CovenantAI - New Insights into Covenant Violations

February 15, 2024

Online Appendix

Contents

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

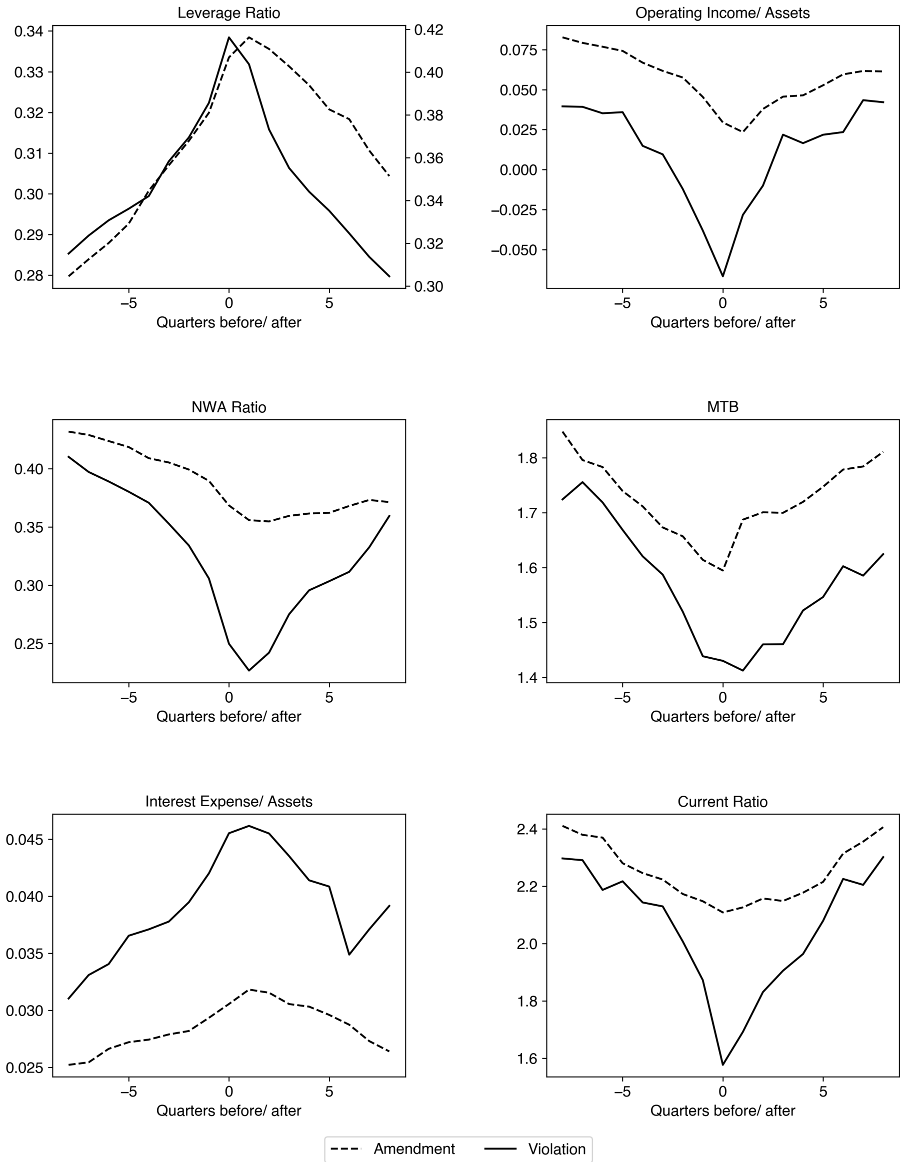
Mapping of S&P Rating Symbol to Rating Number

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

Summary Statistics Dealscan Merged Sample

Panel A: Summary Statistics			
	Whole Dataset	DS-Matched	Difference
Violation	0.47	0.70	-0.23
Amendment	0.45	0.69	-0.24
Technical Default	0.12	0.17	-0.05
Control Variables			
Operating Income/ Assets	-0.03	0.11	-0.14
Leverage Ratio	0.26	0.31	-0.05
Interest Expenses/Assets	0.03	0.03	0.00
NWA/ Assets	0.47	0.40	0.07
Current Ratio	3.08	2.24	0.84
MTB	2.23	1.74	0.49
Dependent Variables			
Ln(Assets)	5.36	6.25	-0.89
Ln(PPE)	3.30	4.62	-1.32
CapEx/ Assets	0.06	0.07	-0.01
CashAqui/ Assets	0.03	0.05	-0.02
Employees	2.95	6.35	-3.40
NDI/ Assets	0.04	0.04	0.00
Ln(Debt)	3.34	4.64	-1.30
Cash/ Assets	0.25	0.12	0.13
Ln(Payout)	0.64	1.05	-0.41
Cash Ratio	0.50	0.43	0.07
Usage	0.29	0.27	0.02
Observations	11,432	4,887	

Control Variables before/ after the Violation



Control Variables before/ after the Violation

This figure plots the annual share of technical defaults and loan amendments in comparison to the number of bankruptcies (Panel A) and the number of downgrades (Panel B). The vertical axis on the left side is the yearly amount of technical defaults and amendments in relation to all companies, while the vertical axis on the right side is expressed in total numbers.

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.

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 Face[3]. 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

[3] `https://huggingface.co/sentence-transformers/all-mpnet-base-v2`

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 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 1a) and that based on our manual classification (Figure 1b).

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 1c) 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 Unversity 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,

[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

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 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

[7] `https://www.sec.gov/Archives/edgar/data/1368365/000136836519000048/mark30sep201910q.htm`
[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`

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]

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 companyś 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 companyś credit facility will

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

[14] https://www.sec.gov/Archives/edgar/data/1409375/000095012309060334/c54540e10vq.htm

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 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 companyś 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]

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

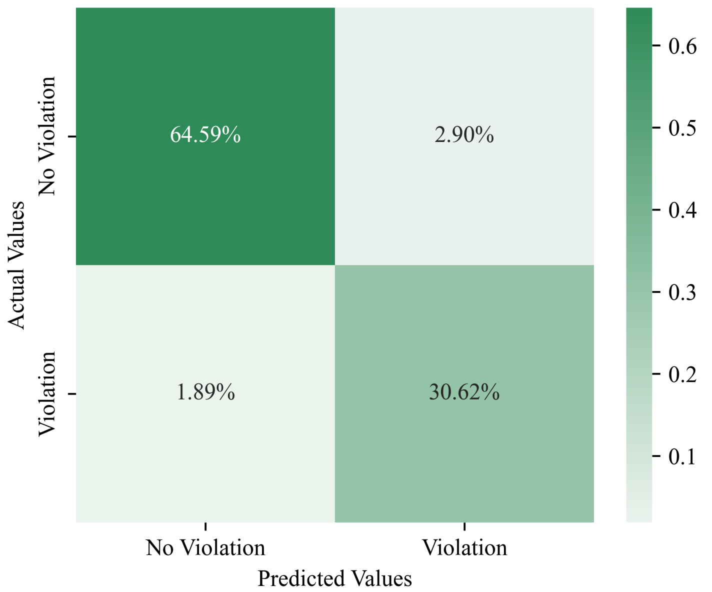
Model Training Hyperparameters

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

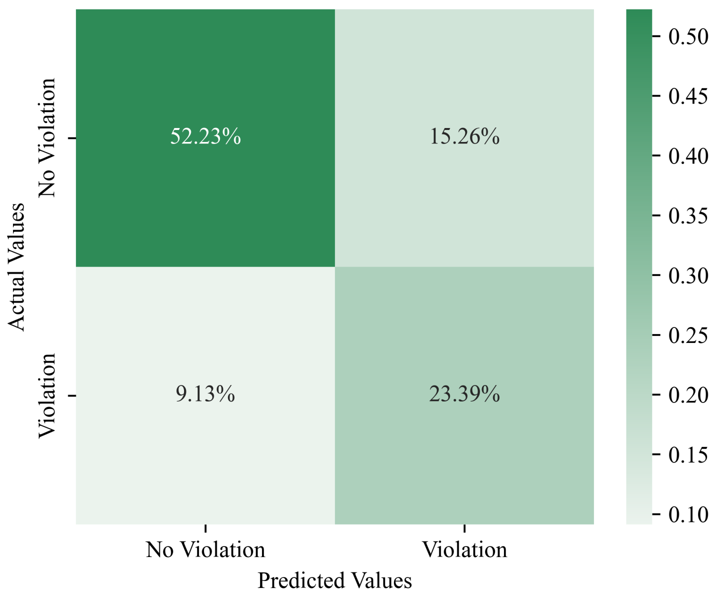
Precision, Recall, F1-score for Test and Validation Data

	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

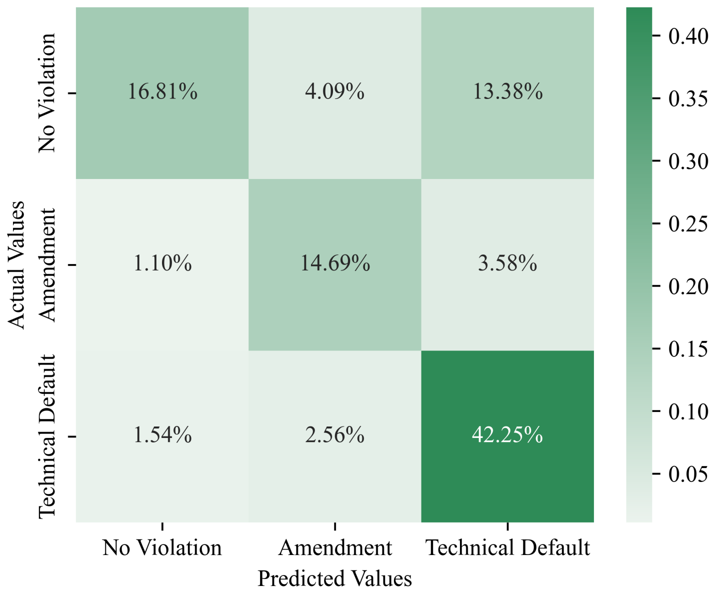
Comparison with the Nini et al. Algorithm



(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 forebearance 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.

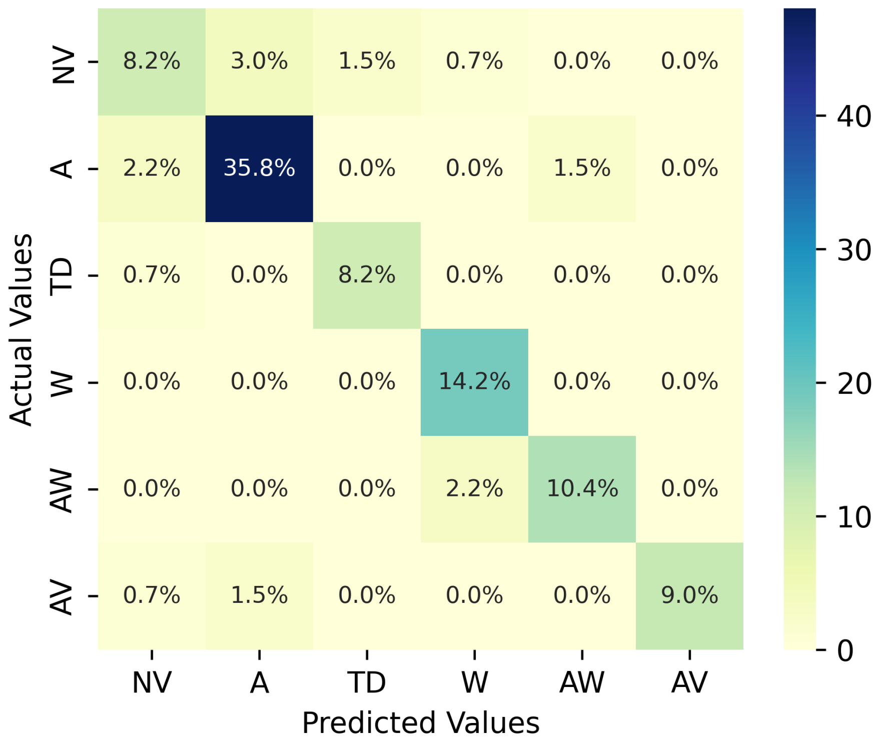
The output format that you have to produce is: json "observation": what is asked of you and what will be useful to consider before completing the task? "thought": based on the observation, how does a person of your capabilities judge the category of the user description? "category label": based on the 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!

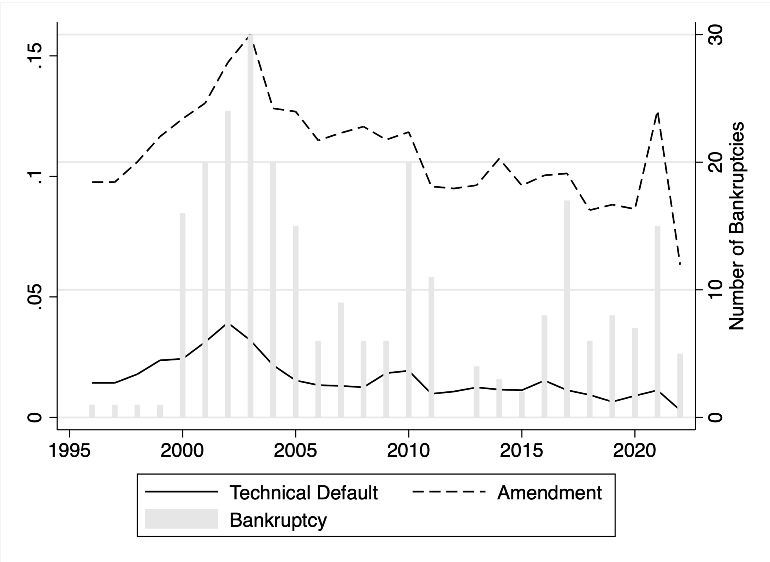
Model Performance Amendment Sub-Categories



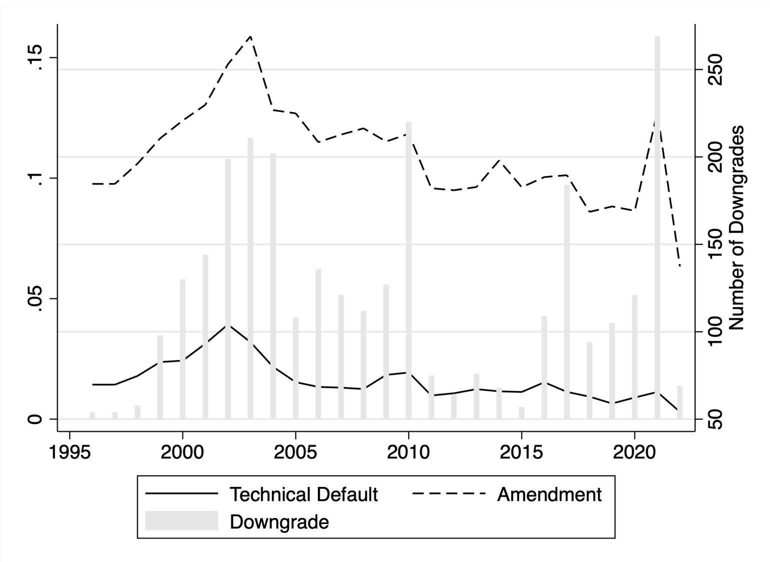
Confusion matrix of CovenantAI with Amendment Sub-Categories
This figure shows the confusion matrix of the dataset after including the amendment sub-categories. We used the following categories: No violation (NV), Amendment without a violation (A), Technical default (TD), Waiver without an amendment (W), Amendment in combination with a waiver (AW), and an Amendment that followed a violation (AV).

D Additional Analyses

Downgrades and Corporate Defaults



Fraction of Bankruptcies



Fraction of Downgrades

Technical defaults and Amendments with Bankruptcies and Downgrades
This figure plots the annual share of technical defaults and loan amendments in comparison to the number of bankruptcies (Panel A) and the number of downgrades (Panel B). The vertical axis on the left side is the yearly amount of technical defaults and amendments in relation to all companies, while the vertical axis on the right side is expressed in total numbers.

Loan Amendments - Financial and Real Adjustments

This table shows the regression results for all dependent variables described in Table 3. This table relates to and is an extension of table 7 and uses therefore the same regression setup. Panel A, D and G show the results just for the Amendment dummy. Panel B, E and H includes the rating categories and Panel C, F and I uses interactions with the rating categories. Panel A, B and C show the regression results for dependent variables giving an indication of the firms investment policy and their employment, Panel D, E and F on the firms financial policies and Panel G, H and I use operational and financial performance variables. We include the first two digits of the standard industry classification and quarter fixed effects and cluster standard errors at the firm and quarter level. Standard errors are reported in parentheses ($^{*}\ p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Investment & Employment

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) $\Delta\frac{CapEx}{Assets}$	(4) $\Delta\frac{CashAcq}{Assets}$	(5) Empl Growth
Amendment	0.039***	0.054***	-0.006	-0.014	-0.907
	(0.015)	(0.018)	(0.006)	(0.009)	(0.760)
Observations	4,953	4,950	4,886	4,722	1,224
R^2	0.176	0.153	0.046	0.047	0.106
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Year
Covenant Controls	YES	YES	YES	YES	YES

Panel B: Policies & Ratings

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) $\Delta\frac{CapEx}{Assets}$	(4) $\Delta\frac{CashAcq}{Assets}$	(5) Empl Growth
Amendment	0.034**	0.051***	-0.006	-0.015	-0.880
	(0.015)	(0.018)	(0.007)	(0.009)	(0.730)
IG	-0.013	-0.017	-0.003	0.038***	-1.043
	(0.016)	(0.019)	(0.004)	(0.013)	(0.658)
Non-IG	0.041***	0.037***	0.000	0.008	-0.483
	(0.011)	(0.013)	(0.004)	(0.009)	(0.490)
Observations	4,953	4,950	4,886	4,722	1,219
R^2	0.180	0.155	0.046	0.049	0.111
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Year
Covenant Controls	YES	YES	YES	YES	YES

Panel C: Policies & Rating Interactions

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) $\Delta\frac{CapEx}{Assets}$	(4) $\Delta\frac{CashAcq}{Assets}$	(5) Empl Growth
IG x Amendment	0.057	0.012	-0.002	-0.021	0.269
	(0.037)	(0.035)	(0.010)	(0.028)	(0.276)
Non-IG x Amendment	0.007	0.008	-0.023	-0.023	0.308
	(0.039)	(0.046)	(0.025)	(0.025)	(0.435)
Unrated x Amendment	0.044***	0.07***	0.000	-0.012	-1.299
	(0.016)	(0.020)	(0.004)	(0.008)	(1.132)
IG	-0.026	0.038	-0.002	0.047*	-2.526
	(0.039)	(0.034)	(0.011)	(0.025)	(1.827)
Non-IG	0.075*	0.095*	0.021	0.018	-2.000
	(0.045)	(0.055)	(0.027)	(0.025)	(1.913)
Observations	4,953	4,950	4,886	4,722	1,219
R^2	0.180	0.156	0.046	0.049	0.115
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Year
Covenant Controls	YES	YES	YES	YES	YES

Panel D: Financial Policies

	(1) $\Delta \frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta \frac{Cash}{Assets}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Amendment	0.033**	0.053	-0.007	-0.027	-0.036**	0.017
	(0.016)	(0.047)	(0.004)	(0.038)	(0.017)	(0.023)
Observations	5,402	4,632	4,951	4,361	2,273	2,553
R^2	0.088	0.100	0.072	0.075	0.100	0.304
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel E: Policies & Ratings

	(1) $\Delta \frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta \frac{Cash}{Assets}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Amendment	0.033**	0.047	-0.007	-0.031	-0.036**	0.019
	(0.016)	(0.047)	(0.004)	(0.038)	(0.017)	(0.023)
IG	-0.012	0.112***	-0.003	-0.059	0.02	-0.086***
	(0.017)	(0.04)	(0.005)	(0.106)	(0.019)	(0.021)
Non-IG	-0.000	0.125***	0.002	0.037	0.014	-0.064***
	(0.013)	(0.033)	(0.003)	(0.039)	(0.011)	(0.016)
Observations	5,402	4,632	4,951	4,361	2,273	2,553
R^2	0.088	0.103	0.072	0.076	0.101	0.309
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel F: Policies & Ratings

	(1) $\Delta \frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta \frac{Cash}{Assets}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
IG x Amendment	0.069	0.053	0.004	0.344	-0.052*	-0.041
	(0.051)	(0.060)	(0.007)	(0.219)	(0.027)	(0.068)
Non-IG x Amendment	0.010	0.014	-0.012*	0.020	-0.083***	0.065*
	(0.040)	(0.090)	(0.006)	(0.109)	(0.028)	(0.035)
Unrated x Amendment	0.040**	0.060	-0.005	-0.082**	-0.007	-0.005
	(0.017)	(0.059)	(0.005)	(0.033)	(0.024)	(0.031)
IG	-0.041	0.118	-0.013	-0.463**	0.063*	-0.049
	(0.054)	(0.085)	(0.009)	(0.222)	(0.036)	(0.084)
Non-IG	0.028	0.169	0.009	-0.057	0.086**	-0.129***
	(0.042)	(0.108)	(0.007)	(0.105)	(0.038)	(0.043)
Observations	5,402	4,632	4,951	4,361	2,273	2,553
R^2	0.088	0.103	0.072	0.077	0.103	0.310
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel G: Operational and Financial Performance

	(1) $\Delta \frac{OpIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) Downgrade	(5) Default
Amendment	-0.012	0.039*	0.061***	-0.004	-0.047***
	(0.012)	(0.020)	(0.020)	(0.028)	(0.012)
Observations	4,815	4,946	4,826	2,334	5,430
R^2	0.313	0.121	0.169	0.146	0.123
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES

Panel H: Policies & Ratings

	(1) $\Delta \frac{OpIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) Downgrade	(5) Default
Amendment	-0.012	0.035*	0.060***	-0.004	-0.048***
	(0.012)	(0.020)	(0.020)	(0.028)	(0.013)
IG	-0.012	0.009	0.002	0.005	-0.013
	(0.010)	(0.023)	(0.021)	(0.026)	(0.008)
Non-IG	0.008	0.055***	0.023	0.000	0.003
	(0.007)	(0.015)	(0.016)	(0.000)	(0.006)
Observations	4,815	4,946	4,826	2,334	5,430
R^2	0.314	0.124	0.170	0.146	0.124
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES

Panel I: Policies & Rating Interactions

	(1) $\Delta \frac{OpIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) Downgrade	(5) Default
IG x Amendment	-0.007	0.031	0.064	-0.094	-0.043
	(0.015)	(0.056)	(0.078)	(0.136)	(0.050)
Non-IG x Amendment	-0.038	0.030	0.132***	0.010	-0.139***
	(0.033)	(0.034)	(0.046)	(0.030)	(0.039)
Unrated x Amendment	-0.003	0.038	0.031	0.000	-0.012
	(0.014)	(0.025)	(0.021)	(0.000)	(0.009)
IG	-0.008	0.015	-0.027	0.104	0.014
	(0.019)	(0.060)	(0.076)	(0.150)	(0.052)
Non-IG	0.042	0.062	-0.070	0.000	0.120***
	(0.038)	(0.040)	(0.055)	(0.000)	(0.041)
Observations	4,815	4,946	4,826	2,334	5,430
R^2	0.314	0.124	0.171	0.147	0.140
FE	Industry Quarter	Industry Quarter	Industry Quarter	Industry Quarter	Industry Quarter
Covenant Controls	YES	YES	YES	YES	YES

Covenant Violations - Amendments vs. Waivers

This table is an extension of Table 8 and uses the same regression setup. Panels A, B, and C show the regression results for all variables used in Table 3. We additionally include the rating categories (Panel D) and interactions with the rating categories (Panel D) for the in Table 8 selected variables. Standard errors are reported in parentheses (* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Panel A: Investment & Employment

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) $\Delta \frac{CapEx}{Assets}$	(4) $\Delta \frac{CashAcq}{Assets}$	(5) Empl Growth
Amendment w/o Violation	0.050***	0.050***	-0.002	-0.001	-0.501
	(0.013)	(0.016)	(0.006)	(0.009)	(0.442)
Amendment w/ Violation	0.013	0.020	-0.005	-0.003	-0.657
	(0.015)	(0.020)	(0.006)	(0.010)	(0.560)
Waiver	0.014	0.031	-0.004	-0.009	-0.303
	(0.016)	(0.020)	(0.007)	(0.008)	(0.441)
Observations	5,914	5,911	5,851	5,673	1,250
R^2	0.191	0.157	0.044	0.043	0.122
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES

Panel B: Financial Policies

	(1) $\Delta \frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta \frac{Cash}{Assets}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Amendment w/o Violation	0.014	0.119***	-0.005	0.004	-0.004	-0.061***
	(0.014)	(0.042)	(0.004)	(0.033)	(0.018)	(0.022)
Amendment w/ Violation	0.026*	0.043	-0.001	0.002	-0.007	0.038
	(0.015)	(0.048)	(0.004)	(0.035)	(0.018)	(0.024)
Waiver	0.043***	0.007	-0.003	0.050	-0.016	0.043*
	(0.015)	(0.048)	(0.004)	(0.039)	(0.018)	(0.025)
Observations	6,507	5,556	5,912	5,185	2,621	2,985
R^2	0.082	0.100	0.063	0.073	0.075	0.266
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter

Panel C: Operational and Financial Performance

	(1) $\Delta \frac{OpIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) Downgrade	(5) Default
Amendment w/o Violation	-0.015**	0.047**	0.055***	0.007	-0.038***
	(0.007)	(0.019)	(0.015)	(0.025)	(0.010)
Amendment w/ Violation	-0.017**	0.014	0.043**	-0.017	-0.034***
	(0.008)	(0.019)	(0.017)	(0.029)	(0.010)
Waiver	-0.007	0.024	0.037**	0.013	-0.032***
	(0.008)	(0.018)	(0.017)	(0.033)	(0.009)
Observations	5,746	5,905	5,756	2,650	6,541
R^2	0.310	0.129	0.173	0.138	0.112
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES

Panel C: Policies & Ratings

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) Ln(Δ Shareholder Payout)	(4) Cash Ratio	(5) Ln(Δ Cost)	(6) $Default_{t+4}$
Amendment w/o Violation	0.0447***	0.0442***	0.00683	-0.00523	0.0552***	-0.0418***
	(0.0133)	(0.0162)	(0.0319)	(0.0182)	(0.0150)	(0.0104)
Amendment w/ Violation	0.0114	0.0188	0.00148	-0.00711	0.0428**	-0.0346***
	(0.0148)	(0.0202)	(0.0351)	(0.0181)	(0.0172)	(0.0102)
Waiver	0.0143	0.0317	0.0481	-0.0160	0.0368**	-0.0312***
	(0.0155)	(0.0202)	(0.0398)	(0.0183)	(0.0170)	(0.00907)
IG	-0.0128	-0.00306	-0.134	-0.000272	-0.0234	0.0202**
	(0.0145)	(0.0173)	(0.101)	(0.0153)	(0.0170)	(0.00831)
Non-IG	0.0411***	0.0441***	0.0116	0.00715	0.00701	0.0204***
	(0.0117)	(0.0132)	(0.0319)	(0.0101)	(0.0134)	(0.00701)
Observations	5,914	5,911	5,185	2,621	5,756	6,541
R^2	0.195	0.160	0.075	0.075	0.173	0.116
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel D: Policies & Rating Interactions

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) Ln(Δ Shareholder Payout)	(4) Cash Ratio	(5) Ln(Δ Cost)	(6) $Default_{t+4}$
IG x Amendment w/o Violation	0.0355*	0.0480*	-0.108	0.0175	0.0199	0.00419
	(0.0190)	(0.0267)	(0.0911)	(0.0334)	(0.0255)	(0.0102)
Non-IG x Amendment w/o Violation	0.0925***	0.0999***	0.000380	0.0214	0.0506**	-0.00562
	(0.0142)	(0.0206)	(0.0429)	(0.0279)	(0.0225)	(0.00977)
Unrated x Amendment w/o Violation	0.0522***	0.0614***	-0.0230	0.0198	0.0446**	-0.00356
	(0.0126)	(0.0206)	(0.0286)	(0.0274)	(0.0190)	(0.00741)
IG x Amendment w/ Violation	0.0147	0.0217	-0.279	0.00172	-0.0689	0.0472
	(0.0259)	(0.0391)	(0.422)	(0.0506)	(0.0725)	(0.0398)
Non-IG x Amendment w/ Violation	0.0619***	0.0799***	-0.0479	0.0198	0.0675**	0.0125
	(0.0190)	(0.0297)	(0.0481)	(0.0318)	(0.0270)	(0.0139)
Unrated x Amendment w/ Violation	0.0165	0.0310	0.00487	0.0169	0.0221	-0.00880
	(0.0170)	(0.0239)	(0.0279)	(0.0293)	(0.0205)	(0.00806)
IG x Waiver	0.0363	0.0954***	-0.352	-0.0303	0.0222	-0.00890
	(0.0271)	(0.0297)	(0.217)	(0.0677)	(0.0403)	(0.0110)
Non-IG x Waiver	0.0468*	0.0777**	0.107	0.0157	0.0242	0.0286*
	(0.0255)	(0.0333)	(0.0848)	(0.0331)	(0.0376)	(0.0147)
Unrated x Waiver	0.0244	0.0462**	0.0205	0.00706	0.0274	-0.00727
	(0.0148)	(0.0230)	(0.0314)	(0.0287)	(0.0189)	(0.00594)
IG x Technical Default	-0.0136	0.0481	-0.281*	0.0580*	0.0623	0.0416
	(0.0357)	(0.0316)	(0.160)	(0.0315)	(0.0782)	(0.0448)
Non-IG x Technical Default	0.0654*	0.0860**	-0.0382	0.0635	-0.0451	0.113***
	(0.0350)	(0.0364)	(0.0865)	(0.0397)	(0.0412)	(0.0339)
Observations	5,914	5,911	5,185	2,621	5,756	6,541
R^2	0.195	0.160	0.076	0.077	0.174	0.129
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

E Evolution of Covenants in Loan Agreements

Development of Covenants

This table shows the development of the covenant violations over time. The values indicate the occurrence within loans and are shown in percentage.

Panel A: Performance-based Covenants							
Year	Debt-to-EBITDA	Fixed-charge Coverage	Interest Coverage	Debt Service Coverage	Senior Debt-to-EBITDA	EBITDA	Cash Interest Coverage
2000	64.10	43.75	47.84	13.14	14.42	9.54	1.84
2001	64.34	48.34	47.29	8.74	11.19	13.99	2.53
2002	66.49	48.10	44.56	9.07	11.92	15.46	1.55
2003	68.46	50.23	44.59	7.22	14.43	18.41	1.85
2004	70.55	53.03	46.51	7.64	18.17	18.27	1.03
2005	68.47	49.56	45.32	6.60	17.34	17.04	0.79
2006	68.04	44.02	43.14	4.71	15.78	14.71	0.98
2007	72.94	42.35	44.55	3.63	17.05	13.86	0.44
2008	70.92	41.05	42.30	3.53	15.17	12.77	0.68
2009	73.96	43.28	40.95	2.08	12.35	8.80	0.12
2010	72.54	42.88	44.17	3.63	12.95	9.07	0.26
2011	74.96	32.98	49.01	2.44	12.21	6.41	1.22
2012	73.63	35.71	44.51	2.38	8.42	5.86	0.37
2013	77.21	28.45	46.82	3.53	8.66	4.24	0.35
2014	75.74	26.40	45.38	2.48	8.42	3.96	0.50
2015	75.63	25.11	42.05	2.38	6.39	2.67	0.30
2016	74.45	23.94	43.07	1.75	9.20	2.77	1.02
2017	77.05	27.38	42.62	0.82	12.79	1.64	0.66
2018	78.54	22.80	38.94	0.83	11.81	1.00	0.67
2019	79.18	20.07	43.49	2.04	9.29	0.56	1.30
2020	86.57	17.16	41.79	1.49	8.96	0.75	2.24

Panel B: Capital-based Covenants									
Year	Tangible Net Worth	Leverage	Debt-to-Tangible Net Worth	Current Ratio	Quick Ratio	Debt-to-Equity	Senior Leverage	Loan-to-Value	Capex
2000	21.71	16.59	12.42	11.54	4.33	0.88	0.16	0.24	25.56
2001	19.41	16.87	9.97	9.70	2.27	0.79	0.17	0.09	30.24
2002	17.10	14.51	7.43	8.98	2.42	0.69	0.09	0.26	35.66
2003	16.84	12.21	7.49	6.85	1.67	0.46	0.09	0.09	40.70
2004	15.56	10.72	5.50	5.31	1.49	0.37	0.37	0.09	45.39
2005	10.94	10.64	5.71	5.52	1.08	0.39	0.00	0.39	42.46
2006	11.08	9.71	5.49	5.20	1.37	0.20	0.29	0.39	39.31
2007	7.59	7.70	3.41	6.16	0.77	0.33	0.55	0.55	37.29
2008	7.18	8.32	3.42	6.39	0.68	0.46	0.00	0.00	36.49
2009	6.11	8.80	2.93	8.19	0.86	0.00	0.24	0.00	31.78
2010	6.09	7.12	2.46	5.57	1.04	0.00	0.39	0.13	33.16
2011	4.58	5.34	1.83	4.58	0.76	0.31	0.31	0.00	31.30
2012	4.58	7.14	1.65	4.58	0.73	0.37	0.00	0.00	28.39
2013	2.30	5.48	1.06	6.18	0.00	0.18	0.18	0.00	24.03
2014	2.15	8.25	0.99	4.95	0.66	0.50	0.33	0.33	18.65
2015	2.82	10.40	1.78	3.86	0.74	0.15	0.30	0.15	12.93
2016	3.07	11.09	1.46	3.21	0.29	0.15	0.15	0.29	10.51
2017	2.46	9.18	0.33	4.10	0.49	0.00	0.49	0.33	9.02
2018	2.50	8.99	0.33	3.66	0.17	0.67	0.33	0.00	5.82
2019	3.34	9.29	1.67	2.79	0.19	0.19	0.00	0.00	5.76
2020	0.00	6.72	0.75	2.99	0.75	0.00	0.00	0.00	4.48

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