Covenant Violations, Loan Amendments, and Financial Distress in US Publicly Listed Firms: A Machine Learning Approach*

Vanessa S. Krockenberger
Frankfurt School of Finance & Management

Anthony Saunders
NYU Stern School of Business

Sascha Steffen
Frankfurt School of Finance & Management

Paulina M. Verhoff
Frankfurt School of Finance & Management

November 22, 2023

PRELIMINARY AND INCOMPLETE VERSION

*Corresponding author: Sascha Steffen, Frankfurt School of Finance & Management, Adickesallee 32-34. 60322 Frankfurt, Germany. E-mail: s.steffen@fs.de.
Authors: Vanessa S. Krockenberger (vanessa.simoes@fs-students.de), Anthony Saunders (asaunder@stern.nyu.edu), Paulina Verhoff (P.Verhoff@fs.de)
We thank Viral Acharya, Alexander Becker, Felix Corell, Iftekhar Hasan, Loriana Pelizzon, Jukka Sihvonen and Daniel Streitz and participants Bonn-Frankfurt-Mannheim PhD Conference 2023, 11th Workshop Banks and Financial Markets in Halle, 4th Vaasa Banking Research Workshop and New (and Old) challenges to Financial Intermediaries Conference in Bayes Business School for comments and suggestions and VS Chaitanya Madduri for excellent research assistance.

Abstract

We create a natural language processing (NLP) machine learning model to identify covenant violations using 10K and 10Q filings provided by the Securities and Exchange Commission (SEC). Our sample includes more than 580,000 filings comprising the universe of all publicly listed U.S. firms and spanning the entire 1996 to 2022 period. We use the MPNET Sentence Transformer as a classification algorithm and obtain a model accuracy of 94.4%, considerably higher than conventional manual approaches. Importantly, we are able to differentiate between firms that obtain an amendment after or before a covenant violation occurs and those that remain in technical default. Covenant violations have significantly declined over the past two decades. During this time, the percentage of firms that received an amendment increased while those in technical default decreased. The decline in violations was driven by non-investment-grade rated and unrated firms and intensified during the COVID-19 pandemic. Firms in technical default perform considerably worse on a number of dimensions, such as leverage or liquidity and they draw down a larger percentage of their credit lines, in the eight quarters before a covenant violation. They recover quickly after a violation, specifically in terms of leverage ratio and operating income. Moreover, they make larger changes in their investment and financial policies as compared to firms that obtain amendments. Again, the effects are mainly driven by non-investment-grade rated and unrated firms. Not surprisingly, non-investment-grade rated firms are about 17% more likely to declare bankruptcy in the eight quarters following a covenant violation. This effect is substantially muted in the sample of firms that obtain loan amendments.

JEL classification: G21, G32, G34

Keywords: Covenant violations, loan amendments, big data, NLP, large language models, ChatGPT, 10K/Q, default, secondary loan market, COVID-19

1 Introduction

Previous studies have established the pivotal role of covenants and covenant violations in both corporate and macro-finance contexts.[1] However, the exploration of covenant violations remains somewhat limited, often focusing on specific, isolated events. This scarcity in research is likely due to the reliance on manually classifying these violations, a process that is both time-consuming and expensive. Moreover, there is a noticeable gap in understanding the significance of loan amendments, which typically precede or result from covenant violations. Sources like Refinitiv Dealscan offer limited insights into covenants, their violations, and subsequent loan amendments. This paper aims to address several key questions: How do the terms of loan contracts, particularly covenants, evolve after an amendment? What factors influence a firm's ability to secure a loan amendment or waiver before or after a covenant violation, as opposed to falling into technical default? What are the outcomes for firms that manage to obtain amendments compared to those that go into technical default? How do these groups differ in their post-violation performance, and does this affect their likelihood of bankruptcy? Additionally, we investigate how these impacts vary among firms with different credit ratings - investment-grade, non-investment-grade, and unrated. These inquiries form the core of our research in this study.

[1] The effects of covenant violations on firm-level outcomes are documented in, for example, (Chava and Roberts, 2008); (Roberts and Sufi, 2009); (Nini et al., 2012); (Falato and Liang, 2016); (Freudenberg et al., 2017), (Chodorow-Reich and Falato, 2022) and (Ersahin et al., 2021). Matvos (2013) and Green (2018) estimate the ex-ante benefits of including financial covenants in debt contracts, Adler (2020) argues that firms reduce investments to avoid a covenant violation. There is also recent macro literature studying models with earnings-based constraints (Drechsel, 2022 and Greenwald et al., 2019).

Our first contribution is methodological in nature. We introduce a new machine learning (ML) algorithm that allows researchers to obtain quarterly information on covenant violations for all U.S. firms directly from their 10K and 10Q filings with the Securities and Exchange Commission (SEC). To calibrate our model, we obtain more than 580,000 10K and 10Q filings using the CIK identifier of the universe of Compustat firms. We apply a small set of filters (described in detail in Section 2). Our final dataset comprises 11,430 U.S. publicly listed non-financial firms over the 1996 to 2022 period. 21.9% of these firms are rated by S&P; 6.2% are investment-grade (IG) rated, and 16.7% are non-investment-grade (non-IG) rated. The average firm in our sample has a rating of BB-.

As a first step, we create a dataset consisting of sentences from 10K and 10Q filings that contain the word covenants as well as the 700 characters surrounding the word. We then establish the ground truth and label firm-quarter observations as "in violation of a covenant (i.e., in technical default)", "not in violation of a covenant" or as an "amendment" based on a quasi-random subset of all SEC filings (we provide examples from SEC filings and how we classify amendments in the Appendix A.4). We split this sample into a training, test, and validation dataset and use the training dataset to calibrate our model.

We use the MPNET Sentence Transformer as our classification model, a reliable model to categorize supervised data, which is pre-trained on an extensive dataset, including 32 diverse sources such as the Semantic Scholar Open Research Corpus, Stack Exchange comments, and WikiAnswers, compromising over one billion sentence pairs in total. We fine-tune our model parameters to minimize the occurrence of the so-called "false negatives", i.e., firms that are identified by the model as being in technical default but which are not, as these firms might have obtained an amendment to cure a covenant violation. We test the final model using our test dataset and find that it identifies all three outcomes with an accuracy of 94.4%.[2] We validate our model and identify covenant violations and amendments for our full sample of quarter-firm observations. To validate our ML algorithm, we implement a manual approach used by Nini et al. (2012) on our final dataset and compare the performance of both approaches. Overall, the accuracy of our ML model is about 20 percentage points higher compared to the manual approach.

Importantly, we show that covenant violations are even more pervasive than previously reported in the literature. Our data suggests that about 50% of all U.S. publicly listed firms violate covenants are some point over our 26-year sample period (1996-2022).

We then investigate the time series of covenant violations and loan amendments. While we observe a cyclicality of violations and amendments (i.e., both increase during an economic downturn), we document a decline in covenant violations since the early 2000s consistent with, for example, Griffin et al. (2021). Interestingly, the percentage of firms that obtain an amendment after a covenant violation has increased, while the number of firms that stay in technical default has decreased. The percentage of firms with covenant violations and amendments has been relatively constant and around 5% for IG-rated firms over our entire sample period. That is, the decline is mainly driven by non-IG-rated and unrated firms.

[2] We use other performance measures to evaluate our model, such as precision and recall, as our data is imbalanced, which is described in Section 3.

The time-series suggest that the COVID period stands out in terms of the likelihood that we observe loan amendments over the 26-year period. Strikingly, 17% of all IG-rated firms obtained a loan amendment during the Q1 to Q4 2020 period, which is about three times higher compared to the long-run average of IG-rated firms that obtain amendments. Also, more than 20% of all non-IG rated firms obtained an amendment, which is similar in magnitude to the 2001-2003 recession.

In the next step, we investigate key performance measures of firms that experience technical default vis-a-vis those that obtain amendments over a period starting 8 quarters before a covenant violation up to 8 quarters after a violation occurred. Overall, the development of these measures is as expected, and we observe a substantial deterioration of firm performance leading up to a covenant violation. For example, operating income relative to assets declines by about 40%, leverage ratio, on average, increase by 20%, and firm liquidity (measured as a firm's current ratio) declines by about 30%. Usage rates of credit lines almost double during this period. Stock prices reflect this, and market-to-book ratios drop by more than 12%. Importantly, firms that stay in technical default perform considerably worse on a number of dimensions, such as liquidity or credit ratings, in the quarters before a covenant violation occurs compared to firms that obtain loan amendments.

After the covenant violation, we observe substantial performance differences between both types of firms. Firms that remain in technical default begin to recover sooner and recover faster. Measures related to debt, which is likely restructured with lenders, improve more for firms that are in technical default, and debt level as well as interest expenses decline. However, firms improve significantly more in terms of the net worth ratio and operating income after a violation.

What do covenant violations and amendments imply for firms' financial and investment policies? We first analyze how firms change their policies in the four quarters after a technical default. We use similar firm characteristics as in Nini et al. (2012) and Roberts and Sufi (2009) show that firms start divesting assets as well as significantly reduce new investments and their tangible assets. Moreover, consistent with more restrictive access to debt markets, we find that firms reduce leverage following a covenant violation, and they repay their credit lines. Also, their performance further deteriorates, as shown, for example, by a reduction in sales in the post-violation period.

We then investigate possible differences across rating categories and show that changes in financial and investment policies are mainly attributed to non-IG and unrated firms. This is intuitive as these firms likely face more difficulties accessing alternative funding sources. Specifically, they reduce total assets, property, plant and equipment but also debt more than IG-grade rate firms, and they also increase their cash holdings.

We find similar changes in policies for firms that obtain amendments after covenant violations. That is, they reduce assets, investments, and leverage. However, compared to firms that go into technical default, the economic magnitude of the effects are substantially muted and about 10% the size. Again, the effects are driven by firms that are non-IG rated or unrated.

As the COVID period clearly stands out in terms of covenant violations and amendments, we show all tests for the full sample period as well as up to (and including) Q4 2019, i.e., before the onset of the COVID-19 pandemic. These tests show that our results are not driven by the COVID pandemic.

In our final tests, we investigate whether firms in technical default are more likely to be downgraded or declare bankruptcy. This appears to be indeed the case, and the results are intuitive. First, firms in technical default are 5.1% (5.3%) more likely to default in four (eight) quarters after a violation. Second, while firms that obtain amendments are also more likely to default, the effect is much smaller. Third, and consistent with our earlier results, the effects are again driven by non-IG and unrated firms. More precisely, a non-IG-rated firm that enters a technical default is between 16.7% and 16.6% more likely to default four or eight quarters after a covenant violation, respectively. Again, the default likelihood drops by more than 90% when a firm obtains an amendment.

Related literature. [To be completed]

The paper proceeds as follows. We discuss the data in Section 2. In Section 3, we develop our ML algorithm and compare it to a traditional manual approach. We discuss the time series of covenant violations and amendments in Section 4. In Section 5, we discuss implications for firm investments, financing, and performance, and in Section 6 on firm rating downgrades and defaults. Section 7 concludes and provides an overview of our ongoing research.

2 Data sources

To identify and analyze the implications of covenant violations, we need information about firm fundamentals, their annual reports as well as performance and rating data. We obtain this information from different data sources.

2.1 Company data

Compustat/CRSP. As a first step, we use the Compustat database to identify the set of companies that is part of our analysis. We download quarterly financial data for all US companies over the 1996 to 2022 period. We apply different filters: we only keep observations with total assets larger than USD 10 million. We further exclude companies that have missing or negative values for the following financial variables: fiscal year, total assets, sales, common shares outstanding, and the share closing price. We keep only non-financial firms and therefore exclude companies with a SIC code between 6000-6999. We use the United States Department of Labor definition to group firms by their SIC codes; the classification can be found in the Appendix (Table 10). Finally, we drop all data with a missing CIK identifier. All variables are described in the Appendix (Table 9). Our final dataset comprises 377,653 firm-quarter observations, including 11,430 US non-financial firms.

Capital IQ. We obtain quarterly information about the usage of credit lines of U.S. publicly listed from from the Capital IQ database. Computstat/CRSP and Capital IQ can be merged using the GVKEY-CIK identifier.

Credit ratings. We obtain credit rating information from Standard & Poor's

(S&P). Our information contains the long-term issuer ratings as well as the rating data and unique company ID. We use the WRDS mapping file to match the gvkey (the common Compustat identifier) to the firm rating. We transform the rating into a numerical scale, as shown in the appendix (Table 11).[3] Overall, 77.6% of our sample firms are unrated, 6.0% are investment-grade (IG) rated, and 16.4% are non-investment-grade (non-IG) rated.

2.2 Loan data

Primary market. We obtain loan data at the deal and facility level from Refinitiv Dealscan. We extend the Chava and Roberts (2008) Dealscan-Compustat link to 2022. From our 11,430 US non-financial firms, we are able to match about 60%, i.e., 6,934 unique firms to Dealscan (which corresponds to 26,561 deals).[4] Dealscan provides us with terms *at origination* of the loan including spread, amount, lenders but also initial covenants.

Secondary markets. We obtain data about daily secondary market trading from Refinitiv Dealscan.

2.3 SEC filings

In this section, we describe how we access, download, and clean the 10K, 10Q and 8K SEC filings for our machine learning algorithm. 10K reports are published at the

[3] If a company has a rating number 26 or 27, it means that it is rated as "D" or in a selective default (SD). We do not use this information but match our companies to the LoPucki bankruptcy database for our empirical tests. Both approaches, however, identify similar corporate defaults.

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

end of a company's fiscal year, while the 10Q reports are required to be published at least for the first three quarters. If a company only publishes three quarters, the 10K reports are about the fourth quarter. Therefore, we merge the 10K filings with the quarterly filings in order to have no gaps in our data set. 8K reports are published for specified events, like bankrupcty or CEO turnover, that may be important for the companies shareholders.

In 2009, the XBRL filing program became mandatory for all companies. This filing program ensures a standardized structure for all reports, which makes it easier for our algorithm to analyze these companies. Covenant violations are reported in both annual and quarterly reports. The downloading and cleaning processes for both formats is similar and described below.

We download the 10K reports for the companies in our dataset from SEC Edgar and access the company fillings using the CIK identifier. Overall, we extract 132,591 10K files and 451,826 10Q files over the 1996 to 2022 period. Because 8Ks can be filed more than four times a year, we download in total 1,285,768 8K reports. The downloaded filings are renamed and stored in predefined folders. In contrast to other machine learning models, like the logistic regression, we do not need to clean the files, since the underlying model can process the whole sentence. We create a data frame with all paragraphs containing the word "covenant" and include 700 characters around the word "covenant" to extract all the useful information for the model. Some of the files were provided in HTML format and others, mostly older, just in txt format. We checked those paragraphs where the model is available in the HTML format again to ensure processing not more than 700 characters, since the model would not be able to handle this. To reduce the number of paragraphs that need to be labeled by the algorithm, we apply a first filter on the dataframe. The filter marks all paragraphs containing specific word combinations as potential amendments or violations.[5]. For validation, we extract a random sample and check if the potential violation and amendment classification was done correctly. After applying this filter we end with a total of 1,081,905 paragraphs that need to be labeled by the algorithm.

3 Identifying covenant violations using a machine learning algorithm

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).

[5] If the following words occured in the paragraphs we marked it as a potential amendment or violation: "amends", "waived", "amending", "violate", "amendment", "amended", "violations", "waiving", "violating", "violates", "waives", "amendments", "compliances", "compliance", "amend", "waive", "violation", "violated"

3.1 Step 1: Labeling covenant violations

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 future 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. If we do not find a loan amendment, the firms are classified as being in technical default. We provide examples of SEC filings to demonstrate our labeling into amendments and technical default in Appendix A.4 of this paper.

We label the observations such that the observations have a value of 0 if there is no covenant violation in the specific quarter. It has a value of 1 if the filings report an amendment of a loan. Finally, the observation is assigned a value of 2, if the firm stays in technical default 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 observations with technical defaults and 606 amendments, which is almost 17,34%, respectively 15,18%, of the firm-quarter sample. The high number of technical defaults and amendments is a mechanic, given our sampling procedure. We try to balance the number of quarterly observations with firms with amendments and in technical default to have enough data to train and validate the model.[6] 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.

3.2 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 the test data (25%) and training data (75%). The training dataset consists of 467 technical default, 409 amendment, and 1,817 no-violation observations, while the test dataset is composed of 156 technical default, 136 amendment, and 606 non-violations. The validation dataset, in turn, consists of 69 technical default, 61 amendment, and 270 non-violation observations. While the train data is

[6] 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.

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[7]. 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

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

in the Appendix A.5.

Figure 1 shows the confusion matrix based on our machine learning algorithm. Panel A represents the confusion matrix based on the 898 test data, while Panel B is calculated based on the 400 validation data. The predicted values are on the horizontal axis, and the true values are on the vertical axis. After the optimization of the parameters of the model, we document an accuracy of our classification model of 94.79% using the test data. To verify the results, the accuracy derived from the validation data is closely approximated with 94%. We find that our text search algorithm detects 90.85% of the violation sentences and 97.15% of the sentences that do not imply a violation using the test dataset.

To get a better understanding of the performance of the machine learning algorithm, we calculate the "precision" and "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. 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. It is used for datasets where the false negatives should be minimized (Müller and 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. Table 12 displays recall, precision, and f1-score of both datasets.

3.3 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 of the SEC filing and the covenant violation date mentioned in the filing. If the difference between both is larger than 182 days, we do not count the observation as a violation, as it contains information about a previous violation that has already been reported (and recognized as such by our model). We apply the same machine learning algorithm to the 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 classify all covenant violations as amendments if they are followed by an amendment in the two quarters after the violation has been first reported. We construct the variable $CovVio^{New}$ that has the value 1 if a company is in technical default in the quarter but has not violated a covenant in the previous two quarters. The variable $Amendment^{New}$ has the value 1 if a company obtained an amendment but did not violate a covenant in the previous two quarters. Applying our ML algorithm using these criteria, we obtain 27,627 (7.32%) loan amendments and 4,351 (1.15%) observations with firms in technical default for all firm quarters. The number of firm quarters, in which we find a "new" technical default is 1,579 (0.42%), and in which we find a "new" amendment is 11,497 (3.04%).

3.4 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 our observations. 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 1) and that based on our manual classification (Figure 6b).

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 (Appendix Figure 6a), 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 occur when our model incorrectly predicts a case as a covenant violation, whereas it is actually a non-violation instance. Conversely, false positives happen when our model identifies a scenario as a non-violation, even though it is, in fact, 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 A.7. 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 7) has an accuracy of 73.75%, which is more than 20% less than the accuracy of our model (Figure 1).

4 Time-series of covenant violations

We first investigate the time series of covenant violations over the 1996 to 2022 period. Panel A of Figure 2 shows the number of new technical defaults and amendments scaled by the total number of observations within a year for our full sample. The shaded areas represent the NBER recession periods. Panel B shows the time-series of new covenant violations (left axis) and the percentage of new technical defaults and amendments relative to the total number of violations in the respective year (right axis).

Panel A shows a cyclicality of covenant violations and amendments during periods of economic downturns and recessions. For example, both time-series spikes during the 2001-2003 period and the burst of the dotcom bubble. The time series spiked again during the global financial crisis, albeit at a lower level compared to the 2001-2003 period. Most strikingly, we observe a decline of firms in technical default since the 2001-2003 period, which (if anything) even intensified during the COVID-19 recession. For example, we find that 14% of firms violated covenants in 2008 during the global financial crisis; this percentage decreased and then rose to a similar level during the COVID-19 pandemic.

Interestingly, loan amendments have also declined (but somehow less compared to technical defaults) since the 2001-2003 recession. However, they increase significantly during the COVID-19 episode, likely highlighting lenders' willingness to help their borrowers address the challenges arising from the pandemic and avoid covenant violations. That is, more loan amendments at least partially explain the decrease in covenant violations.[8]

Panel B illustrates the temporal progression of covenant violations (represented on the left y-axis) alongside the proportion of either technical defaults or amendments (indicated on the right y-axis). Initially, in 1996, approximately 12% of firms experienced covenant violations. This figure rose to just over 19% by 2001 before gradually declining to around 5% over the subsequent two decades. A consistent pattern observed is the high percentage of amendments relative to technical defaults. In 1996, amendments constituted about 85% of cases, with the remaining 15% being technical defaults. Over time, there has been a notable shift, with the incidence of technical defaults decreasing and amendments becoming more prevalent. This trend particularly intensified during the COVID period. By the end of the observed timeframe, amendments accounted for over 95% of all cases, with technical defaults making up less than 5%.

Figure 3 presents a time series analysis of technical defaults and loan amendments, categorized by credit ratings for Investment Grade (IG)-rated firms (Panel

[8] Griffin et al. (2021) also document a decline in covenant violations using annual data over the 1996 to 2016 period. They, however, do not differentiate between violations and amendments, which is the focus of this paper. They suggest that the decline in violations might be due to less restrictive covenants to prevent costly renegotiations of debt contracts.

A), Non-IG-rated firms (Panel B), and Unrated firms (Panel C). This figure also highlights periods of economic recession as defined by the National Bureau of Economic Research (NBER) through shaded areas. Across all rating classes, a similar pattern of cyclicality is evident. Notably, IG-rated firms show a consistently low and stable occurrence of covenant violations across the 25-year period. In contrast, the observable decrease in both covenant violations and amendments is predominantly attributed to Non-IG-rated and Unrated firms.

During the COVID-19 pandemic, there was a significant increase in the number of amendments. For instance, the proportion of Investment Grade (IG)-rated firms experiencing covenant violations tripled during this period compared to their long-term average. Specifically, around 17% of IG-rated firms in our dataset encountered at least one covenant violation during the pandemic quarters (Q1 - Q4 2020). The prevalence of amendments in this group was comparable to that observed in the non-IG rated firms, around 20%, and almost double that of unrated firms. Intriguingly, by the end of the period we studied, the percentage of amendments converged to around 5% across all categories of credit ratings.

5 Implication of covenant violations

In this section, we investigate the implications of covenant violations for our sample of US non-financial firms. Initially, we provide a concise overview of key characteristics of these firms through summary statistics. Following this, we employ graphical methods to examine the performance of firms prior to covenant violations, focusing on specific firm metrics commonly utilized in loan covenants. Subsequently, we explore how covenant violations influence the investment and financing strategies of these firms. A critical aspect of our analysis involves distinguishing between firms that secure amendments and those that remain in technical default. This distinction is vital for understanding the effects of lender intervention and control rights in the aftermath of covenant breaches.

5.1 Summary statistics

Full sample. Table 1 shows the summary statistics of our sample consisting of 11,430 non-financial US companies over the 1996 to 2022 period. All quarterly variables are annualized. Panel A shows firm characteristics and Panel B shows the distribution of covenant violations and amendments across the rating categories over the 26-year sample period.

On average, 12% (45%) of our sample firms remain in technical default (amend a loan) after a covenant violation at some point during our sample period. The median firm has total assets of USD 191 million with a leverage ratio of 20% and a PPE/Asset ratio of 0.15. The median company has a BB- (i.e., non-IG) rating.

Panel B shows the distribution of firms that violate a covenant across rating categories over our sample period. For example, of all firms that violate a covenant, about 21.43% are non-IG-rated and 78.57% are unrated. As expected, the percentage of IG-rated firms that amend their loans or never violate is higher, 6.02% and 5.54%, respectively. Consistently, the percentage of non-IG-rated firms that at one point during our sample period violate (amend) a loan is higher compared to those that never violate, i.e., 21.43% (29.45%) and 13.33%, respectively.

Violations vs. amendments. In Table 2, we provide summary statistics of firms that (a) remain in technical default in Panel A and (b) obtain an amendment in Panel B. In Panel C, we provide differences in mean tests for key firm characteristics.

Overall, 288 firms (i.e., 2.52% of the 11,430 firms that we observe across the entire sample period) stay in technical default, and 4,088 firms (or 35.77%) violate covenants but obtain an amendment. Panels A and B show the respective firm characteristics. Focusing on the differences-in-mean test in Panel C, we find that firms that experience a technical default have a higher leverage ratio, a higher debt-asset ratio, and a worse credit rating.

In the next section, we investigate the pre- and post-violation performance of these types of firms.

5.2 Pre- vs. post-violation performance

Figure 4 shows the development of key performance measures for firms spanning the 8 quarters leading up to a covenant violation up to 8 quarters following a covenant violation.[9] There are: (1) Operating Income-to-Assets (*OpIncome/Assets*), (2) Market Value-Assets (*MV/Assets*), (3) Debt-to-Assets (*Leverage ratio*), (4) Interest Expense-Assets (*IntExp/Assets*), (5) the *Current ratio* (measured as the firm's current ratio, the ratio of current assets over current liabilities), and (6) *Credit line drawdowns*. We plot these measures separately for firms that obtain an amendment after a violation (*Amendment*) and those that do not obtain an amendment (*Viola-*

9 We provide the same graphs using 16 quarters before and after a violation in the Online Appendix. The graphs are qualitatively very similar.

tion).

Pre-violation. Overall, the performance of these measures prior to a covenant violation is as expected, and violations appear to be the consequence of a substantial deterioration of firm performance leading up to the violation. Operating income scaled by average total assets declines by more than 40%. The leverage ratio (defined as total debt over total assets) increases by about 20%. The corresponding increase in the interest expense over asset ratio is in the order of magnitude of about 25%. Firm liquidity (measured as the firm's current ratio) declines by more than 30% and credit line drawdowns almost double to 40% of the credit line limit, on average. Consequently, market equity is deteriorating, and the market-to-book ratio declines by more than 12%. Interestingly, qualitatively, firms that obtain an amendment perform similar, however, the magnitudes differ. For example, they have higher market values, have lower interest expense over total assets, and they draw down their credit lines less before a covenant violation. For other measures, such as operating income over assets, these firms are virtually identical.

Post-violation. Post-violation, however, we observe significant performance differences. While the performance of both types of firms has similarly deteriorated before the violation, firms that remain in technical default begin to recover sooner and also recover faster. Measures related to interest expense and current ratio recover similarly for both firms. The leverage ratio recovers even more and sooner for firms that violate a covenant. However, measures related to operating income or leverage ratio recover relatively more for firms that obtain an amendment. A possible interpretation is that firms that violate covenants and stay in technical default experience a different and maybe even more stringent restructuring process based on their interactions with their lenders. We explore these conjectures below in this paper.

5.3 Investments, financing choices and firm performance post covenant violation

In the next step, we investigate changes in a firm's investment and financing policies as well as its performance in the four quarters following a covenant violation. We investigate both types of firms separately and assess changes in these policies for firms in different rating categories.

5.3.1 Methodology

We estimate the following regression model using OLS:

$$y_{i,t+4} - y_{i,t} = \alpha + \beta \times Violation_{i,t}^{New} + \theta \times X_{i,t} + \gamma_j \times \delta_t + \varepsilon_{i,t} \tag{1}$$

The dependent variable $y_{i,t+4} - y_{i,t}$ is the change in our proxies for firm investments, financing, and performance over the four quarters following a covenant violation. $Violation_{i,t}^{New}$ can take two values: $CovVio_{i,t}^{New}$ is an indicator that is 1 if the firm is in technical default in the quarter but has not been in technical default in the past four quarters. Alternatively, we use $Amend_{i,t}^{New}$, an indicator that is 1 if a firm has obtained an amendment in the quarter but not in the past four quarters. $X_{i,t}$ is a vector of firm control variables (operating cash flow scaled by assets, leverage ratio, the ratio of interest expense to assets, the ratio of net worth to assets, the current ratio, and the market-to-book ratio). We also add industry x quarter ($\gamma_j \times \delta_t$) fixed effects. All regressions include higher-order covenant control variables, and the four-quarter lag of these variables.[10] Standard errors are clustered at the firm level.

5.3.2 Implications of covenant violations for investments, financing and firm performance - Firms in technical default

We first investigate changes in investment and financing policies for firms that stay in technical default following a covenant violation relative to those firms that never violate a covenant (i.e., we drop those firms that obtain amendments).

Full sample. Table 3 shows the regression results and reports the results for implications of covenant violations on firm investment policies (Panel A) and financing policies (Panel B).[11] For each proxy, we show two specifications, over the full sample period and for the period up to (and including) Q4 2019, i.e., before the COVID-19 pandemic. Figure 3 suggests a significant increase in covenant amendments during this period and we want to make sure that our results are not driven by this period. Our proxies that have been used in previous literature (for example, Nini et al. (2012) and Roberts and Sufi (2009)) and our results confirm our economic intuition based on this literature. For example, Panel A of Table 3 shows that investments are significantly impaired in the four quarters following a (new) covenant violation, and assets, as PPE declines significantly, likely caused by divestitures of violating

[10] Including also a four-quarter lag of $Violations_{i,t}^{New}$ does not change our results.

[11] Other firm characteristics, for example, related to the operationg performance of the firms, is documented in the Online Appendix.

firms. Interestingly, capital expenditures, are no significantly different in the post-violation quarters. While lenders include explicit limitations on capital expenditures and acquisitions in corporate credit agreements to curtail investments if needed, they appear not to be binding.

Similarly, Panel B of Table 3 shows that firms significantly reduce leverage while they are in technical default. Total debt decreases (in levels) increases but mainly driven by the COVID-19 period. These firms also significantly decrease credit line drawdowns after the violation. Overall, debt investors appear to be somewhat more restrictive in offering funding to firms in technical default following covenant violations with an immediate impact on firm leverage.

By rating category. Table 4 shows the same regression as in Table 3 but interacting $CovVio^{New}$ with an indicator (1) that is one if a firm has a non-IG rating (*Non-IG*) or (2) that is one if a firm is unrated (*Unrated*). Indicators for rating categories are included individually, with IG rated firms as the omitted rating category. Panel A of Table 4 shows that investment policies are driven mainly by unrated firms. The latter reduces PPE by 16.5% and assets by 14.8%. The impact is likely larger for these firms due to limited funding options vis-a-vis, for example, rated firms.

Changes in financing policies of firms are driven particularly by non-IG rated firms, but also unrated firms exhibit adjustments. For example, both firms significantly reduce their debt levels after a covenant violation. Non-IG rated (unrated) firms reduce their debt by 29.3% (14.1%), likely driven by limited funding options. These results are reported in Panel B of Table 4. Non-IG rated firms increase cash and unrated firms repay their credit lines. None of our results appear to be driven by the COVID period.

5.3.3 Implications of covenant violations for investments, financing and firm performance - Amendments

In the next step, we investigate changes in investment and financing policies and firm performance for firms that obtain an amendment following a violation relative to those firms that never violate (i.e., we drop those firms that stay in technical default).

Full sample. We report these results in Table 5. Similar to our prior tests, we find that firms that obtain amendments change their policies in a similar way; however, the effects are far less pronounced. Firms reduce their assets as well as PPE, while CAPEX remains unchanged (Panel A). They also reduce debt, increase cash, and repay credit lines (Panel B). Comparing the coefficients to those obtained from the regressions shown in Table 3, we find that the magnitudes are 90% less, on average, for firms with loan amendments. Again, the effects are not driven by the COVID period. Firms reduce their outstanding credit lines more during the COVID period (the point estimate is somewhat smaller when this period is dropped from the sample). This is consistent with the literature highlighting the "dash for cash" and run on credit lines at the onset of the COVID pandemic (e.g., Acharya and Steffen (2020); Acharya et al. (2023)).

By rating category. Consistent with our earlier results, Table 6 also shows that changes are mainly driven by non-IG and unrated firms. Panel A of Table 6 shows that non-IG and unrated firms reduce assets, PPE, CAPEX, and cash acquisitions. The economic magnitude of the effects appears similar for firms in both rating categories.

Similarly, in Panel B of Table 6, we show that mainly non-IG rated and unrated firms reduce leverage and increase cash. This is intuitive as unrated firms lack access to alternative funding sources. The effects seem to be less pronounced compared to our results for violating firms. Figure 4 suggests that firms that obtain an amendment have a weaker deterioration in firm performance in the quarters before the violation, a possible explanation why our regression results are weaker for these firms in the first four quarters after a covenant violation. Overall, these results suggest that - also when firms obtain amendments - covenant violations have an important impact on the investment and financing policies of firms. These results are also mainly observed among non-IG and unrated firms (not among IG-rated firms).

6 Do covenant violations predict rating downgrades and bankruptcy?

In the previous sections, we highlighted the decline in covenant violations over the last decades, the increase in loans that eventually have been amended relative to those borrowers that went into technical default, and the differences for firms that are IG-rated, non-IG-rated or unrated. Moreover, we have shown performance differences between firms that have or have not obtained an amendment after the covenant violation. Broadly, firms with violations recovered earlier and faster across various proxies for firm financial or investment policies, even though their pre-violation performance was very similar. Specifically, our results suggest that the market value and the leverage ratio of firms that went into technical default improved relatively more compared to firms that have obtained an amendment. Both results could point to elevated bankruptcy risk of the former.

6.1 Descriptive analysis

We first investigate this question graphically in Figure 5. We plot the percentage of firms that remain in technical default in each year as well as those that obtain amendments together with bankruptcies in Panel A and together with downgrades in Panel B. Both bankruptcies and downgrades exhibit a similar cyclicality compared to technical defaults and loan amendments. Downgrades, however, are somewhat leading indicators to bankruptcies, as the latter usually occur with a specific time lag.

To put the importance of bankruptcies and downgrades into perspective, we focus on the COVID period. The number of defaults has reached its highest point after the 2008 global financial crisis (albeit substantially lower compared to 2008). In 2020, we record 46 firms that declare bankruptcy or about 1.4% of the firms in this year. Correspondingly, the number of downgrades in this year even exceeds the downgrades observed in 2008. In 2020, we identify 275 downgrades, which corresponds to 8.6% of firms in this year.

Overall, there is an association between covenant violations/ amendments and defaults or downgrades. In the next subsection, we explore this association empirically.

6.2 Empirical analysis

In this subsection, we test this empirically and ask whether a covenant violation (that is not followed by an amendment) is more predictive of future rating downgrades and, eventually, corporate bankruptcy compared to amendments. We bring this hypothesis to the data and estimate the following regression model using OLS:

$$y_{i,t+h} = \alpha + \beta \times CovVio_{i,t}^{New} + \theta \times X_{i,t} + \gamma_j \times \delta_t + \varepsilon_{i,t} \tag{2}$$

The dependent variable $y_{i,t+h}$ is a dummy variable that is one if the firm has experienced a rating downgrade by S&P within the next h (either four or eight) quarters ($Downgrade_{t+h}$); alternatively, it takes the value one if the firm declared bankruptcy within the next h (four or eight) quarters using the LoPucki bankruptcy data ($Default_{t+h}$). $CovVio_{i,t}^{New}$ is an indicator that is 1 if the firm was in technical default in quarter t but did not violate covenants in the past four quarters. $X_{i,t}$ is a vector of firm control variables (operating cash flow scaled by assets, leverage ratio, the ratio of interest expense to assets, the ratio of net worth to assets, the current ratio, and the market-to-book ratio). We also include industry x time ($\gamma_j \times \delta_t$) fixed effects. Standard errors are clustered at the firm level.

We report the results in Table 7 for firms in technical default (Panel A) and amendments (Panel B). We focus on firms in technical default first and drop all firms that violate covenants but obtain loan amendments. Columns (1) and (2) of Table A show the results in the subsample of rated firms and using $Downgrade_{t+h}$

with $h = 4$ ($h = 8$) as the dependent variable. We do not show the control variables for brevity. We find that firms with covenant violations are 2.7% (2.1%) more likely to be downgraded in the four (eight) quarters after a covenant violation. We then use $Default_{t+h}$ as the dependent variable in columns (3) to (5) with $h = 4$ and $h = 8$, respectively. We find that firms with covenant violations are 5.1% (5.3%) more likely to declare bankruptcy in the four (eight) quarters after violating a covenant compared to firms that do not violate. Again, the results are not driven by the COVID period.

In Panel B of Table 7, we investigate the implications of amendments on downgrades and bankruptcy using $Amend^{New}$ as the explanatory variable and run the same regressions. We drop all firms that violate covenants but stay in technical default. In the first eight quarters after the amendment, firms are about 1.3% more likely to be downgraded (column (3)). A higher downgrade likelihood vis-a-vis firms with violations, but no amendment is consistent with the former having, on average, better ratings to begin with. Firms are also more likely to default after amendments, that is, 0.6% (after four quarters) or 1.3% (after eight quarters, conditionally on not having defaulted earlier) relative to firms that do not violate covenants. Bankruptcy risk, however, is lower compared to firms that stay in technical default after covenant violations.

By rating category. As covenant violations have a large impact on the likelihood that a firm declares bankruptcy, we investigate these implications further for firms in different rating categories. Previous results suggest that changes within firms were more important for non-IG-rated and unrated firms, for example, because they might have less access to capital compared to IG-rated firms.

In Table 8, we document consistent results. IG-rated firms do not have a higher bankruptcy likelihood, if anything, it declines eventually after a violation when firms have implemented different policies. The increase in default rates stems mainly from non-IG-rated firms, which have a 16.6% to 16.7% higher likelihood to default (four and twelve quarters after a covenant violation, respectively). The increase in bankruptcy likelihood (while significant) is economically much smaller for unrated firms. We show these results in columns (1) to (3).

With respect to loan amendments, we find a statistically significant increase in default likelihood for non-IG-rated firms. This increase, however, is about 1.6% to 3% of the magnitude observed for firms that do not obtain amendments (columns (4) to (6)). We observe a similar dynamic for unrated firms.

Overall, these results are consistent with the interpretation that borrowers who violate covenants and do not obtain an amendment are financially weak, which might make it difficult for lenders to support the borrower after a violation.

7 Conclusion and ongoing research

7.1 Conclusion

We introduce a new machine learning (ML) algorithm that allows researchers to obtain quarterly information on covenant violations and loan amendments for all U.S. firms directly from their 10K and 10Q filings with the Securities and Exchange Commission (SEC). To calibrate our model, we obtain more than 580,000 10K and 10Q filings using the CIK identifier of the universe of Compustat firms. Our final dataset comprises 11,430 U.S. publicly listed non-financial firms over the 1996 to 2022 period.

We use the MPNET Sentence Transformer as a classification algorithm and obtain a model accuracy of 94.4% (in contrast to about 75% when using a manual approach, which has been frequently done in the past). Importantly, we are able to differentiate between firms that obtain an amendment after a covenant violation and those that enter a technical default. Covenant violations have significantly declined over the past two decades. During this time, the percentage of firms that received an amendment increased while those in technical default decreased. The decline in violations was driven by non-investment-grade rated and unrated firms and intensified during the COVID-19 pandemic. Firms that obtain amendments perform very similar to those that do not in the eight quarters before a covenant violation occurs, but their magnitude diverges. Firms with violations recover sooner and faster and, particularly, recover more in terms of leverage ratio and operating income. Firms in technical default make larger changes in their investment and financial policies as compared to firms that obtain amendments. Again, the effects are mainly driven by non-investment-grade rated and unrated firms. Not surprisingly, non-investment-grade rated firms are about 17% more likely to declare bankruptcy in the four quarters following a covenant violation. This effect is substantially muted in the sample of firms that obtain amendments after covenant violations.

7.2 Ongoing research

Going forward, we are going to expand the analysis in this paper in different ways:

1. We are going to extract information on the specific type of covenants that were included in the contract. While Dealscan provides covenants at origination, the SEC filings suggest that the covenant structure is actually much more dispersed compared to what Dealscan suggests. Moreover, covenants change over time (possibly through amendments outside of technical defaults). We then obtain information as to which covenants firms were not in compliance with and those for which the firms obtained an amendment. How do loan contracts change after a covenant violation with respect to different loan terms, especially loan covenants? When do lenders provide an amendment or waiver? While Dealscan provides some information about loan amendments, they do not show which covenants have been amended. Overall, this analysis aims to gain deeper insights into how lenders restrict borrower behavior and the dynamics of the lender-borrower relationships.

2. We provide a more in-depth discussion about the economic differences between firms that remain in technical default and those that obtain loan amendments. What determines the lenders' decision to provide (or not provide) a loan amendment or waive a covenant violation? What happens to firms in our sample that remain in technical default? Do lenders demand repayment? How constraint are these firms? Do they obtain loans from other lenders and, if so, at what terms?

3. We pair our covenant violations and loan amendments with secondary loan market credit spreads on an aggregate as well as firm level. To what extent can covenant violations or amendments be predicted by changes in loan spreads?

And how do spreads respond to violations?

4. The COVID-19 period is unprecedented in terms of covenant violations and amendments (particularly also for IG-rated firms). Why do we observe these large number of amendments? How has the use of covenants change after after COVID and has there been a permanent change in contract structures?

These are some of the questions that we aim to address in this paper in the near future.

References

V. V. Acharya and S. Steffen. The risk of being a fallen angel and the corporate dash for cash in the midst of covid. *The Review of Corporate Finance Studies*, 9 (3):430–471, 2020.

V. V. Acharya, R. F. Engle, M. Jager, and S. Steffen. Why did bank stocks crash during covid-19? Technical report, National Bureau of Economic Research, 2023.

K. Adler. Financial covenants, firm financing, and investment. *Firm Financing, and Investment (December 11, 2020)*, 2020.

S. Chava and M. R. Roberts. How does financing impact investment? the role of debt covenants. *The journal of finance*, 63(5):2085–2121, 2008.

K. C. Chen and K. J. Wei. Creditors' decisions to waive violations of accounting-based debt covenants. *Accounting review*, pages 218–232, 1993.

G. Chodorow-Reich and A. Falato. The loan covenant channel: How bank health transmits to the real economy. *The Journal of Finance*, 77(1):85–128, 2022.

A. M. Christenfeld. Forbearance agreements in funded credit arrangements. *UCC LJ*, 42:385–406, 2010.

D. J. Denis and J. Wang. Debt covenant renegotiations and creditor control rights. *Journal of Financial Economics*, 113(3):348–367, 2014.

T. Drechsel. Earnings-based borrowing constraints and macroeconomic fluctuations. *DP16975*, 2022.

N. Ersahin, R. M. Irani, and H. Le. Creditor control rights and resource allocation within firms. *Journal of Financial Economics*, 139(1):186–208, 2021.

A. Falato and N. Liang. Do creditor rights increase employment risk? evidence from loan covenants. *The Journal of Finance*, 71(6):2545–2590, 2016.

F. Freudenberg, B. Imbierowicz, A. Saunders, and S. Steffen. Covenant violations and dynamic loan contracting. *Journal of Corporate Finance*, 45:540–565, 2017.

D. Green. Corporate refinancing, covenants, and the agency cost of debt. *Covenants, and the Agency Cost of Debt (December 18, 2018)*, 2018.

D. Greenwald et al. *Firm debt covenants and the macroeconomy: The interest coverage channel*, volume 1. MIT Sloan School of Management, 2019.

T. P. Griffin, G. Nini, and D. C. Smith. Losing control? the 20-year decline in loan covenant violations. Technical report, Working Paper, 2021.

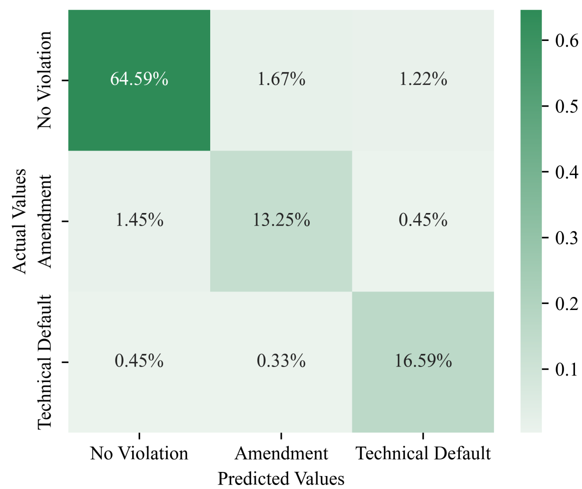
G. Matvos. Estimating the benefits of contractual completeness. *The Review of Financial Studies*, 26(11):2798–2844, 2013.

A. C. Müller and S. Guido. *Introduction to machine learning with Python: a guide for data scientists.* " O'Reilly Media, Inc.", 2016.

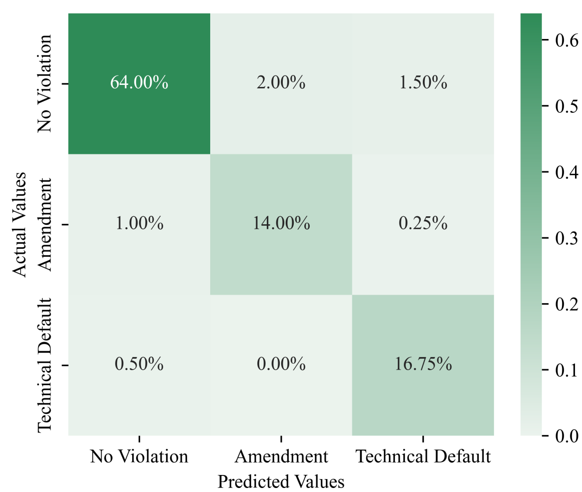
G. Nini, D. C. Smith, and A. Sufi. Creditor control rights, corporate governance, and firm value. *The Review of Financial Studies*, 25(6):1713–1761, 2012.

M. R. Roberts and A. Sufi. Financial contracting: A survey of empirical research and future directions. *Annu. Rev. Financ. Econ.*, 1(1):207–226, 2009.

Figures and Tables

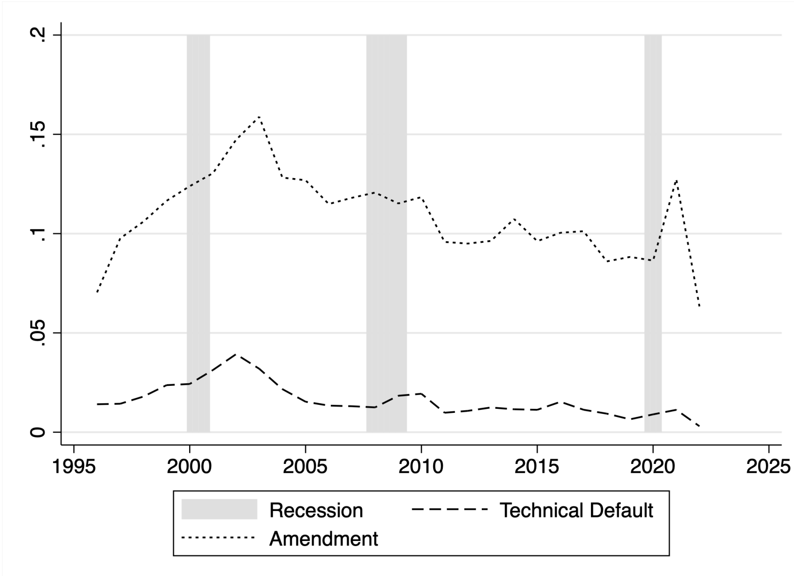


(a) Confusion matrix of the Test Data

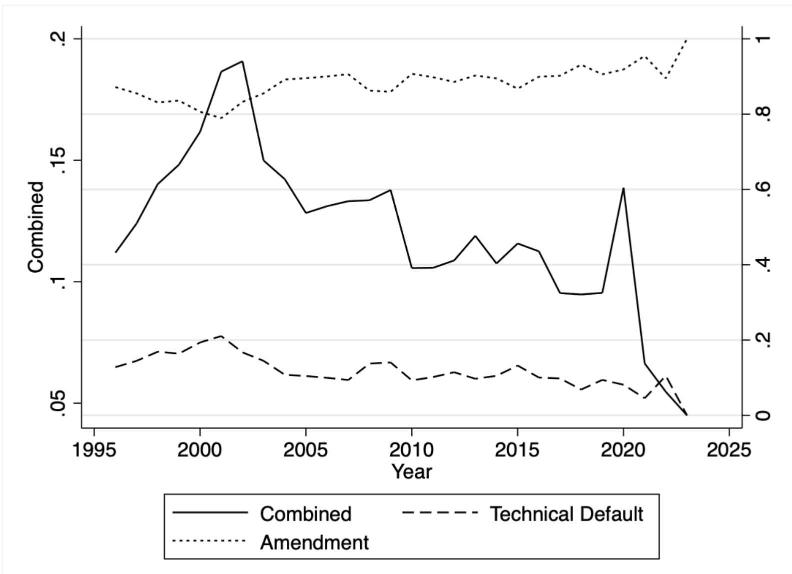


(b) Confusion matrix of the Validation Data

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

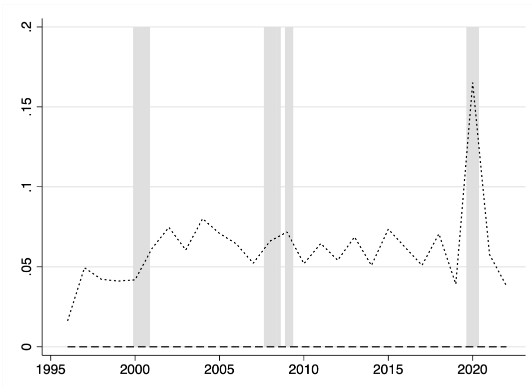


(a) Technical defaults and loan amendments

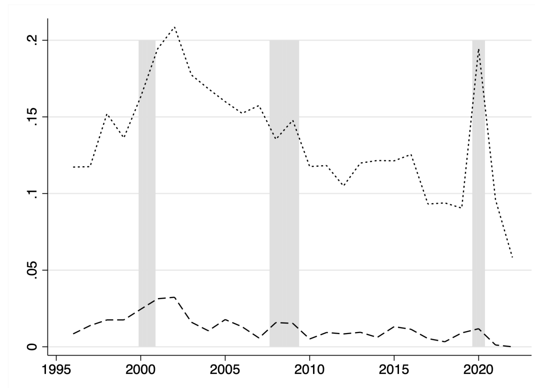


(b) Combined

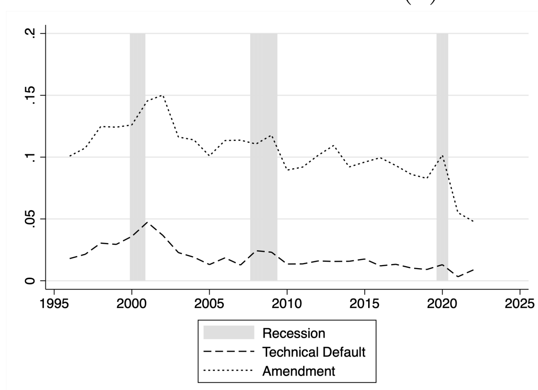
Figure 2: **Covenant Violation Distribution**
This figure plots the annual share of technical defaults and loan amendments for the full sample of U.S. publicly listed, non-financial firms. The shaded areas represent the NBER recession periods (Panel A). Panel B plots the combined share of technical defaults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



(a) IG rated firms



(b) Non-IG rated firms



(c) Unrated firms

Figure 3: **Technical defaults and Loan Amendments by credit rating**
This figure plots the annual share of technical defaults and loan amendments within their credit rating. The shaded areas represent the NBER recession periods. The right side plots the combined share of technical defaults and amendments and the proportion of technical defaults and amendments by credit rating.

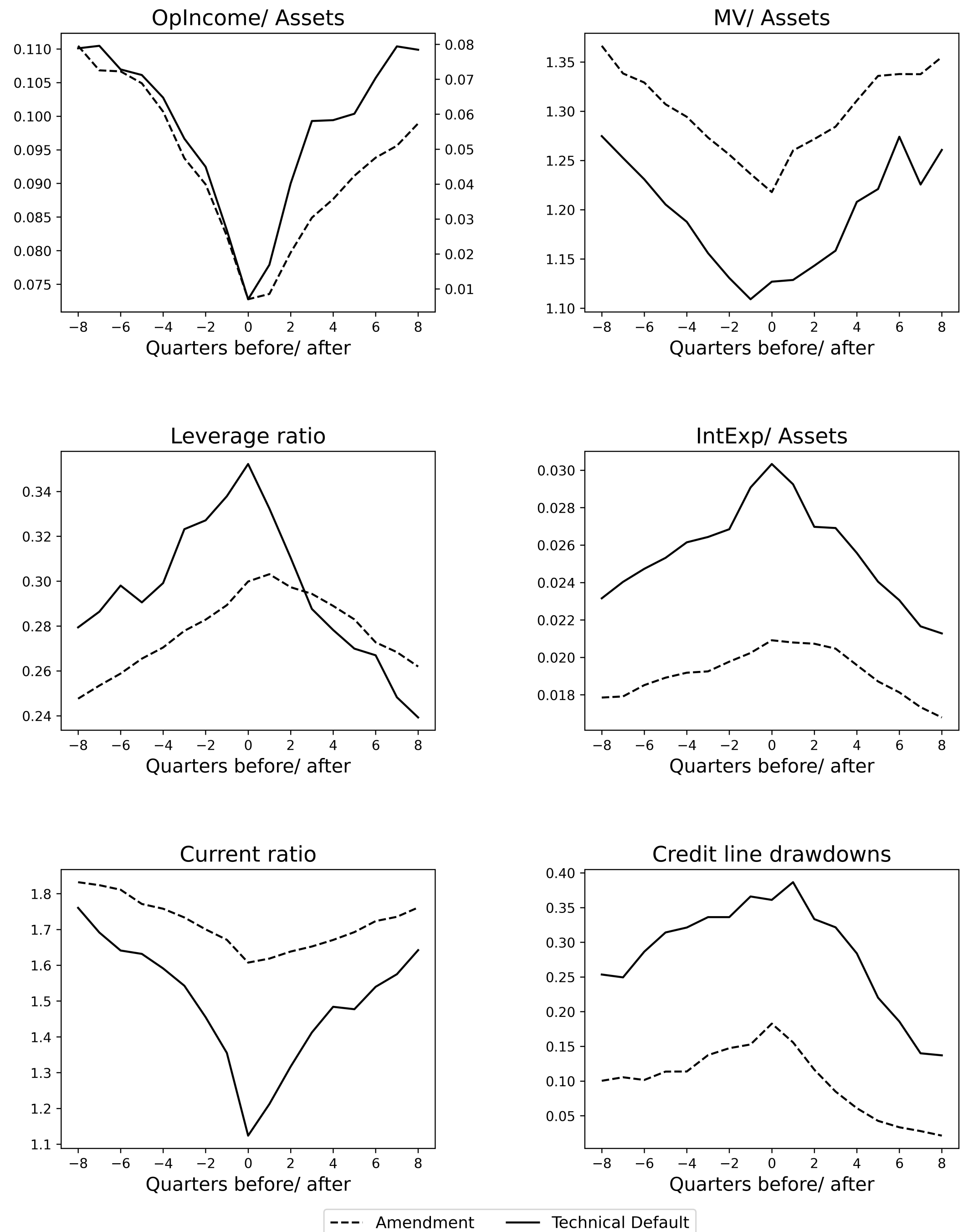
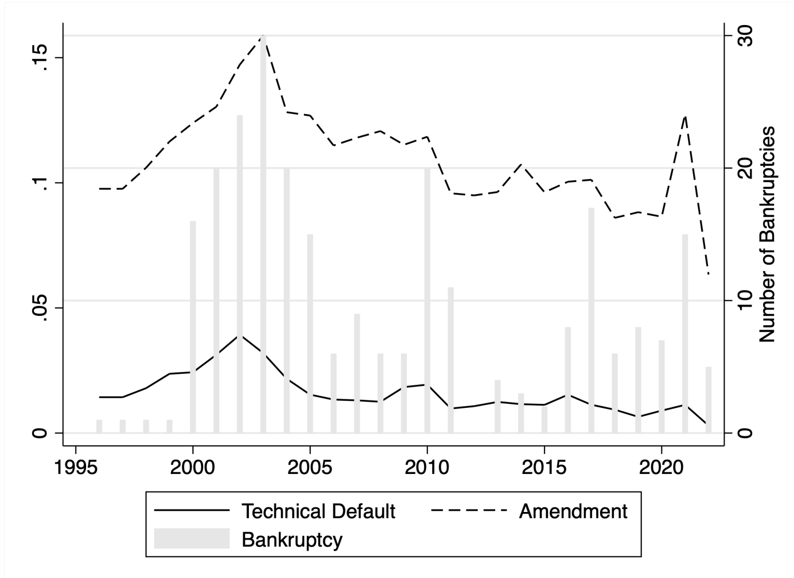
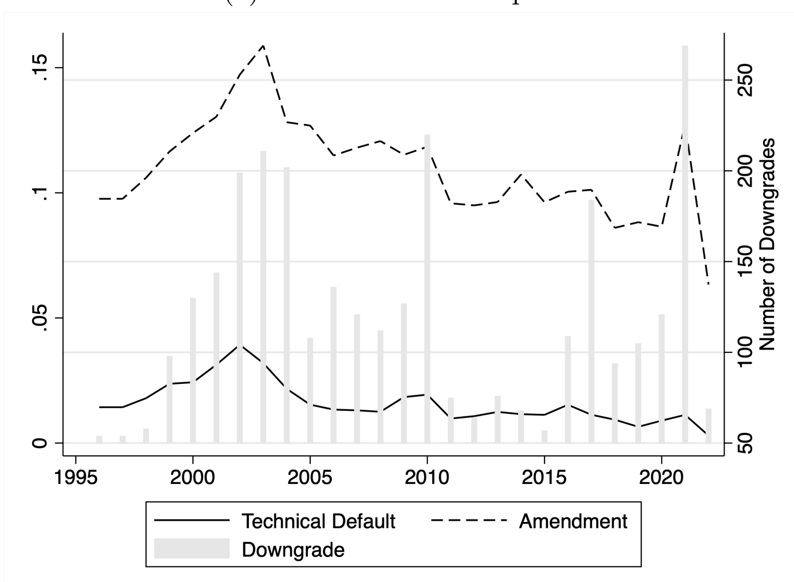


Figure 4: **Pre- vs. Post-Violation Performance**
This figure plots the performance of our sample firms up to eight quarters prior to and eight quarters post a covenant violation.



(a) Fraction of Bankruptcies



(b) Fraction of Downgrades

Figure 5: **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.

Table 1: **Summary Statistics**

This table provides the summary statistic for important firm characteristics and dependent variables of all firm quarter observations from 1996 to 2022. All absolute values are given in USD million. Panel B shows the distribution of violations and amendments for IG rated, non-IG rated, and unrated companies. The Rating data is based on the 2,337 rated companies. All variables are defined in the Appendix (Table 9).

Panel A: Firm characteristics

	Mean	Median	Min	Max	SD
CovVio	0.12	0.00	0.00	1.00	0.32
Amend	0.45	0.00	0.00	1.00	0.50
Assets	1,973.33	190.88	10.01	519,629.94	11,057.07
PPE/ Assets	0.24	0.15	0.00	1.00	0.23
Leverage ratio	0.25	0.20	0.00	8.64	0.27
Current ratio	4.25	2.27	0.00	1,126.37	13.94
MV/ Assets	4.18	1.66	0.05	12,509.97	140.88
PPE	631.33	25.88	0.00	162,525.95	3,636.17
CapEx/$\overline{Assets}$	0.06	0.04	-0.46	2.98	0.08
CashAqui/$\overline{Assets}$	0.03	0.01	-0.74	5.31	0.09
NetDebt/$\overline{Assets}$	0.04	0.01	-1.32	3.03	0.13
Debt	651.49	28.45	0.00	275,684.41	4,008.49
Cash/Assets	0.29	0.13	-0.00	1.00	0.32
Shareholder Payout	22.69	1.12	-14.67	6,758.34	165.60
OpIncome/Assets	0.99	0.81	-0.15	17.26	0.82
Sales	1,451.70	134.80	0.00	372,128.94	7,894.82
OpCosts	1,258.50	137.87	-0.43	342,734.69	6,979.07
Rating	BB-	BB-	D	AAA	
Observations	11,430				

Panel B: Violation and Amendment Distribution

	IG rated	Non-IG rated	Unrated
CovVio	0%	21.43%	78.57%
Amend	6.02%	29.45%	64.53%
No Covenant Violation	5.54%	13.33%	81.13%

Table 2: **Summary Statistics . Covenant Violations vs. Amendments**

This table provides the summary statistic for firms that violate covenants but obtain no amendment in Panel A and firms that violate a covenant but obtain an amendment in Panel B. Panel C provides a difference in mean test for those variables (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Firms in Technical Default

	Mean	Median	Min	Max	SD
Assets	1,566.73	88.18	10.88	197,238.28	12,251.69
PPE/ Assets	0.26	0.15	0.00	0.91	0.24
Leverage ratio	0.33	0.29	0.00	2.24	0.29
Current ratio	2.72	1.76	0.11	22.37	2.89
MV/ Assets	1.96	1.56	0.33	16.94	1.46
PPE	411.00	12.41	0.00	53,478.40	3,315.78
CapEx/$\overline{Assets}$	0.07	0.04	-0.05	0.96	0.12
CashAqui/$\overline{Assets}$	0.03	0.00	-0.14	0.93	0.07
NetDebt/$\overline{Assets}$	0.06	0.02	-0.29	0.84	0.14
Debt	480.54	21.34	0.00	66,167.95	3,997.15
Cash/Assets	0.24	0.14	0.00	0.99	0.26
Shareholder Payout	14.07	1.01	0.63	1,445.20	103.97
OpIncome/Assets	1.06	0.92	0.08	4.70	0.71
Sales	1,050.63	68.23	0.00	144,333.61	8,719.43
OpCosts	948.17	71.68	3.77	128,088.62	7,786.50
Rating	B	BB-	C+	A	
IG Rated	2%				
Non-IG Rated	7%				
Unrated	91%				
Observations	288				

Panel B: Firms with Amendments

	Mean	Median	Min	Max	SD
Assets	2,232.33	325.84	10.48	247,270.20	8,583.93
PPE/ Assetss	0.28	0.19	0.00	0.95	0.23
Leverage ratio	0.30	0.27	0.00	2.36	0.22
Current ratio	2.56	1.99	0.05	36.09	2.29
MV/ Assets	1.92	1.51	0.42	47.19	1.47
PPE	779.40	59.37	0.00	79,924.69	3,335.59
CapEx/$\overline{Assets}$	0.06	0.04	-0.01	0.88	0.07
CashAqui/$\overline{Assets}$	0.04	0.02	-0.09	1.38	0.06
NetDebt/$\overline{Assets}$	0.04	0.02	-0.62	1.22	0.09
Debt	807.34	79.26	0.00	138,285.48	3,537.77
Cash/Assets	0.19	0.07	0.00	1.00	0.25
Shareholder Payout	23.90	1.52	-1.85	4,725.94	134.50
OpIncome/Assets	1.12	0.94	0.01	17.26	0.88
Sales	1,738.70	301.50	0.00	151,409.36	6,097.47
OpCosts	1,498.59	260.31	1.99	131,462.94	5,346.37
Rating	BB-	BB-	D	AA+	
IG Rated	6%				
Non-IG Rated	20%				
Unrated	74%				
Observations	4,088				

Panel C: T-Test

	Assets	PPE/ Assets	Leverage ratio	Current ratio
Difference	665.59	0.02	-0.03**	-0.16

	MV/ Assets	PPE	CapEx/$\overline{Assets}$	CashAqui/$\overline{Assets}$
Difference	-0.04	368.40*	-0.01*	0.01

	NetDebt/$\overline{Assets}$	Debt	Cash/Assets	Shareholder Payout
Difference	-0.02***	326.79	-0.03***	9.84

	OpIncome/Assets	Sales	OpCosts	Rating
Difference	0.06	688.07*	550.42	-2.02***

Table 3: **Firms in Technical Default & Firm Policies**

Panel A shows the regression results using the change in Ln Assets, the change in Ln PPE, and the change of CapEx over Average Assets as dependent variables. The changes are always calculated based on four quarters following the covenant violation. Panel B shows the results using the change in Ln Debt, the ratio change of Cash and Average Assets, and the change in Credit Line Drawdowns as dependent variables. All regressions include the following firm characteristics: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. The regressions also include a lag of four quarters and higher order controls for these variables. We include industry times quarter fixed effects and cluster standard errors at the firm level. Standard errors are reported in parentheses (* $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Investment Policies

	Ln(Δ Assets)		Ln(Δ PPE)		Δ CapEx/$\overline{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CovVio^{New}	-0.128***	-0.126***	-0.129***	-0.129***	-0.005	-0.004
	(0.026)	(0.027)	(0.022)	(0.022)	(0.004)	(0.004)
Observations	185,810	171,180	184,790	170,336	182,380	167,837
R^2	0.233	0.229	0.370	0.378	0.125	0.124
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Panel B: Financing Policies

	Ln(Δ Debt)		Δ Cash/Assets		Δ Drawdown	
	(1)	(2)	(3)	(4)	(5)	(6)
CovVio^{New}	-0.182***	-0.173***	0.041***	0.008*	-0.053**	-0.055**
	(0.041)	(0.041)	(0.004)	(0.004)	(0.0257)	(0.027)
Observations	161,524	147,070	192,485	177,380	74,832	67,380
R^2	0.189	0.192	0.248	0.243	0.226	0.214
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Table 4: **Firms in Technical Default & Firm Policies - Rating Categories**

Panel A shows the regression results using the change in Ln Assets, the change in Ln PPE, and the change of CapEx over Average Assets as dependent variables. Panel B shows the results using the change in Ln Debt, the ratio change of Cash and Average Assets, and the change in Credit Line Drawdowns as dependent variables. The changes are always calculated based on four quarters following the covenant violation. We add Non-IG Rated and Unrated as indicator variables for rating classes. IG Rated is the omitted category. We also add interaction terms of our rating categories with $CovVio^{New}$. All regressions include the following firm characteristics: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. The regressions also include a lag of four quarters and higher order controls for these variables. We include industry times quarter fixed effects and cluster standard errors at the firm level. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment Policies

	Ln(Δ Assets)		Ln(Δ PPE)		Δ CapEx/$\overline{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CovVio^{New} x Non-IG	-0.063**	-0.059*	-0.008	-0.004	-0.004	-0.003
	(0.030)	(0.032)	(0.034)	(0.035)	(0.011)	(0.011)
CovVio^{New} x Unrated	-0.148***	-0.146***	-0.165***	-0.166***	-0.004	-0.004
	(0.014)	(0.035)	(0.019)	(0.027)	(0.002)	(0.003)
Non-IG Rated	0.026***	0.030***	0.031***	0.035***	-0.002***	-0.003***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.001)	(0.001)
Unrated	-0.038***	-0.034***	-0.021***	-0.019***	-0.005***	-0.005***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.001)	(0.001)
Observations	185,810	171,180	184,790	170,336	182,380	167,837
R^2	0.237	0.233	0.372	0.379	0.126	0.125
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Panel B: Financing Policies

	Ln(Δ Debt)		Δ Cash/Assets		Δ Drawdown	
	(1)	(2)	(3)	(4)	(5)	(6)
CovVio^{New} x Non-IG	-0.293***	-0.286***	0.013**	0.013**	-0.038	-0.032
	(0.101)	(0.103)	(0.006)	(0.006)	(0.042)	(0.045)
CovVio^{New} x Unrated	-0.141***	-0.131***	0.007	0.006	-0.055*	-0.056*
	(0.045)	(0.046)	(0.005)	(0.005)	(0.031)	(0.032)
Non-IG Rated	0.043***	0.041***	-0.001	-0.001	0.002	0.006*
	(0.010)	(0.010)	(0.001)	(0.001)	(0.003)	(0.004)
Unrated	-0.056***	-0.063***	-0.002*	-0.000	-0.012***	-0.011**
	(0.013)	(0.014)	(0.001)	(0.001)	(0.004)	(0.004)
Observations	155,219	141,235	185,782	171,152	75,484	67,877
R^2	0.193	0.197	0.250	0.244	0.228	0.216
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Table 5: **Amendments & Firm Policies**

Panel A shows the regression results using the change in Ln Assets, the change in Ln PPE, and the change of CapEx over Average Assets as dependent variables. Panel B shows the results using the change in Ln Debt, the ratio change of Cash and Average Assets, and the change in Credit Line Drawdowns as dependent variables. The changes are always calculated based on four quarters following the covenant violation. The regressions include the following control variables: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. The regressions also control for a lag of four quarters and higher order controls for those variables. We include industry x quarter fixed effects and cluster standard errors at the firm level, reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment Policies

	Ln(Δ Assets)		Ln(Δ PPE)		Δ CapEx/$\overline{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Amend^{New}	-0.028***	-0.027***	-0.026***	-0.027***	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.002)	(0.002)
Observations	191,745	176,663	190,715	175,810	188,236	173,245
R^2	0.234	0.231	0.369	0.377	0.122	0.121
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Panel B: Financing Policies

	Ln(Δ Debt)		Δ Cash/Assets		Δ Drawdown	
	(1)	(2)	(3)	(4)	(5)	(6)
Amend^{New}	-0.036***	-0.037***	0.004***	0.004***	-0.019***	-0.016***
	(0.012)	(0.012)	(0.001)	(0.001)	(0.006)	(0.006)
Observations	160,810	146,377	191,716	176,634	78,339	70,425
R^2	0.189	0.192	0.249	0.244	0.228	0.214
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Table 6: **Amendments & Firm Policies - Rating Categories**

Panel A shows the regression results using the change in Ln Assets, the change in Ln PPE, and the change of CapEx over Average Assets as dependent variables. Panel B shows the results using the change in Ln Debt, the ratio change of Cash and Average Assets, and the change in Credit Line Drawdowns as dependent variables. The changes are always calculated based on four quarters following the covenant violation. We add Non-IG Rated and Unrated as indicator variables for rating classes. IG Rated is the omitted category. We also add interaction terms of our rating categories with $Amend^{New}$. All regressions include the following firm characteristics: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. The regressions also include a lag of four quarters and higher order controls for these variables. We include industry times quarter fixed effects and cluster standard errors at the firm level. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Investment Policies

	Ln(Δ Assets)		Ln(Δ PPE)		Δ CapEx/$\overline{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Amend^{New} x IG	0.009	0.015	0.013	0.014	-0.002	-0.003
	(0.013)	(0.015)	(0.013)	(0.015)	(0.003)	(0.003)
Amend^{New} x Non-IG	-0.035***	-0.036***	-0.025***	-0.029***	-0.001	-0.002
	(0.007)	(0.008)	(0.008)	(0.009)	(0.004)	(0.004)
Amend^{New} x Unrated	-0.030***	-0.028***	-0.033***	-0.032***	-0.002	-0.002
	(0.006)	(0.007)	(0.008)	(0.008)	(0.002)	(0.002)
Non-IG Rated	0.026***	0.029***	0.031***	0.034***	-0.002***	-0.003***
	(0.005)	(0.005)	(0.005)	(0.006)	0.001)	(0.001)
Unrated	-0.038***	-0.034***	-0.022***	-0.020***	-0.005***	-0.005***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.001)	(0.001)
Observations	191,745	176,663	190,715	175,810	188,236	173,245
R^2	0.238	0.235	0.371	0.378	0.122	0.121
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Panel B: Financing Policies

	Ln(Δ Debt)		Δ Cash/Assets		Δ Drawdown	
	(1)	(2)	(3)	(4)	(5)	(6)
Amend^{New} x IG	0.054**	0.057**	-0.006*	-0.005	0.007	0.014
	(0.023)	(0.025)	(0.003)	(0.004)	(0.014)	(0.015)
Amend^{New} x Non-IG	-0.029*	-0.030*	0.004**	0.004***	-0.030***	-0.027***
	(0.016)	(0.017)	(0.002)	(0.002)	(0.009)	(0.009)
Amend^{New} x Unrated	-0.053***	-0.053***	0.006***	0.006***	-0.014*	-0.012
	(0.017)	(0.018)	(0.002)	(0.002)	(0.008)	(0.008)
Non-IG Rated	0.040***	0.038***	-0.001	-0.001	0.001	0.005
	(0.010)	(0.010)	(0.001)	(0.001)	(0.003)	(0.003)
Unrated	-0.058***	-0.064***	-0.002*	-0.001	-0.012***	-0.011**
	(0.013)	(0.014)	(0.001)	(0.001)	(0.004)	(0.004)
Observations	160,810	146,377	191,716	176,634	78,339	70,425
R^2	0.190	0.194	0.249	0.244	0.228	0.214
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES

Table 7: **Downgrade and Default**

This table provides the regression results using *Downgrade* and Default as dependent variables (both over $t+4$ and $t+8$ quarters after a covenant violation). *Downgrade* is an indicator that is one if the firm was downgraded during this period. *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period. We show specifications for the full sample period as well as until (and including) Q4 2019, i.e., before the onset of the COVID-19 pandemic. Panel A regresses the outcome variables on $CovVio^{New}$, an indicator that is one if the company remained in technical default after a covenant violation. Panel B regresses the outcome variables on $Amend^{New}$, an indicator that is one if the company obtained an amendment after a covenant violation. The regressions include the following control variables: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. We include industry x quarter fixed effects and cluster standard errors at the firm levels, which are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Violations

	Downgrade$_{t+4}$		Downgrade$_{t+8}$		Default$_{t+4}$		Default$_{t+8}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CovVio^{New}	0.030	0.033	0.006	0.018	0.051***	0.049***	0.053***	0.051***
	(0.028)	(0.028)	(0.033)	(0.033)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	85,134	77,054	85,319	77,225	256,641	230,614	256,641	230,614
R^2	0.311	0.299	0.379	0.381	0.151	0.152	0.167	0.168
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Amendments

	Downgrade$_{t+4}$		Downgrade$_{t+8}$		Default$_{t+4}$		Default$_{t+8}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Amend^{New}	0.013**	0.015**	0.013	0.012	0.006***	0.006***	0.013***	0.013***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	79786	79786	88353	79967	264485	237795	264485	237795
R^2	0.309	0.296	0.377	0.379	0.148	0.149	0.165	0.166
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 8: **Covenant Violations & Defaults**

This table provides the regression results using Default as dependent variable (over $t+4$ and $t+8$ quarters after a covenant violation). *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period. We show specifications for the full sample period as well as until (and including) Q4 2019, i.e., before the onset of the COVID-19 pandemic. In columns (1) - (4), we regress the outcome variable on $CovVio^{New}$, an indicator that is one if the company remained in technical default after a covenant violation. In columns (5) - (8), we regress the outcome variable on $Amend^{New}$, an indicator that is one if the company obtained an amendment after a covenant violation. We add Non-IG Rated and Unrated as indicator variables for rating classes. IG Rated is the omitted category. We also add interaction terms of our rating categories with $CovVio^{New}$ (columns (1) - (4)) and $Amend^{New}$ (columns (5) - (8)). The regressions include the following control variables: the ratio of Operating Income and Average Assets, the Leverage Ratio, the ratio of Net Worth and Assets, the Market-to-book-ratio, the ratio of Interest expenses and Average Assets, and the Current ratio. We include industry x quarter fixed effects and cluster standard errors at the firm levels, which are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	CovVio^{New}				**Amend**^{New}			
	Default$_{t+4}$		Default$_{t+8}$		Default$_{t+4}$		Default$_{t+8}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CovVio^{New} x Non-IG	0.167***	0.158***	0.166***	0.156***				
	(0.023)	(0.023)	(0.025)	(0.025)				
CovVio^{New} x Unrated	0.018***	0.018***	0.020***	0.019***				
	(0.006)	(0.006)	(0.006)	(0.007)				
Non-IG Rated	0.008***	0.008***	0.018***	0.019***				
	(0.001)	(0.001)	(0.002)	(0.002)				
Unrated	0.002***	0.002***	0.004***	0.005***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Amend^{New} x IG					0.001	0.001	0.004	0.004
					(0.003)	(0.004)	(0.006)	(0.007)
Amend^{New} x Non-IG					0.016***	0.015***	0.030***	0.031***
					(0.003)	(0.003)	(0.004)	(0.004)
Amend^{New} x Unrated					-0.000	-0.000	0.002	0.002
					(0.001)	(0.001)	(0.002)	(0.002)
Non-IG Rated					0.008***	0.008***	0.018***	0.019***
					(0.001)	(0.001)	(0.002)	(0.002)
Unrated					0.002***	0.002***	0.004***	0.004***
					(0.001)	(0.001)	(0.001)	(0.002)
Observations	256,641	230,614	256,641	230,614	264,485	237,795	264,485	237,795
R^2	0.155	0.156	0.170	0.171	0.149	0.150	0.167	0.169
Sample	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID	Full	Pre-COVID
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Yq FE	YES	YES	YES	YES	YES	YES	YES	YES

A Appendix

A.1 Variable Definition

Table 9: Compustat Variables used for quarterly financial data

Variable Names	Variables	Compustat Variables
Assets	Total assets	= atq
$\overline{Assets}$	Average assets	= (Total assets + lagged Total assets) /2
MV	Market value	= Market value of equity – book value of equity + total assets
MV Equity	Market value of equity	= prccq * cshoq
BV Equity	Book value of equity	= Total assets – ltq + txditcq
Debt	Total debt	= dltcq + dlttq
PPE / Assets	PPE scaled by assets	= ppentq / Total assets
Div	Dividends	= dv adjusted for fisical quarter accumulation
Stock purchased	Purchase of common and preferred stocks	= prstkc adjusted for fisical quarter accumulation
CapEx	Capital expenditures quarterly	= capxy adjusted for fiscal quarter accumulation
CashAcqui	Cash acquisitions quarterly	= aqcy adjusted for fiscal quarter accumulation
Sales	Sales	= saleq
	Control Variables	
OpIncome/$\overline{Assets}$	Operating income scaled by average assets	= oibdpq / Average assets
Leverage ratio	Leverage ratio	= Total debt / Total assets
NW / Assets	Net worth to assets ratio	= seqq / Total assets
MV / Assets	Market-to-book-ratio	= Market value / Total assets
IntExp / $\overline{Assets}$	Interest expense scaled by average assets	= xintq / Average assets
Current ratio	Current ratio	= actq / lctq
	Dependent Variables	
Ln(Δ Assets)	Change in Ln(assets)	Ln(total assets)$_{t+4}$-Ln(total assets)$_t$
Ln(Δ PPE)	Change in Ln(PPE)	Ln(PPE)$_{t+4}$-Ln(PPE)$_t$
Δ CapEx/$\overline{Assets}$	Capital expenditures scaled by average assets	= Capital expenditures / Average assets
Δ CashAqui/$\overline{Assets}$	Cash acquisitions scaled by average assets	= Cash acquisitions / Average assets
Δ NetDebt/$\overline{Assets}$	Net debt issuance scaled by average assets	= (Total debt – Total lagged debt) / average assets
Ln(Δ Debt)	Change in Ln(total debt)	= Ln(total debt)$_{t+4}$-Ln(total debt)$_t$
Δ Cash/Assets	Cash scaled by assets	= cheq /Total assets
Ln(Δ Payout)	Change in Ln(shareholder payout)	Ln(shareholder payout)$_{t+4}$-Ln(shareholder payout)$_t$
Δ OpIncome/$\overline{Assets}$	Change Operating cash flow by average assets	= (OpIncome/Assets)$_{t+4}$ - (OpIncome/Assets)$_t$
Ln(Δ Sales)	Change in Ln(sales)	Ln(sales)$_{t+4}$-Ln(sales)$_t$
Ln(Δ OpCosts)	Change in Ln(Operating Costs)	= Ln(Operating Costs)$_{t+4}$-Ln(Operating Costs)$_t$

A.2 Industry classification

Table 10: Mapping of SIC Code to Industry classification

SIC range	Industry classification[12]
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

A.3 Ratings

Table 11: Mapping of 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

A.4 Covenant Violation and Amendment Classification

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)[13]. 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)[14]. Information on a firm's bankruptcy probability, leverage ratio, size, and security of the issued debt are deciding determinants of waiver decisions (Chen and 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

[13] https://corporatefinanceinstitute.com/resources/commercial-lending/debt-covenants/

[14] https://dictionary.cambridge.org/de/worterbuch/englisch/waiver

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 covenent 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 EDITDA 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 non-compliance with the EBITDA covenant for the third quarter ended September 30, 2011, but the Bank has not yet done so. [15]

- 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

[15] $https://www.sec.gov/Archives/edgar/data/1463972/000114420411066092/v241021_10q.htm$

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.[16]

- 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. [17]

- 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. [18]

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

[16] https : //www.sec.gov/Archives/edgar/data/1368365/000136836519000048/mark30sep201910q.htm
[17] https : //www.sec.gov/Archives/edgar/data/1590695/000143774920018261/tlcc20200630$b_1$0q.htm
[18] https : //www.sec.gov/Archives/edgar/data/1046057/000143774914015440/tcec20140630$_1$0q.htm

not in compliance with its covenants as of December 31, 2007, but not in default because a Bank waiver has been received. [19]

- 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.[20]

- 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

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

[20] https://www.sec.gov/Archives/edgar/data/1042173/000104217313000018/scil-20130630x10q.htm

of the Lumata Facility and payment schedule remain unchanged.[21]

- 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.[22]

[21] https://www.sec.gov/ix?doc=/Archives/edgar/data/0001052054/000156276221000443/evol-20210930x10q.htm

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

A.5 MPNET Sentence Transformer Model

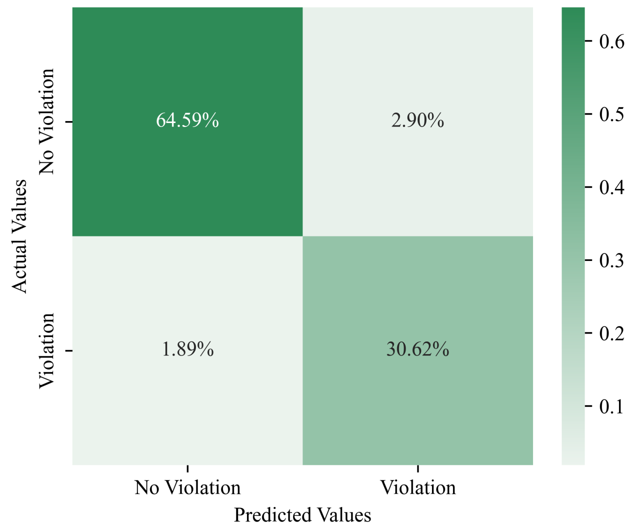
Table 12: Precision, Recall, F1-score for Test and Validation Data

	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

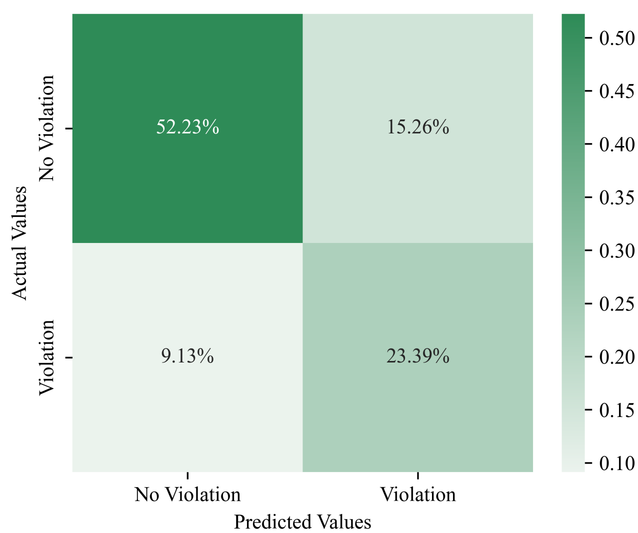
Hyperparameter	**Description**
Num_train_epochs = 12	Total number of training epochs
Per_device_train_batch_size = 10	Batch size per device during training
Per_device_eval_batch_size = 10	Batch size for evaluation
Warmup_steps = 500	Number of warmup steps for learning rate scheduler
Weight_decay = 0.01	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

Table 13: Model Training Hyperparameters

A.6 Comparison with the Nini et al. Algorithm



(a) Confusion matrix of our ML algorithm



(b) Confusion matrix of the Nini et al. (2012) algorithm

Figure 6: Confusion matrix of ML and Nini et al. (2012) algorithm

A.7 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 forebearance 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!

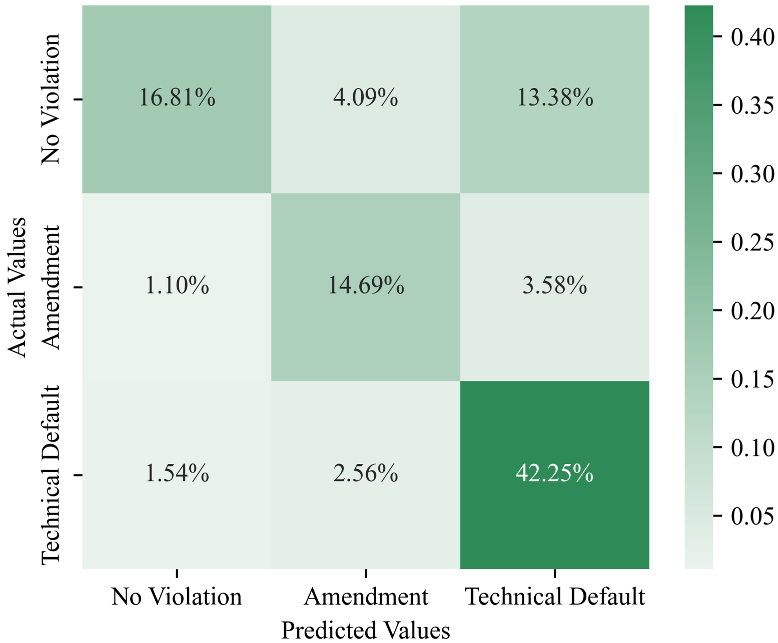


Figure 7: Confusion matrix of Chat GPT labeling