reporting date. This method ensured that we retrieved accurate reporting dates, even for corrupted entries. After obtaining the reporting dates, we calculated the time difference between the extracted paragraph date and the corresponding filing’s reporting date. If the difference exceeded six months (180 days), we assigned the paragraph a label of 0, regardless of its previous classification. This adjustment indicated that the violation had already been reflected in the dataset within the last two quarters. We also labeled any paragraph without an extracted date as 0, since we determined that these paragraphs were irrelevant and could not be labeled accurately. For the time series analysis, we examined three consecutive quarters for each company to refine the labels based on how violations were addressed in later quarters. If a company reported a technical default in one quarter but disclosed a resolution (Waiver, Amendment and Waiver, or Amendment with Violation) in subsequent quarters, we updated the original technical default label to match the resolution (W, AW, or AV). We then replaced the resolution label in the following quarter with 0. This approach reflects how companies sometimes violate covenants but only later disclose in their filings that they cannot guarantee a waiver or amendment after the violation.

As a classification model, we use the MPNET Sentence Transformer Model as a benchmark model to categorize supervised data. For the specific application, we utilize the "all-mpnet-base-

v2 sentence transformer” provided by Hugging Face³. MPNET Sentence Transformer converts sentences into dense vector representations with a dimensionality of 768 and it creates compact representations for sentences. During the initial fine-tuning, the model learns to distinguish between different classes by comparing positive pairs from the same class and negative pairs from different classes. These embeddings are then fine-tuned further, resulting in dense vectors for each example. What sets it apart from previous models is its unique encoding step. During this process, it directly incorporates the similarity and dissimilarity between labels into the sentence embeddings. In the subsequent step, the classification head is trained using these encoded embeddings, which contain information about the corresponding class labels. This approach enables the model to learn essential discriminative features required for precise classification. This model has the advantage that it has been pre-trained on an extensive dataset of one billion sentence pairs and is intended for general-purpose usage. Notably, it accepts entire sentences, rather than just tokens, as input. Therefore, its data does not require cleaning, simplifying the workflow. The Sentence Transformer model acts as a corpus for our model and is further trained with our 2,693 labeled data, which finds the best combination of input parameters to optimize the model’s accuracy. These variables used are shown in [section C](#).

To get a better understanding of the performance of the machine learning algorithm, we calculate the precision and the recall of the model as two additional success indicators for unbalanced datasets. The precision is calculated as the ratio of the true positives divided by the sum of true positives and false negatives.

$$Precision = \frac{TP}{TP + FP}$$

This indicator is used for datasets where the false positives are to be minimized. The performance measure Recall is calculated as the ratio between true positive observations and the sum of true positives and false negatives.

$$Recall = \frac{TP}{TP + FN}$$

It is used for datasets where the false negatives should be minimized ([Müller & Guido, 2016](#)).

In our analysis, we compute precision and recall metrics for both datasets using two different methods: the macro average and the weighted average. The macro average is determined by taking the arithmetic mean of precision and recall scores for individual classes. On the other hand, the weighted average incorporates class distribution to adjust the contributions of each component accordingly. Our model achieves a precision of 91% and a recall of 93% using the macro average and a precision of 94% and a recall of 94% using the weighted average method. [section C](#) displays recall, precision, and f1-score of both datasets.

Step 3: Full sample analysis We merge the 10K/10Q 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 and the mentioned date. If the delta is higher than 182 days, we do not count the observation as a violation or amendment, because it contains information about a previous violation that has already been reported. We applied the same machine learning algorithm to the 8K filings, to validate our results. 8Ks give us real-time information because they need to be filed within four days after the event. We further count all violation observations that are followed by an amendment in the following two quarters as no violations. We construct the variable $CovVio^{New}$ that has the value 1 if a company has violated a covenant in the quarter but has not violated a covenant in the previous two quarters. We call

³ <https://huggingface.co/sentence-transformers/all-mpnet-base-v2>

these "new" covenant violations. The variable $Amendment^{New}$ has the value 1 if a company has amended a covenant violation in the quarter but has not amended a covenant violation in the previous two quarters. Applying our ML algorithm with the optimized criteria, we obtain 27,627 (7.32%) amendments and 4,351 (1.15%) total covenant violations for all firm quarters. The number of firm quarters in which we find new covenant violations is 1,579 (0.42%), and that of new amendments is 11,497 (3.04%).

Step 4: Validation exercise To show the relevance of our machine learning classification algorithm in identifying covenant violations, we compare its performance with a manual classification based on the previous literature following the classification outlined in [Nini et al. \(2012\)](#).

The data preprocessing is similar to our earlier approach to ensure comparability. We first stem the sentences to reduce the words to their roots. The algorithm searches for the stemmed words "waiv", "violat", "in default", "not in complianc" and "reset" and assigns a violation label to those sentences. We exclude those sentences where the words "if", "should", "could", "shall", "would", "in the event", "may" appear since they give an indication of an uncertain scenario.

For ease of comparison and to reduce computation time, we classify firm-quarters into violation and non-violation and assign possible amendments to the non-violation firm-quarters. This is feasible as it does not affect performance evaluation measures such as accuracy or false negatives and false positives. When the program finds the expression "not in compl" that does not include an "if" in the sentence, we call it a violation. We further define knock-out criteria such as "compan was in complianc" and "no violat" that directly mark the sentences as a non-violation. We delete those sentences that do not specify actual violations but contractual changes if a violation occurs. We finally split the dataset into train and test data sets.

As indicated above, as we want to classify observations into both non-violations and amendments, we focus on reducing false negatives in our optimization procedure. In contrast, [Nini et al. \(2012\)](#) focus on reducing false positives to accurately identify all covenant violations. The difference in the optimization becomes visible comparing the confusion matrix from our machine learning algorithm ([Figure 4a](#)) and that based on our manual classification ([Figure 4b](#)).

The confusion matrix displays the predicted values on the horizontal axis and the true values on the vertical axis, where 1 represents a covenant violation and 0 a no-violation. The accuracy of our machine learning algorithm, which is defined by the sum of true positives and true negatives, is 95.21%. This is almost 20% higher compared to the manual algorithm, with an accuracy of 75.62%. False negatives are observations that our model predicts as a violation, but that is actually a no-violation. False positives are observations that our model predicts as a no-violation but is actually a violation. Based on the confusion matrix, it can be seen that the false negatives percentage has a lower value compared to that of [Nini et al. \(2012\)](#) (2.90% vs. 15.26%), and also performs better in terms of false positives and the identification of violations (1.89% vs. 9.13%).

We further validated our results by labeling a subsample of the manually labeled database with the "gpt-3.5-turbo-0613" model provided by OpenAI. To explain how the algorithm classifies the three categories, we used a specific set of instructions as input. In these instructions, we defined the three labels and included special cases that need extra attention. Furthermore, we provided the algorithm with an example for each category to help it understand and perform the classification better. This data-tailored prompt containing the instructions can be seen in [Section B](#). When comparing the confusion matrix of our machine learning model with the "gpt-3.5-turbo-0613" model, it becomes evident that our model outperforms the latter. The "gpt-3.5-turbo-0613" model ([Figure 4c](#)) has an accuracy of 73.75%, which is more than 20% less than the accuracy of our model.

If the borrower is not in compliance with a debt covenant, the lender can take several

actions depending on the severity of the violation. These actions include terminating the debt agreement and demanding penalty payment or full immediate repayment of the loan. However, the lender may also decide to make changes to the contract, such as increasing the interest rate or the amount of collateral or changing the ratio threshold agreed on in the initial contract (CFI Education Inc., 2022)⁴. These renegotiations are commonly commenced by borrowers seeking to modify the terms of the original credit agreement and involve a lessening of the restrictions for the debt holder. Denis and Wang (2014) find that less than 30% of covenant renegotiations lead to tighter financial thresholds. Furthermore, they find that renegotiations are not always triggered by a technical default but also occur in specific economic circumstances and at various times over the lifetime of the contract. A creditor also has the possibility to waive the covenant violation, meaning that the agreement does not have to be obeyed and that the rights are given up (Cambridge University Press, 2014)⁵. Information on a firm’s bankruptcy probability, leverage ratio, size, and security of the issued debt are deciding determinants of waiver decisions (Chen & Wei, 1993). For instance, a creditor is more likely to waive a covenant breach for a loan that is secured and of a smaller size than for a larger, unsecured loan. Alternatively, a forbearance agreement can be entered. This is a contract between a borrower and a lender in which the lender refrains from executing its rights under a violated credit agreement for a certain period of time if the borrower satisfies a series of predetermined criteria. A forbearance agreement is frequently used as a short-term replacement for restructuring or refinancing of a loan transaction or for curing the defaults (Christenfeld, 2010).

The following paragraphs are examples from SEC filings reporting a covenant violation:

- Vuzix Corp: The Company cannot predict with any certainty the amount of credit that will be available to it under this facility at any time or whether the application of that formula will require that the Company repay previous borrowings at any time. The loan agreement relating to this facility requires the Company to meet certain quarterly and annual EBITDA covenants. The Company was not in compliance with the EBITDA covenant for the third quarter of 2011. The Company has requested that the Bank waive the Company’s noncompliance with the EBITDA covenant for the third quarter ended September 30, 2011, but the Bank has not yet done so.⁶
- REMARK HOLDINGS: The Financing Agreement contains certain affirmative and negative covenants, including but not limited to a covenant requiring us to maintain a minimum of \$1.0 million in unrestricted cash in designated bank accounts. As of September 30, 2019, we were not in compliance with such minimum cash covenant. We were also not in compliance with certain other covenants under the Financing Agreement, including a covenant requiring us to obtain and pay for a tail directors’ and officers’ liability insurance policy (the “Tail Policy”) by June 4, 2019 in connection with the VDC Transaction, and a covenant requiring us to make the final Earnout Payment by June 14, 2019. Additionally, although we have actively taken steps to monetize our ownership interest in Sharecare, we did not comply with certain procedural requirements stipulated by the Sharecare Covenant. Our non-compliance with such covenants constitutes events of default under the Financing Agreement.⁷
- TWINLAB CONSOLIDATED HOLDINGS: As of June 30, 2020, we were in default for lack of compliance with the EBITDA-related financial covenant of the debt agreement

⁴ <https://corporatefinanceinstitute.com/resources/commercial-lending/debt-covenants/>

⁵ <https://dictionary.cambridge.org/de/worterbuch/englisch/waiver>

⁶ https://www.sec.gov/Archives/edgar/data/1463972/000114420411066092/v241021_10q.htm

⁷ <https://www.sec.gov/Archives/edgar/data/1368365/000136836519000048/mark30sep201910q.htm>

with MidCap. The amount due to MidCap for this revolving credit line is \$2,953 as of June 30, 2020.⁸

- TransCoastal Corp: As of June 30, 2014 the Company is in compliance with all covenants. As of December 31, 2013, the Company was not in compliance with its current ratio. Accordingly, the balance as of December 31, 2013 is classified as current.⁹

The following paragraphs are examples from SEC filings reporting a covenant amendment:

- SPIRE Corp: At December 31, 2007, the Company's outstanding borrowings from the equipment line of credit amounted to \$2,917,000. The Company was not in compliance with its covenants as of December 31, 2007, but not in default because a Bank waiver has been received.¹⁰
- SCIENTIFIC LEARNING CORP: As of June 30, 2013, we had no borrowings outstanding on the line of credit. During the months ending January 31, 2013, February 28, 2013, May 31, 2013 and June 30, 2013 we were not in compliance with our line of credit covenants. Comerica granted us waivers of the covenant violations for these periods. On August 9, 2013 the Company again amended the credit line. In the amendment, Comerica agreed to waive past covenant violations and agreed not to measure compliance with the financial covenants until such time as the Company seeks to borrow against the line of credit. The amendment also requires that the financial covenants be renegotiated prior to the Company borrowing against the line of credit. There is no assurance that the Company would be able to successfully do so.¹¹
- Symbolic Logic: On September 24, 2019 the Company agreed in principle to the terms of a new amendment and on October 4, 2019, we entered into the First Amendment ("First Amendment") to the Lumata Facility. The purpose of the First Amendment was to waive certain events of non-compliance with respect to covenants not achieved in prior periods and to amend future covenant requirements. The First Amendment also required Evolving Systems to make an advance payment of principal of \$666,667. The remaining terms and conditions of the Lumata Facility and payment schedule remain unchanged.¹²
- RECYCLING ASSET HOLDINGS: During the second quarter of 2019, the Company was out of compliance with its financial covenant related to the Fixed Charge Coverage Ratio ("FCCR") set forth in the BofA Loan Agreement. On August 14, 2019, the Company entered into a second amendment to the BofA Loan Agreement, through which BofA waived the Company's breach of the aforementioned covenant through July 31, 2019 and amended the financial covenants as more fully described in Note 3 – Long-Term Debt and Notes Payable to Bank in the accompanying Notes to Consolidated Financial Statements for future periods beginning August 1, 2019. Although we expect operating cash flow and borrowings under our working capital line of credit to be sufficient to meet our ongoing obligations, we cannot provide assurance that sufficient liquidity can be raised from one or both of these sources. Additionally, we must maintain compliance with our financial covenants in order to continue to borrow under the BofA revolving facility.¹³

⁸ https://www.sec.gov/Archives/edgar/data/1590695/000143774920018261/tlcc20200630b_10q.htm

⁹ https://www.sec.gov/Archives/edgar/data/1046057/000143774914015440/tcec20140630_10q.htm

¹⁰ https://www.sec.gov/Archives/edgar/data/731657/000107261308000843/form10-k_15786.txt

¹¹ <https://www.sec.gov/Archives/edgar/data/1042173/000104217313000018/scil-20130630x10q.htm>

¹² <https://www.sec.gov/ix?doc=/Archives/edgar/data/0001052054/000156276221000443/evol-20210930x10q.htm>

¹³ <https://www.sec.gov/ix?doc=/Archives/edgar/data/0000004187/000089710119000787/idsa-20190630.htm>

Examples for Amendment Sub-Categories

The following provides examples for the sub-categories cases of Amendments: We define this paragraph as an amendment without violation, therefore also without a waiver (A):

- Orion Energy Systems, Inc.: n March 18, 2008, the Company entered into a credit agreement (“Credit Agreement”) to replace a previous agreement between the Company and Wells Fargo Bank, N.A. The Credit Agreement provides for a revolving credit facility (“Line of Credit”) that matures on August 31, 2010. The initial maximum aggregate amount of availability under the Line of Credit is \$25.0 million. The Company has a one-time option to increase the maximum aggregate amount of availability under the Line of Credit to up to \$50.0 million, although any advance from the Line of Credit over \$25.0 million is discretionary to Wells Fargo even if no event of default has occurred. Borrowings are limited to a percentage of eligible trade accounts receivables and inventories, less any borrowing base reserve that may be established from time to time. In December 2008, the Company briefly drew \$4.0 million on the line of credit due to the timing of treasury repurchases and funds available in the Company’s operating account. In May 2009, the Company completed an amendment to the Credit Agreement, effective as of March 31, 2009, which formalized Wells Fargo’s prior consent to the Company’s treasury repurchase program, increased the capital expenditures covenant for fiscal 2009 and revised certain financial covenants by adding a minimum requirement for unencumbered liquid assets, increasing the quarterly rolling net income requirement and modifying the merger and acquisition covenant exemption. As of March 31, 2009 and September 30, 2009, there was no outstanding balance due on the Line of Credit. The Company must currently pay a fee of 0.20% on the average daily unused amount of the Line of Credit and fees upon the issuance of each letter of credit equal to 1.25% per annum of the principal amount thereof. The Credit Agreement provides that the Company has the option to select the interest rate applicable to all or a portion of the outstanding principal balance of the Line of Credit either (i) at a fluctuating rate per annum one percent (1.00%) below the prime rate in effect from time to time, or (ii) at a fixed rate per annum determined by Wells Fargo to be one and one quarter percent (1.25%) above LIBOR.¹⁴

We define this paragraph as an amendment with violation but without obtaining a waiver (AV):

- EQUITY OIL CO: as of december 31, 1998 the company was in violation of the ”tangible net worth” covenant contained in the facility. in march 1999, the company’s bank amended the facility to remedy the covenant violation. the company is now in compliance with all covenants in the facility. the company believes that existing cash balances, cash flows from operating activities, and funds available under the company’s credit facility will provide adequate resources to fund on going operations and will allow the company to meet limited capital and exploration spending objectives for 1999.¹⁵

The following paragraph is classified as an amendment with violation and in combination with a waiver (AW):

- CLARK HOLDINGS INC.: accordingly, the company amended the credit facility with bank of america on april 17, 2009, and in return, the bank issued a waiver with respect to the breached covenants. interest is payable at 4.00% over libor or at the prime interest rate. the non use fee is 0.675% per year and the letter of credit fees are 4.00%. due

¹⁴ <https://www.sec.gov/Archives/edgar/data/1409375/000095012309060334/c54540e10vq.htm>

¹⁵ <https://www.sec.gov/Archives/edgar/data/33325/0000033325-99-000005.txt>

to continuing losses during the second quarter, the company was not in compliance with three of its financial covenants as of the end of the may 2009 reporting period and a notice of events of default was issued by bank of america on july 6, 2009. accordingly, the company amended the credit facility again and entered into an amendment and forbearance agreement on september 15, 2009. interest is payable at 4.00% over libor, with a libor floor of 3% or at prime interest rate plus 2.50%. the non use fee is 0.675% per year and the letter of credit fees are 4.00%. the agreement expires on february 28, 2010. while the company does not expect the bank to terminate the credit facility and/or demand repayment of outstanding debt on february 28, 2010, it would have the right to do so.¹⁶

Waiver without change of contract terms (without an amendment) (W):

- DATAWATCH CORP: beginning as of september 30, 1998, the company was not in compliance with one of the financial covenants contained in the letter agreement with the bank. the bank has effectively waived through maturity (january 29, 1999) a default under the line of credit as a result of the company's non compliance with this financial covenant, but has restricted the company from further advances above the \$1,150,000 currently outstanding. the company is currently negotiating the renewal of the line of credit which expires in january 1999.¹⁷

¹⁶ https://www.sec.gov/Archives/edgar/data/1338401/000114420409060463/v166697_10q.htm

¹⁷ <https://www.sec.gov/Archives/edgar/data/792130/0000792130-98-000018.txt>

C CovenantAI

MPNET Sentence Transformer Model

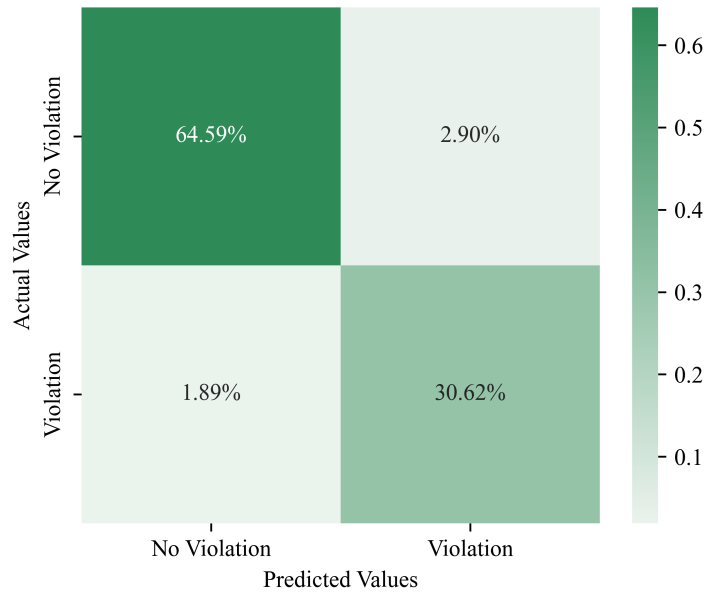
Model Training Hyperparameters

Hyperparameter	Description
Num_train_epochs = 12	Total number of training epochs
Per_device_train_batch_size = 10	Batch size per device during training
Per_device_eval_batch_size = 10	Batch size for evaluation
Warmup_steps = 500	Number of warmup steps for learning rate scheduler
Weight_decay = 0.01	Strength of weight decay
Logging_dir = 'logs'	Directory for storing logs
Load_best_model_at_end = True	load the best model when Finished training (default metric is loss)
Metric_for_best_model = F1	select the base metrics
Logging_steps = 200	Log & save weights each logging_steps
Save_steps = 200	Save steps
Evaluation_strategy = "steps"	Evaluate each logging_steps
Optimizer= AdamW(model.parameters(), lr=1e-5)	Define the optimiser and the learning rate

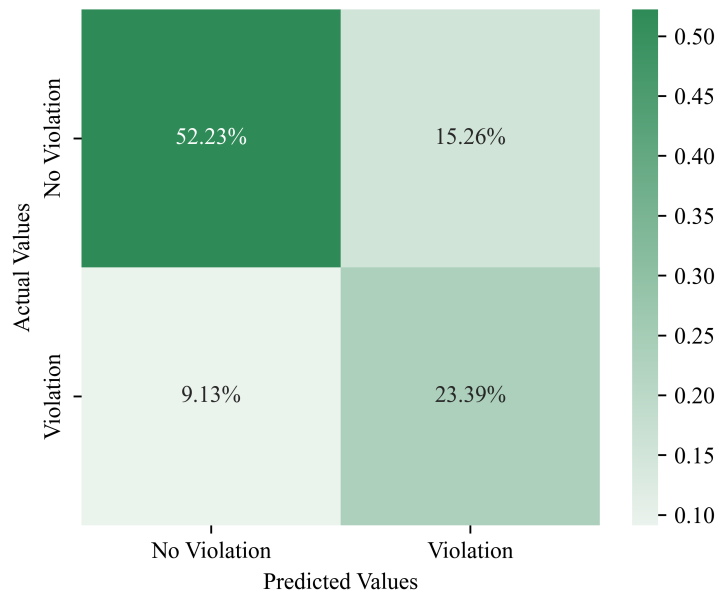
Precision, Recall, F1-score for Test and Validation Data

	Precision	Recall	F1-score	Number
Test Data				
0	0.97	0.96	0.96	606
1	0.87	0.88	0.87	136
2	0.91	0.96	0.93	156
Accuracy			0.94	898
Macro Average	0.92	0.93	0.92	898
Weighted Average	0.94	0.94	0.94	898
Validation Data				
0	0.97	0.95	0.96	270
1	0.85	0.90	0.87	61
2	0.92	0.94	0.93	69
Accuracy			0.94	400
Macro Average	0.91	0.93	0.92	400
Weighted Average	0.94	0.94	0.94	400

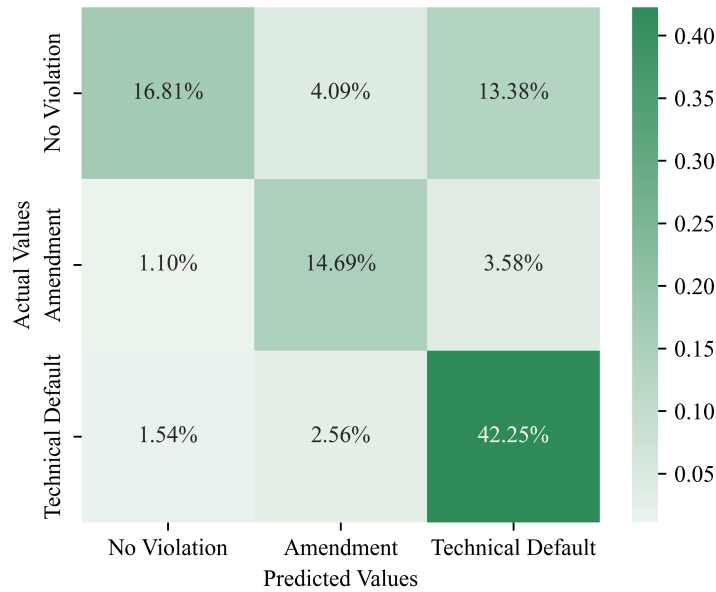
Comparison with the Nini et al. Algorithm



(a) Confusion matrix of our ML algorithm



(b) Confusion matrix of the [Nini et al. \(2012\)](#) algorithm



(c) Confusion Matrix of Chat GPT labeling

Comparison with the prediction of Chatgpt

Prompt

The various categories for the classification task are:

We will call making amendments or obtaining waivers or obtaining forbearance agreements as 'amendments activities' in the following.

Amendment - The company has made amendments or obtained waivers or forbearance agreements for the covenants due to noncompliance or challenging economic conditions. If amendments are currently being negotiated or have been obtained, classify the paragraph as an 'Amendment'. This includes cases where the paragraph explicitly states that certain covenants were amended or modified to allow for compliance.

Violation - The company has failed to comply with the covenants without obtaining waivers or making amendments, thus violating them. If the violation occurs after a waiver has been granted, label it as a violation. Just label it as a 'Violation' if it does not talk about a potential violation. If it just talks about the potential violation or non-compliance with current covenants, by using words like if, would, could etc, classify it as a 'No Violation'.

No Violation - In this scenario, the paragraphs do not provide any information indicating whether the company violated a covenant or if the covenant was changed through a waiver or an amendment. If it is a possibility of needing an Amendment or wavier of a covenant Violation also classify it as 'No Violation'. Do not categorize paragraphs as amendments or violations if the event is uncertain.

The output format that you have to produce is: json "observation": what is asked of you and what will be useful to consider before completing the task? "thought": based on the observation, how does a person of your capabilities judge the category of the user description? "category label": based on the labels provided, which category should the profile belong to? Here are some examples:

Example: "the company was not in compliance with various covenants contained in the mufg credit facility agreement, including those related to interest coverage and debt service coverage ratios and a no-net-loss requirement under the mufg credit facility, beginning in the third quarter of 2019." category label: Violation

Example: "make investments, (iv) acquire businesses, or (v) pay dividends to rmci. in addition, the credit facility contains financial covenants related to senior debt to cash flow, interest coverage, and minimum stockholders equity. at june 30, 1996, fpm s minimum stockholders equity was less than the requirement. the bank waived this requirement for the year ended june 30, 1996." category label: Amendment

Example: "than as to going concern or a qualification resulting solely from the scheduled maturity of term loans occurring within one year from the date such opinion is delivered) would be a violation of an affirmative covenant" category label: No Violation

The paragraphs for which you have to do this is: context

Remember to follow the output format that I have told you about!

D Additional Analyses

The following tables present an overview of all proxies used by [Nini et al. \(2012\)](#) to give an indication of the firms changes in Investment and financing policies and firm performance in the four quarters after the violation.

Table 1: **Firm Adjustments to Covenant Violations - Using Nini et al. (2012) Violation Data**

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 relates covenant violations to firm adjustments in investment and employment over a period of four quarters ($t + 4$) after a covenant violation. $\text{Ln}(\Delta \text{Assets})$ is the natural logarithm of the change in total assets (column 1), $\text{Ln}(\Delta \text{PPE})$ is the natural logarithm of the change in property, plant and equipment (column 2), $\Delta \frac{\text{CapEx}}{\text{Assets}}$ is the change in capital expenditures over assets (column 3), $\Delta \frac{\text{CashAcq}}{\text{Assets}}$ is the change in cash acquisitions over assets (column 4), $\Delta \text{Employment}$ is defined as employment growth (column 5). Panel B relates covenant violations to firm adjustments in financial policies over a period of four quarters ($t + 4$) after a covenant violation. $\Delta \frac{\text{NDI}}{\text{Assets}}$ is the change in net debt issuances over total assets (column 1), $\text{Ln}(\Delta \text{Debt})$ is the natural logarithm of the change in total debt (column 2), $\Delta \frac{\text{Cash}}{\text{Assets}}$ is the change of cash over average assets (column 3), $\Delta \text{Ln}(\text{Payout})$ the change in the natural logarithm of shareholder payouts (column 4), $\Delta \text{CashRatio}$ is the change in firm's cash over the sum of the undrawn credit lines and cash (column 5), and ΔUsage is the change in the drawn amount of credit lines over the total balance of credit lines outstanding (column 6). Panel C relates covenant violations to firm adjustments in operational and financial performance over a period of four quarters ($t + 4$) after a covenant violation. $\Delta \frac{\text{OpIncome}}{\text{Assets}}$ is the change in operating income over Assets (column 1), $\text{Ln}(\Delta \text{Sales})$ is the natural logarithm of the change in sales (column 2), $\text{Ln}(\Delta \text{Cost})$ is the natural logarithm of operating costs (column 3), $\Delta \frac{\text{EBIT}}{\text{Assets}}$ is change in EBIT over assets (column 4), *Downgrade* is an indicator that is one if the firm was downgraded during this period (column 5), and *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period (column 6). 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. $\Delta \text{Employment}$ and $\Delta \frac{\text{EBIT}}{\text{Assets}}$ 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: Investment & Employment				
	(1) $\Delta \text{Ln(Assets)}$	(2) $\Delta \text{Ln(PPE)}$	(3) $\Delta \frac{\text{CapEx}}{\text{Assets}}$	(4) $\Delta \frac{\text{CashAcq}}{\text{Asset}}$
Violation	-0.027*** (-4.522)	-0.033*** (-4.643)	-0.003*** (-3.235)	-0.002* (-1.963)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.176	0.131	0.029	0.015
N	97,753	97,028	94,556	92,037
Violation_{t-4}	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel B: Financial Policies				
	(1) $\Delta \frac{\text{NDI}}{\text{Assets}}$	(2) $\Delta \text{Ln(Debt)}$	(3) $\Delta \frac{\text{Cash}}{\text{Asset}}$	(4) $\Delta \text{Ln(Payout)}$
Violation	-0.002** (-2.298)	-0.078*** (-5.987)	0.002 (1.036)	-0.022** (-2.210)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.087	0.095	0.065	0.023
N	96,276	81,992	97,720	82,123
Violation_{t-4}	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance

	(1) $\Delta \frac{\text{Operating Income}}{\text{Assets}}$	(2) $\Delta \text{Ln}(\text{Sales})$	(3) $\Delta \text{Ln}(\text{Cost})$
Violation	0.006* (1.947)	-0.044*** (-5.965)	-0.044*** (-5.318)
Industry FE	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No
R^2	0.189	0.077	0.101
N	94,177	95,531	94,430
Violation_{t-4}	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes

Table 2: Firm Adjustments to Covenant Violations - Using CovenantAI Violation Data

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 . We use the same dependent variables and specifications as in Table 1. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment & Employment				
	(1) $\Delta \text{Ln(Assets)}$	(2) $\Delta \text{Ln(PPE)}$	(3) $\Delta \frac{\text{CapEx}}{\text{Assets}}$	(4) $\Delta \frac{\text{CashAcq}}{\text{Asset}}$
Violation	-0.036*** (-5.653)	-0.037*** (-5.019)	-0.004*** (-5.136)	-0.002** (-2.273)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.179	0.133	0.029	0.015
N	92,766	92,091	90,091	87,675
Violation_{t-4}	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel B: Financial Policies				
	(1) $\Delta \frac{\text{NDI}}{\text{Assets}}$	(2) $\Delta \text{Ln(Debt)}$	(3) $\Delta \frac{\text{Cash}}{\text{Asset}}$	(4) $\Delta \text{Ln(Payout)}$
Violation	-0.002* (-1.985)	-0.090*** (-5.215)	0.003 (1.485)	-0.002 (-0.168)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.088	0.095	0.065	0.023
N	91,378	77,533	92,733	78,235
Violation_{t-4}	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance			
	(1) $\Delta \frac{\text{OperatingIncome}}{\text{Assets}}$	(2) $\Delta \text{Ln(Sales)}$	(3) $\Delta \text{Ln(Cost)}$
Violation	0.009** (2.667)	-0.048*** (-5.716)	-0.048*** (-5.127)
Industry FE	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No
R^2	0.190	0.078	0.102
N	89,320	90,667	89,558
Violation_{t-4}	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes

Table 3: Firm Adjustments to Covenant Violations - Using the Nini et al. (2012) Keyword-based Approach without Manual Adjustments

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 . We use the same depended variables and specifications as in Table 1. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment & Employment				
	(1) $\Delta \text{Ln(Assets)}$	(2) $\Delta \text{Ln(PPE)}$	(3) $\Delta \frac{CapEx}{Assets}$	(4) $\Delta \frac{CashAcq}{Asset}$
Violation	-0.009** (-2.487)	-0.010 (-1.550)	-0.001** (-2.659)	-0.002*** (-3.003)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.176	0.131	0.029	0.015
N	97,753	97,027	94,552	92,033
$Violation_{t-4}$	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel B: Financial Policies				
	(1) $\Delta \frac{NDI}{Assets}$	(2) $\Delta \text{Ln(Debt)}$	(3) $\Delta \frac{Cash}{Asset}$	(4) $\Delta \text{Ln(Payout)}$
Violation	-0.003*** (-4.922)	-0.019 (-1.608)	0.000 (0.100)	0.004 (0.307)
Industry FE	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
R^2	0.087	0.094	0.065	0.023
N	96,276	81,996	97,720	82,113
$Violation_{t-4}$	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance				
	(1) $\Delta \frac{OperatingIncome}{Assets}$	(2) $\Delta \text{Ln(Sales)}$	(3) $\Delta \text{Ln(Cost)}$	
Violation	0.000 (0.062)	-0.011** (-2.139)	-0.007 (-1.492)	
Industry FE	Yes	Yes	Yes	
Firm Quarter FE	Yes	Yes	Yes	
Calendar Quarter FE	Yes	No	No	
R^2	0.189	0.076	0.100	
N	94,177	95,531	94,427	
$Violation_{t-4}$	Yes	Yes	Yes	
Covenant Controls	Yes	Yes	Yes	
Higher Order Controls	Yes	Yes	Yes	
Lagged Covenant Controls	Yes	Yes	Yes	

Table 4: **Firm Adjustments to Covenant Violations - Using the Nini et al. (2012) Keyword-based Approach without Manual Adjustments**

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 . We use the same dependent variables and specifications as in Table 1. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment & Employment					
	(1) $\Delta \text{Ln(Assets)}$	(2) $\Delta \text{Ln(PPE)}$	(3) $\Delta \frac{\text{CapEx}}{\text{Assets}}$	(4) $\Delta \frac{\text{CashAcq}}{\text{Asset}}$	(5) Empl Growth
Violation	-0.006** (-2.167)	-0.011*** (-3.103)	-0.002* (-1.931)	-0.005** (-2.560)	0.079 (0.892)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	No
Calendar Quarter FE	Yes	Yes	Yes	Yes	No
Year FE	No	No	No	No	Yes
R^2	0.140	0.100	0.011	0.013	0.065
N	206,946	205,206	203,614	196,051	21,632
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Financial Policies						
	(1) $\Delta \frac{\text{NDI}}{\text{Assets}}$	(2) $\Delta \text{Ln(Debt)}$	(3) $\Delta \frac{\text{Cash}}{\text{Asset}}$	(4) $\Delta \text{Ln(Payout)}$	(5) $\Delta \text{Cash Ratio}$	(6) ΔUsage
Violation	-0.034 (-0.545)	-0.006 (-0.833)	-0.001 (-1.528)	-0.008 (-0.744)	0.002 (0.986)	-0.002 (-0.663)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.004	0.068	0.068	0.030	0.047	0.048
N	203,531	174,550	206,899	182,754	76,883	70,534
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance					
	(1) $\Delta \frac{\text{OperatingIncome}}{\text{Assets}}$	(2) $\Delta \text{Ln(Sales)}$	(3) $\Delta \text{Ln(Cost)}$	(4) Downgrade_{t+4}	(5) Default_{t+4}
Violation	0.001 (1.222)	-0.005 (-1.259)	-0.004 (-1.308)	-0.002 (-0.409)	0.011*** (7.052)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No	No	No
R^2	0.209	0.059	0.093	0.073	0.116
N	202,360	199,009	202,928	19,663	230,030
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Table 5: **Firm Adjustments to Covenant Violations - Using CovenantAI Violation Data**

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 . We use the same dependent variables and specifications as in Table 1. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment & Employment					
	(1) $\Delta \text{Ln(Assets)}$	(2) $\Delta \text{Ln(PPE)}$	(3) $\Delta \frac{\text{CapEx}}{\text{Assets}}$	(4) $\Delta \frac{\text{CashAcq}}{\text{Asset}}$	(5) Empl Growth
Violation	-0.053*** (-9.082)	-0.054*** (-6.798)	-0.006*** (-3.249)	0.002 (0.837)	-0.005 (-0.127)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	No
Calendar Quarter FE	Yes	Yes	Yes	Yes	No
Year FE	No	No	No	No	Yes
R^2	0.133	0.093	0.010	0.011	0.059
N	224,882	222,334	220,660	212,649	23,475
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Financial Policies						
	(1) $\Delta \frac{\text{NDI}}{\text{Assets}}$	(2) $\Delta \text{Ln(Debt)}$	(3) $\Delta \frac{\text{Cash}}{\text{Asset}}$	(4) $\Delta \text{Ln(Payout)}$	(5) $\Delta \text{Cash Ratio}$	(6) ΔUsage
Violation	-0.080 (-1.075)	-0.102*** (-6.545)	0.003* (1.956)	-0.013 (-1.212)	0.006 (0.800)	-0.019** (-2.198)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.004	0.068	0.071	0.028	0.046	0.048
N	221,076	188,624	224,802	197,895	78,235	71,716
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance					
	(1) $\Delta \frac{\text{OperatingIncome}}{\text{Assets}}$	(2) $\Delta \text{Ln(Sales)}$	(3) $\Delta \text{Ln(Cost)}$	(4) Downgrade_{t+4}	(5) Default_{t+4}
Violation	0.011*** (3.182)	-0.062*** (-7.401)	-0.060*** (-6.670)	-0.013 (-0.697)	0.020*** (6.585)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No	No	No
R^2	0.208	0.057	0.085	0.072	0.110
N	219,531	214,739	220,262	20,601	252,476
Violation_{t-4}	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

References

- Chen, K. C., & Wei, K. J. (1993). Creditors' decisions to waive violations of accounting-based debt covenants. *Accounting review*, 218–232.
- Christenfeld, A. M. (2010). Forbearance agreements in funded credit arrangements. *UCC LJ*, 42, 385–406.
- Denis, D. J., & Wang, J. (2014). Debt covenant renegotiations and creditor control rights. *Journal of Financial Economics*, 113(3), 348–367.
- Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with python: a guide for data scientists*. " O'Reilly Media, Inc."
- Nini, G., Smith, D. C., & Sufi, A. (2012). Creditor control rights, corporate governance, and firm value. *The Review of Financial Studies*, 25(6), 1713–1761.
- Xu, O., & Set, V. (2018). A comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. *J. Anal. Test.*, 2, 249.